

Optimization of High-speed Dry Milling Process Parameters Based on Improved ELM and Genetic Algorithm

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Abstract. High-speed dry grinding has the characteristics of high processing efficiency and clean environment. The high-speed dry grinding method meets the requirements of the green and efficient development of the national manufacturing industry. However, inappropriate cutting parameters seriously affect the surface quality of the workpiece and cause the workpiece to be scrapped. Therefore, this paper proposed an optimization method based on the combination of the improved extreme learning machine neural network (ELM) for high-speed dry milling surface roughness prediction model and genetic algorithm (GA). The Taguchi orthogonal experiment results show that the surface roughness of high-speed dry milling can be accurately predicted by the improved ELM and thereafter the optimal cutting parameter combination can be determined by GA.

Keywords: Genetic Algorithm (GA), ELM, High-speed dry grinding.

1. Introduction

In recent years, the level of machine manufacturing has become more mature with the progress of society and economic development. The quality requirements for mechanical products are also increasing in all areas. For critical parts used in high-end complex environments such as aerospace and precision manufacturing, surface roughness has a serious impact on skin hardness (HRC), abrasion performance, fatigue strength, cooperate with the performance and other product properties [1]. Surface defects can lead to component failure or significant losses. In actual processing, process parameters can directly affect the surface quality of the product. The choice of process parameters usually depends on the operator's experience or processing manual. This method of selecting process parameters has limitations. Therefore, adopting new and smarter methods to optimize the process parameters of high-speed dry grinding is of great significance to the improvement of product quality.

At present, domestic and foreign experts are conducting a lot of research on optimizing grinding process parameters. According to the study of LIANG et al. [2], a method based on fuzzy control to optimize the process parameters of milling and cutting aluminum alloys is proposed. This study obtained optimal feed rates and spindle speeds for milling aluminum alloys. Mativenga et al. [3] proposed the minimum energy standard and proposed a method to optimize milling process parameters with the minimum energy as the optimization objective. In the research of CNC milling, Deng Congying et al. [4] selected the tool overhang and the traditional milling amount as input, respectively established the back-propagation neural network model of the limit cutting depth and surface roughness, and then combined the sparrow search algorithm to search the optimal machining process parameters. Zeng Shasha et al. [5] proposed an intelligent process parameter optimization method for high-speed milling of thin-walled materials based on reverse transfer neural network combined with genetic algorithm. The research shown the effectiveness of the hybrid algorithm in optimizing the process parameters for high-speed milling of thin-walled materials. Li Congbo et al. [6] used the Taguchi orthogonal method to establish the regression equation of milling machine parameters, specific energy and processing time in the research of milling processing. The intelligent PSO algorithm was used to optimize the process parameters. JUAN et al. [7] proposed a method to establish the relationship model between machining parameters and tool life based on BP network. The paper discussed the optimal combination of machining parameters for SKD61 steel milling with

the goal of minimizing machining costs. In the research of plane end milling, Li Aiping et al. [8] proposed a method to obtain the optimal combination of milling process parameters based on genetic algorithm, taking the total energy consumption and total production efficiency as the optimization goal. From the study of Chen et al. [9], the BP artificial neural network combined with the genetic algorithm was employed to establish the surface roughness prediction model of high-speed dry milling. A multi-objective optimization mathematical model was established and the high-speed milling process parameters were optimized according to the required range of the actual machining parameters and the best combination of process parameters was obtained. Li et al. [10] conducted high-speed dry milling experiments on AISI 1045 steel with different hardness. The research adopted the Taguchi experiment method to optimize the cutting parameters (milling speed, milling depth, feed per tooth) and workpiece hardness and obtained the optimal combination of cutting parameters with the minimum surface roughness as the goal. From the above studies, the researchers focused on tool life, surface roughness and energy consumption during grinding. Researchers used experimental regression models or neural network model methods to establish the mapping relationship between cutting parameters and objects of interest, such as tool life, surface roughness etc. and optimal parameter combination was obtained through using optimization algorithms.

