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Milling Tool Wear Prediction Method Based on Deep Learning Under Variable Working Conditions

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ABSTRACT Tool wear prediction is essential to ensure part quality and machining efficiency. Tool wear is affected by factors such as the material, structure, process, and processing time of the parts. Tool wear under the variable working conditions and the above factors show a complex coupling and timing correlation, which makes it challenging to predict tool wear under variable working conditions. This article aims to resolve this issue. First, we establish a unified representation of working condition factors. The stacked autoencoder (SAE) model adaptively extracts tool wear features from the machining signal. The extracted wear features and respective working conditions then combine into a working condition feature sequence for predicting tool wear. Finally, the advantages of the long short-term memory (LSTM) model to solve memory accumulation effects learn the regular wear pattern of the working condition feature sequence to realize the prediction of the tool wear. An experiment illustrates the effectiveness of the proposed method.

INDEX TERMS Variable working conditions, tool wear prediction, long short-term memory, stacked auto-encoder.

I. INTRODUCTION

The tool is a direct executor of machining operation, and its wear prediction is of great significance for ensuring the quality of parts, improving efficiency, and reducing costs. With the multi-variety and small batch production requirements, tools aid in different processing techniques, parts materials, and processing forms. The variable mentioned above, working conditions, make it challenging to monitor tool wear. It is difficult to estimate the available tool time under variable working conditions. An early tool replacement increases cost because limited device utilization, while overly frequent tool change increases processing time. If the replacement of the tool is not timely, the quality of the components will be affected. The machine tool will shatter or even damage the machine tool. About 20 % of the machine tool downtime stems from tool breakage. The cost of the instrument and the device changed accounts for 3 % to 12 % of the total cost [1], [2]. Therefore, it is necessary to study tool wear under variable working conditions.

The tool wear features are extracted from these signals to determine the tool wear status indirectly. Developments in sensing allow the collection of sensor signals related to tool wear during processing. The collection includes cutting force signal, vibration signal, acoustic emission signal, current signal [3], [4]. It has become an effective method for real-time monitoring of tool wear during machining [5]. Existing tool wear prediction methods [6], [7] mostly assume fixed working conditions, but the processing objects and processing techniques are often changeable when using the tool. The following difficulties exist with achieving tool wear prediction under variable operating conditions:

(1) Tool wear is affected by the coupling of various working conditions, and the effect mechanism is complicated and unclear. In the single-piece and small-batch production mode, the tool is used under the terms of changing processing objects and processing techniques. There is a coupling relationship between tool wear, working condition factors

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(parts materials, parts structure, processing technology, processing time), and machining signals (force signal, vibration signal). Because the above factors change dynamically, it is difficult to establish a precise mathematical model to analyze the complicated relationship between tool wear and these factors.

(2) Tool wear shows a cumulative effect on the time series, and the cutting time of the tool is not fixed every time. It is difficult for general prediction models to meet this variable time series forecasting requirement. In the actual cutting scene, the tool wear is not only related to the current working conditions but also related to the historical processing information of the tool, that is, the tool wear has a time-series correlation. At the same time, the different processing time will have different effects on tool wear. The established prediction model needs to have the ability of ''memory'' and to adapt to tool wear prediction under different time series flexibly.

Given the above difficulties, we propose a method for predicting tool wear under variable working conditions based on deep learning. Thoroughly consider the factors that affect the tool wear, study the complicated relationship between the working condition factors and the milling tool wear, and use the LSTM [8] network to establish the milling tool wear prediction, model. LSTM network cells have a unique ''gate'' structure, which can remember information for a long time. This structure can memorize the historical processing information of the tool during the milling process, to solve the problem of the cumulative effects of tool wear over time. Since LSTM hidden layer cells are connected orderly, the number of connected input nodes is determined according to the characteristics of the problem to be solved. LSTM has superior performance in solving variable sequence problems. Therefore, we attempt to use LSTM to deal with the complex relationship between working conditions and tool wear.

In summary, we propose a unique method to solve the problem of tool wear prediction under variable operating conditions. First, the factors of the working condition of different types are expressed in a unified way. Then, the signal features related to wear are extracted from different machining signals, and they are fused at the feature layer to obtain the tool wear features. Finally, the wear feature and the corresponding working conditions information merge to derive the working condition feature sequence, and the input establishes the LSTM model. Thus, the tool wear rule under variable working conditions is obtained.

