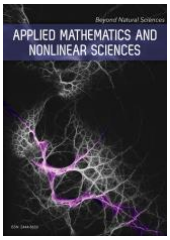

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Tool wear prediction method based on the SVM-Clara model

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Abstract

To reduce the damage of mechanical parts during machining, a tool wear prediction method based on the SVM-Clara model is proposed. By analyzing the support vector machine (SVM) and Clara algorithm, using regular prediction data or unobservable data, the average dissimilarity of all objects is concentrated, and the characteristics of the overall data are accurately represented. Randomly select data samples from the overall data samples according to a certain proportion, and standardize them to improve the clustering quality. Find the best objective function to minimize the damage function and make the predicted value closer to the actual value. Through experiments, it is proved that the method in this paper can accurately predict the tool wear condition, the mean square error value is 0.03, the prediction method is better, and the production efficiency is ensured.

Keywords: SVM model; Clara algorithm; Tool wear prediction; Data preprocessing
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1 Introduction

In machining, cutting [1] is the most common machining method, so cutting tools have a special effect on the performance of machine tools. Its service life has a great impact on the quality of mechanical products [2], and will also cause corresponding fluctuations in its process and economic benefits [3]. Severe tool wear can cause tool damage, and tool damage can cause parts to be scrapped [4], thereby damaging expensive instruments. To make matters worse, the normal operation of the machine is affected. Therefore, the prediction of tool wear and damage status has become a hot research topic.

During machining, strong friction, and extrusion occur between the tool and the chip [5], which causes wear. Tool wear can lead to reduced tool life, reduced surface quality, and increased material loss. Therefore, the wear of cutting tools plays a key role in increasing productivity [6] and improving product quality. Based on studying the rationality of the geometric parameters of cutting tools, it is necessary to observe the wear conditions of cutting tools and analyze their causes, which is very necessary for in-depth research on the wear laws of cutting tools.

Wear of cutting tools is a vague phenomenon [7], which will be affected by factors such as environment and instruments during the acquisition process. Therefore, it is very meaningful to analyze and predict the tool wear state and combine randomness and fuzzy to identify and predict the tool wear state. Many scholars at home and abroad have established different models to predict tool wear. Reference [8] uses ADNLSSVM to establish a dynamic model of tool wear, extracts feature vectors from the data set of the open database of the milling process through time-frequency domain analysis, and selects parts through correlation analysis. The feature vector is used as the model input to monitor the tool wear state. Reference [9] proposed a tool wear prediction method based on the uncertainty cloud inference model. The inverse cloud algorithm was used to calculate the three cloud characteristic parameters of the tool wear acoustic emission signal, and the relationship between the wear trend in different wear stages and the cloud characteristic parameters in different wear stages was mined. A multi-condition single-rule wear prediction model is established. Reference [10] used a three-dimensional mechanical frequency-domain chatter model to consider the effect of tool wear and proposed a new formula to simulate the process of damping force along the nonlinear tool geometry, and to simulate the chip cross-sectional area by analyzing the axial and radial displacements, determine the stability boundary under different cutting conditions and different flank wear states. [8-10]

There are two main types of tool wear: ordinary wear and abnormal wear. When the tool is designed and used properly [11], and the machining and grinding quality meet the requirements, wear will gradually occur during cutting. The common wear of the tool is divided into three kinds of wear: front, rear, and rear. Abnormal wear, also known as tool damage, is generally an abnormal failure [12]. While the tool is in use, when the tool is worn to a certain extent, it will no longer be usable. This wear limitation is called the passivation of the tool [13]. The durability of the tool refers to the entire process from the start of cutting to the level of passivation. The lower the grinding rate, the longer the tool life. Therefore, tool life is a good evaluation tool. There are usually two ways to determine the tool durability: one is to determine the tool durability from the angle with the shortest cutting time of the workpiece, that is, the maximum labor intensity [14]. The second approach is to determine the durability of the tool based on the minimum cost of machining the part, that is, the minimum cost of durability. The lowest durability is usually used in production. When the production task is relatively tight or the production is unbalanced, the lowest durability can be selected.

