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SOFT SENSOR MODELING OF MILL LOAD BASED ON FEATURE SELECTION USING SYNERGY INTERVAL PLS

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ABSTRACT

Mill load is an important equipment index which is closely related to operating efficiency, product quality and energy consumption of grinding process. Due to high dimension and collinearity of spectral data, mill load model has high complexity, poor interpretability and generalization. A soft sensor modeling method of mill load parameters is proposed based on frequency spectrum feature using Synergy Interval Partial Least-Squares Regression (SiPLS). Based on the spectrum feature of the shell vibration or acoustic signal, three soft sensor models of mill load, such as mineral to ball volume ratio, charge volume ratio and pulp density are developed, respectively. The proposed method is tested by the wet ball mill in the laboratory grinding process. The experimental results have demonstrated the proposed method has higher accuracy and better generalization performance than the full-spectrum model and iPLS feature spectrum model, and the feature spectrum model based on the shell vibration is superior to the acoustic feature spectrum model.

Keywords: *Ball Mill, Mill Load, Feature Selection, Synergy Interval Partial Least Square*

1 INTRODUCTION

Ball mills are widely used for grinding in most comminution circuits. The crushed crude ores are grinded into enough fine slurry to ensure good liberation of the value minerals to be recovered. Mill load is the most important parameter for control and optimization of the grinding process [1]. It is difficult to online measure the mill load for poor conditions inside ball mills because of a series of complex impact and grinding among steel balls and materials, steel balls and lining. Mill load measurements mainly depend on the skilled operator in the industrial fields so that some economic benefits lost in order to ensure equipment safety and process continuity. Due to frequent fluctuations of ore properties and operation states, ball mills are difficult to keep stable and optimal operation. Some abnormal phenomena, such as empty grinding and block grinding, result in low efficiency, high energy consumption, and even damage. Therefore, online reliable measurements of internal instantaneous load of ball mill, including the new feed ore, slurry, water and steel balls inside the ball mill, have important significance for improving the production efficiency, quality of grinding mineral and saving energy.

In the industrial application, mineral to ball volume ratio, charge volume ratio and pulp density are important parameters to describe the mill load [3]. There are two main methods: direct measurement and indirect measurement. Unfortunately, direct measurement sensors are not widely applied because of assembly difficulty, post-maintenance complexity and high cost of investment [4]. Indirect measurement method is commonly used by using easily measurement external response signal of ball mill, such as power, bearing vibration, acoustic emission and shell resilience. An intelligent information fusion monitoring method of mill load was proposed to overcome the subjectivity and arbitrariness of the operator experience by combining the domain specialist knowledge, rule reasoning and statistical process control with the multi-source signals [5, 6]. However, it cannot obtain the quantitative parameters of the mill load, which constraints the control and optimization of the grinding process. Y. G. Zeng (1994) found that feature intervals of vibration signal are directly related to the parameters of mill load [7] and the acoustic signal includes more information on mill operating parameter than the bearing vibration signal, but the study only involved the pulp density of the mill load. Li et al. (2006) [8] used RBF neural network to real-time predict the charge volume ratio

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using acoustic, pressure and power signal by consistent correlation analysis method. Although amplitude, energy and the other global features of the signal are extracted, plenty of information in acoustic signal spectrum is ignored so that it is difficult to guarantee the measurement accuracy and sensitivity.

With the development of sensors, data processing and communication technology, the analysis and monitoring of the ball mill load based on shell vibration signal with high sensitivity and strong anti-interference improve the quantitative and qualitative measurement performance of mill load. Gugel et al (2007) [9] proposed dual-array accelerometers to obtain vibration signals from the shell wall, the result shows that the detection accuracy based on vibration is better than acoustic method. Although the vibration and acoustic frequency spectrum contain plenty of information about the mill load, mill load model is difficult to build effectively. This is because the hyper-high dimension and high colinearity in the frequency spectrum variables and vibration / acoustic signal is difficult to extract time-domain feature.