In view of this, this paper proposed a high-speed dry milling process parameter optimization method based on improved extreme learning machine network (PSO-ELM) and genetic algorithm. The Taguchi orthogonal test was carried out to obtain the machining data of high-speed milling. The improved ELM network was used to establish the surface roughness prediction model of high-speed dry milling and the experimental processing data constituted the model training set and test set. The well-trained prediction model was used as the fitness function of the genetic algorithm to be optimized to obtain the best combination of process parameters. The experiment finally verified the effectiveness and feasibility of the optimization method.

2. Optimization method of high-speed dry milling process parameters

During the milling process, different combinations of process parameters have a significant effect on the surface roughness of the workpiece. In this paper, a confluent method for optimizing the process parameters of high-speed dry milling based on improved ELM and genetic algorithm was proposed. Firstly, the paper improved the ELM network model. A predictive model for high-speed dry milling cutting parameters and surface roughness was created. Secondly, the paper used the predictive model as the fitness function of the GA. The best combination of cutting parameters was obtained by a new mode of genetic optimization algorithm.

2.1 Extreme Learning Machine and Particle Swarm Optimization

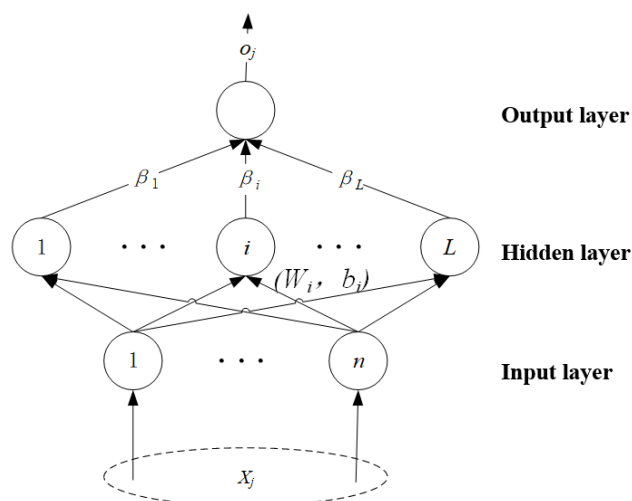


Figure 1. Schematic diagram of ELM structure.

Extreme Learning Machine (ELM) is a rapid learning algorithm based on Moore-Penrose matrix theory [11]. ELM is characterized by input layer weights and hidden layer biases can be set by themselves. Applying ELM to the prediction model of surface quality of high-speed dry milling can quickly obtain the prediction model. The schematic diagram of the ELM structure is shown in Figure 1.

As shown in Figure 1, a single hidden layer ELM network [12][13] contains N random data samples (X_j, t_j) and a hidden layer node L. The ELM neural network can be expressed as:

$$\sum_{i=1}^L \beta_i g(W_i \cdot X_j + b_i) = o_j, j = 1, \dots, N \quad (1)$$

where $X_j = [x_{j1}, x_{j2}, \dots, x_{jm}]^T \in R^n$, $t_j = [t_{j1}, t_{j2}, \dots, t_{jm}]^T \in R^m$, $g(x)$ represents the activation function of the ELM network, $W_i = [w_{i1}, w_{i2}, \dots, w_{in}]^T$ is the ELM input weight, β_i is the ELM output weight, b_i is the bias of the i th hidden layer unit of the ELM network, W_i and X_j represent the inner product of $W_i \cdot X_j$.

Particle swarm optimization (PSO) is often used in optimization problems. Using particle swarm optimization to optimize the relevant parameters of extreme learning machine can improve the reliability of the ELM network model.

The update expression of the speed and location of the "particle" can be formulated as:

$$V_{id}^{t+1} = V_{id}^t + c_1 r_1 (p_{id}^t - X_{id}^t) + c_2 r_2 (p_{gd}^t - X_{id}^t) \quad (2)$$

$$X_{id}^{t+1} = X_{id}^t + V_{id}^{t+1} \quad (3)$$

where p_{id}^t, p_{gd}^t represent the personal optimal solution and the global optimal solution, r_1, r_2 are the random numbers between 0-1, c_1, c_2 are the learning factors, usually set to 2 (too large or too small will affect the algorithm).