In the research of tool wear prediction technology, there are many reliable experimental data which is the premise of technical research [15]. In different machining conditions, different tool wear,

different machining methods, different materials, different materials, different tool materials, these are very difficult. Therefore, an ideal prediction method must have the ability to learn, diffuse [16] and adapt to changes in the external environment [17] to finally realize the industrial application of tool wear prediction. In this paper, an SVM model is mainly established by the Clara algorithm to predict the wear of the tool, and it is verified by experiments that the relative error prediction of the tool wear predicted by this method is reduced to 0.5371. It can be seen from the data that the SVM-Clara model proposed in this paper has high accuracy and strong practicability.

2 SVM Model Principle and Clara Algorithm Analysis

2.1 Principle of the SVM Model

Support vector machines (SVMs) have great advantages for solving small-sample, nonlinear, and high-dimensional pattern recognition [18]. It starts with observational data, looks for patterns contained in it, and uses those patterns to predict future or unobservable data. It solves some basic problems in the case of limited samples of statistical learning theory to a large extent, such as model selection problems, nonlinear and dimensionality curse problems, and local [19] minima problems, which has quickly attracted the attention of various fields and Research Interests [20]. People have carried out in-depth theoretical and applied research on it and achieved many results [21].

The basic idea of SVM is to find a hyperplane that can separate [22] all samples and maximize the separation distance in a multidimensional space i.e. the optimal hyperplane. The support vector machine regression model starts from the spatial transformation and builds a regression model for prediction based on the principle of structural risk minimization. Its principles are as follows:

It is known that a set of sample sets $D=\{(X,Y)\}$, $X\in R^n$, $Y\in R$, $\Psi(X)$ is a nonlinear transformation, which maps the original space R^n to the high-dimensional feature space Ω, and constructs the optimal regression function.

$$f(X)=\omega\cdot\Psi(X)+b, X\in R^n, Y\in R \tag{1}$$

The regression estimation problem is defined as the problem of minimizing the risk of a loss function. According to the principle of structural risk minimization, parameters ω and b can be obtained by solving equation (3).

$$\min\Phi\left(\omega,\xi_i^+,\xi_i^-\right)=\frac{1}{2}\left\|\omega\right\|^2+C\sum_{i=1}^{n}\left(\xi_i^+,\xi_i^-\right) \tag{2}$$

$$s.t.\begin{cases} y_i-\left(\omega\cdot\Psi\left(x_i\right)\right)-b\le\xi_i^++\varepsilon \\ \left(\omega\cdot\Psi\left(x_i\right)\right)+b-y_i\le\xi_i^-+\varepsilon \quad i=1,2,\cdots,n \\ \xi_i^+\ge 0,\xi_i^-\le 0 \end{cases} \tag{3}$$

In the formula: C is the penalty [23] parameter, and an appropriate constant is taken to control the degree of the penalty of the sample to exceed the error limit. Considering the allowable regression error, ξ_i^+, ξ_i^- slack variables are introduced. ε Insensitive loss function.

For the quadratic optimization problem of formula (3), the Lagrangian multiplier is introduced to construct the Lagrangian functional, and the dual problem of the original problem is obtained.

$$\max L\left(a,a^*\right)=-\frac{1}{2}\sum_{i,j=1}^{l}\left(a_i-a_i^*\right)\left(a_j-a_j^*\right)\left(\Psi\left(x_i\right)\cdot\Psi\left(x_j\right)\right)+\sum_{i=1}^{i}a_i\left(y_i-\varepsilon\right)-\sum_{i=1}^{i}a_i^*\left(y_i+\varepsilon\right) \tag{4}$$

Its constraints:

$$s.t.\begin{cases}\sum_{i=1}^{l}\left(a_i-a_i^*\right)=0 & i=1,2,\cdots,n\\ C\geq a_i,a_i^*\geq 0\end{cases} \tag{5}$$