Feature extraction and selection is an effective method to avoid the curse of dimensionality, improve generalization and enhance interpretability. Tang et al (2010) [10] analyzed the vibration signal time/ frequency feature under different grinding conditions in experimental scale ball mill. Genetic algorithm-partial least square (GA-PLS) was used to select the vibration spectrum feature. The selected feature frequency bands by using GA were the suboptimal solutions and their physical significance are difficult to explain. Tang et al. (2010) [11] developed three support vector machine (SVM) models to predict the mill operating parameters based on feature variables at low, medium and high frequency bands using principal component analysis (PCA). But the soft sensor modeling method exits manual division of frequency bands, extraction of linear features, and SVM needs to solve the quadratic programming problem.

Multivariate data analysis and latent variable methods can achieve data dimensionality reduction by projecting multivariate data to low dimensional space. Interval partial least squares (*i*PLS) regression is an efficient method to select the spectral data [12]. The *i*PLS algorithm splits the full spectrum into many sub-intervals of equal width, where each sub-interval builds a local PLS regression model. The best regression model based on sub-intervals produce the lowest RMSECV values by using leave-one-out cross validation (LOO-CV). *i*PLS and its extension methods are widely used in the spectral engineering field to analyze various of the spectrum information [13-15]. Synergy Interval Partial Least-Squares Regression (SiPLS) calculates all possible sub-interval combination models [16]. The combination with the lowest RMSECV will be chosen.

The relationship between external response signals and mill load parameters is very complex. It is difficult to build the mechanism mathematical model to describe. The vibration / acoustic signal contains plenty of information, and there is physical mapping between vibration mode and ball mill running state. However, only one local interval of vibration spectrum or acoustic spectrum is insufficient to build the effective prediction model of ball mill load [13]. That is because the frequency spectrum variables of the response signals are superimposed by a series of impact with different intensity, different frequencies, and there are hyper-high dimension and high colinearity in the frequency spectrum variables. A soft sensor modeling method of SiPLS is proposed to build the PLS model of ball mill load where sub-interval combination with the lowest RMSECV and the maximum correlation coefficient. The method is verified on the laboratory small ball mill.

2 SPECTRAL FEATURE SELECTION AND SOFT SENSOR OF BALL MILL LOAD USING SIPLS

Mechanism model of mill load parameter are difficult to build due to complex slurry theological properties in wet ball mill. Mill load parameters are related to different intervals of frequency spectrum. It is difficult to select the feature of vibration/acoustic frequency spectrum due to the hyper-high dimension, high collinearity and redundancy in the frequency spectrum. Therefore, a feature selection method of ball mill vibration / acoustic frequency spectrum feature is proposed. Soft measurement models of ball mill load are built based on the informative intervals of vibration and acoustic frequency, as shown in Figure 1.

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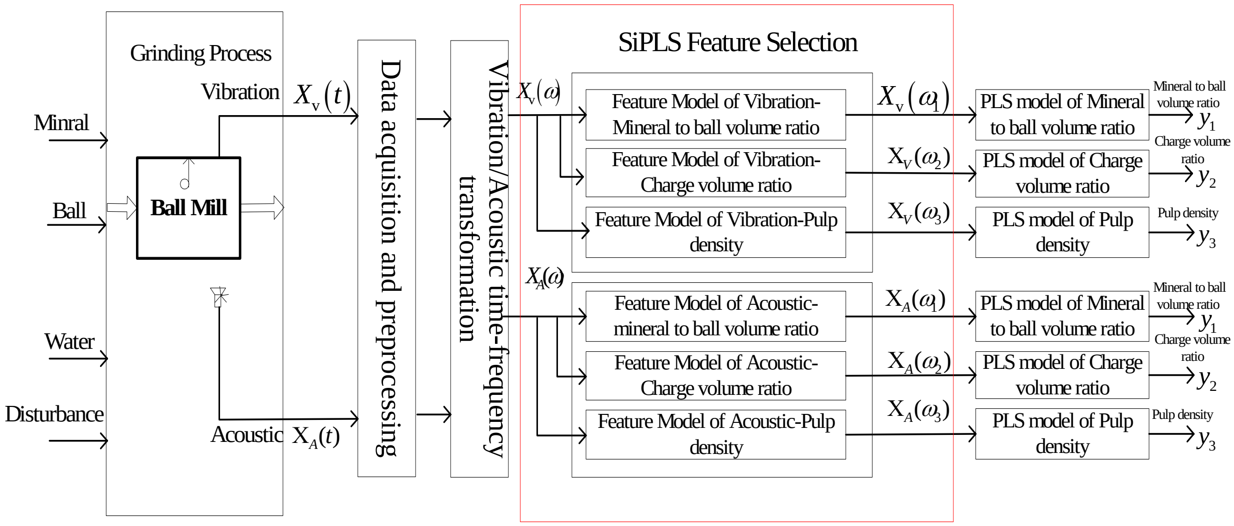

