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An Effective PSO-LSSVM-Based Approach for Surface Roughness Prediction in High-Speed Precision Milling

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ABSTRACT Surface roughness is one of the important indicators to measure the surface quality of parts processed, in addition to the cutting parameters affecting the surface roughness, the inevitable tool wear during the cutting process also makes the surface roughness constantly changing. In order to achieve high-precision prediction of machined surface roughness, a high-speed precision milling surface roughness prediction method based on particle swarm optimization least squares support vector machine (PSO-LSSVM) is proposed in this paper. The prediction method uses standardized cutting parameters and tool wear as the input variables, and uses the LSSVM algorithm to model the relationship between the input variables and the surface roughness, the improved PSO algorithm is used to optimize the hyperparameters of LSSVM so as to improve the generalization ability. In order to verify the effectiveness and superiority of PSO-LSSVM predictive performance, two surface roughness prediction models have been developed based on support vector machine (SVM) and response surface method (RSM), respectively. With the same sample conditions, average relative error and root mean square error of PSO-LSSVM prediction model are the smallest, and the correlation coefficient of PSO-LSSVM method is the largest. It is indicate that the surface roughness prediction accuracy and generalization ability based on PSO-LSSVM are the best under different cutting parameters.

INDEX TERMS Surface roughness prediction, least squares support vector machine, PSO algorithm, precision milling.

I. INTRODUCTION

Surface roughness is one of the important indicators to evaluate the surface quality of precision machining, which directly affects the performance and service life of parts [1], according to statistics, more than 80% of fatigue cracks in aerospace parts start from the roughness of the processed surface [2]. Therefore, realizing the accurate prediction of the surface roughness in the intelligent and automatic machining process, and adjusting the cutting parameters in the machining process in time can not only improve the machining quality and efficiency, but also reduce the processing cost, which has important application value for the actual production. For this, many scholars have conducted in-depth research on the prediction method of surface roughness.

In the process of precision milling, it is necessary to construct a high-precision and robust surface roughness prediction model in order to evaluate the surface roughness of milling. At present, surface roughness prediction method are mainly divided into two aspects, one is online surface roughness detection, such as the use of photoelectric sensor technology to directly measure the surface roughness [3], [4], but due to the influence of cutting chips and coolant in the machining process, the direct detection accuracy and efficiency are low. The other is indirectly detect surface roughness by monitoring the process state. In recent years, many scholars have studied surface roughness prediction methods based on cutting parameters and tool geometric parameters, which mainly include theoretical modeling method [5], [6], empirical regression analysis modeling method [7]–[9] and artificial intelligence modeling law [10]–[12] etc. In terms of theoretical modeling research, Montgomery and Altitas [5] proposed a theoretical model to predict the surface

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roughness during processing with a flat-end milling cutter as $Ra = f_z^2/[32 \times (R \pm f_z n_z/\pi)]$, where f_z is the feed rate per tooth, R is the tool radius and n_z is the number of tool teeth. He *et al.* [6] proposed a new theoretical surface model, which takes into account the influence of cutting edge shape, workpiece material properties and other random factors. In terms of empirical regression analysis modeling, Agrawal *et al.* [7] developed a surface roughness prediction model based on multiple regression modeling by studying the influence of cutting parameters on machined surface roughness. Li *et al.* [8] established a high-speed milling surface roughness regression prediction model based on RSM, and verified the accuracy of the prediction model. Rao *et al.* [9] used variance analysis to determine the importance of cutting parameters to surface roughness, and established a statistical model for surface roughness prediction based on RSM.

Artificial neural network (ANN) is an integrated knowledge tool that does not need to establish a specific mathematical or mechanical analysis model, but uses a large amount of data to train it to reflect the complex relationship between input variables and output variables. Considering the complex nonlinear relationship among cutting parameters, tool parameters and surface roughness in precision milling process, therefore, many researchers have made a lot of attempts and research in this filed. Abu-Mahfouz *et al.* [10] established a surface roughness prediction model based on SVM by collecting vibration signals under different cutting conditions and extracting signal features. Kumar and Hynes [11] established a prediction model based on ANFIS and optimized the cutting parameters using genetic algorithm (GA), and the experimental results show that the cutting speed and tool angle in the machining process have an important influence on the drilling quality. Zhang and Shetty [12] established a prediction model of the machining process based on the method of effective least squares support vector machine. Wu and Yin [13] combined the classic theoretical model and the ANN model to study the surface roughness of the workpiece under different milling parameter combinations, and based on NSGA-II optimization algorithm to obtain the best process parameters. Mia and Dhar [14] proposed an ANN-based surface roughness prediction method. They also found that effective lubrication conditions can improve processing quality through comparison. He *et al.* [15] analyzed the formation mechanism of machined surface quality, and based on the ANN algorithm established a machined surface quality prediction model with the cutting vibration and machining parameters. Chiu and Lee [16] established an adaptive fuzzy neural network prediction model that takes machining parameters as input and milling accuracy and surface quality as outputs. Through simulation and experiments, the authors show that the model can well predict target values. Misaka *et al.* [17] proposed a machining surface quality prediction model based on the Co-Kriging method. They proved through experiments that the developed model achieves a satisfactory prediction accuracy only when the amount of data is small.