II. RELATED WORK

A. PATTERN RECOGNITION OF TOOL WEAR STATE

Traditional machine learning methods include support vector machines, decision trees, clustering, artificial neural networks. These procedures are data-driven and based on statistical theory. The cutting process provides relevant data. Factors related to tool wear establish the regression or inference model. Scholars at home and abroad emphasize the traditional machine learning methods to predict tool wear. Rizal *et al.* [9] proposed a signal statistical method I-Kaz and combined with the adaptive network fuzzy reasoning system to establish the prediction model of the turning tool. McParland *et al.* [10] proposed a method to develop a tool wear prediction model using Bayesian hierarchical Gaussian process. Wu *et al.* [11] proposed a tool wear prediction method based on random forest, and the effectiveness of the plan was verified by using the open milling tool wear data set. Wu *et al.* [12] used an acoustic emission sensor to collect data and extract characteristic parameters to establish a real-time monitoring system for the wear state of the boring cutter. Liu [13] used time-domain, frequency-domain, wavelet packet analysis, and other methods to extract features of machining signals. They constructed an autoregressive moving average model and three-layer backpropagation neural network combination model respectively to predict tool wear. Xie *et al.* [14] used principal component analysis to extract the characteristics of current and power signals and established the c-support vector machine tool wear state recognition model. Bustillo *et al.* [15] used five regression methods to predict tool wear, including decision tree-based regressors, ensemble regressors, artificial neural networks, support vector regression, and k-nearest neighbor regressor. By comparing the results of each model, they concluded that the most accurate model was the rotation forest with unpruned REPTree as its base regressors.

Traditional machine learning methods have made significant progress in tool wear prediction. The network of conventional machine learning methods usually adopts a shallow structure. Modeling the relationship between working conditions and tool wear in high-dimensional space is challenging and limits the complex nonlinear relationship between tool wear and cutting signal feature information, and the establishment of the model depends on the selection of feature information. Therefore, how to extract the features of the massive cutting data in the cutting process and accurately predict the tool wear has become an urgent problem to be solved.

Deep learning is a kind of deep-seated neural network which simulates the structure of the human brain under the driving of data. It has a better ability to feature learning and nonlinear function approximation and can find complex feature information in high-dimensional data independently. At present, deep learning has made a lot of progress in the field of image processing [16], speech recognition [17], natural language processing [18] and text retrieval [19]. In recent years, deep learning aids in tool wear prediction. Zhao *et al.* [20] first proposed the empirical evaluation of LSTM based machine health monitoring system, which verified the feasibility of using the raw sensor data to predict the actual tool wear. Sun *et al.* [21] proposed a deep transmission learning network based on a sparse automatic encoder and established a prediction model of the remaining tool life. Feng [22] proposed a self-service fault detection algorithm for aircraft. By building a fault detection model based on the deep constrained Boltzmann machine, the current fault state can be conclusively determined. Zhang *et al.* [23] obtained the energy spectrum by wavelet transform of the vibration signal and constructed the tool wear state classification model based on the convolutional neural network (CNN).

The above literature points out the research status of deep learning in the field of tool wear prediction. The deep learning method can realize multiple and multi-dimensional transformations of high-dimensional and non-stationary data, and solve the shortcomings of traditional machine learning methods. Current research fixes the cutting process scenario of the tool and uses a single kind of processing signal to establish the wear prediction model. The timing correlation of tool wear is ignored, and the time segment corresponding to the input of the model is relatively fixed. This problem makes the accuracy of the model prediction results low, and the application of the model is limited. Therefore, the tool wear under different working conditions needs further study.

The research group proposed to use the unique advantages of the LSTM model to solve the problem of complex correlation and memory accumulation effect, and established the prediction model of remaining tool life under variable working conditions [24]. Limited by the situation at that time, the model only studies the tool wear prediction under a single kind of monitoring signal. Due to the complexity of the machining process of a single small batch of structural parts, it is difficult to capture the overall information of the tool state by an individual monitoring signal. In this paper, the tool wear prediction based on multi-source parameter fusion is studied. Secondly, the Hilbert Huang transform (HHT) is selected for feature extraction, which takes a long time and does not have the characteristics of migration. In this paper, an adaptive wear feature extraction method is proposed, and a tool wear prediction model based on multi-source parameter fusion is established.