Figure 1: The Feature Selection Strategy Of Frequency Spectrum Based On Ipls

Redundancy information from vibration and acoustical signals was removed in order to reduce the complexity of the soft sensing model and enhance understanding of ball mill grinding mechanism. The proposed feature selection and soft sensor modeling method mainly consist of vibration/acoustic data acquisition and preprocessing, time-frequency transformation, SiPLS feature selection and soft sensor modeling. Input variables include vibration signal X_V and acoustic signal X_A, output variables are three mill load parameters, such as mineral to ball volume ratio y_1, charge volume ratio y_2 and pulp density y_3. Firstly, vibration signals were measured by a vibration acceleration sensor installed on the shell surface of ball mill, and or acoustic signals were obtained by an acoustic sensor installed near the inlet of ball mill. Secondly, remove the outliers and noise from the original vibration or acoustical signals. The time domain waveforms of the shell vibration or acoustic signals are transformed into the frequency domain power spectrum by PWELCH method. Then, combine vibration and acoustic signal generation mechanism with the change of spectrum structures, full-spectrum are split into a number of subintervals with equal width. Next, calculate all possible subinterval combination models by interval numbers of 2, 3 or 4 and choose the combination with the lowest RMSECV as the feature frequency spectrum subinterval. Finally, build mineral to ball volume ratio model, charge volume ratio model and pulp density model based on vibration or acoustic frequency spectrum feature and verify the accuracy of the mill load model based on feature of frequency spectrum. Spectral feature selection and soft sensor modeling of mill load in the ball mill are as follows:

(1) Remove the outliers and noise from the original vibration signal $X_V(t)$ or the acoustic signal $X_A(t)$. The time domain waveform of shell vibration or acoustical signal are preprocessed and transformed into the frequency domain power spectrum by PWELCH method, and the vibration power spectrum $X_V(\omega)$ and acoustic power spectrum $X_A(\omega)$ are averaged by several rotation periods of frequency spectrum [10].

(2) Split the whole frequency spectrum of the shell vibration signals or acoustic spectrum into a number of intervals I along the spectrum variables.

(3) Combine two, three or four intervals from the I subintervals with equal width, $X_{\omega k}, k = 1, \cdots, K$. The number of all interval combinations is

$$C_K^j = \frac{K!}{j!(K-j)!} \tag{1}$$

where j is the combination number of two, three or four intervals should to be lower than the number of intervals, $j < I$.

(4) Calculate all possible PLS model combinations of two, three or four intervals. For the

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spectral feature selection of the vibration signals, the input of the PLS regression model is the frequency spectrum of the vibration signals. For the spectral feature selection of the acoustic signals, the input of the PLS regression model is the frequency spectrum of the acoustic signals. The outputs of PLS model are mill load parameters y_i ($i=1,2,3$), such as mineral to ball volume ratio, charge volume ratio and pulp density.

The PLS is expressed as a bilinear decomposition of both the full frequency spectrum X and the mill load parameter variables Y as

$$\begin{cases} X = TP^{\mathrm{T}} + E = \sum_{k=1}^{h} t_k p_k^{\mathrm{T}} + E \\ Y = UQ^{\mathrm{T}} + F = \sum_{k=1}^{h} u_k q_k^{\mathrm{T}} + F \end{cases} \quad (2)$$

where $T = [t_1, t_2, ..., t_h] \in R^{N\times h}$, $U = [u_1, u_2, ..., u_h] \in R^{N\times h}$ are X and Y latent score vectors with the extracted h principal components, respectively; the $(n\times h)$ matrix $P = [p_1, p_2, ..., p_h]$ and the $(m\times h)$ matrix $Q = [\mathrm{q}_1, q_2, ..., q_h]$ represent X- and Y- loadings vectors, respectively; the $(N\times n)$ matrix $\boldsymbol{E}$ and the $(N\times m)$ matrix $\boldsymbol{F}$ are X- and Y- residuals, respectively. If enough component are remained in the PLS, residual E and F can equal to zeros.

