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Prediction Method of Ball Mill State Parameters Based on FWA-LSSVM Model

Xiao-Yan Luo*, Hua-Zhi Xu**, Wen-Cong Tang** and Wen-Hai Lu***

Keywords: mill vibration, firework algorithm, least squares support vector machine, state parameter prediction.

ABSTRACT

Aiming at the problem that it is difficult to accurately judge the working state parameters during the grinding process of the ball mill, a method for predicting the working state parameters of the ball mill based on fireworks algorithm optimized LSSVM (Least Squares Support Vector Machine) is proposed. Firstly, the LSSVM algorithm is employed to establish the predictive model for the working state parameters of the ball mill. Then, the FWA (Firework Algorithm) algorithm is used to optimize the radial basis kernel function parameters and penalty factors of the LSSVM model. Afterwards, time-domain features, frequency-domain features, and entropy features are extracted from the vibration signals of the mill shell to generate a set of feature vectors; finally, feature vectors are used as the input of FWA-LSSVM, and the ratio of material to ball, rotation speed and filling rate are used as the output to establish a mill state parameter prediction model. The superiority of the method is proved by grinding experiments. The results showed that the LSSVM model optimized with the FWA algorithm had less error between the predicted and actual values of filling speed, Material-ball ratio and rotational speed than the GA (Genetic Algorithm) and PSO (Particle Swarm Optimization) optimization algorithms, indicating that the mill state parameter prediction model has higher precision and stability.

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* *Professor, Department of Mechanical Engineering, Jiangxi University of Science and Technology, Ganzhou, Jiangxi 341000, China.*

** *Graduate Student, Department of Mechanical Engineering, Jiangxi University of Science and Technology, Ganzhou, Jiangxi 341000, China.*

*** *Master,Department of Mechanical Engineering, Jiangxi University of Science and Technology, Ganzhou, Jiangxi 341000, China.*

INTRODUCTION

The reliable and steady operation of the ball mill is essential for the entire grinding system. In recent years, there has been an increasing focus on detecting the working state parameters of ball mills, especially given the challenging operating environment, which makes it difficult to identify these parameters accurately (Cai et al., 2019; Du et al., 2018). During the grinding process of the ball mill, both the cylinder and the bearing will generate vibration signals, with the former containing more abundant status information. Therefore, analyzing the relationship between the cylinder vibration signals and the working state, and accurately identifying the state parameters of ball mill, can effectively reduce the energy consumption during the grinding process and has a good guiding significance for optimizing the control of the mill (Bai and Chai, 2009; Hu et al., 2018; Yan et al., 2014). The essence of load detection in mechanical equipment is the pattern recognition problem regarding its load status. Starting from the basic idea, many pattern recognition methods have been proposed as the basis of recognition and classification, such as neural networks, support vector machines, and cluster analysis (Cai et al., 2019). Kuo et al. (2023) used neural network to build tool wear prediction model in turning process, and achieved good results (Wang et al., 2019; Zhang et al., 2019). Dai et al. (2022) used support vector machine to predict the power load of ships, and got high-precision prediction results. Lu et al. (2019) employed GMM clustering to recognize the thermal load status. Therefore, by leveraging the aforementioned methods, many researchers have successfully established prediction models for various working state parameters, and have obtained a large number of practical results. LSSVM is a very effective method for pattern recognition, which does not have complex network structures and local minimum problems. It can solve nonlinear classification problems and has greater advantages in small sample data recognition and prediction problems. Therefore, it has been widely used in engineering problems (Niu et al., 2019). However, the prediction effect of LSSVM is greatly affected by the radial basis kernel function parameter

δ^2 and the penalty coefficient γ. If δ^2 is incorrectly selected, it is prone to large errors. FWA can automatically optimize the radial basis kernel function parameters in LSSVM, and overcome its shortcomings so that the optimized model has better ball mill load prediction ability (Chen et al., 2018).

Therefore, this paper attempts to extract the time domain features, frequency spectrum features and entropy features of the mill vibration signal to form a feature set, and build an LSSVM prediction model optimized by the firework algorithm to achieve accurate prediction of the mill speed, filling rate and material-ball ratio.

INTRODUCTION TO BASIC THEORY

Principle of Least Squares Support Vector Machine (LSSVM)

SVM (Support Vector Machine) is a machine learning algorithm for supervised learning models that analyze data in classification and regression analysis (Liu, 2015). The basic idea is to project the existing low-dimensional space data vectors into high-dimensional space data vectors, and then use the theory of risk minimization to construct a decision function to solve nonlinear problems with a small number of samples and high dimensions. The LSSVM converts the inequality constraints of the original support vector into equality constraints, and replaces the decision function in the support vector machine, thereby reducing the computational cost in the original algorithm. LSSVM projects the nonlinear vector $\Phi(x)$ in SVM to a high-dimensional space and converts it into a linear problem. The expression is:

$$y = \omega^T \Phi(x) + b \tag{1}$$

where ω is the weight vector; $b$is the deviation.