2.2 Prediction model based on improved ELM

The ELM don't need to adjust the weights and biases in reverse. So ELM can reduce the calculation amount by half and greatly improve the running speed of the model [14]. The reliability of the improved ELM model largely depends on the setting of hidden layer connection weights and biases. In this paper, PSO is used to optimize the weights and biases of ELM to improve the prediction reliability and accuracy of the model.

The weights and biases of the ELM network were determined by PSO and the fitness function [15][16] of PSO can be expressed by Eq. (4).

$$\text{s.t.} \sum_{i=1}^{\hat{N}} \beta_i g(W_i \cdot X_i + b_i) - t_j = \varepsilon_j \quad (j = 1, 2, \dots, N) \quad (4)$$

Where $\varepsilon_j = [\varepsilon_{j1}, \varepsilon_{j2}, \dots, \varepsilon_{jm}]$ is the error of the j th sample.

The high-speed dry milling quality prediction algorithm flow of PSO-ELM was as follows:

Step 1: Sample data processing. Input and normalize high-speed dry milling data samples to establish training samples and test samples of the model.

Step 2: Particle swarm parameter settings.

Step 3: Input the training data samples into the ELM.

Step 4: Calculating the fitness function. Calculate the fitness function value of each particle personal according to the target formula (4).

Step 5: Updating personal best locations. Compare the current fitness value of each particle with the optimal fitness value corresponding to the particle's previous best location, if the current particle is larger, update the particle's personal historical best location with the larger particle location P_g .

Step 6: Updating the global best locations. Compare the fitness value corresponding to the best location of all particles in each history record with the global corresponding fitness value g_{best} . If there is a particle with a higher fitness value, replace the global best location with the location of this particle.

Step 7: Checking for particles update. Determine whether the optimal particle in the particle swarm has been updated in the latest M generation. If it is found that the speed and location of the particle are not updated, update the particle according to Equation (2) and Equation (3).

Step 8: The termination condition to break out of the loop. If the required number of iterations is reached or the error of the model is small enough, it will jump out of the loop and terminate the optimization. Otherwise, go to step 4.

Step 9: The weights and biases (a_i, β_i, b_i) of the ELM model after optimization are obtained through PSO.

Step 10: Feed the test dataset into the improved ELM model for testing.

Step 11: Output the test error results to get the trained improved ELM prediction model.

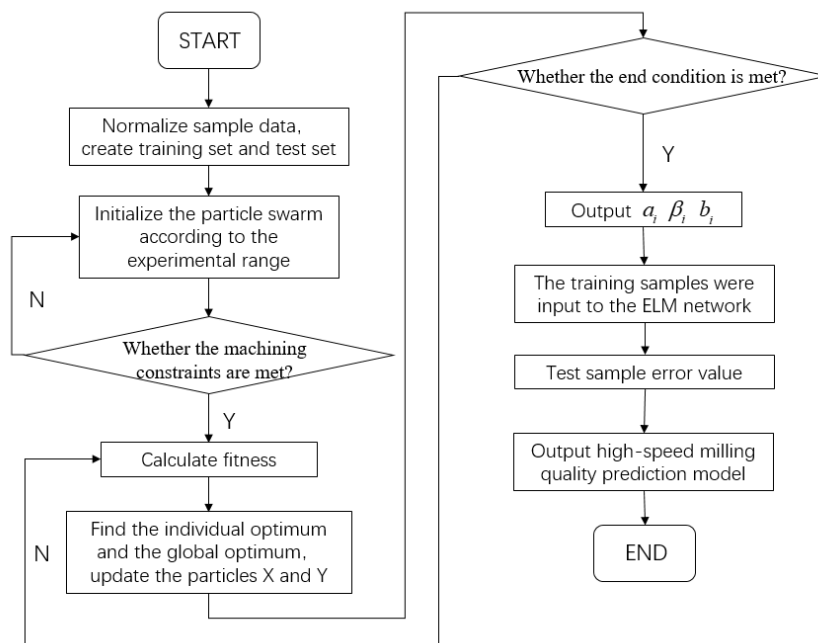


Figure 2. PSO-ELM algorithm flow chart.