From the previous studies, we can see that in the theoretical and regression prediction research, the modeling process has been simplified to a great extent, such as they only consider the cutting parameters and tool geometry parameters, and do not consider the influence of the changing factors in the cutting process on the surface roughness. However, the tool parameters in the milling process are dynamically changing (such as tool face wear, etc.). When the tool wears, it directly affects the integrity of the machined surface. Due to the complexity and uncertainty of the milling process, especially in the high-speed precision milling process, when the feed per tooth is small, there is a large accuracy error between the established prediction model and the actual measurement. However, the current surface roughness prediction model based on neural networks or other intelligent methods lacks consideration of related physical quantities which directly affect the quality of the processed surface, such as tool wear. These deficiencies limit the prediction accuracy and generalization ability of the proposed method, hence, it cannot accurately reflect the actual processing process.

In the high-speed precision milling process, it is necessary to adopt a more reliable method to predict the surface roughness and control the surface roughness within a reasonable range to improve the performance of the parts. Therefore, this article first briefly describes the main factors affecting surface roughness, and analyzes the impact of tool wear on surface roughness from the perspective of the formation mechanism of surface roughness. Then, a surface roughness prediction method based on PSO-LSSVM in high-speed precision milling process is proposed, which fully considers the influence of tool wear on surface roughness. In this work, we first use the adaptive weight algorithm to improve PSO algorithm, and then use the improved PSO algorithm to iteratively optimize the hyperparameters in the LSSVM to ensure the learning ability of the predictive model. Finally, three sets of milling experiments with different cutting parameters verify the prediction accuracy and generalization ability of the surface roughness prediction model established in this paper.

II. ANALYSIS OF SURFACE ROUGHNESS

Surface roughness is the roughness of small spacing and small peaks and valleys on the machined surface, which is mainly caused by the friction marks caused by the tool wear and the system vibration during the cutting process. Research shows that process parameters such as tool geometry parameters, cutting parameters, cooling and lubrication methods in the cutting process all affect the surface quality of the parts, and there is a mutual coupling relationship between these factors. The main factors that affect the roughness of the processed surface are listed in table 1 [18], [19], [20].

In high-speed precision milling, the higher cutting speed makes the tool wear faster, the tool nose radius r_ε and the flank wear VB will increase and leads to an increase in the contact area between the tool and the workpiece, which intensifies the plough and friction of the tool, as shown in Figure 1. In the process of precision milling, irregular tool cutting

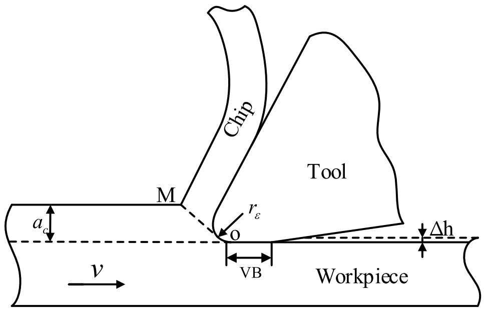

FIGURE 1. The formation of the processed surface.

TABLE 1. The main influencing factors of surface roughness.

	Influence factors	Remarks
Cutting parameters	Cutting Speed, Feed of per tooth, Axial depth of cut, Radial depth of cut	Static parameters
Tool parameters	Tool nose radius, Cutting edge shape, Extended length of tool	
Material properties	Material hardness	
Cutting process variables	Cutting Force, Tool wear, System vibration, Cooling method, cutting temperature	Dynamic variables

edge wear will leave wear marks on the machined surface, as the tool flank wear continues to expand, the friction and temperature between the tool and the workpiece will change significantly, which seriously affects the surface roughness of the finishing process.

Cutting parameters and tool wear not only affect the machining accuracy and surface roughness of the workpiece, but also affect the machining efficiency and production cost. Therefore, this article studies the influence of cutting parameters and tool wear on the surface roughness of the precision milling process, and takes the cutting parameters and tool wear as the input, establishes an accurate surface roughness prediction model to solve the problem of accurate prediction of machined surface roughness.

III. SURFACE ROUGHNESS PREDICTION MODEL BASED ON PSO-LSSVM

A. PRINCIPLE OF LSSVM

SVM is a supervised machine learning method based on statistical learning theory, which uses the principle of risk minimization to construct a decision function to solve the nonlinear problem of small sample size and high digits. LSSVM is simplified on the basis of the support vector machine, which takes equations as its constraints and adopts different decision functions, so as to reduce the computational complexity of SVM and improve its learning ability. The main principles of LSSVM are as follows.