By using the principle of structural risk minimization, the original linear regression problem in the algorithm can be transformed into an optimal solution problem, let the training set $\{(x_i, y_i)\}$, $i = 1,2,\dots N$, $x_i \in R^d$, where x_i is the i-th input variable, y_i is the category corresponding to x_i, its value is generally +1 or -1, d is the number of samples, the original function optimization problem is transformed into:

$$\begin{cases} min\, J(\omega,\xi) = \frac{1}{2}\omega^T\omega + \frac{1}{2}\gamma\sum_{i=1}^{l}\xi_i^2 \\ y_i = \omega^T\Phi(x_i) + b + \xi_i \text{ , } i = 1,2,\dots,l \end{cases} \tag{2}$$

Where, ξ_i is the error; i is the i-th dimension in the space vector; ω is the weight vector; γ is the penalty factor. Using the Lagrangian method to solve the optimization problem, the expression is transformed into:

$$L(\omega,b,\xi,\alpha) = J(\omega,\xi) - \sum_{i=1}^{l}\alpha_i\,(\Phi(x_i)\cdot\omega + b + \xi_i - y_i) \tag{3}$$

where, α_i is the Lagrange multiplier. Since ω belongs to a high-dimensional space and cannot be solved directly, the kernel function is introduced into the optimization problem. Defining kernel function $K(x_i, x_j) = \phi(x_i)\cdot\phi(x_j)$, then the optimization problem turns into solving the following system of equations:

$$\begin{bmatrix} 0 & 1 & \cdots & 1 \\ 1 & K(x_i,x_i)+\frac{1}{\gamma} & \cdots & K(xi,xl) \\ 1 & \vdots & \cdots & \vdots \\ 1 & K(x_i,x_i) & \cdots & K(x_i,x_l)+\frac{1}{\gamma} \end{bmatrix} \cdot \begin{bmatrix} b \\ a_i \\ \vdots \\ a_l \end{bmatrix} = \begin{bmatrix} 0 \\ y_i \\ \vdots \\ y_l \end{bmatrix} \tag{4}$$

Using the least square method to find the regression coefficient a_i and the deviation b in the optimization problem, the nonlinear prediction model can be obtained:

$$y = \sum_{i=1}^{l} a_i K(x, x_i) + b \tag{5}$$

To ensure the operational efficiency of the LSSVM, RBF is used as the kernel function of the model, the parameters that can be set manually in this model are the parameter δ^2 and the penalty factor γ in the radial basis kernel function.

Principle of Firework Algorithm (FWA)

The firework algorithm is a swarm intelligence algorithm proposed by Tan (2015), its basic idea is to use the fireworks explosion process to simulate the process of finding the optimal solution in space. The search range for finding the optimal solution is considered as the space range where sparks of the fireworks explosion scatter, and the feasible solution in the optimization problem is transformed into the explosion point and the position of the sparks generated during the explosion process. Then, the advantages and disadvantages of each explosion point and spark position are evaluated, and the optimal position is selected to continue to the next generation through iteration, repeatedly until the global optimal solution is obtained or the iteration termination condition is reached. The core components of the firework algorithm include explosion operators, mutation operators, mapping rules and selection strategies.

(1). *Explosion operator*: The explosion operator is an algorithm multiplier introduced to make fireworks explode and produce sparks. Assuming that each individual firework is x_i, the number of sparks and the explosion radius of the offspring of its explosion can be calculated according to the fitness function $f(x_i)$. Under normal circumstances, a firework with a smaller fitness level will generate a smaller distribution radius and a larger number of offspring after exploding, so it is closer to the optimal solution and has stronger local search capabilities.

To realize the firework explosion phenomenon, suppose the total number of sparks generated after the explosion is s_i and the explosion radius is A_i, then the expressions of s_i and A_i are:

$$s_i = M\frac{f_{max} - f(x_i) + \theta}{\sum_{i=1}^{N}(f_{max} - f(x_i)) + \theta} \quad (6)$$

$$A_i = A\frac{f(x_i) - f_{min} + \theta}{\sum_{i=1}^{N}(f(x_i) - f_{min}) + \theta} \quad (7)$$

where M is the coefficient for adjusting the number of explosion sparks produced by the explosion; A is the coefficient for adjusting the size of the blast radius; θ is a constant value introduced to avoid division by zero; $f_{max} = max(f(x_i))(i = 1,2,\dots,N)$ represents the best fitness value among N fireworks, and $f_{min} = min(f(x_i))(i = 1,2,\dots,N)$ represents the worst fitness value among N fireworks.