3. Optimization method of high-speed dry milling process parameters based on improved ELM and GA.

3.1 Optimization model

(1) Determination of optimization model variables. In high-speed dry milling, the surface roughness of the workpiece is affected by the combination of process parameters(Spindle speed n , feed per tooth f_z , back engagement a_p and side engagement a_e). So, these four elements of milling were used as an optimization decision variable.

(2) Determination of the optimization target. The trained PSO-ELM quality prediction model was used as the fitness function in the genetic algorithm.

3.2 Constraints

In the process of CNC milling, the decision variables should meet the constraints of various processing conditions. According to the requirements of processing specifications and processing safety requirements, the paper selected the constraints of machine tools and tools as constraints:

(1) Machine tool constraints. CNC milling machine constraint is the key constraint of machining. Any cutting processing needs to be carried out within the reasonable range of the CNC milling machine. The machine tool constraints can be expressed as:

$$\begin{cases} x_{\min} < x_i < x_{\max} (i = 1, \dots, n) \\ F_c < F_{\max} \\ P < \eta P_{\max} \end{cases} \quad (5)$$

where x_i is the decision variable, $F_{\max}$ is the allowable maximum cutting force, $P_{\max}$ is the rated power of the machine tool, η is the efficiency of the machine tool.

(2) Tool constraints. Too frequent tool changes will affect the unremitment of machining. The tool constraints can be expressed as:

$$T_{\min} < T \quad (6)$$

Where $T_{\min}$ is the lower limit of tool life.

In summary, the optimization model of high-speed dry milling process parameters can be expressed as:

$$\min F(n, f_v, a_p, a_e) = \min Ra \quad (7)$$

$$s.t. \begin{cases} x_{\min} < x_i < x_{\max} (i = 1, \dots, 4); \\ F_c \leq F_{c \max}; \\ P < \eta P_{\max}; \\ T_{\min} < T; \end{cases} \quad (8)$$

2.3.3 Optimization method

Genetic algorithm (GA) is a computational model that simulates Darwin's biological evolution process of survival of the fittest. GA can avoid the problem that traditional search algorithms can only find local optimal solutions. The algorithm flow is shown in Fig. 3.

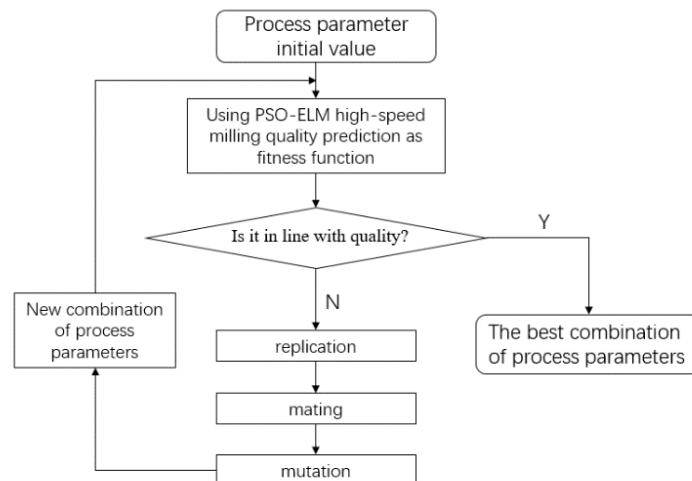


Figure 3. Genetic algorithm flow chart.

Aiming at the optimization of high-speed dry milling cutting parameters, this paper optimized the process parameters based on improved ELM and genetic algorithm. The steps were as follows:

Step 1: The prediction model of high-speed dry milling cutting parameters and surface roughness was constructed by improving ELM neural network. The input items of the prediction model were 25 sets of four elements of cutting (n , f_z , a_p , a_e) data obtained from the Taguchi orthogonal experiment. The output item was the surface roughness value. And then, 5 sets of random samples

were used as the test of the improved ELM network. If the termination condition was reached, the prediction model of the improved ELM high-speed dry milling cutting parameters was output.