Solving can get a regression function:

$$f(X)=\sum_{i=1}^{n}\left(a_i^*-a_i\right)\cdot\left(\Psi\left(x_i\right)\cdot\Psi(X)\right)+b^*,X\in R^n \tag{6}$$

To avoid the curse of dimensionality problem in the high-dimensional feature space of [24], it is necessary to choose the kernel function $k\left(x_i,x_j\right)$ to be equivalent to the inner product form $\Psi\left(x_i\right)\cdot\Psi\left(x_j\right)$ of the high-dimensional space, to solve the high-dimensional computational problem ingeniously. The RBF function is most widely used due to its excellent local approximation properties [25]. The expression formula of radial basis kernel function (RBF) is:

$$k\left(x_i,x_j\right)=e^{-\frac{\left\|x_i-x_j\right\|^2}{2\sigma^2}}\quad i=1,2,\cdots,n \tag{7}$$

2.2 Clara's algorithm

Instead of finding representative objects from the entire dataset, the Clara algorithm selects the center point from the sample using the reset [26] cost calculation method from the sample in the dataset. If the sample is randomly selected, it should represent the original dataset. However, the sampling method is not guaranteed to be truly random, and the clustering quality is based on the average dissimilarity of all objects in the entire dataset [27], not just the average dissimilarity of these objects over the sample. To get a better approximation, Clara takes multiple samples and takes the best cluster as output [28]. To improve the efficiency of spatial clustering, the Clara algorithm randomly selects $40+2k$ number of spatial object data for spatial clustering (k is the desired number of clusters). Therefore, the samples can be sampled v times and the best clustering result can be output as the output.

The basic idea of the Clara algorithm is to randomly sample all the data, and then use some data samples to express the overall data. Second, the PAM method is used for segmentation [29], and atypical objects are repeatedly used to replace typical objects, substitution cost is used to determine the replacement, and finally, the overall cluster quality is obtained. Using this method, random sampling is performed repeatedly, and a clustering scheme with better clustering quality competitiveness is selected. In the case of a large number and size of samples, the scheme can represent the clustering scheme of the whole data and can accurately represent the characteristics of the whole data under the condition of tolerance of [30] deviation. Figure 1 shows the basic steps of the Clara algorithm.

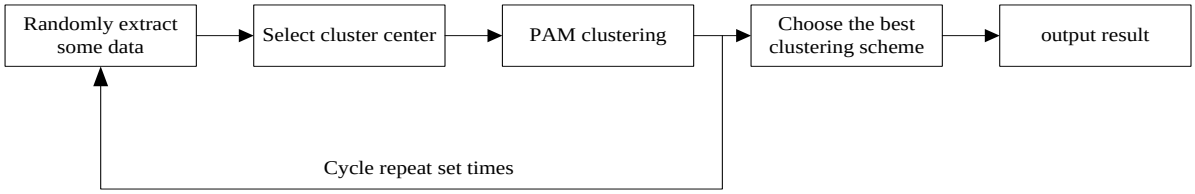

Figure 1. Clara algorithm steps

3 Data preprocessing

3.1 A random sampling of data

To reduce the scale of processed data [31], data samples are randomly selected in a certain proportion from the overall data samples. The sample size of the extracted data is shown in equation (8).

$$N = \frac{A}{\lambda} \tag{8}$$

Among them, A is the overall data sample size, and λ is the reduction multiple of the cluster data scale.

Randomly selected data were normalized and mapped to a range of 0–1 to remove the effects of [32] physical meaning and dimensional differences among different variables.

$$\overline{x} = \frac{x - x_{\min}}{x_{\max} - x_{\min}} \tag{9}$$

In the formula, x is the data before normalization, $\overline{x}$ is the data after normalization, and $x_{\max}$ and $x_{\min}$ represent the maximum and minimum values of such data, respectively.