(2). *Mutation operator*: To make the search range of spark generated by explosion wider, the mutation operator is introduced into the algorithm, that is, the Gaussian mutation is employed to get m mutation sparks. The expression is as follows:

$$\hat{x}_d^k = x_d^k \times N(1,1) \quad (8)$$

Where x_d^k represents the $k(k = 1,2,\dots,m)$ dimensional coordinate of the $d(d = 1,2,\dots,m)$ spark, $N(1,1)$ represents Gaussian distribution with mean and variance of 1.

(3). *Mapping rules*: When the explosion spark x_i crosses the boundary in k dimension, it can be projected to a new position $\bar{x}_i^k$ through the mapping rule:

$$\bar{x}_i^k = x_{\min}^k + \left|x_i^k\right| \%(x_{\max}^k - x_{\min}^k) \quad (9)$$

where, x_{min}^k and x_{max}^k indicate that the spatial position of the fireworks is in the top and bottom bounds of the k dimension, and % represents the modulo operation.

(4). *Selection strategy*: The selection strategy is to choose N better offspring from the set K of feasible solutions as the new generation of fireworks. Among them, the individual with the lowest fitness value is regarded as a new generation of fireworks, and then the roulette method is used to screen the remaining $N-1$ fireworks. The calculation formula is:

$$R(x_i) = \sum_{j=1}^{K} d(x_i - x_j) \quad (10)$$

$$p(x_i) = \frac{R(x_i)}{\sum_{j=1}^{K} d(x_j)} \quad (11)$$

where, $R(x_i)$ is the total of Euclidean distance between the i offspring and other offspring in set K; $p(x_i)$ is the probability of being selected. It can be seen from equation (11) that the smaller the distance of the firework, the lower the probability of being selected, which avoids the emergence of the global optimal problem prematurely.

Based on the above steps, this paper proposes to use the Firework algorithm to optimize the Least Squares Support Vector Machine model, thereby establishing a FWA-LSSVM based ball mill working state parameter prediction model. In this method, FWA algorithm is used to optimize the parameters of LSSVM model, and the parameter combination that can achieve the optimal performance of LSSVM model is found in the range of [0,300]. Let each individual $z = (z_1, z_2)$ in a firework explosion be a set of parameter combinations (γ, δ^2) of the LSSVM model, and use individual fitness to measure the algorithm performance of this set of parameters.

FWA algorithm optimizes the establishment of LSSVM ball mill working state parameter prediction model

Firework Algorithm considers every possible solution of each space as a firework, and obtains the optimal iteration times by designing explosion operators, mutation operators, mapping rules, and selection strategies. The steps for optimizing LSSVM through fireworks algorithm are as follows:

Step 1: Randomly initialize the population. Randomly generate $N = 20$ fireworks whose maximum number of sparks produced by the explosion is $m = 50$, the explosion radius is $\hat{A} = 40$, and the Gaussian mutations number is 5. According to the sample data of the vibration signal of the mill barrel collected under different load conditions, 8 time-domain characteristic parameters and 5 spectral characteristic parameters were extracted respectively (Luo et al., 2020): mean value, variance, root square amplitude, effective value, peak value, Skewness index, kurtosis index, crest factor, mean frequency, standard deviation frequency, spectral skewness, spectral kurtosis, center of gravity frequency; two entropy feature parameters: sample entropy (Ma, 2015) and fuzzy entropy (Xiang and Ge, 2014) constitute feature vectors. Select 100 groups of vibration signal feature samples of the mill cylinder, use 50 sets of low-dimensional feature sets for model training, and the remaining 50 groups of data low-dimensional feature sets are used as tests.

Step 2: Calculate the individual fitness value. In order to improve the learning and generalization ability of the LSVVM model, the fitness function is constructed by introducing training sample data and test sample data. First, use the fireworks individual as the parameter of the LSSVM model, and use 50 sets of training samples to train the LSSVM model to obtain the LSSVM function estimation model, as shown in equation (12). Then, use 50 sets of test samples to test the LSSVM model, and combine the training samples and test samples to establish the fitness function based on the errors obtained. From equation (13), the fitness value of each individual firework can be solved.

$$\hat{y}(i, X) = \sum_{o=1}^{l_1} a_o K(X, X_o) + b \quad (12)$$

$$f(i) = max(E_{train}(i)) + max(E_{test}(i)) + \\ +|max(E_{train}(i)) - max(E_{test}(i))| \tag{13}$$

where, $\hat{y}$ is the output of the model; a and b are the regression coefficients and deviations obtained after the training of the LSSVM model respectively; $K(\cdot)$ is the kernel function; f is the fitness value; E_{train} and E_{test} are the absolute value set of training error and the absolute value set of test error, respectively.

Step 3: Use the explosion operator to generate sparks. The amplitude range and the number of sparks generated by explosion are solved by formulas (6) and (7), and the sparks are displaced according to formula (14).

$$\square z_i^k = z_i^k + rand(A_i) \tag{14}$$

Where, $\square z_i^k$ is the displacement of the i individual on the k dimension, and $rand(A_i)$ is a random number automatically generated within the explosion amplitude A_i.