Step 2: The optimization of high-speed dry milling cutting parameters was carried out by combining the improved ELM and genetic algorithm optimization model. The combination of Taguchi experimental control factors was used as the initial value of the genetic algorithm. Then, the trained improved ELM neural network prediction model was used as the fitness function of the genetic algorithm to search for optimization. Finally, a set of machining process combinations that can optimize the surface roughness were obtained.

The optimization model process was shown in Fig.4:

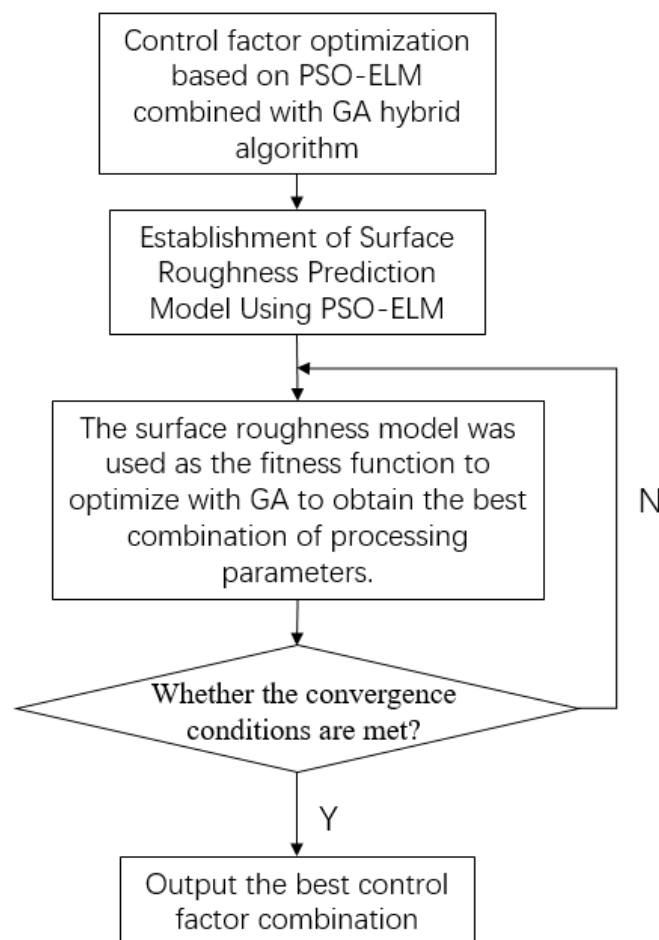


Figure 4. Optimization process based on improved ELM-GA

4. Experiment Procedure

4.1 Optimal experimental design and analysis based on Taguchi method

4.1.1 Experimental equipment and conditions

(1) Surface roughness testing equipment

The surface roughness of the processed workpiece was detected by the online three-dimensional optical topography (white light interferometric) module of the highly integrated multi-function friction and wear tester (equipment model: MFT-5000). Vertical RMS repeatability: 0.01 nm; sample thickness: up to 100mm; vertical measurement range: 0.1nm-10mm; vertical measurement accuracy: 0.5nm; minimum lateral resolution: 400nm.