3.2 K-means clustering to get the initial cluster center

The PAM method randomly selects the initial cluster center, which has the disadvantage of a large amount of computation. Therefore, a K-means clustering method is introduced to obtain the initial cluster centers of the PAM method. Since the PAM method clustering can be performed after K-means clustering, only coarser cluster centers [33] need to be obtained by K-means clustering. Combining the K-means clustering method with the PAM method improves computational accuracy and speed [34].

3.3 PAM cluster analysis method

The $N-K$ non-central data in the selected dataset are divided into cluster classes of K data centers based on the nearest Euclidean distance between the non-central data and the data center. The Euclidean distance is calculated as shown in equation (10):

$$d\left(x_n, c_k\right) = \sqrt{\sum_{j=1}^{J}\left(x_{nj} - c_{kj}\right)^2} \tag{10}$$

$$n=1,2,\cdots,N-K;\ k=1,2,\cdots,K \tag{11}$$

Where x_n is the n-th data vector, the dimension is J, and x_{nj} is the m-dimensional data value of the n-th data vector. c_k is the k-th data center, and c_{km} is the m-dimensional data value of the k-th data center. $d\left(x_n,c_k\right)$ is the Euclidean distance between the non-central data vector x_n and the central data vector c_k.

When the central data is replaced by the non-central data, the replacement cost is calculated to determine whether the replacement helps to improve the clustering quality. The calculation formula of the replacement cost is shown in Equation (12):

$$E\left(x_n,c_k\right)=\sum_{i=1}^{N-K}e_{ink} \tag{12}$$

$$n=1,2,\cdots,N-K;\ k=1,2,\cdots,K \tag{13}$$

In the formula, $\mathrm{E}(x_n,c_k)$ is the replacement cost of non-central data x_n instead of central data c_k; e_{ink} is the replacement cost of non-representative point x_i when non-central data x_n replaces central data c_k. Its calculation method is as follows:

(1) When x_i is the cluster class of c_k:

$$e_{ink}=\begin{cases}d\left(x_i,x_n\right)-d\left(x_i,c_k\right),d\left(x_i,x_n\right)<d\left(x_i,c_i^{sub}\right)\\ d\left(x_i,c_i^{sub}\right)-d\left(x_i,x_n\right),d\left(x_i,x_n\right)\geq d\left(x_i,c_i^{sub}\right)\end{cases} \tag{14}$$

Where c_i^{sub} is the second neighborhood center data of x_i, which is a non-representative [35] point.

(2) When x_i is the cluster class of $c_l(l\neq k)$:

$$e_{ink}=\begin{cases}0,d\left(x_i,c_l\right)<d\left(x_i,x_n\right)\\ d\left(x_i,x_n\right)-d\left(x_i,c_l\right),d\left(x_i,c_l\right)\geq d\left(x_i,x_n\right)\end{cases} \tag{15}$$

When the replacement cost is less than 0, it indicates that the replacement operation [36] is beneficial to improve the clustering quality. Therefore, when the following conditions are met, the replacement operation of [37] non-central data x_n to replace central data c_k is performed.

$$E\left(x_n,c_k\right)<0 \tag{16}$$

Repeat the above steps to calculate the replacement cost, and determine whether to perform the replacement operation, until the replacement cost of all non-central data to replace the central data is greater than 0.

4 Tool wear prediction based on the SVM-Clara model

The linear ε-insensitive [38] damage function is defined as:

$$|y-f(x)|_{\varepsilon}=\begin{cases}0, & |y-f(x)|\le\varepsilon\\ |y-f(x)|-\varepsilon, & |y-f(x)|>\varepsilon\end{cases} \tag{17}$$

In the above formula, $|y-f(x)|_{\varepsilon}$ is the value of the damage function, and if there is $|y-f(x)|\le\varepsilon$, the damage function can be regarded as 0.