Step 4: Perform Gaussian mutation operation. The spark is subjected to Gaussian mutation according to formula (8), and the search range of the period is wider.

Step 5: Processing of mapping rules. The sparks that have crossed the search space are processed according to equation (9) using modular arithmetic mapping rules to make them return to the search space.

Step 6: Population selection. Choose the best one among the obtained populations, and then select the remaining populations by roulette method according to equations (10) and (11).

Step 7: Judge whether the termination condition is met. If it is met, the optimization operation is ended, and the optimized LSSVM model parameter z^* is obtained; otherwise, go to step 3.

Step 8: Use the FWA algorithm to optimize the obtained parameter z^*, and then use the training sample data to train the LSSVM model, thereby establishing a ball mill working state parameter prediction model based on FWA-LSSVM algorithm.

In summary, the process of using the FWA-LSSVM algorithm to establish the parameter prediction model of the ball mill working state is shown in Fig 1.

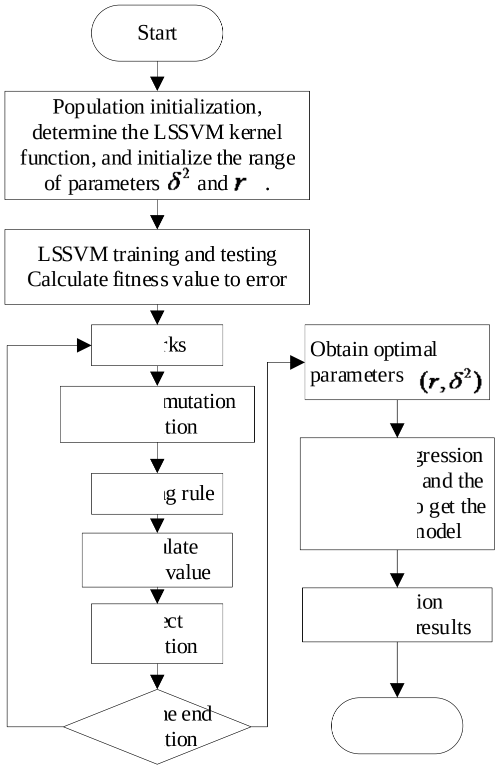


Fig. 1. Flow chart of the predictive model of ball mill working state parameters based on FWA-LSSVM algorithm

Validity verification

Simulation verification and analysis

To verify the prediction effect of FWA-LSSVM algorithm, constructs LSSVM model optimized by particle swarm optimization (PSO) and genetic algorithm (GA), and they are compared with the LSSVM optimized based on the firework algorithm (FWA), Table 1 shows the initial parameters of the three optimization algorithms. The initial parameters of all three algorithms include the population number and the maximum number of iterations, which have little effect on the prediction results of the algorithms. To ensure the accuracy of the experimental results, the initial population and the maximum number of iterations of the three algorithms are set to 20 and 400, respectively. The other parameters are set according to the values commonly used by the algorithm.

Table 1 Initial parameter settings of three optimization algorithms

Algorithm	Parameter	Corresponding value or interval
PSO	Particle population size	20
	Maximum number of iterations	400
	Inertia weight	[0.3,0.9]
	Learning factor 1, 2	1.2、1.5
GA	Population size	20

	Maximum number of iterations	400
	Crossover probability	0.4
	Mutation probability	0.01
FWA	Fireworks population size	20
	Maximum number of iterations	400
	Explosion radius	40
	Explosion spark number range	[1,50]
	Gaussian variation spark number	5

To test the prediction performance of the LSSVM model after optimization of these three algorithms, four types of data in the UCI standard data set are used for simulation experiments, the UCI data set is a general data set, which often appears in most papers or studies to verify the performance of the algorithm model. The data set contains samples and labels. By comparing the training results with the labels, the effect of the prediction model can be known. The data set is shown in Table 2.

Table 2. Four types of data in the UCI standard data set

Data set	Sample (training/testing)	Number of input data	Number of output data
Machine_CPU	209(165/44)	8	1
Servo_data	167(134/23)	15	1
California_Housing	20640(10340/10320)	6	1
Auto_price	159(116/33)	4	1

The simulation test uses 10-fold cross-validation method to determine the model prediction accuracy, that is, all sample data in the data set are divided into 10 parts, in which 9 pieces of data are used as training samples, and the remaining data are used as test samples. The program runs 10 times, each sample data is used as a test sample to verify the effect of the prediction model, finally, the mean values of the mean absolute error (MAE), mean absolute percentage error (MAPE) and mean square error (MSE) between the predicted data and the actual data after the program has been run for 10 times are calculated.