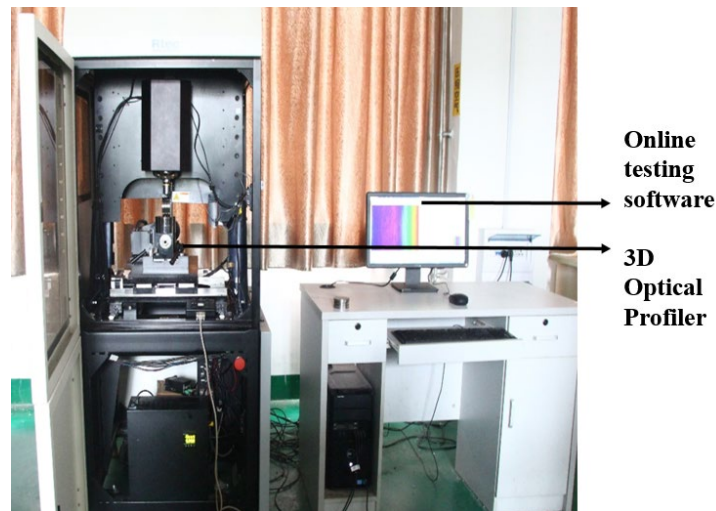


Figure 5. Highly integrated multifunctional friction and wear testing machine

(2) Information on processing machines, materials and tools

Taking the milling plane of the CNC machine tool as an example, the processing process was shown in Fig. 6. The CNC milling machine tool of VMC850B machining center model was used in the experiment and the machine tool information was shown in Table 1. Choosing an End Mill for Milling Experiments and the specific parameters were shown in Table 2. The workpiece material for milling was high-strength steel 30CrMnSiNiA with a length of 80mm, a width of 80mm and a height of 10mm.

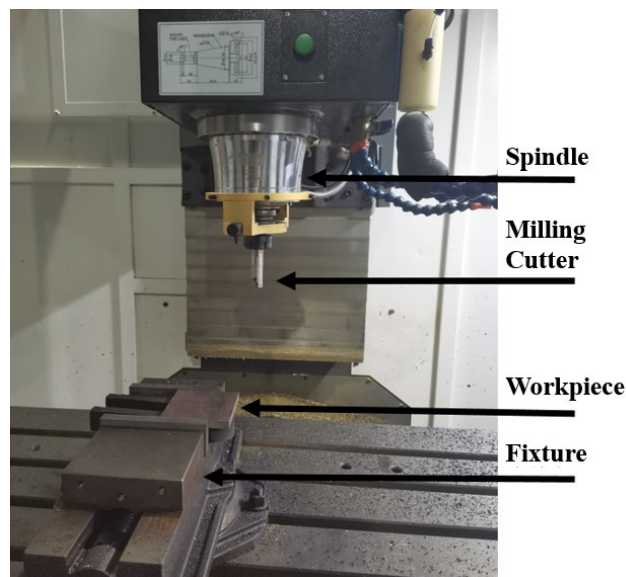


Figure 6. Milling process diagram

Table 1. Machine Tool Information Table

Machine model	spindle motor power	spindle speed range	X-axis travel	Y-axis travel	Z-axis travel
VMC850B	7.5/11kW	0-12000 r/min	800mm	500mm	550mm

Table 2. Tool information table

Tool name	material	coating	specification	quantity
insert	carbide body	PVD	APMT1135PDER	10
Tool holder	42CRMNTI	-	300R-C20-21-120-2TMilling shank, Ø20	1

4.1.2 Orthogonal Taguchi experimental design and results

There are many factors that determine the size of surface roughness. In this paper, the four elements of cutting in the process of high-speed dry milling were used as variable elements. Each element was set to five level values. The experimental settings are listed in Table 3.

Table 3. Milling cutting parameters and level settings

level	1	2	3	4	5
Spindle speed (r/min)	3500	4500	5500	6500	7500
Feed per tooth (mm/z)	0.045	0.075	0.105	0.135	0.165
Cutting width (mm)	1	2	3	4	5
depth of cut (mm)	0.1	0.3	0.5	0.7	0.9

Using Taguchi L25 (54) orthogonal experiment to obtain surface roughness (including 25 sets of data and 5 sets of test data of Taguchi orthogonal experiment). The surface roughness value in the table was the arithmetic mean as shown in Table 4.

Table 4. Experimental data

Serial number	Spindle speed (r/min)	Feed per tooth (μm)	Cutting width (mm)	depth of cut (mm)	surface roughness Ra (μm)
1	3500	0.045	1	0.1	0.18
2	3500	0.075	3	0.7	0.29
3	3500	0.105	5	0.3	0.34
4	3500	0.135	2	0.9	0.36
5	3500	0.165	4	0.5	0.99
6	4500	0.045	5	0.7	0.39
7	4500	0.075	2	0.3	0.28
8	4500	0.105	4	0.9	0.71
9	4500	0.135	1	0.5	1.05
10	4500	0.165	3	0.1	0.98
11	5500	0.045	4	0.3	0.43
12	5500	0.075	1	0.9	0.28
13	5500	0.105	3	0.5	0.44
14	5500	0.135	5	0.1	1.00
15	5500	0.165	2	0.7	1.33
16	6500	0.045	3	0.9	1.31
17	6500	0.075	5	0.5	1.67
18	6500	0.105	2	0.1	0.25
19	6500	0.135	4	0.7	0.64
20	6500	0.165	1	0.3	0.38
21	7500	0.045	2	0.5	0.95
22	7500	0.075	4	0.1	0.31
23	7500	0.105	1	0.7	0.45
24	7500	0.135	5	0.3	0.57
25	7500	0.165	3	0.9	0.99
*26	3800	0.12	5	0.2	0.37
*27	7200	0.09	4	0.6	0.28
*28	6700	0.03	7	0.3	0.76
*29	4600	0.09	8	0.7	0.42
*30	5400	0.15	6	0.8	0.85