B. RESEARCH ON SIGNAL FEATURE EXTRACTION METHOD

Feature extraction of monitoring signal is the premise of tool wear prediction. Commonly used signal feature extraction methods include statistical methods [12], [25], Fourier transform [26], wavelet transform [27], Hilbert Huang transform [28], etc. The methods mentioned above of manually acquired signal features have the following shortcomings: (1) they rely on advanced signal processing technology and have a general extraction effect; (2) feature selection is time-consuming and labor-consuming and greatly influenced by human subjective factors. In recent years, deep learning method has become an effective means to extract non-stationary and dynamic change data. Zhao *et al.* [29] proposed a general fault feature extraction and diagnosis method based on a deep belief network (DBN). Fu *et al.* [30] establish the feature space of cutting condition monitoring based on DBN. Compared with the Mel frequency cepstrum coefficient and wavelet method, the results show that DBN has a better ability to characterizing cutting state monitoring signals.

Deep learning has the potential to adaptively and objectively learn the representative features of the original data. Therefore, this method has gradually become an important method for high-dimensional, nonlinear, and non-stationary data feature extraction. This method can reduce or even get rid of the feature extraction dependence on artificial experience.

C. LSTM NETWORK APPLICATIONS

In recent years, with the help of the advantages of the LSTM network model in solving sequence problems, scholars at home and abroad have devoted themselves to the research of the LSTM network application and made some progress. Cho *et al.* [31] take advantage of the recurrent neural network (RNN) to solve the sequence problem and improve the performance of the machine translation system by enhancing the RNN encoder-decoder network model. Liu *et al.* [32] regards the issue of spectrum feature extraction as a sequence learning problem and proposes an automatic spectrum feature learning method based on the bidirectional convolution long-term and short-term memory network. On the other hand, the LSTM model is also emerging in solving the problems of time correlation and historical information memory. Wang *et al.* [33] uses the LSTM network to predict the fault time sequence based on the historical fault data of the complex system. Zhao *et al.* [34] makes use of CNN's advantages in image information processing and RNN's advantages in dealing with time sequence correlation, and finally, realize the prediction of part deformation.

From the above research, it can be seen that The LSTM network has unique advantages in solving the sequence problem with complex time correlation and long-term memory of historical information. Therefore, this paper attempts to establish the LSTM model for tool wear prediction, to solve the problem of tool wear related to the historical data of tool use and time sequence correlation.

III. PRINCIPLE EXPLANATION

A. MAIN PROCESS

The milling tool wears prediction method under variable working conditions we propose is based on the SAE network and LSTM network. The schematic diagram is shown in Figure 1.

The entire process of tool wear prediction in this paper is viewed in two stages: training and application.

1) TRAINING PROCESS

Step 1: The data collected during processing is divided into working condition factors *Con* and milling cutter wear values. The working condition factors are expressed uniformly. For example, operating condition factors include process parameters, workpiece information, tool information, monitoring signals, etc. Machining signals include cutting force signals, vibration signals, etc.

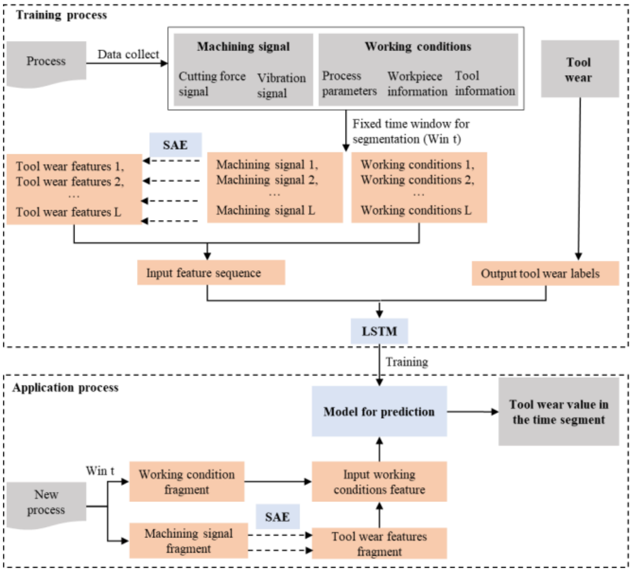

FIGURE 1. The Diagram of the milling tool wears a prediction method.

Step 2: For each processing step of the k-th machining signal S_k, the fixed time window length is win_t, and the working condition factors Con and the machining signal S_k are sequentially divided into L data fragments in time series, that is

$$Con = \{Con_1, Con_2, \ldots, Con_L\}, \quad S_k = \{S_{k1}, S_{k2}, \ldots, S_{kL}\}.$$

Step 3: For each machining signal S_{ki}, SAE is established to extract the signal features F_{ki}, and these signal features are fused in the feature layer to obtain the tool wear features F_i.