Give a sample of N points $\{(x_i, y_i), i = 1, 2, \ldots, N\}$, with input vectors $x_i \in R^n$ and output $y_i \in R^n$, where n is the data dimension. For nonlinear regression problems, LSSVM maps the original data to a high-dimensional space by using a nonlinear mapping function $\varphi(\cdot)$, and then constructs a linear regression equation in this space. Then the regression model based on LSSVM can be expressed as:

$$y = w^T \varphi(x_k) + b \tag{1}$$

where w is the weight vector, b is the deviation. Then the minimization problem of the regression objective function can be expressed as:

$$\begin{cases} \min_{w,b,e} J(w, e) = \frac{1}{2} w^T w + \frac{1}{2}\gamma \sum_{k=1}^{N} e_k^2 \\ s.t.\ y_k = w^T \varphi(x_k) + b + e_k,\ k = 1, \ldots, N \end{cases} \tag{2}$$

where γ is the regularization parameter or penalty factor, which determines the degree of punishment for samples that exceed the error, b is the deviation, e_k is the slack variable, which represents the error expectation of the approximation function at the sample data point. According to Eq. (2), the Lagrange function of LSSVM can be expressed as:

$$L(w, b, e, \alpha) = J(w, e) - \sum_{k=1}^{N} \alpha_k [w^T \varphi(x_k) + b + e_k - y_k] \tag{3}$$

where α_k is the Lagrange multiplier. According to the Karush-Kuhn-Tucker (KKT) condition, the following equality constraints can be obtained as:

$$\begin{cases} \frac{\partial L(w, b, e, \alpha)}{\partial w} = 0 \to w = \sum_{k=1}^{N} \alpha_k \varphi(x_k) \\ \frac{\partial L(w, b, e, \alpha)}{\partial b} = 0 \to \sum_{k=1}^{N} \alpha_k = 0 \\ \frac{\partial L(w, b, e, \alpha)}{\partial e_k} = 0 \to \alpha_k = \gamma e_k, k = 1, \ldots, N \\ \frac{\partial L(w, b, e, \alpha)}{\partial \alpha_k} = 0 \to w^T \varphi(x_k) + b + e_k - y_k = 0 \end{cases} \tag{4}$$

Eliminating the variables w and e_k in Eq. (4), we can get the following linear equation:

$$\begin{bmatrix} 0 & \boldsymbol{I}^T \\ \boldsymbol{I} & \Omega + \gamma^{-1}\boldsymbol{I} \end{bmatrix} \begin{bmatrix} b \\ \boldsymbol{\alpha} \end{bmatrix} = \begin{bmatrix} 0 \\ \boldsymbol{y} \end{bmatrix} \tag{5}$$

where Ω represents the inner product of the kernel matrix, $\boldsymbol{y} = (y_1, y_2, \ldots, y_N)^T$, $\boldsymbol{\alpha} = (\alpha_1, \alpha_2, \ldots, \alpha_N)^T$, and $\boldsymbol{I} = (1_1, 1_2, \ldots, 1_N)^T$. The kernel function can be expressed as:

$$\Omega = \varphi(x_i)^T \varphi(x_i) = K(x_i, x_j) \tag{6}$$

where $i, j = 1, 2, \ldots, m$.

According to Mercer's theorem, the kernel function is defined as:

$$K(x_k, x_l) = \varphi(x_k)^T \varphi(x_l) \tag{7}$$

We can obtain α_N and b by solving Eq. (6), and the regression function of LSSVM can be expressed as:

$$y(x) = \sum_{k=1}^{N} \alpha_k K(x, x_k) + b \tag{8}$$

where $K(x, x_k)$ is the kernel function.

At present, the commonly used kernel functions include radial basis kernel function, linear kernel function, polynomial kernel function, multi-layer perceptron kernel function, etc. Among them, the radial basis function has a wide convergence range and strong generalization ability [21], through experimental comparison and analysis of the above kernel functions, this paper chooses the radial basis function as the kernel function of LSSVM, and its expression is:

$$K(x_i, x_j) = \exp\left(-\frac{||x_i - x_j||^2}{2\sigma^2}\right) \tag{9}$$

where σ is the width of the kernel function.

From the above analysis, it can be seen that the penalty factor γ and the kernel parameter σ are the two main parameters that affect the prediction performance of LSSVM, the commonly used parameter solving methods include trial and error method, grid search method, and crossover method [22], but these methods mainly use exhaustive parameters to obtain the global optimal solution, which is cumbersome and inefficient. Artificial intelligence optimization algorithm can solve this kind of problem well, and it has the advantages of high accuracy, fast convergence and easy implementation.

B. PSO-LSSVM NEURAL NETWORK MODELING

The PSO algorithm is a group of heuristic intelligent algorithm, each particle in the algorithm looks for the global optimum solution by following the current optimal position. Assuming that there are a total of N particles in a multi-dimensional solution space, the velocity and position of the i-th particle can be expressed as: $V_i = (v_{i1}, v_{i2}, \ldots, v_{in})$, and $X_i = (x_{i1}, x_{i2}, \ldots, x_{in})$. The best position experienced by a single particle i is marked as: $P_i = (p_{i1}, p_{i2}, \ldots, p_{in})$, and the best position experienced by the population is marked as: $P_g = (p_{g1}, p_{g2}, \ldots, p_{gn})$. The update of particle speed and position can be expressed as:

$$V_{id}^{k+1} = \omega(s)V_{id}^{k} + c_1 r_1 \cdot (P_{id}^{k} - X_{id}^{k}) + c_2 r_2 \cdot (P_{gd}^{k} - X_{gd}^{k}) \tag{10}$$

$$X_{id}^{k+1} = X_{id}^{k} + V_{id}^{k+1} \tag{11}$$

where w is the inertia weight coefficient; d is the dimension of the solution space, c_1 and c_2 are acceleration factor, and they are non-negative constants; r_1 and r_2 are two random numbers with values between (0,1) to increase the randomness of the search, k represents the current iteration number.