Given a set $S=\{(x_i,y_i),x_i\in R^n,y_i\in R\}_{i=1}^{l}$, find the best objective function $f(x)$ to minimize the damage function, that is, let the predicted value of the SVM model under the Clara algorithm be closer to the actual value. The function $f(x)$ can be expressed by equation (18):

$$f(x)=w^T\varphi(x)+b \tag{18}$$

Using the SVM model, the optimization problem corresponding to function[39] $f(x)$ is:

$$\min_{\mathbf{w},b,e}J(\mathbf{w},b,\mathbf{e})=\frac{1}{2}\square\,\mathbf{w}\,\square^2+\frac{\gamma}{2}\sum_{i=1}^{l}e_i^2 \tag{19}$$

$$y_i=\mathbf{w}^T\varphi(\mathbf{x}_i)+b+e_i(i=1,2,\cdots,l) \tag{20}$$

Observing equations (19) and (20), it can be seen that the two equations have obvious differences in the constraints [40] conditions, so the corresponding functions of the two equations also have obvious differences.

$$L(w,b,e,a)=Q(w,b,e)-\sum_{i=1}^{l}\alpha_i\left[w^T\phi(x_i)+b+e_i-y_i\right] \tag{21}$$

The optimal numerical condition in formula (21) is:

$$\begin{cases}\dfrac{\partial L}{\partial w}=0\Rightarrow w-\sum_{i=1}^{l}\alpha_i\phi(x_i)=0\\ \dfrac{\partial L}{\partial b}=0\Rightarrow\sum_{i=1}^{l}\alpha_i=0\\ \dfrac{\partial L}{\partial e_i}=0\Rightarrow Ce_i-\alpha_i=0\\ \dfrac{\partial L}{\partial \alpha_i}=0\Rightarrow w^T\phi(x_i)+b+e_i-y_i=0\end{cases} \tag{22}$$

Writing Equation (22) in matrix form and eliminating the intermediate variables w and e, Equation (23) can be obtained:

$$\begin{bmatrix}0 & \vec{1}\\ \vec{1} & \mathbf{\Omega}+\gamma^{-1}\mathbf{I}\end{bmatrix}\begin{bmatrix}b\\ \alpha\end{bmatrix}=\begin{bmatrix}0\\ \mathbf{y}\end{bmatrix} \tag{23}$$

$\Omega_{ij} = K\left(x_i, x_j\right)$ in formula (23). Solving equation (23) can get the function:

$$f(x) = \sum_{i=1}^{l} \alpha_i K\left(x, x_i\right) + b \tag{24}$$

In formula (24), the matrix form of $\alpha_i (i = 1, 2, \cdots, l)$ and b are:

$$b = \frac{\vec{1}^T \mathbf{A}^{-1} \mathbf{y}}{\vec{1}^T \mathbf{A}^{-1} \vec{1}} \tag{25}$$

$$a = A^{-1}(y - b\bar{l}) \tag{26}$$

In tool wear prediction, there are many uncertain factors in the cutting process, so there is often a certain error between the predicted wear amount and the actual wear amount. The size of the error can be used to measure the accuracy of the prediction. Common mistakes are calculated as follows:

(1) Relative error RE_i:

$$RE_i = \frac{v_j - v_j^{'}}{v_i} \times 100 \tag{27}$$

(2) Average relative error *MRE*:

$$MRE = \frac{1}{T} \sum_{i=1}^{T} \left| \frac{v_i - v_i}{v_i} \right| \times 100 \tag{28}$$

(3) Mean square error *MSE* and mean square error *RMSE*:

$$MSE = \frac{1}{T} \sum_{i=1}^{r} \left(v_i - v_i^{'}\right)^2 \tag{29}$$

$$RMSE = \sqrt{MSE} \tag{30}$$

In the above formula, v_i and $v_i^{'}$ respectively represent the actual wear value and predicted value at time i.

5 Experiments and experimental results

This paper will be based on the tool prediction model of SVM-Clara, and the experiments show that the prediction model proposed in this paper is more practical.