Figure 2 shows the optimal fitness of the LSSVM prediction model optimized by the three algorithms on the UCI data set. As can be seen from the figure, the LSSVM prediction model optimized by the FWA algorithm proposed in this paper has the highest fitness through iterative search, indicating that its feature selection and parameter optimization abilities are stronger compared to LSSVM prediction models optimized by GA and PSO algorithms. In addition, the GA-LSSVM prediction model prematurely entered the premature state, resulting in being trapped in a local optimum.

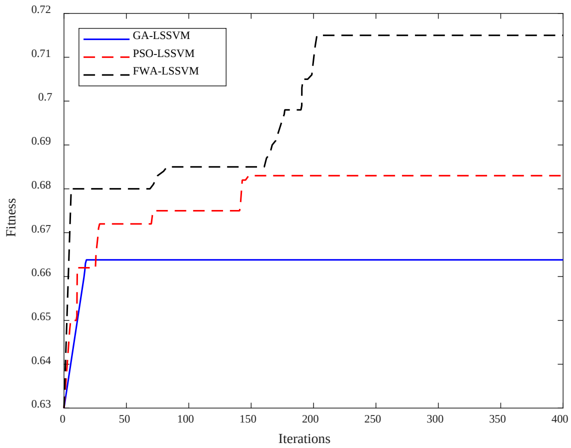


Fig. 2. The best fitness of the three optimization algorithms on the UCI dataset

Table 3. Comparison of prediction accuracy results

Algorithm	Evaluation index	Machine_CPU	Servo_data	California_Housing	Auto_price
LSSVM	MAE	2.365	8.365	1.322	8.373
	MAPE（%）	12.36	6.325	8.332	6.325
	MSE	1.963×10^{-1}	6.372×10^{-1}	4.686×10^{-1}	6.372×10^{-2}
GA-LSSVM	MAE	1.673	6.325	0.843	5.385
	MAPE（%）	8.372	6.022	6.272	4.234
	MSE	1.523×10^{-1}	4.383×10^{-1}	1.575×10^{-1}	5.690×10^{-2}
PSO-LSSVM	MAE	1.236	4.226	0.432	3.258
	MAPE（%）	5.653	5.361	3.256	2.584
	MSE	9.852×10^{-2}	2.617×10^{-1}	8.454×10^{-2}	3.262×10^{-2}
FWA-LSSVM	MAE	0.832	1.332	0.158	1.562

MAPE（%）	2.381	2.866	1.324	1.256
MSE	3.462×10^{-2}	1.321×10^{-1}	4.386×10^{-2}	1.386×10^{-2}

Table 3 is a comparison table of prediction errors between the traditional LSSVM model and the three optimized LSSVM models. As is shown in the table, the LSSVM model optimized by the FWA algorithm has more accurate data prediction on the UCI dataset than the traditional LSSVM model, GA-LSSVM model, and PSO-LSSVM model. Its average absolute error (MAE), mean absolute percentage error (MAPE), and mean squared error (MSE) between the predicted value and actual value are smaller than the other three prediction models, which fully demonstrates that the FWA-LSSVM model has smaller prediction errors and higher accuracy compared to the other three models. Therefore, the FWA-LSSVM prediction model can effectively improve the accuracy of model prediction, verifying the effectiveness and superiority of the FWA-LSSVM prediction model.

Experimental verification and analysis

To verify the effectiveness of the method proposed in this paper in the prediction of the state parameters of the ball mill, a small experimental ball mill of model $\varphi330\,mm\times330\,mm$ was used for experiments, its motor power is 0.75kw. In the experiment, tungsten ore was used as the material, its density was 1800Kg/m^3, and $\varphi50\,mm$ steel ball was used for the experiment, the experimental schematic diagram is shown in Figure 3.

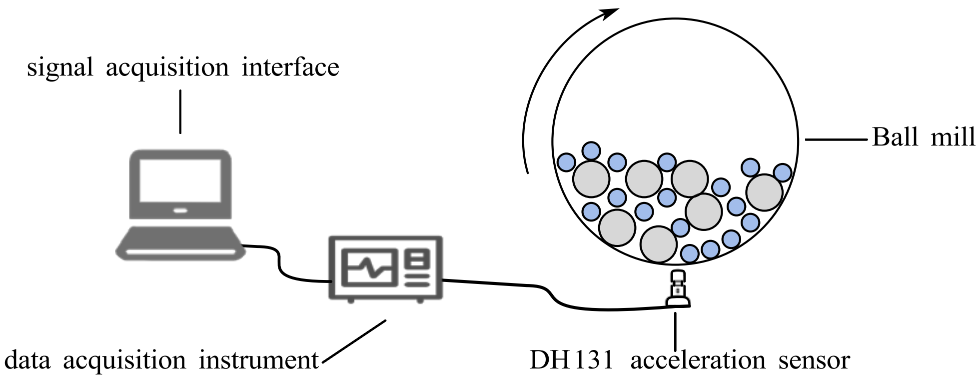
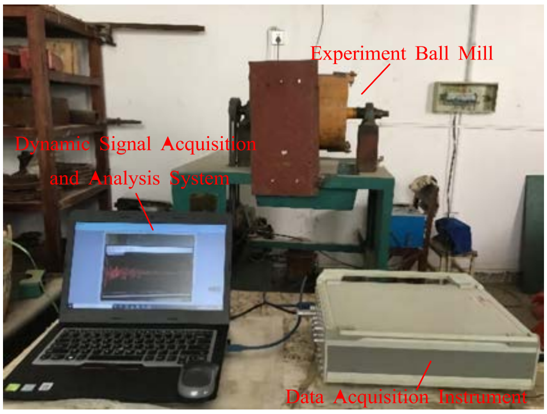