Compared with other classic intelligent optimization algorithms, the obvious feature of PSO is that the search speed is fast and efficient, and the algorithm is relatively simple. But it also has a defect that if the inertia weight is too large, it will lead to ''premature convergence'' and oscillations when the particles are close to the global optimal solution, and if the inertia weight is smaller, it will help to improve the local search capability of local particle swarms. Therefore, in order to more effectively control the flight speed of the particles and adjust the position of the particles, this article uses an adaptive adjustment strategy to update the inertia weight coefficient to improve the global search capability of the PSO algorithm and improve the problem of local imbalance. The calculation formula of the adaptive weight coefficient can expressed as:

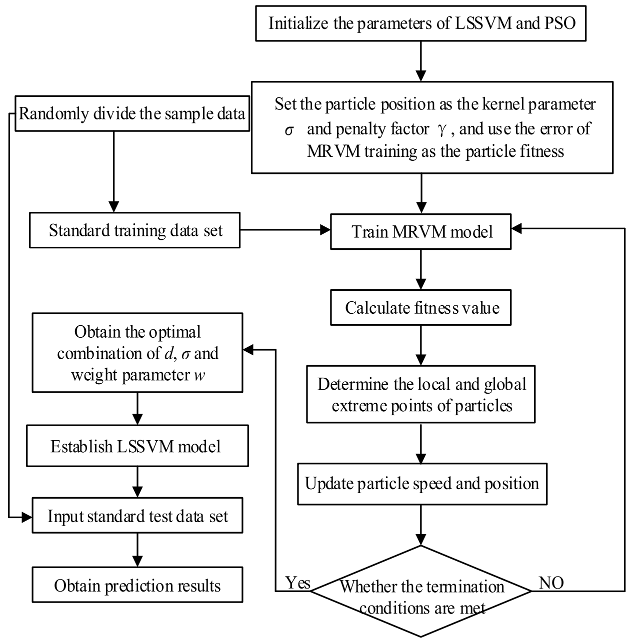

FIGURE 2. Flow diagram of PSO-LSSVM neural network optimization.

$$w = \begin{cases} w_{\min} - \dfrac{(w_{\max} - w_{\min}) \cdot (f - f_{\min})}{(f_{avg} - f_{\min})}, & f \le f_{avg} \\ w_{\max}, & f \ge f_{avg} \end{cases} \tag{12}$$

where f is the current value of the particles, f_{avg} and f_{min} are the mean and minimum value in the particle swarm, respectively, and $w_{\min}$ and $w_{\max}$ are the maximum and minimum weight coefficients.

The flowchart of optimizing LSSVM with improved PSO algorithm is shown in Figure 2. The specific steps are as follows:

Step 1: Standardize the collected data samples according to Eq. (13), and then randomly obtain 80% of the sample data as training samples, and 20% of the sample data as test samples.

$$\hat{x}_i = \frac{x_i - x_{\min}}{x_{\max} - x_{\min}} \tag{13}$$

where x_i is a variable data in the data set, $x_{\max}$ is the maximum value in the variable, and $x_{\min}$ is the minimum value in the variable.

Step 2: Set the range of the penalty factor γ and the kernel parameter σ in LSSVM, and initialize the particle swarm randomly according to the parameter range.

Step 3: Set the number of optimization iterations to 200, the acceleration factors c_1 and c_2, the maximum inertia weight $w_{\max}$ to 0.8, the minimum inertia weight to $w_{\min}$ to 0.5, the variance of the random weight average to 0.2, and the weights are adaptively updated according to Eq. (12).

Step 4: Calculate the fitness value of each particle according to the Eq. (14), and then determine the individual optimal value and population optimal value of the current particle

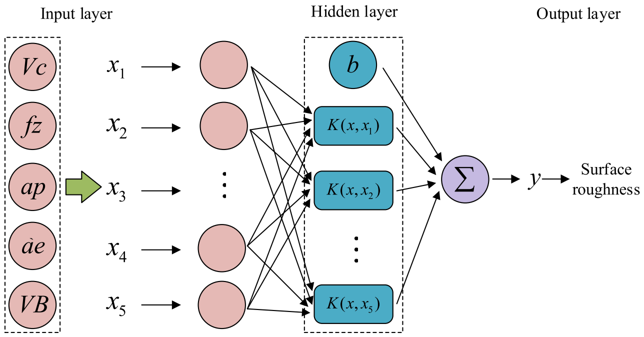

FIGURE 3. Schematic diagram of surface roughness prediction based on PSO-LSSVM.

according to the fitness value.

$$e_{RMSE} = \sqrt{\frac{1}{N}\sum_{i=1}^{N} ||f(x_i) - y_i||^2} \tag{14}$$

Step 5: Iteratively update the position and velocity of the particles according to the Eq. (10) and Eq. (11), then produce a new generation of populations.

Step 6: Calculate the fitness value of each particle in the new population again, and then compared with the optimal position of the historical individual and the optimal position of the population. If it is better, replace it, otherwise it will remain unchanged.

Step 7: Check whether the requirements are met (usually the preset maximum number of iterations and the lower limit of the fitness value), if the termination requirements are not met, return to step (4). If the conditions are met, the program ends and the global optimal is obtained, that is, the optimal γ and σ^2 are obtained.