Based on the SVM model, Clara algorithm, and SVM-Clara prediction model, the classification and prediction of variable parameter milling tool wear state will be studied. Select 30 wear parameters for each set of tool wear signals. Then, for each signal sample, a new feature is extracted from the

coefficient of variation (CV) to form a new feature vector sample with feature mean, standard deviation, and peak value. After generating new eigenvector samples, three models are used to classify and predict tool wear status based on these eigenvector samples. Due to the different influence laws of the feed per tooth and the cutting width on the force signal, the influence on the features extracted from the force signal is also different. Next, the classification and prediction of tool wear states for variable tooth feed and variable width of cut are investigated, respectively.

Since the traditional support vector machine model is proposed for binary classification problems, it cannot be directly applied to multi-classification (the number of categories is greater than 2), so multi-class support vector machine models must be selected when dealing with multi-classification problems. This paper adopts a one-to-many classification model. At this point, multiple categories must be numerically encoded. The specific coding format is shown in the following table.

Table 1. Correspondence of tool wear and code

State of wear	State one	State two	State three	State four
Coding	[-1,-1]	[-1,1]	[1,-1]	[1,1]

After encoding, the new feature vector samples need to be segmented. This paper uses the randperm of the MATLAB random function to generate a random number sequence from 1 to 30 and then divides the 30 eigenvector samples corresponding to each tool wear state at each feed rate into two parts. The feature vector samples corresponding to the first 15 numbers generated by randperm are used as the training sample set, and the feature vector samples corresponding to the last 15 numbers are used as the verification sample set. Then, for each feed rate, based on the above training sample set and validation sample set, the SVM grid cross-validation method is used to optimize the model parameters. The optimized model parameters are shown in the table below.

Table 2. Model optimization parameters at different feed rates

	fz=0.10mm	fz=0.12mm	fz=0.14mm	fz=0.16mm
Penalty factor C	0.2617	0.2146	0.0674	0.0609

After obtaining the model optimization parameters, the 30 new feature vector samples corresponding to fz=0.10mm in each wear state were randomly divided into 4 groups with 7 samples in each group. One group of samples is selected for training in turn, and the remaining three groups of samples are used for 4 times of verification and recognition. Based on the features under this set of cutting parameters, the average classification accuracy obtained from the 4 validations was used as the model classification accuracy. Likewise, 4-fold cross-validation was performed on the eigenvector samples under the other three sets of cutting parameters, and 4-fold cross-validation was performed according to the model optimization parameters under the feature. Figure 2 shows a comparison of the average classification and recognition accuracy of cross-validation using the three methods, respectively, after optimizing the model parameters using the new feature vector samples.

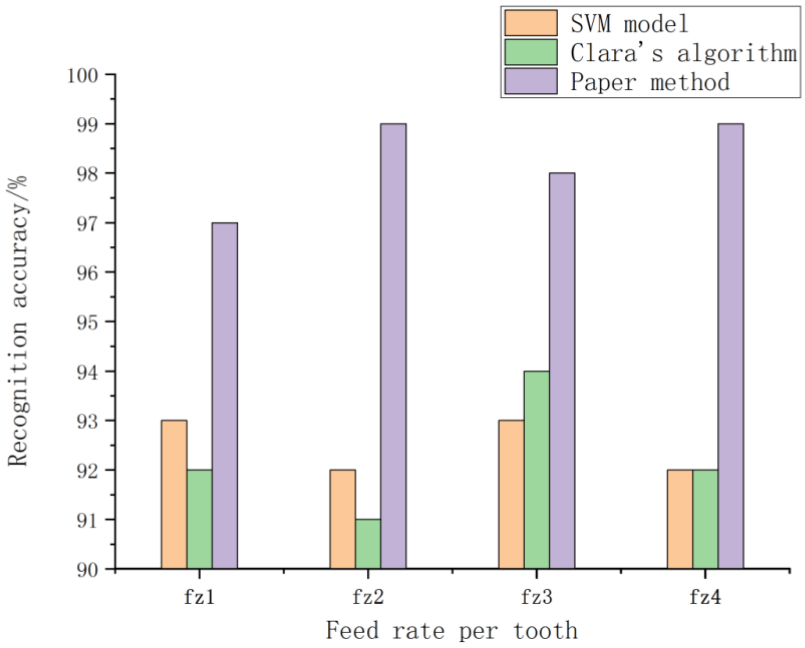

Figure 2. The average classification and recognition accuracy of cross-validation of the model under fixed cutting parameters