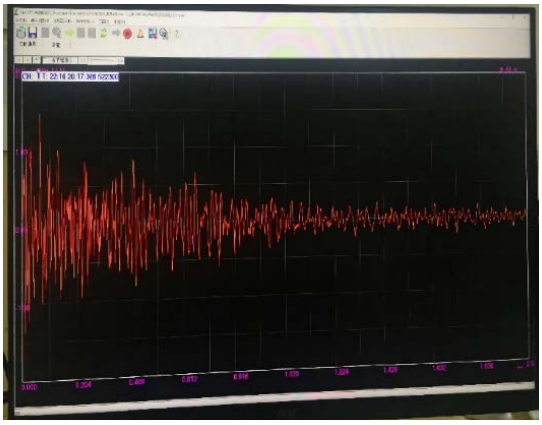
Fig. 3. Schematic diagram of experimental device

The DH131 acceleration sensor is selected to measure the vibration of the ball mill cylinder, and the DH5922N dynamic data acquisition instrument is used to collect the vibration signal. In this experiment, the sampling frequency of the data acquisition instrument is 20kHz, and the number of sampling points is 20000. Take the filling rate(the percentage of the material volume in the ball mill equipment in the effective volume of the mill) of 0.2, 0.3, 0.4, 0.5, the material-to-ball ratio(the ratio of the material in the ball mill to the mass of the grinding steel ball) of 0.5, 0.6, 0.7, 0.8, 0.9, 1.0, 1.1, 1.2 and the speed of 40r/min, 50r/min, 60r/min as the state parameters to collect the vibration signal of the ball mill barrel area Of multiple samples. The experimental device is shown in Figure 4. Figure 4(a) is the vibration signal collection experimental system of the mill barrel, and Figure 4(b) is the vibration signal collection location of the mill barrel. The vibration sensor is installed within the impact zone of the balls in the ball mill cylinder, and the signal collected at this location is the most reflective of the ball impact and load status information in the cylinder compared to other locations. Figure 4(c) is the data acquisition interface. In order to reduce the impact of noise on the signal as much as possible, set the sampling frequency to more than 5 times the maximum frequency of the mill cylinder vibration signal.



(a) Signal acquisition experimental system

(b) Vibration signal collection location



(c) Signal acquisition interface

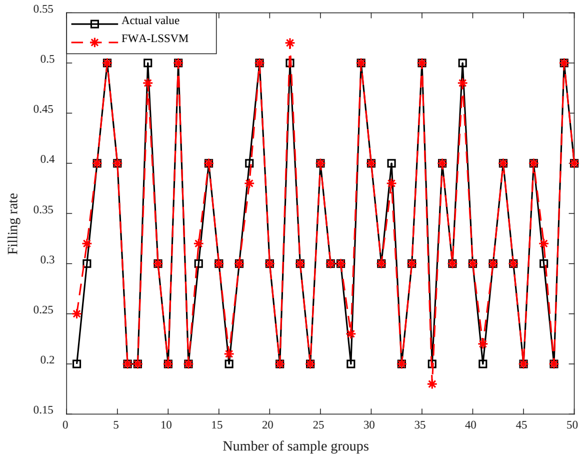
Fig. 4. Vibration signal acquisition platform of ball mill

Simulation analysis and experimental comparison of the parameter prediction model of the mill working state

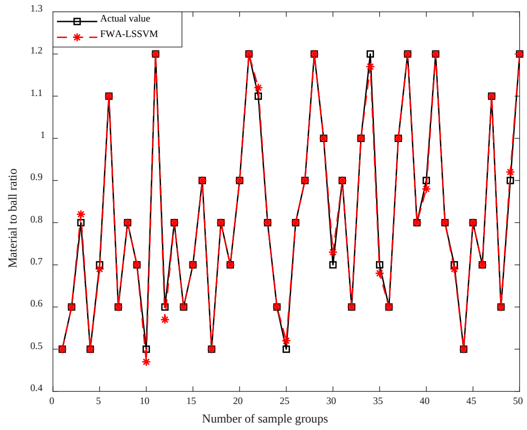
The FWA-LSSVM model is used to establish a ball mill working state parameter prediction model. The working state parameters and actual values of the mill predicted by the training samples are shown in Figure 5.