Step 8: Assign the obtained optimal position (γ, σ) of the particle swarm to the LSSVM prediction model to obtain the optimal prediction model.

The PSO-LSSVM method is used to establish the non-linear mapping relationship between cutting variables and surface roughness, where cutting variables include cutting parameters and tool wear. Suppose there are n sets of training sample data (x_i, y_i) $(i = 1, 2, \ldots, n)$, in this model, cutting parameters and tool wear are input sample data, where x_i is a five-dimensional real number input vector, including water cutting speed Vc, feed per tooth fz, cutting width a_p, cutting depth a_e, and tool wear value VB, y_i is the output sample data, that is, the surface roughness measured by the experiment. The schematic diagram of the nonlinear mapping relationship model between the input vector x_i and the output value y_i established in this paper is shown in Figure 3.

The steps needed to use the PSO-LSSVM model are:

Step 1. Normalize the turning experimental sample data and divide them into two parts: training data and test data.

Step 2. For training data, using PSO algorithm to train LSSVM model and after many iterations, get the optimal γ and σ for LSSVM.

FIGURE 4. Details of experimental measurement system.

TABLE 2. Physical and mechanical properties of 7050 aluminum alloy.

Properties	Value	Properties	Value
Tensile strength	572 (MPa)	Elastic Modulus	70.3 (GPa)
Yield Strength	503 (MPa)	Density	2.82 (g/cm3)
Hardness HB	150 (N/mm^2)		

Step 3. Use optimized LSSVM model to predict surface roughness based on the test data.

IV. MILLING EXPERIMENT DESIGN AND RESULT ANALYSIS

A. PRINCIPLE OF LSSVM

The milling experiment was performed on a JDCT1200T_A15SH three-axis machine tool, as shown in Figure 4 (a), tool wear measured using microscope system (Figure 4 (b)), workpiece surface roughness measured using MarSurf GD 25 (Figure 4 (c)).

The experimental material is 7050 aluminum alloy developed and produced by Alcoa, which has excellent performance such as high strength, plasticity and toughness, and is widely used in aerospace, mold and other application fields. Its main properties are listed in Table 2. Before the experiment, the aluminum alloy sheet was processed into a workpiece with a size of 120 × 80 × 10 mm.

The tool used in the experiment is a solid carbide tool, and the main parameters are listed in Table 3. This experiment mainly focuses on high-speed finishing and semi-finishing, the cutting parameter and their level settings are listed in Table 4.

B. EXPERIMENTAL RESULTS

1) SURFACE ROUGHNESS MEASUREMENT

At present, the commonly used surface roughness evaluation method in the world is to make a quantitative evaluation of the height of the actual contour curve between the peak and valley (the amplitude of the contour waveform) on the French

TABLE 3. Main structural parameters of solid carbide end mills.

Parameters	Value	Parameters	Value
Diameter	8 (mm)	Rake angle	16 (°)
Number of teeth	3	Back angle	12 (°)
Helix angle	30 (°)	Cutting edge length	11(mm)

TABLE 4. Cutting parameter.

v (m/min)	fz(mm/tooth)	a_p(mm)	a_e(mm)
400	0.03	0.3	2
500	0.045	0.5	4
600	0.06	0.7	6

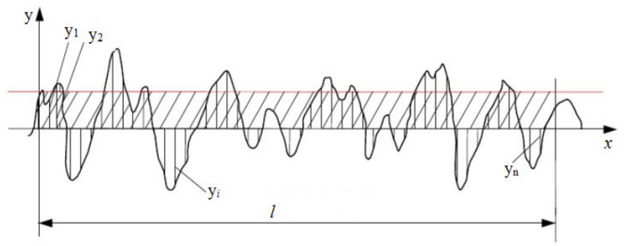

FIGURE 5. Arithmetic mean deviation R_a.

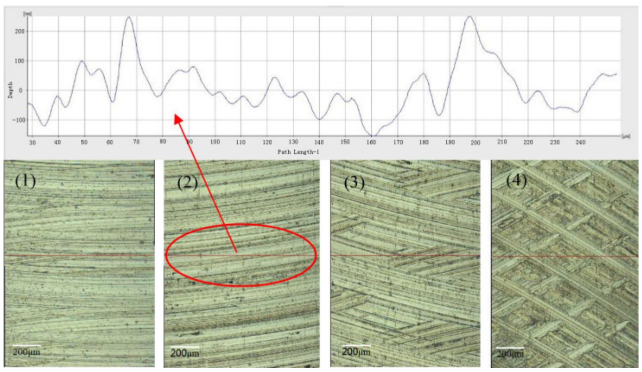

FIGURE 6. Surface roughness measurement micrograph.

phase cross section of the measured surface [23], as shown in Figure 5.

The arithmetic mean deviation of the profile is a parameter used in most countries to evaluate the surface roughness, and its calculation can be expressed as:

$$R_a = \frac{1}{l}\int_0^l |y(x)|\,dx \approx \frac{1}{n}\sum_{i=1}^{n}|y_i| \tag{15}$$

For each experiment, when measuring the surface roughness, the processed surface is cleaned with alcohol, each R_a measurement is repeated at least three times at different locations and the average value was used in the analysis. Part of the surface roughness measurement morphology during the experiment as shown in Figure 6.