The goal of PLS is to minimize $\|F\|$ and achieve the relations between X and Y scores. A link between X and Y space is established by linear regression (least squares) between u_h and t_h , which is known as the inner relationship.

$$u_k = t_k b_k, k = 1, ...h \quad (3)$$

where $b_h = \left(t_h^T t_h\right)^{-1} t_h^T u_h$ is regression coefficient of the ordinary least squares. The scalar b is stored as an element of diagonal matrix $B = diag\{b_1, b_2, ..., b_h\}$. The inner relationship is expressed in the matrix notation

$$U = TB \quad (4)$$

When h principal components are retained in the PLS model, the latter principal components have very small variance and are considered to be noise or the cause of the collinearity. In this work, the non-linear iterative partial least squares (NIPALS) algorithm is used to build the PLS models.

(5) The root mean squared error (RMSE) is used as a measure of how a model performs. RMSE is defined as follows:

$$RMSE_i = \sqrt{\frac{\sum\left(\hat{y}_{i,k} - y_i\right)^2}{N}}, i = 1, 2, 3 \quad (5)$$

where N is the number of samples, y_i is the laboratory measured value and $\hat{y}_{i,k}$ is the predicted value. RMSECV is calculated from the cross-validated samples, and RMSEP is calculated from the independent test set. RMSECV is calculated for each combination region. Correspondingly, the correlation coefficients of the three output parameters are calculated for the predicted versus measured variables for a combination of several intervals. The combination of the intervals with the lowest RMSECV and the highest correlation coefficient is selected as the spectral feature for each mill load parameter.

(6) Develop PLS models of the mill load parameter on the selected intervals from SiPLS and predict for the new data sets.

3 EXPERIMENT RESULTS AND DISCUSS

3.1 Experiments and Data Processing

The experiments were performed on a laboratory scale lattice-type ball mill (XMQL-420×450) with the drum of 460 mm in diameter and 460 mm in length. The vibration signals were measured by a vibration acceleration sensor with sampling frequency 51,200 Hz, which was installed on the outer shell of the ball mill. The acoustic sensor was installed near the inlet of ball mill. The experimental ball mill has maximum ball load of 80 kg, pulverizing capacity of 10 kg per hour and a rated revolution of 57 per minute. A series of grinding experiments with the different operation conditions are done by adding the steel balls of different size (diameter of 30, 20 and 15mm), copper ores and water into the ball mill. Steel balls, ores and water have been homogenized inside the ball mill, which lasted about one minute. Grinding experiments are shown in Table 1.

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Table 1: Grinding Experimental Conditions Of The Ball Mill Operation

No.	Ball (kg)	Ore (kg)	Water (kg)	time (s)
01	40	10	10	40
02	40	10	15	40
03	40	10	20	40
04	40	10	30	40
05	40	10	40	40
06	40	10	2	60
07	40	12	2	60
08	40	14	2	60
09	40	16	2	60
10	40	18	2	60
11	40	20	2	60
12	40	20	5	60
13	40	20	7.5	60
14	40	20	10	60
15	40	20	12.5	60
16	40	20	15	60
17	40	20	20	60
18	40	22	10	60
19	40	24	10	60
20	40	26	10	60
21	40	28	10	60
22	40	30	10	60
23	40	35	10	60
24	40	40	10	60
25	40	45	10	60
26	40	50	10	60

In this section, the performance of the mill load modes was evaluated on the experimental ball mill and compared with full spectrum PLS model, *i*PLS model. All the evaluations were carried out in the Matlab R2010a software (The Mathworks). The power spectral density (PSD) was calculated using Welch's method with the overlap fraction length of 512 [10]. Shell vibration PSD with the ranges of 1-10100 Hz and acoustic PSD with the ranges of 1-4500 Hz are used to construct PLS model. The region before 100 Hz was excluded according to the prior knowledge. The preprocessing methods are implemented by the mean centering.