In the figure, fz1, fz2, fz3, and fz4 indicate that the feed rate per tooth is 0.10mm/tooth, 0.12mm/tooth, 0.14mm/tooth, and 0.16mm/tooth, respectively. As can be seen from the above figure, when the cutting parameters are fixed, the classification and recognition effect of the prediction method in this paper is very ideal (the classification accuracy reaches more than 96%).

To simulate a cutting simulation experiment, to fully train the hybrid model, the tool wear data were recorded every 30 steps, and a total of 37 experimental data were recorded. The 37 sets of data obtained were divided into a training set and a test set, the first 27 data were selected as the mixed model training set, and the last 10 data $\{x_t | t = 28, 29, \cdots 37\}$ was used as the test set. The specific modeling process and training prediction of the hybrid model is realized by programming on MATLAB software. This paper does not describe the algorithm program and specific calculation process of the hybrid model in detail, only the corresponding calculation results are given.

Modeling and forecasting are performed according to the SVM model approach described above. The tool wear data is clustered by the Clara algorithm, and the corresponding regression coefficient estimates $\hat{\varphi}_1 = -0.7063$, $\hat{\varphi}_2 = -0.4874$, $\hat{\varphi}_3 = -0.5578$, $\hat{\varphi}_4 = -0.2977$, and $\hat{\varphi}_5 = -0.2268$ are obtained after the difference is obtained according to the correlation function, and the prediction is made and compared with the predicted value. Subtract the simulated value from its corresponding value to obtain the residual sequence, then reconstruct the one-dimensional residual into a five-dimensional Gaussian process regression parameter through MATLAB software, and finally add the predicted values of the two models to obtain the predicted value of the mixed model.

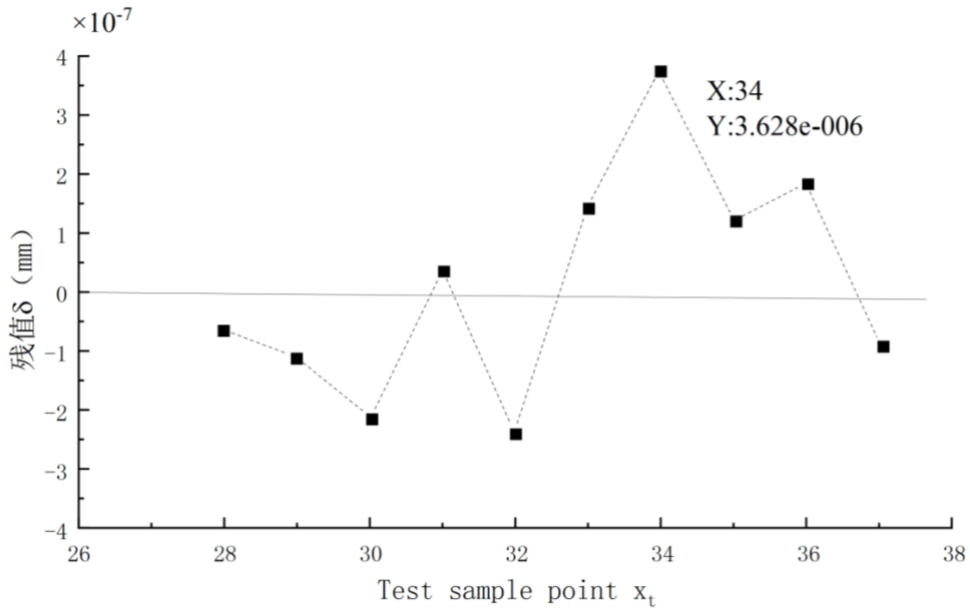

Figure 3. Residuals between actual and predicted values

Figure 3 is the difference between simulated and predicted mixed models. As shown, the remaining maximum value is 3.628e-006. Figure 3 is a relatively wrong prediction point. The results show that the largest relative error is 0.5371. Figure 3 shows that the established model is in good agreement with the simulation results, indicating that the proposed hybrid model can predict tool wear well.