2) TOOL WEAR MEASUREMENT

In the finishing process, the cutting tool needs to be replaced before the wear increases drastically or the surface roughness is seriously affected. The microscopic schematic of tool flank wear in the actual machining process as shown in Figure 7. The wear in the middle part of the wear zone (area B in Figure 7) is relatively uniform, and VB is often used to indicate average wear, and the maximum wear width is represented by $VB_{\max}$. In the measurement of tool wear status, the average width of the wear zone is generally used to measure the wear of the flank surface according to the literature [31].

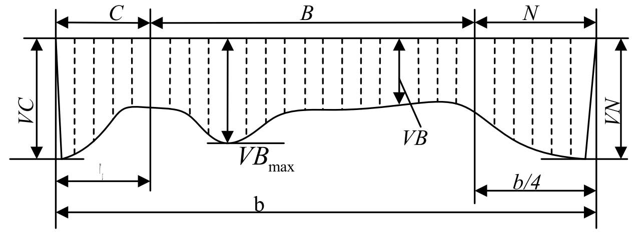

FIGURE 7. Schematic diagram of tool flank wear.

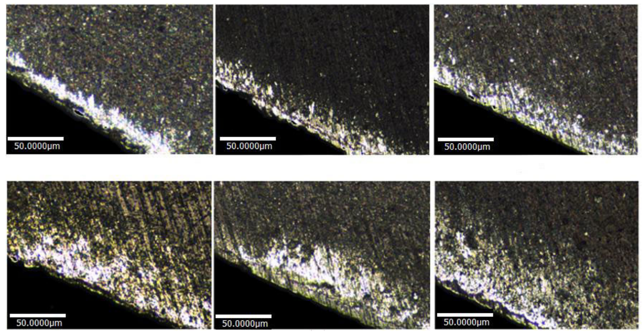

FIGURE 8. Micrograph of tool flank wear change.

Therefore, in the research process of this article, the average value of tool wear is defined as the value measured every 10 minutes of machining. When measuring the tool wear value, we first clean the worn flank surface with alcohol, and then repeat the measurement at least 3 times at different positions, and use the average of the three measurements in the analysis.

Part of the tool wear measurement morphology during the experiment as shown in Figure 8.

During the experiment, due to the large experimental data, in order to save space, the values of tool wear and surface roughness collected during the experiment are shown in Figure 9.

It can be seen from the surface roughness topography map of Figure 6 and the tool flank topography map of Figure 8 that when a brand-new tool is used to cut the workpiece, the flank of the tool has a certain degree of microscopic unevenness, so the texture of the tool marks on the machined surface is dense but not evident. This is because the cutting edge and tool tip are in a sharp state at this time, and have good material removal performance, so that the surface of the processed workpiece reaches a good state. When the tool wear reaches a certain level, the micro-concave and convex surface of the flank face is gradually smoothed, and the pressure of the contact between the flank face and the workpiece decreases. At this time, the cutting edge is still in an ideal geometric state in structure, and the cutting performance of the tool reaches the best state, and the surface quality of the workpiece

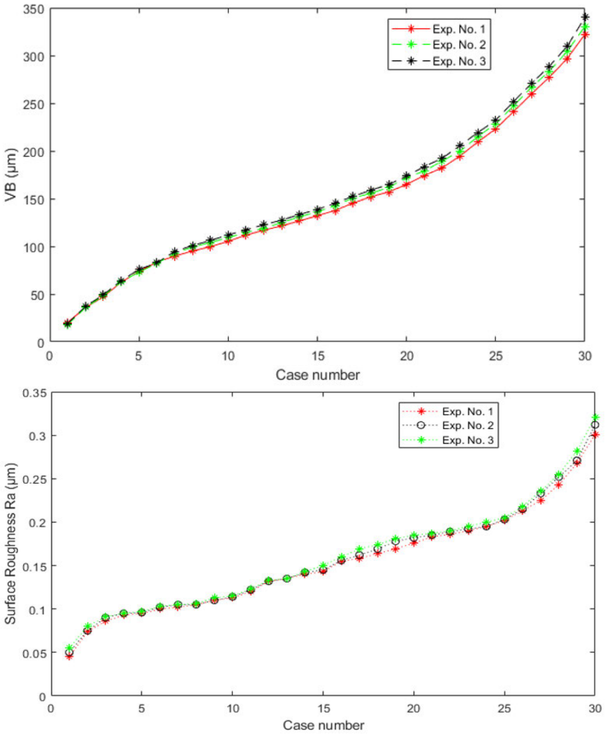

FIGURE 9. Experimental measurements values.

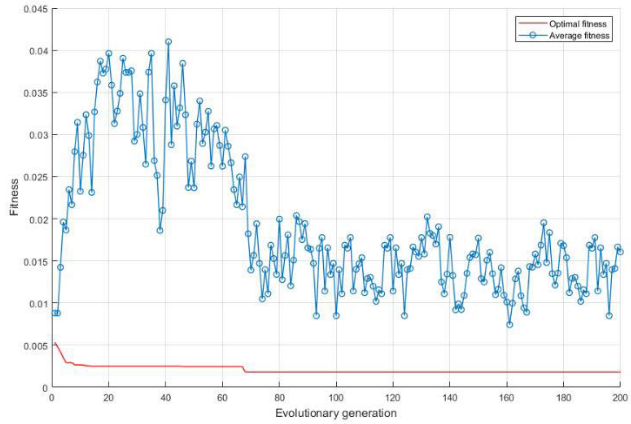

FIGURE 10. The fitness curve of particle swarm optimization.