Step 4: Combine the working condition factor fragments Con_i and the corresponding tool wear features F_i into a working condition feature sequence. Take this sequence as input, and use the maximum value W of the milling cutter flank wear after this process as the output to train the LSTM network.

2) APPLICATION PROCESS

Step 1: Take out the working condition segment Con_t and the machining signal segment S_t in the new processing process with time segment length t.

Step 2: The machining signal fragments S_t can be processed by the SAE network to obtain the characteristic parameters F_t sensitive to tool wear.

Step 3: The working condition fragments Con_t and the corresponding tool wear features F_t are fused into a working condition feature sequence, which is input into the trained LSTM model, and finally, the tool wear amount *wear* is predicted.

B. UNIFIED EXPRESSION OF WORKING CONDITION FACTORS

In the actual milling process, there are various factors (machine tool, workpiece information, process parameters, etc.) that affect the milling cutter wear, which makes the tool wear prediction process extremely complicated. Since this article ignores the influence of machine tool information, we represent the condition factor under variable conditions in the form of a working condition vector. The working condition information includes process parameter sub-conditions P, workpiece information sub-conditions W, tool information sub-conditions TL and process monitoring sub-conditions M (tool processing time). Then the working condition vector Con can be expressed as:

$$Con = [\,P \quad W \quad TL \quad M\,] \tag{1}$$

1) PROCESS PARAMETER SUB-CONDITIONS

When other processing conditions are the same, selecting different process parameters will produce different processing effects, which will affect the tool wear state. During the milling process, the changed process parameters mainly include cutting speed (spindle speed), cutting depth, cutting width, and feed rate. The process parameter sub-vector P is expressed as:

$$P = [\,n \quad a_p \quad w_e \quad f\,] \tag{2}$$

where n represents the spindle speed, a_p represents the cutting depth, w_e represents the cutting width, and f represents the feed speed.

2) WORKPIECE INFORMATION SUB-CONDITIONS

In the actual milling process, the workpiece information is a critical factor that affects the machining process, and it is also an essential factor that influences the tool wear state. The workpiece information sub-vector W is expressed as [19]:

$$W = \begin{bmatrix} K & \mu s & E & Rm & \tau & HRA & e & Ak & C \end{bmatrix} \tag{3}$$

where K represents the thermal conductivity, μs represents the friction coefficient, E represents the positive elastic modulus, Rm represents the tensile strength, τ represents the shear strength, HRA represents Rockwell hardness, e represents elongation, Ak represents impact toughness, and C represents clamping strength.

3) TOOL INFORMATION SUB-CONDITIONS

This article studies the same type of milling tool. The material and geometric information of the device is the same. Therefore, the tool information can be defined as the initial state of the tool TL.

4) PROCESS MONITORING SUB-CONDITIONS

The monitoring signal M of the machining process can reflect the tool wear after the actual machining starts. Standard process monitoring signals include cutting force signals, vibration signals, acoustic emission signals, current signals, etc., which are time-varying and critical elements for tool wear monitoring. Therefore, it is listed separately in this article.

C. TOOL WEAR FEATURE EXTRACTION

Machining monitoring signals, including force, vibration signals, and acoustic emission, can indirectly reflect the actual milling tool wear in the process of machining, so the feature parameters sensitive to tool wear can be obtained by feature extraction of the monitoring signals.

The machining process monitoring signal has the characteristics of high dimension, non-stationary and dynamic. Traditional feature extraction methods in the time domain, frequency domain, and time-frequency domain are challenging to capture representative, comprehensive, and valid data features. This paper takes advantage of the combination of unsupervised learning and supervised learning possessed by the SAE network to continuously perform the nonlinear transformation on the monitoring signal to obtain the features that are sensitive to tool wear.

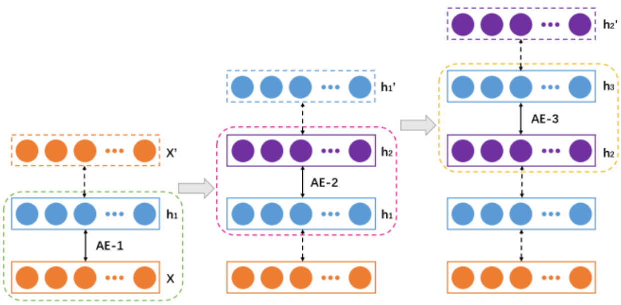

FIGURE 2. The construction process of an SAE model with three hidden layers.