Note: * means test data

Improved ELM-GA optimization algorithm programming using MATLAB. A surface roughness prediction model for high-speed dry milling was constructed by using an improved extreme learning machine network. The data in Table 4 were selected as the training samples and test samples of the improved extreme learning machine network. The parameter settings for particle swarm optimization optimization were shown in Table 5.

Table 5. parameter settings for PSO

Maximum number of iterations	500
Population size	30
Learning factor	$c_1 = c_2 = 2$
Inertia weight	$w_{\max} = 0.9, w_{\min} = 0.4$

The improved ELM network training parameter settings were shown in Table 6. The input items based on the improved ELM prediction model were four elements of cutting of the high-speed dry milling process parameters, and the output item was the surface roughness value.

Table 6. Improved extreme learning machine network parameter settings

Input layer	4neurons
Hidden layer	5neurons
Output layer	1neuron
Activation function	Sigmoid function
Training error target	0.001
Number of training samples	25
Number of test samples	5

The relevant parameters of the GA were set such as: the mating method was single-point mating and the mating rate was 0.3. The mutation mode was single point mutation and the mutation rate was 0.3. The normalized range was 0.1-0.9. The number of iterations was 10,000. The search range of the genetic optimization target was shown in Table 7.

Table 7. Genetic algorithm parameter setting range

search range	Spindle speed (r/min)	Feed per tooth (μm)	Cutting width (mm)	depth of cut (mm)
Upper Bound	8000	0.165	8	0.9
Nether	3500	0.030	4	0.1

4.2 Optimization results and analysis

It can be seen from Fig.7 that the surface roughness prediction model of high-speed dry milling based on the PSO-ELM algorithm has fast convergence speed and small model error. When the number of iterations approached 150, the prediction error tended to plateau and the average error of the model was 0.035927. In Fig. 8, the prediction model based PSO-ELM had an average error of 0.07746 and a correlation coefficient of 0.98106. The prediction model trained on a single ELM had a square root error of 0.45306 and a correlation coefficient of 0.21197. By comparison, it is found that the accuracy of high-speed surface quality prediction of the PSO-ELM type is 92.25%, while the accuracy of the single ELM model is only 54.69%. At the same time, the correlation coefficient of PSO-ELM approach to 1 and the predicted correlation is very high, which conform to the actual processing. Therefore, the surface roughness prediction model of high-speed dry milling based on PSO-ELM is more accurate and has higher reference value.