3.2 Selection Of The Relevant Spectral Intervals

The dataset was divided into calibration and prediction data. The iToolbox [17] was used to explore feature selection of vibration and acoustic spectral data sets with many collinear variables. In the SiPLS, all models are built on the vibration spectral data (every 2nd Hz is recorded), acoustic spectral data and the dependent data with the three mill load parameters. PLS combination models are calculated and are cross validated by Venetian blinds with five segments and systematic exclusion. The mill load parameter models are tested by an independent data set.

In the SiPLS models, maximum number of PLS components is set as 30, the other parameters are as follows: independent data (Vibration or acoustic spectrum), dependent data (ball volume ratio, charge volume ratio and pulp density), the number of intervals (10, 20, 30, 40, 50), the number of interval combinations tested (2, 3 or 4), the number of segments (5, 10). Through calculating all possible PLS model with the above parameters setting for the different independent data and dependent data, selection results of relevant spectral intervals are as shown in Table 2-4. Table 2-4 show main feature of vibration frequency spectrum and acoustic frequency spectrum which are closely relevant to the mill load parameters, such as mineral to ball volume ratio, charge volume ratio and pulp density.

Table 2: Results Of The Selection Of Relevant Spectral Intervals And Soft Sensor For The Mineral To Ball Volume Ratio

Model Data	Modeling method	Intervals	Combination number(Comb)	PLS comp.	optimal interval combinations	RMSECV	r_{CV}
vibration	Full-spectrum PLS	1	1	4	1	0.5138	0.7846
vibration	Feature-spectrum iPLS	20	8	5	[16 11 17 10 14 9 13 1]	0.7704	0.6688
vibration	Feature-spectrum SiPLS	40	2	8	[1 3]	0.0961	0.9637
acoustic	Full-spectrum PLS	1	1	1	1	0.5823	0.7325
acoustic	Feature-spectrum iPLS	10	7	5	[7 9 6 5 3 1 4]	0.4728	0.8135
acoustic	Feature-spectrum SiPLS	20	4	4	[7 8 9 17]	0.1213	0.9370

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Table 3: Results Of The Selection Of Relevant Spectral Intervals And Soft Sensor For The Charge Volume Ratio

Model Data	Modeling method	Intervals	Combination number(Comb)	PLS comp.	optimal interval combinations	RMSECV	r_{CV}
vibration	Full-spectrum PLS	1	1	5	1	0.1732	0.7381
vibration	Feature-spectrum iPLS	20	7	4	[18 15 14 13 17 1 16]	0.1379	0.6933
vibration	Feature-spectrum SiPLS	30	2	11	[4 19]	0.0456	0.9579
acoustic	Full-spectrum PLS	1	1	1	1	0.2737	0.7152
acoustic	Feature-spectrum iPLS	10	5	2	[10 2 6 5 3]	0.1352	0.3700
acoustic	Feature-spectrum SiPLS	40	2	7	[16 23]	0.0074	0.6572

Table 4: Results Of The Selection Of Relevant Spectral Intervals And Soft Sensor For The Pulp Density

Model Data	Modeling method	Intervals	Combination number(Comb)	PLS comp.	optimal interval combinations	RMSECV	r_{CV}
vibration	Full-spectrum PLS	1	1	5	1	0.1384	0.7208
vibration	Feature-spectrum iPLS	20	3	6	[11 17 9]	0.2449	0.7376
vibration	Feature-spectrum SiPLS	10	4	3	[1 2 9 10]	0.1064	0.7398
acoustic	Full-spectrum PLS	1	1	4	1	0.7802	0.5825
acoustic	Feature-spectrum iPLS	20	6	5	[12 10 9 5 1 11]	0.1844	0.5451
acoustic	Feature-spectrum SiPLS	30	4	7	[9 14 17 18]	0.0717	0.9599

Table 2 to 4 list the optimal interval combinations, corresponding RMSECVs and PLS components. When the combination number is bigger than 50 for the vibration signals, computation costs expensively. Computation time depends on the number of intervals and the selected number of intervals to combine. Take feature selection of shell vibration signal for instance, RMSECVs as a function of the number of PLS components and spectral subintervals selected by SiPLS algorithm are shown in Figure 2. From Figure 2 (a) to (c), it can be seen that mineral to ball volume ratio is relevant to the low frequency bands of shell vibration spectral data, charge volume ratio is relevant to the middle frequency bands of shell vibration spectral data, and pulp density is relevant to low and high frequency bands of shell vibration spectral data.