The construction process of an SAE model with three hidden layers is shown in Figure 2. First, the original data X is used as input, and the first AE (AE-1) model is pre-trained using unsupervised learning to obtain hidden layer features h_1. Then, the hidden layer feature h_1 is used as the input of the next AE (AE-2) model, and the new hidden layer feature h_2 is obtained by unsupervised learning. By analogy, the hidden layer feature data h_3 of the next AE (AE-3) model is finally achieved. On this basis, supervised fine-tuning of the entire network can get better feature expression.

Given the machining process monitoring signal $S = \{S_1, S_2, \ldots, S_n\}$, Among them, S_k $(1 \leq k \leq n)$ is any kind of monitoring signal, such as cutting force signal, vibration signal, acoustic emission signal, etc., n $(n \geq 1)$ is the number of types of monitoring signal. For any kind of monitoring signal S_k, there is $S_k = \{S_{k1}, S_{k2}, \ldots, S_{kL}\}$, and $L = [t/win\_t]$, Where, S_{ki} $(1 \leq i \leq L)$ is any segment signal that sequentially divides the signal S_k into L segments according to the time window win_t.

For each monitoring signal S_{ki}, the extraction process of wear characteristics can be expressed as:

$$F_{ki} = g(S_{ki}) \tag{4}$$

where $g(\cdot)$ represents the feature extraction process through the SAE network, and F_{ki} is the feature parameters sensitive to tool wear extracted.

D. ESTABLISHMENT OF TOOL WEAR PREDICTION MODEL

Tool wear under variable working conditions has a complex coupling correlation. In this paper, the advantages of LSTM in solving the variable sequence problem and time correlation problem are used to solve the problem of tool wear prediction. The multi-sequence input and single-output LSTM network structure, as shown in the figure, is constructed. Among them, the input of the model is a characteristic sequence composed of the typical segment of the working condition factor and the tool wear feature segment, and the output of the model is the tool wear value corresponding to this period. In the network structure, the output of the next time segment network is determined by the current input, the cell output state of the previous time segment, and the state of the hidden layer cell. This feature solves the problem of the cumulative effects of tool wear over time. Also, the LSTM quiescent layer cells are connected in an orderly manner. During training, the number of input nodes is determined by the time window of signal division. When using the trained LSTM network to make predictions, the number of input nodes is determined by the length of the signal segment under different processing time lengths. This feature can solve the requirement of the variable length of input sequence nodes in the application process.

The fixed time window is win_t $(t_1, t_2, \ldots, t_L = win\_t)$. Divide the data in the milling process into L segments, and the input of the model after segmentation is:

$$X = \{X_1, X_2, \ldots, X_L\} \tag{5}$$

Set the initial time of the time window as $t_{initial}$, and the working condition feature of i-th is X_i:

$$X_i = [\, Con_i \quad F_{1i} \quad F_{2i} \quad \ldots \quad F_{ni} \,] \tag{6}$$

In the formula, Con_i $(t_{initial} \leq t \leq t_{initial+win\_t})$ represents the working condition factors corresponding to the i-th data segment, F_{ki} is the tool wear feature extracted from the k-th monitoring signal in the i-th data segment.

In this paper, the flank wear of each tooth of the milling tool is used as the calibration wear. Milling tools are multi-tooth cutters, and the amount of wear is closely related to the wear of each cutter tooth. The milling tool is a kind of multi-tooth tool, and its wear is closely related to the wear of each tooth. Excessive wear on any tooth will cause the tool to be unusable. Therefore, this paper uses the maximum flank wear value of the multi-tooth milling tool to characterize the tool wear. The theoretical output corresponding to the LSTM model is W:

$$W = max\{W_1, W_2, \ldots, W_n\} \tag{7}$$

Among them, W_i represents the flank wear value corresponding to the i-th tooth.

Then, input X the LSTM hidden layer. As can be seen from Figure 3, the hidden layer of the LSTM network contains L LSTM cells connected by time series. The output through the hidden layer is P:

$$P = LSTM(X, C, H) \tag{8}$$

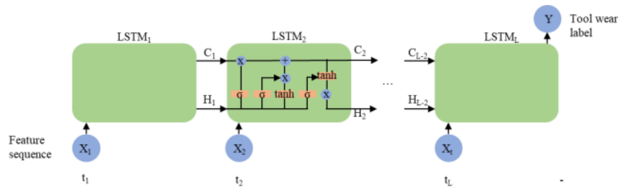

FIGURE 3. LSTM model structure.

where C and H respectively represent the state and output of each LSTM cell, and $LSTM$ is the forward propagation algorithm of LSTM cells. The mean square error (MSE) is selected as the error calculation formula, so the loss function in the process of network training is:

$$loss = \sum\nolimits_{i=1}^{N} (P_i - W_i)^2/N \tag{9}$$

With the minimum loss function as the optimization objective, the network weight was updated continuously by Adam's optimization algorithm. Finally, the LSTM hidden layer network revealed itself.