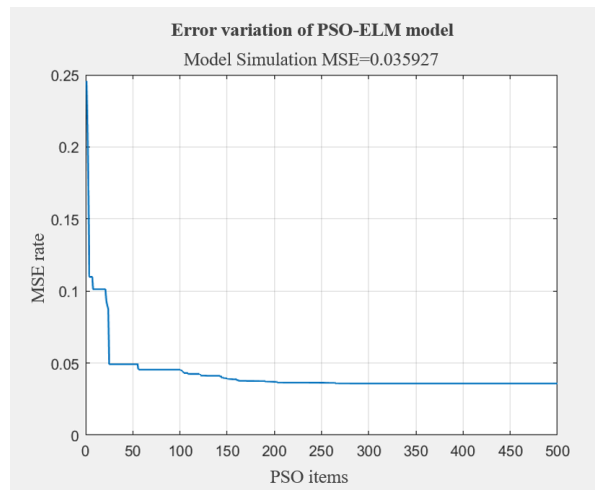


Figure 7. Iterative diagram of PSO-ELM error variation

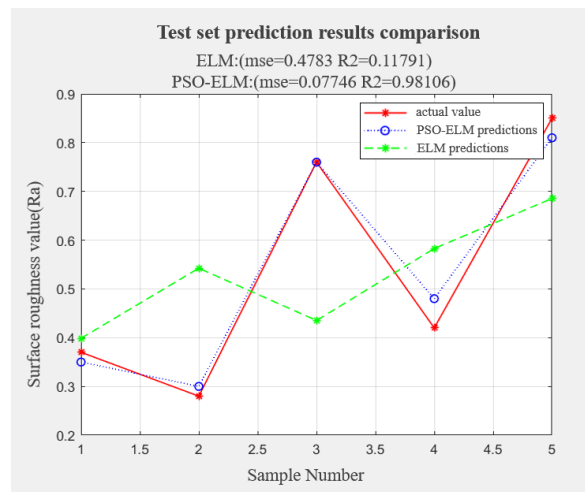


Figure 8. Comparison of test set results

In this paper, the above improved ELM-GA was used to establish a surface roughness optimization model for high-speed dry milling. The optimal combination of high-speed dry milling machining parameters was obtained as shown in Table 8.

Table 8. Optimized combination of process parameters

Spindle speed	3500r/min
Feed per tooth	0.03 μm
Cutting width	4mm
Cutting depth	0.1mm

The surface topography of the workpiece after milling was detected by a highly integrated multi-functional friction and wear testing machine. The inspection results shown in Figures 9 and 10. By comparison, it can be found that when the optimized process parameters are used for high-speed dry milling, the surface morphology of the workpiece is smoother and the surface roughness value is lower. This shows that the optimization method proposed in this paper can promote the surface quality of the workpiece and the method is effective in the optimization of the cutting parameters of high-speed dry milling.

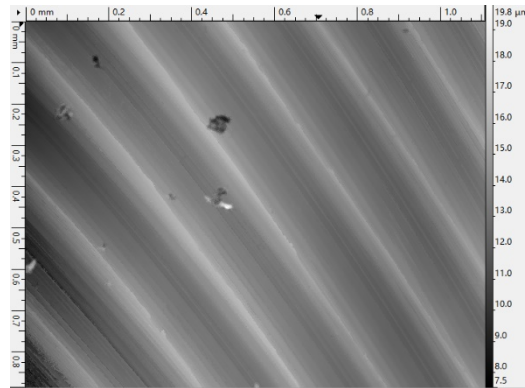


Figure 9. Surface roughness before optimization

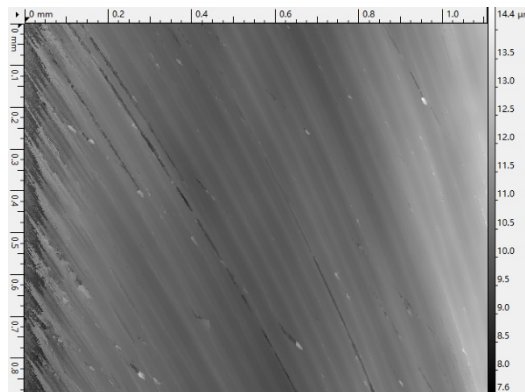


Figure 10. Surface roughness after optimization

5. Conclusions

(1) By comparing the PSO-ELM prediction model with a single ELM prediction model, the predicted value of the PSO-ELM model is more anastomose with the measured value and the prediction effect is more accurate. The established PSO-ELM model can be better used to predict the surface quality of high-speed dry milling.

(2) In this paper, aiming at optimizing the surface roughness of the product, an optimization algorithm based on the combination of improved ELM and GA was used to optimize the high-speed dry milling cutting parameters. Finally, the optimum combination of cutting parameters for surface roughness was obtained. Milling experiments show that the improved ELM-GA optimization method is effective and feasible in high-speed dry milling. After optimization, the surface finish of the workpiece is significantly improved and the surface quality of the workpiece is improved.

Acknowledgments

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