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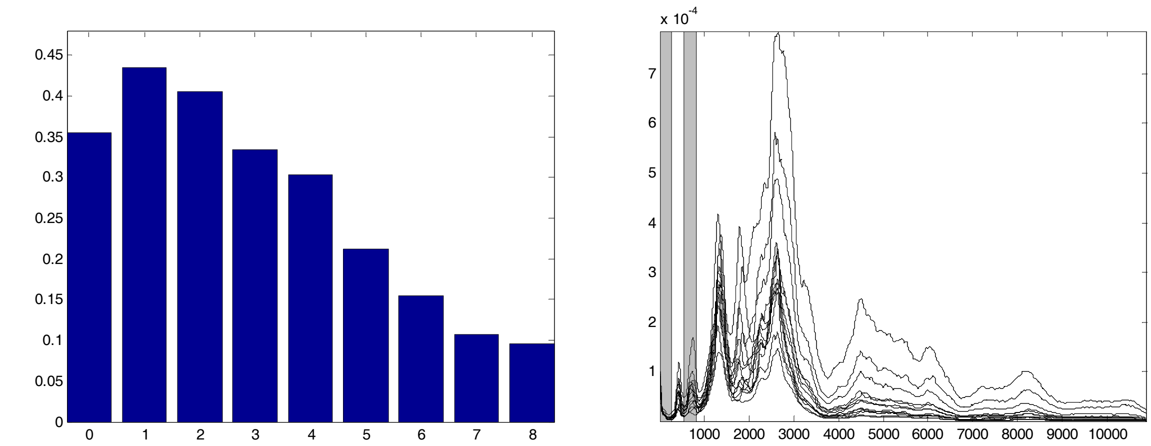
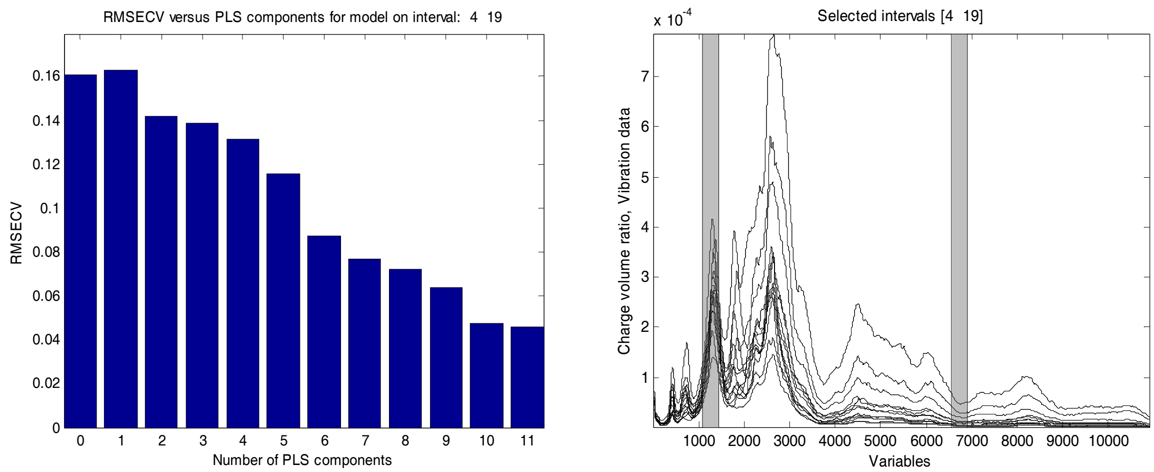
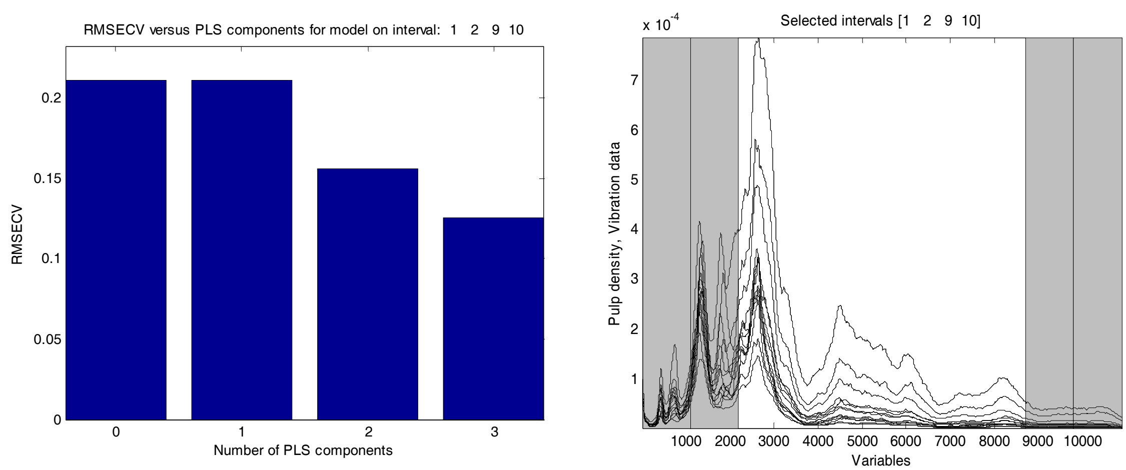