IV. EXAMPLE VERIFICATION

A. INTRODUCTION OF EXPERIMENTAL DATA

In this paper, the method proposed was verified by using the public data set [30] of the American PHM Association in the 2010 tool health prediction contest. The experimental platform is the Röders-TechRFM760 high-speed CNC milling machine; the innovative tool is a three-edged ball head milling cutter made of tungsten carbide. The cutting material is stainless steel(HRC 52).

In the experiment, several sensors collected the data of the milling process, including force sensors, acceleration sensors, and acoustic emission sensors. The milling method is end milling. Each time 108mm is cut along the X direction, recorded as a cutting stroke. The cutting tests used a total of 3 tools, marked as C1, C4, and C6, respectively. Each tool contained 315 cutting strokes, a total of 945 cutting strokes, that is, 945 samples. After each cut, record the wear value of the flank of each cutting edge of the milling tool. Table 1 lists the milling parameters.

TABLE 1. Milling parameters.

Spindle speed (rpm)	Feed speed(mm /min)	Cutting width (mm)	Cutting depth(mm)	Cooling conditions
10400	1555	0.125	0.2	Dry milling

Whenever the wear of any edge of the milling cutter exceeds a certain threshold when machining, the quality of the workpiece will be severely affected, therefore, in our study, we used the maximum wear of each cutting edge as the measurement standard. The wear curve of tool C1 is shown in Figure 4. According to the value of wear and the changing trend of the curve, the initial wear stage, normal wear stage, and sharp wear stage of tool wear correspond to A, B, and C in the figure.

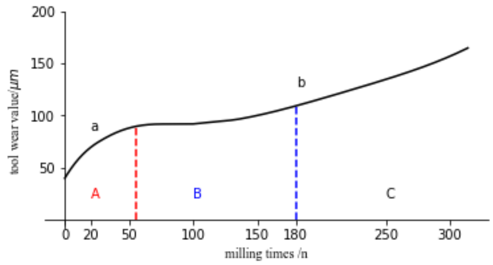

FIGURE 4. Tool wear curve (C1).

B. RESULTS AND DISCUSSION

The milling tool is a sample every milling, and the data of the stable machining stage is divided into 82ms (4096 data points) as the time window to obtain the milling force signal segment and the vibration signal segment corresponding to the time window. There are ten segments in total, corresponding to tool wear. The sample with tool number C1, milling times 13 (C1-13), and section 1 (the first 328ms data) are used as an example to illustrate the construction process of the input condition feature sequence of the training model.

1) WORKING CONDITION FACTORS OF SAMPLE C1-13 (SEGMENT 1)

The working condition factors of sample C1-13 include four elements: spindle speed n, feed speed v_f, radial cutting depth a_w and axial depth of cut a_p. Then the working condition factor Con of sample C1-13 can be expressed as:

$$Con = [\,10400 \quad 1555 \quad 0.125 \quad 0.2\,]$$

2) SAMPLE C1-13 (SEGMENT 1) MONITORING SIGNAL WEAR FEATURE EXTRACTION

In the network that extracts tool wear features, the number of hidden layer nodes is set to 4096-2048-1024-512-128-60. Input force signal (4096 * 3 dimension) and vibration signal (4096 * 3 dimension) into the SAE network, you can get the force signal feature vector (60 dimensions) and vibration signal feature vector (60 dimensions) sensitive to tool wear. Then the force signal feature vector $xf_{1\times60}$ and vibration signal feature vector $xv_{1\times60}$ extracted from the sample are:

$$xf_{1\times60} = [\,14.802 \quad 5.6861 \quad \ldots \quad 7.8767\,]$$
$$xv_{1\times60} = [\,0.408 \quad 0.1067 \quad \ldots \quad 3.1449\,]$$

3) CONSTRUCTION OF INPUT SEQUENCE

By doing the same for fragments 2∼9, the LSTM network input condition sequence of sample c1-13 one obtains F.