From Figure 5, it can be seen that the working state parameters predicted by the FWA-LSSVM model are basically consistent with the actual values. Although there is a slight difference between the predicted values and the actual values of some working state parameters, the overall prediction accuracy is high, which can accurately achieve the purpose of predicting the working state parameters of the grinder.

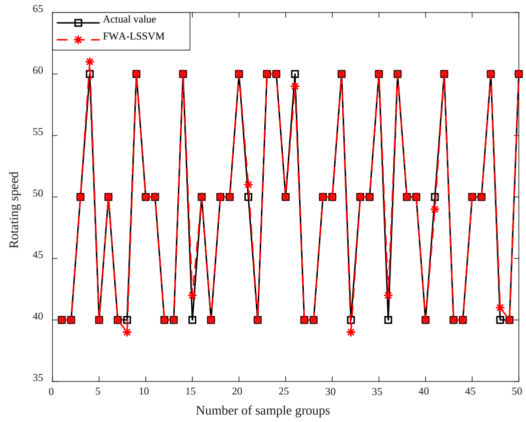
It can be seen from Table 4 that the mill working state parameter prediction model based on the FWA-LSSVM algorithm can more accurately predict the working state parameters of the ball mill. The prediction accuracy of filling rate, material-ball ratio and rotational speed of the mill has been greatly improved compared with the traditional prediction model of LSSVM algorithm.



(a) Filling rate



(b). Material to ball ratio



(c). Rotating speed

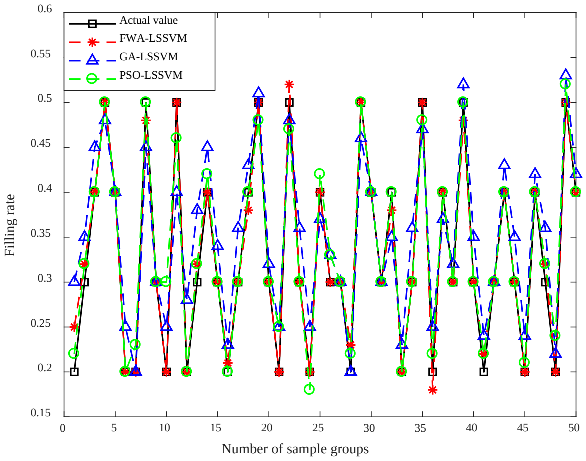
Fig. 5. Comparison of predicted values and actual values of mill working state parameters based on FWA-LSSVM model

Table 4. FWA-LSSVM mill working state parameter prediction error table

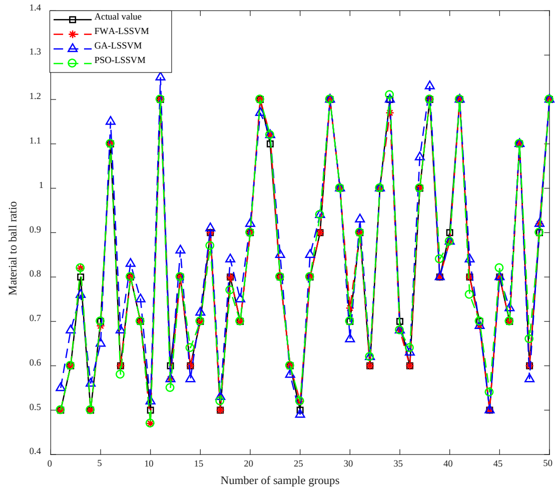
State parameter	MAE	MAPE (%)	MSE
Filling rate	0.0058	2.14	1.5×10^{-4}
Material to ball ratio	0.0054	0.75	1.26×10^{-4}
Rotating speed	0.22	0.049	0.3

To further verify the prediction performance of the mill working state parameter prediction model based on the proposed algorithm, the prediction model based on the GA-LSSVM algorithm and the prediction model based on the PSO-LSSVM algorithm were used to predict the working state parameters of the mill. Figure 6 is a comparison diagram between the predicted results and the actual values of the mill operating parameters for the prediction models of the three different algorithms.