(A) Mineral To Ball Volume Ratio



(B) Charge Volume Ratio



(C) Pulp Density

Figure 2: Feature Selection Of Mill Load Model Based On Vibration Signals

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3.3 Prediction Based on SiPLS Models

Full-spectrum model performance of the shell vibration signals and acoustic signals are compared with feature spectrum PLS model using the optimal parameters in Table 2 to 4 for three parameters of the mill load. Performance comparison result of mill load parameter prediction is shown in Table 5. From Table 5, RMSE prediction based on the vibration and acoustic feature spectral model are less than their full spectrum model for all three mill load parameters. Only the mineral to ball volume ratio parameter, prediction RMSE of the full spectrum model of acoustic signal is less than the full spectrum model of the shell vibration signal. For the charge volume ratio and pulp density parameters of the mill load, the performances of shell vibration full-spectrum models are superior to the acoustic full-spectrum model. For all three mill load parameters, prediction performances of feature-spectrum SiPLS models are better than feature-spectrum iPLS model and full spectrum model based on vibration or acoustic signals, and performances of feature spectrum model of shell vibration signal are better than the acoustic signal feature spectrum model.

Table 5: Comparison Of Full Spectrum PLS Model And Feature Spectrum Model Based On Ipls And Sipls

Model Data	Modeling method	mineral to ball volume ratio		charge volume ratio		pulp density	
		RMSEP	r_p	RMSEP	r_p	RMSEP	r_p
vibration	Full-spectrum PLS	0.7976	0.7372	0.0582	0.9471	0.1314	0.8117
vibration	Feature-spectrum iPLS	0.2907	0.9521	0.0498	0.9509	0.0550	0.9692
vibration	Feature-spectrum SiPLS	0.2723	0.8383	0.0465	0.9601	0.0545	0.9695
acoustic	Full-spectrum PLS	0.4500	0.8623	0.2277	0.5758	0.2164	0.2459
acoustic	Feature-spectrum iPLS	0.3579	0.9326	0.1073	0.7255	0.1091	0.8808
acoustic	Feature-spectrum SiPLS	0.2049	0.9563	0.1027	0.7470	0.1075	0.8972

4 CONCLUSION

A soft sensor modeling method of mill load parameters are proposed based on feature space of frequency spectrum using synergy interval PLS. Three mill load parameter models including mineral to ball volume ratio model, charge volume ratio model and pulp density model are built and compared with the full-spectrum PLS model and iPLS feature spectrum model. The experimental results show that prediction performances of mill load parameters based on the SiPLS model are better than the corresponding full-spectrum models, iPLS feature spectrum models, and the feature spectrum models based on the shell vibration are superior to the acoustic feature spectrum models. Due to the experiment limitations to small samples of a wide range of operating conditions change, the more experiments should be done further.

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