The output wear of this sample LSTM network is 76.0616μm, and F is:

$$F = \{F_1, F_2, \ldots, F_{10}\}$$

$$\begin{cases} F_1 = \begin{bmatrix} Con & xf_{1\times 60} & xv_{1\times 60} \end{bmatrix} = [104001555 \ \ldots \ 2.8767] \\ F_2 = \begin{bmatrix} Con & xf_{1\times 60} & xv_{1\times 60} \end{bmatrix} = [104001555 \ \ldots \ 2.5358] \\ \ldots \\ F_{10} = \begin{bmatrix} Con & xf_{1\times 60} & xv_{1\times 60} \end{bmatrix} = [104001555 \ \ldots \ 3.01022] \end{cases}$$

In this paper, the cross-validation method is used to verify the accuracy of the wear prediction model for the three tools C1, C4, and C6. In the three experiments, two groups are the training set, and one group is the verification set. The cross-validation scheme is shown in Table 2.

TABLE 2. Cross-validation scheme.

Serial number	Training set	Number of training set samples	Validation set	Number of validation set samples
1	C1 C4	630	C6	315
2	C1 C6	630	C4	315
3	C4 C6	630	C1	315

The prediction model based on the wear of the tool is a multi-sequence input and single output LSTM model. The number of LSTM hidden layer nodes is 129, the learning rate is 0.0001, the optimization method is Adam, the weight L2 regularization coefficient is 0.003, the input batch size is 21, and the number of iterations is 3000. After 3000 iterations, the loss curve converges, and the training time on GeForce RTX 206 is 1.3 hours.

The No. 1 verification scheme illustrates that the data samples in C1 and C4 are used as the training set, and the data samples in C6 is the verification set. The change curve of the loss function (MSE) of the LSTM network with the training process presents in Figure 5.

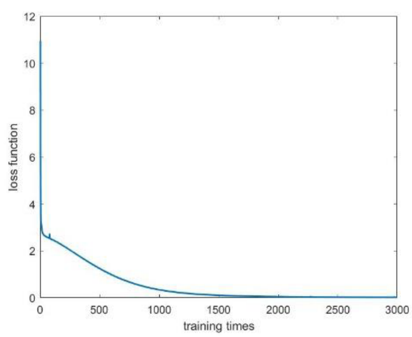

FIGURE 5. Loss function curve of the LSTM model.

In Figure 4, the abscissa represents the number of iterations, and the ordinate represents the loss function.

TABLE 3. Loss function convergence values.

Verification scheme serial number	Training set convergence value	Validation set convergence value
1	0.0147	0.0253
2	0.0198	0.0267
3	0.0089	0.0174

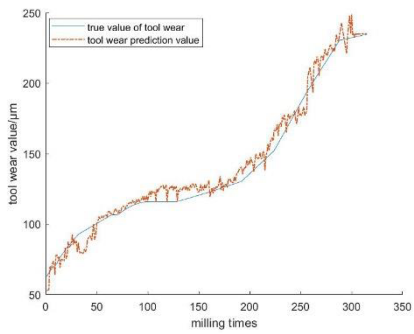

FIGURE 6. Tool wear prediction curve (C6).

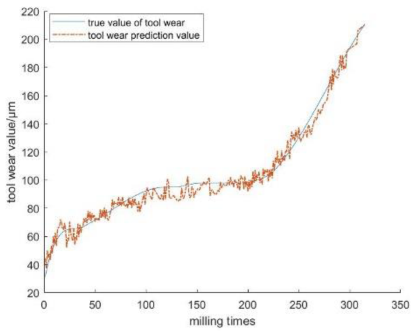

FIGURE 7. Tool wear prediction curve (C4).

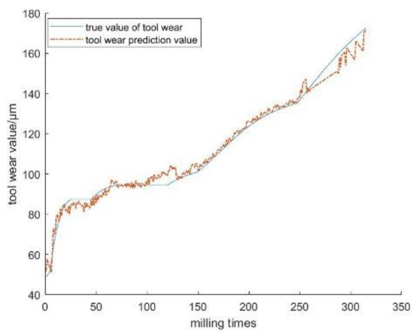

FIGURE 8. Tool wear prediction curve (C1).

Figure 4 shows: as the training process progresses, the loss function curve shows a downward trend and eventually reaches convergence. The loss function of the training set finally converges to 0.0178, and the loss function of the verification set finally converges to 0.0473.

TABLE 4. Results of statistical indicators.

Statistical index	Value
$MAPE$	5.3142
Cv	0.0606
R^2	0.9671

TABLE 5. Test case design table under variable operating conditions.