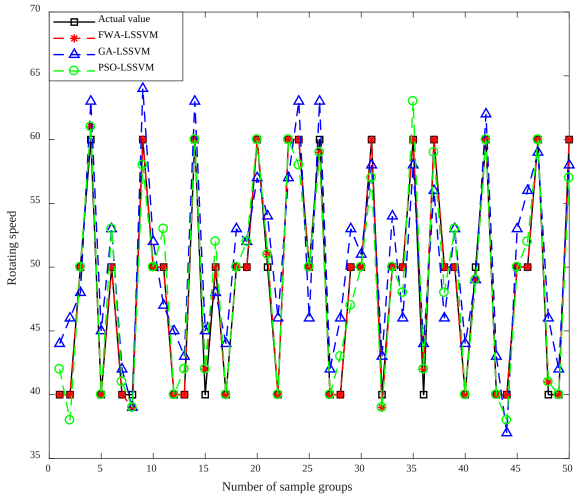
As can be seen from Figure 6, compared with GA-LSSVM and PSO-LSSVM, the prediction model of mill working state parameters based on FWA-LSSVM algorithm has higher accuracy of media filling rate, material-ball ratio and speed, especially in the prediction of mill speed. The prediction results of GA-LSSVM algorithm prediction model and PSO-LSSVM algorithm prediction model differ greatly from the actual value, while the difference between the prediction results of FWA-LSSVM prediction model and the actual value is small.



(a). Filling rate



(b). Material to ball ratio



(c) Rotating speed

Figure 6 Comparison of predicted values and actual values of mill working state parameters under three different prediction models

Table 7 Comparison of prediction errors of three mill working state parameter prediction models

algorithm	State parameter	MAE	MAPE(%)	MSE
	Filling rate	0.036	12.6	0.095
GA-LSSVM	Material to ball ratio	0.0298	4.1	0.0013
	Rotating speed	3.22	6.93	12.42
	Filling rate	0.0136	4.75	3.52×10^{-4}
PSO-LSSVM	Material to ball ratio	0.0162	2.36	4.5×10^{-4}
	Rotating speed	2.36	1.92	1.98
	Filling rate	0.0058	2.14	1.5×10^{-4}
FWA-LSSVM	Material to ball ratio	0.0054	0.75	1.26×10^{-4}
	Rotating speed	0.22	0.049	0.3

According to the analysis in Table 7, the MAE and MSE between the predicted results and the actual values of the mill working state parameter prediction model of the algorithm proposed in this paper are the smallest, which shows that compared to the GA-LSSVM algorithm prediction model and PSO-LSSVM algorithm prediction model, FWA-LSSVM algorithm prediction model has higher prediction accuracy; at the same time, its average absolute percentage error is smaller than the other two prediction models, which shows that the FWA-LSSVM algorithm model has the most predictive stability.

Conclusion

This study carried out the prediction of the ball mill state parameters, built the prediction model of the ball mill state parameters using FWA-LSSVM algorithm, and verified the algorithm with the ball mill vibration signal, and the following conclusions were obtained.

(1). Using LSSVM algorithm to establish a ball mill working state parameter prediction model, and using FWA algorithm to optimize the radial basis kernel function parameter δ^2 and penalty coefficient γ of the LSSVM model, then the effectiveness of the algorithm is verified by predicting the standard UCI data set, and compared with the GA-LSSVM algorithm and the PSO-LSSVM algorithm, the results show that the FWA-LSSVM model has better prediction performance.

(2). Through the experimental analysis of the prediction model of the working state parameters of the ball mill, the FWA-LSSVM algorithm prediction model has the smallest MAE and the MSE between the predicted result and the actual result, and its prediction accuracy for the working state parameters of the mill is significantly higher than the GA-LSSVM algorithm and the PSO-LSSVM algorithm prediction model.

(3). The MAPE of the FWA-LSSVM algorithm prediction model is lower than that of the other two optimized LSSVM models, indicating that the mill working state parameter prediction model based on the FWA-LSSVM algorithm has the best prediction stability. The research results of this paper will lay a technical foundation for reducing the energy consumption in the grinding process and optimizing the ball mill control process, which has important theoretical significance and engineering application value.

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基於FWA-LSSVM模型的球磨機狀態參數預測方法

羅小燕　徐華誌　湯文聰　盧文海

江西理工大學機電工程學院

摘 要

針對球磨機磨礦過程中難以準確判斷球磨機工作狀態參數的問題，提出了壹種基於煙花算法(FWA)優化最小貳乘支持向量機(LSSVM)的球磨機工作狀態參數預測方法。首先，利用LSSVM算法建立球磨機運行狀態參數的預測模型，並利用FWA算法優化LSSVM模型的徑向核函數參數和懲罰因子；然後提取磨機筒體振動信號的時域特徵、頻譜特徵和熵值特徵，構成壹組特徵向量；最後，將特徵向量作為煙花算法優化最小貳乘支持向量機（FWA-LSSVM）的輸入，以料球比、轉速和填充率作為輸出，建立了磨機狀態參數預測模型。通過磨礦實驗證明了該方法的優越性。結果表明，採用FWA算法優化的LSSVM模型與遺傳算法(GA)和粒子群(PSO)優化算法相比，填充率、料球比和轉速的預測值與實際值之間的誤差較小，表明球磨機狀態參數預測模型具有較高的精度和穩定性。