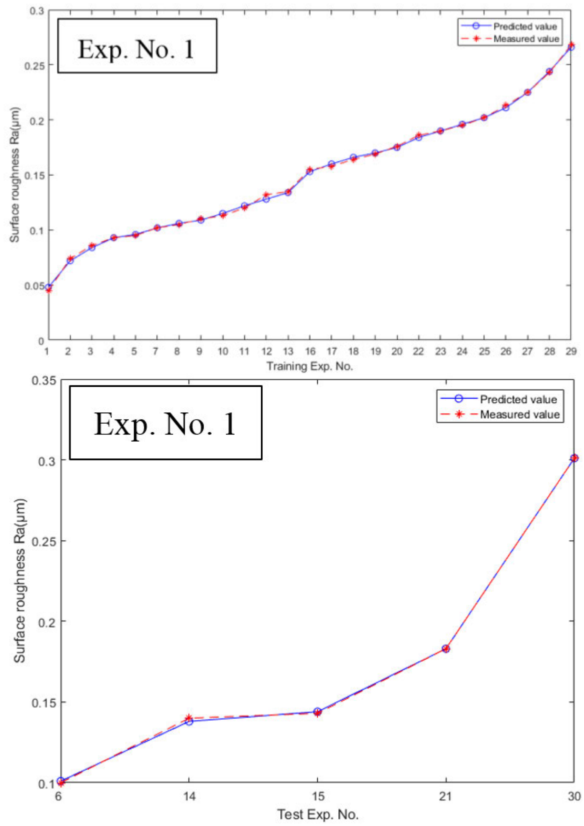

FIGURE 11. Surface roughness training and testing based on PSO-LSSVM.

decreases but changes slowly. However, as the cutting time increases, the tool begins to wear faster, the contact pressure between the flank face and the surface of the workpiece increases, and the gradual passivation of the cutting edge of the tool degrades the processing performance of the tool, resulting in a faster rate of decline in the quality of the machined surface. However, with the increase of cutting time, the tool wear is accelerated, the contact pressure between the flank face and the workpiece surface increases, and the gradual passivation of the cutting edge leads to the degradation of the machining performance of the cutting tool and the decrease of the surface roughness.

It can be found from Figure 9 that there is almost the same change trend between the surface roughness R_a and the tool wear value VB under three groups of different cutting parameters, it is indicate that there is a strong correlation between the tool wear and the surface roughness.

C. SURFACE ROUGHNESS PREDICTION USING PSO-SVM

According to the steps of optimizing LSSVM with PSO algorithm in Section 3.2, we divide the 30 sets of data obtained in experiment No. 2 in Table 4 into two parts, 25 groups of experimental data were randomly selected to train the prediction model, and the other 5 groups of experimental data were used to verify the prediction model.

The fitness convergence curve of the improved PSO algorithm for parameter optimization of LSSVM surface roughness prediction model as shown in Figure 10. It can be seen from the figure that after 68 iterations, the fitness value tends to be stable and reaches the optimal. At this time, the optimal feature parameters γ and σ^2 are 72.256 and 0.017, respectively.

Assigning the optimized model feature parameters to the LSSVM model, we get the surface roughness prediction based on PSO-LSSVM. In order to verify the prediction accuracy of the prediction model, we divide the data obtained from Exp. No. 1 and Exp. No. 3 in Table 4 into training data and test data respectively. The prediction results and test results based on PSO-LSSVM are shown in Figure 11 and Figure 12.

It can be seen from Figure 11 and Figure 12 that the surface roughness training results and test results based on PSO-LSSVM basically agree with the actual value change

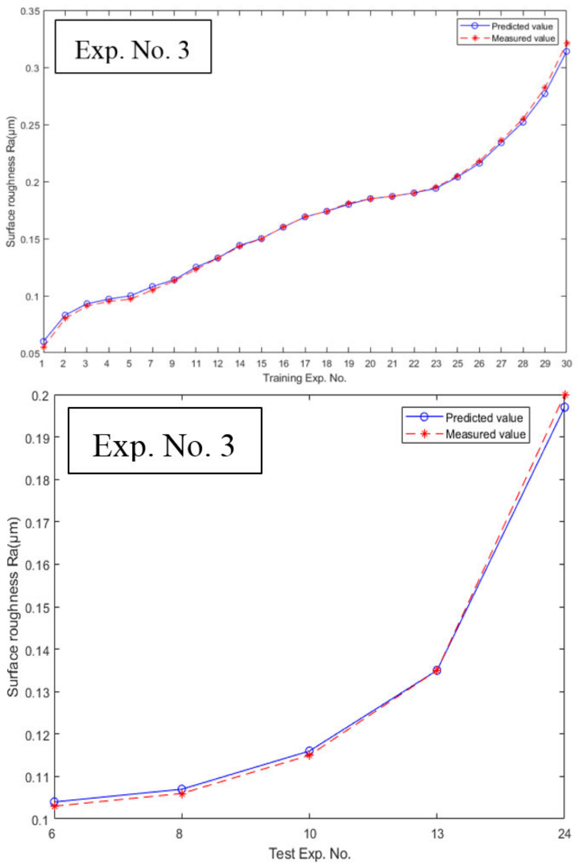

FIGURE 12. Surface roughness training and testing based on PSO-LSSVM.

curve, average prediction accuracy is as high as 97.8%. It shows that the prediction model still has good prediction accuracy and generalization ability when the cutting parameters and the tool wear change.