Tool number	Testing conditions	Tool initial state	Processing time	Tool wear/μm
C1	Condition 1	after 50 cuts	1 cutting stroke	90.2189
	Condition 2	after 50 cuts	2 cutting stroke	90.6096
	Condition 3	after 160 cuts	1 cutting stroke	106.0722
	Condition 4	after 160 cuts	2 cutting stroke	106.5424
C4	Condition 5	after 50 cuts	1 cutting stroke	71.9468
	Condition 6	after 50 cuts	2 cutting stroke	72.3631
	Condition 7	after 160 cuts	1 cutting stroke	97.9476
	Condition 8	after 160 cuts	2 cutting stroke	97.9476
C6	Condition 9	after 50 cuts	1 cutting stroke	100.9076
	Condition 10	after 50 cuts	2 cutting stroke	101.3329
	Condition 11	after 160 cuts	1 cutting stroke	122.9008
	Condition 12	after 160 cuts	2 cutting stroke	123.1411

The above analysis is also performed on the verification schemes 2 and 3 in Table 2, and the loss function convergence value of the training set can be obtained. As shown in Table 3 below, it can be seen from the table that each scheme of cross-validation has a good convergence effect.

Verify all the verification schemes in Table 2, and get the C6, C4, C1 tool wear prediction curve. As shown in Figure 6, Figure 6, and Figure 8, the abscissa is the number of milling times, and the ordinate is the maximum wear of each tooth of the tool.

We used three statistical indicators, namely mean absolute percentage error ($MAPE$), coefficient of variation (Cv), and square correlation coefficient (R^2), as evaluation criteria for model accuracy. Ten repetitions of the model derived the average value of each index to eliminate the influence of contingency factors. The results follow in Table 4.

It can be seen from Table 4 and Figure5-7 that the predicted values of the three tools can reflect the measured values well, and the prediction results of the model are accurate. The generalization is excellent, which can indicate the wear process of the tool.

Further, the design of the test case of the model under variable working conditions mainly reflects the variable working conditions from the initial state of the tool, the processing time of the instrument, and the continuous change of the process monitoring signal. The specific test case design is as follows: From the tools C1, C4, and C6, randomly select two samples with the different initial state of the tool and set the processing time of each sample to have two changes, so there are $3 * 2 * 2 = 12$ change test scenarios in total. We tested the proposed model for milling tool wear prediction. Select a suitable sample design test scenario and its actual maximum wear amount, as shown in Table 5 below:

Our method predicts the test samples noted in the above table, while the following table shows the results.

TABLE 6. Comparison of actual and predicted wear.

Testing conditions	True value /μm	Prediction value /μm	Relative error
Condition 1	90.2189	89.7943	0.0047
Condition 2	90.6096	91.7623	0.0127
Condition 3	106.0722	108.1663	0.0197
Condition 4	106.5424	108. 3417	0.0169
Condition 5	71.9468	73.1279	0.0164
Condition 6	72.3631	73.8405	0.0204
Condition 7	97.9476	100.2671	0.0237
Condition 8	97.9476	103.6379	0.0581
Condition 9	100.9076	101.3196	0.0041
Condition 10	101.3329	103.5298	0.0217
Condition 11	122.9008	119.2507	0.0297
Condition 12	123.1411	122.8742	0.0021

The prediction results in Table 6 above show that the SAE-LSTM milling wear model can realize the prediction of tool wear when the initial state of the tool changes and the processing time changes. The maximum relative error is 0.0581. However, due to space limitations, other changing factors, such as changes in processing objects, have not been verified. Subsequent research will carry out model verification work on different variable scenarios.

V. CONCLUSION

Our innovative method based on deep learning uses engineering requirements of the tool wear prediction to deal with the complicated relationship between working condition factors and tool wear; this method extracts working condition characteristics. It takes the long short-term memory network as the core. First, we established a unified representation of operating condition factors. Then, the stacked autoencoder network model is designed to realize the adaptive extraction of wear features under variable operating conditions. The feature extraction results of different kinds of machining signals are fused, and the fused wear features and working conditions are constructed into feature sequence vectors. Next, the long short-term memory model is established, and its advantages of solving sequence problems and time correlation problems are used to realize the prediction of milling tool wear under variable operating conditions. Finally, an example verifies the effectiveness of this method. The experimental results show that the proposed method can accurately and efficiently predict the tool wear under the current working conditions, providing a reliable reference for tool replacement and tool compensation optimization in real-time.

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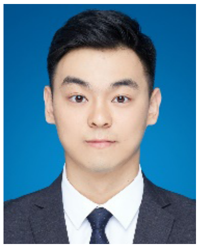

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