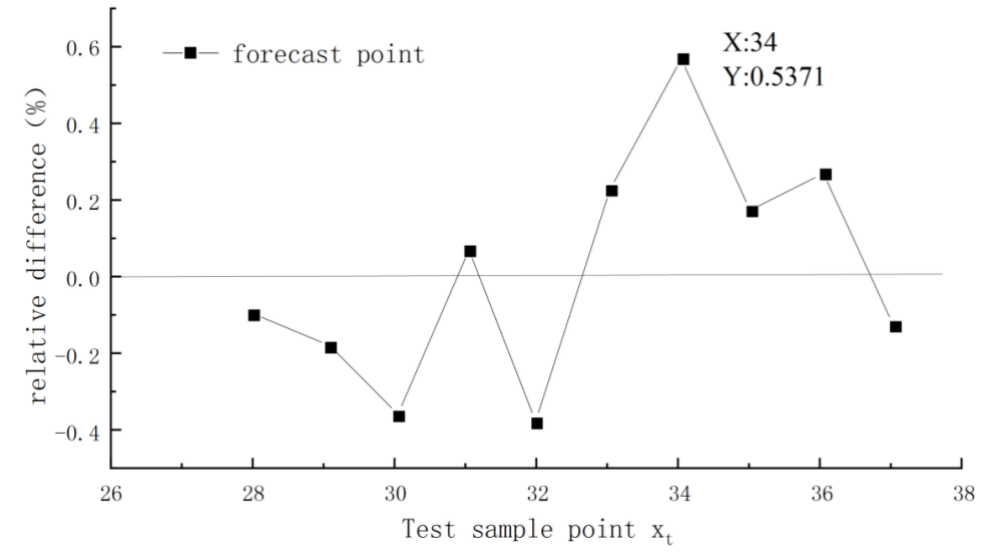

Figure 4. Relative error of predicted points

To quantify the prediction performance of the SVM-Clara model, four indicators of absolute mean square error (MAE), mean square error (MSE), mean absolute percentage error (MAPE), and root mean square error (RMSE) was used. The SVM-Clara model was compared with other models, and the results are shown in Table 3. It can be seen from Table 3 that the four error evaluation criteria of

the SVM-Clara model are the smallest, which also shows that the SVM-Clara model is better than the other two models in predicting tool rake wear.

Table 3. Error comparison results of the four models

Model	MAE	MSE	MAPE	RMSE
SVM Model	1.59274e-7	0.2463	3.3672e-14	1.75567e-7
Clara's Algorithm	3.26074e-7	0.5409	3.5726e-13	5.48035e-7
SVM-Clara Model	1.47396e-7	0.2236	3.2974e-14	1.69674e-7

Through the above comparative study on the tool prediction model based on SVM-Clara and the variable parameter milling tool wear state prediction model based on SVM, it can be seen that the SVM-Clara tool prediction model proposed in this paper is better than the SVM variable parameter milling tool wear state prediction model. It is more suitable for predicting the degree of tool wear.

6 Conclusion

In actual operation, to predict the use effect of the tool more intuitively, the service life of the tool can be improved and the safety of the tool can be enhanced. Using the Clara algorithm, the SVM prediction model of tool wear is established. Compared with the traditional prediction model, the mean square error of the SVM-Clara model is nearly 0.03 lower than the prediction value of other models, and the relative error prediction is reduced to 0.5371.

On this basis, the tool wear simulation test is carried out and compared with the measured results. The results show that the SVM-Clara model can better predict the tool surface wear, which proves that the establishment of the SVM-Clara model is reasonable and accurate. It provides a reliable basis for improving tool life and reducing machining costs.

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