Based on the above results, it is shown that by introducing an improved PSO algorithm to optimize the parameters of LSSVM, the problem of LSSVM parameter optimization is effectively solved, so that the prediction model can reduce the error of artificial selection of parameters and overcome the inefficiency of traditional exhaustive method, and effectively solves the problem of parameter optimization of LSSVM, so that the prediction model can still have the advantages of high accuracy, fast convergence and easy implementation under different cutting strategies.

D. COMPARISONS OF EVALUATION RESULTS

In order to further verify the performance of the established model, we have established RSM and SVM surface roughness prediction models to verify the effectiveness of the PSO-LSSVM model. The RSM model can expressed as Eq. (16). The training data required for the two models is the same as the training data of PSO-LSSVM.

$$Ra = p_0 + \sum_{i=1}^{5} p_i x_i + \sum_{i=1}^{5}\sum_{j=1}^{5} p_{ij} x_i x_j + \sum_{i=1}^{5} p_{ii} x_i^2 \tag{16}$$

TABLE 5. Comparison of prediction accuracy of different methods.

Models	PSO-LSSVM	SVM	RSM
ARE	0.0326	0.03861	0.0365
RMSE	0.0213	0.0267	0.0325
R^2	0.9857	0.9768	0.9745

where R a is the polynomial regression prediction value of surface roughness, $Px(x = 0, i, ij, ijl)$ are the unknown parameters of the polynomial, x_1 is the reciprocal of the cutting speed v, x_2 is the feed per tooth fz, x_3 is the cutting depth a_p, x_4 is the reciprocal of the cutting width a_e, x_5 is the value of tool wear.

Average relative error (ARE), Root Mean square error (RMSE) and correlation coefficient R^2 are used to evaluate the prediction effect of the mode, there calculation formulas are the Eq. (17), Eq. (18) and Eq. (19), respectively. The prediction results we get based on different prediction models are listed in Table 5.

$$E_R = \frac{1}{n}\sum_{i=1}^{n}\frac{|x_i - x_i|}{x_i} \tag{17}$$

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}|x_i - x_i|^2} \tag{18}$$

$$R^2 = 1 - \frac{\sum_{i=1}^{n}(x_i - i_x)^2}{\sum_{i=1}^{n}(x_i - \frac{1}{n}\sum_{i=1}^{n} x_i)^2} \tag{19}$$

where x_i are the experimental measured values, $(\widehat{x}_i)$ are the predicted values of the established model, n is the number of experimental data samples.

It can be seen that the prediction errors of the ARE and RMSE obtained by PSO-LSSVM are the smallest, and the value of R^2 is the largest. It is indicate that when using cutting parameters and tool wear as inputs, the prediction model based on PSO-LSSVM model has high prediction performance and can guide the practice well, because it makes full use of the optimization ability of the improved particle swarm optimization algorithm and the advantages of LSSVM in small sample data prediction. Therefore, in the case of less training data, it still has better generalization ability and higher prediction accuracy when changing the input parameters.

V. CONCLUSION

This paper mainly studies the surface roughness prediction method during the high-speed precision milling. It aims to obtain a reliable prediction method of milling surface roughness, and provide the basis for improving the surface quality of high-speed precision milling. Based on the current work, the following conclusions we are obtained:

(1) An effective high-speed milling surface roughness prediction method based on PSO-LSSVM algorithm has been developed. The adaptive weight algorithm is used to calculate and update the inertia weight coefficient in the

PSO algorithm to improve the global search ability and local improvement ability. The improved PSO is used to optimize the regularization coefficient σ^2 and the kernel parameter γ of the LSSVM algorithm. This method can better solve the network learning problem in a small sample space to improve the prediction accuracy and generalization ability of the LSSVM prediction model.

(2) The main factors that affect the surface roughness are described, and three different milling experiments have found that there is a positive correlation between tool wear and surface roughness during high-speed precision milling. Taking cutting parameters and tool wear as input variables, and surface roughness as output variables, the surface roughness prediction model for high-speed precision milling based on PSO-LSSVM can well reflect the relationship between tool wear, cutting parameters and surface roughness, and achieve high accuracy prediction of the surface roughness of high-speed milling workpieces under different cutting conditions.

(3) In order to further verify the effectiveness of the proposed model, we also established two high-speed precision milling surface roughness prediction models based on RSM and SVM, respectively, and compared the prediction accuracy of several models. The results show that under the same sample conditions, ARE and RMSE of PSO-LSSVM prediction model are the smallest, which are 0.0326 and 0.0213 respectively, and the correlation of PSO-LSSVM method is the largest, which is 0.9857. It can be seen that the prediction method based on PSO-LSSVM is superior to other prediction methods in terms of prediction accuracy and generalization ability, which provides a basis for further development and optimization of the actual production process.

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