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Soft sensor modeling of mill output in direct fired system based on improved FIR filter and least squares support vector machines

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According to the multivariable, strongly nonlinear and large time delay system, the computing time of least squares support vector machines (LS-SVM) as a soft sensor modeling method is longer because of its lacking sparseness. It goes against on-line realization. In this paper, FIR digital filter was used because of its linear phase properties. Firstly, finite impulse response (FIR) digital filter was optimized by Remez algorithm. Simulation results show that the optimization effect is better. Secondly, the improved algorithm was combined with LS-SVM and formed a new soft sensor modeling method, FIR-LSSVM. Lastly, FIR-LSSVM was used to establish the soft sensor model of mill output of direct-fired system with duplex inlet and outlet ball pulverizer in power plant. Field tests show that the learning speed of FIR-LSSVM is faster and the error is less. FIR-LSSVM is more suitable online learning.

Keywords: Least squares support vector machines(LS-SVM), duplex inlet & outlet ball pulverizer, direct-fired system, improved FIR filter, mill output, soft sensor modeling.

1. INTRODUCTION

The mill output of direct-fired system must always satisfy the demand of boiler. This is the main feature of direct-fired system with duplex inlet and outlet ball pulverizer in power plant. So, it is very important to measure the mill output online. Because of its adverse circumstances, it is more difficult to realize direct measurement [1]. Soft sensor is a better way to overcome this problem. But, the soft sensor method according to mill output of direct-fired system is seldom reported at present.

In recent years, support vector machines (SVM) has been introduced to the soft sensor modeling field because it can better overcome the problems such as small samples, over learning and local minimum, etc [2-4]. However, the standard SVM is a quadratic programming problem with constrains, it goes against online realization because of long training time. In order to improve the training efficiency, Suykens had changed the constrains and risk functions of SVM, and derived least squares support vector machines (LS-SVM) [5-7]. The training of LS-SVM only needs one linear equations. It has improved the training efficiency greatly. But on the other hand, almost all training data was regarded as support vector in LS-SVM, the sparseness had been lost. The training time is still longer, and the bad samples have a great influence on training results[8].

According to the above problems, a new filter is proposed in this paper to remove the larger deviation data from the samples in order to reduce the interference of bad samples and to improve the training efficiency. It is well known that FIR filter is widely used in various industrial processes because of its good linear characteristics and stability. But, the error of FIR filter is bigger and the calculation time is longer [9-11]. So, the FIR filter was optimized by Remez algorithm [12] in this paper. Simulation results show that the optimization effect is better. Then the optimized FIR filter was combined with LS-SVM, and formed a new soft sensor modeling method, FIR-LSSVM. The new method was used

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to establish the soft sensor model of mill output of direct fired system with duplex inlet and outlet ball pulverizer in power plant. Field tests show that the learning speed of FIR-LSSVM is faster and the error is less. FIR-LSSVM is more suitable online learning.

2. LS-SVM THEORIES

Let $\{(x_i, y_i) \mid i = 1,2,\cdots,l\}$ be the training sample set, where $x_i \in R^N$ is input pattern of the ith sample, $y_i \in R$ is desired output corresponding to the ith sample, l is the training sample number. The linear function in high dimensional feature space as following is used to fit sample.

$$f(x) = w^T \varphi(x) + b \tag{1}$$

The input data is mapped into high dimensional feature space by nonlinear mapping function $\varphi(x)$. Then, LS-SVM can be expressed by the following constrained optimization problem [13,14].

$$\min_{w,b,e} J(w,e) = \frac{1}{2} w^T w + \frac{1}{2}\gamma \sum_{i=1}^{l} e_i^2$$
$$s.t.\ \ y_i = w^T \varphi(x_i) + b + e_i \tag{2}$$

Where, weight vector $w \in R^{N_C}$, error variable $e_i \in R$; and b is deviation, γ is normalization parameters. In order to solve the above optimization problem, the lagrange function is defined as

$$L(w,b,e;\alpha) = J(w,b,e) - \sum_{i=1}^{l} \alpha_i \left\{ w^T \phi(x_i) + b + e_i - y_i \right\} \tag{3}$$

Where, lagrange multiplier $\alpha_i \in R$, i=1,2, …, l. The criterions for optimization problems can be written as

$$\begin{cases} \partial L / \partial w = 0 \rightarrow w = \sum_{i=1}^{l} \alpha_i \varphi(x_i) \\ \partial L / \partial b = 0 \rightarrow \sum_{i=1}^{l} \alpha_i = 0 \\ \partial L / \partial e_i = 0 \rightarrow \alpha_i = \gamma e_i \\ \partial L / \partial \alpha_i = 0 \rightarrow w\varphi(x_i) = b + e_i - y_i \end{cases} \tag{4}$$

After elimination of w and e_i , the matrix equation is obtained as

$$\begin{bmatrix} 0 & Z^T \\ Z & K+D \end{bmatrix}\begin{bmatrix} b \\ a \end{bmatrix} = \begin{bmatrix} 0 \\ y \end{bmatrix} \tag{5}$$

Where, $y = [y_1, y_2, \cdots, y_l]^T$, $Z = [1, \cdots, l]^T$, $\alpha = [\alpha_1, \cdots, \alpha_l]^T$, $D = diag(\gamma^{-1}, \cdots \gamma^{-l})$, $K = \{K_{ij} = K(x_i, x_j)\}_{i,j=1}^{l}$.

The values of α_i and b can be obtained by solving the linear equations in Eqs.(5). Then, the LS-SVM model can be presented as following:

$$f(x) = \sum_{i=1}^{l} \alpha_i K(x, x_i) + b \tag{6}$$

In the regression model of LS-SVM, each of the coefficients is not zero, almost all training data was regarded as support vector, sparseness had been lost. So, the computation of this model is complicated, and the consumed time is still longer.

3. OPTIMIZATION OF FIR FILTER AND SIMULATION

3.1 FIR Filter Theory and Optimization

The transfer function of FIR filter can be expressed as following:

$$H(\mathrm{z}) = \sum_{k=0}^{N-1} h(k) z^{-k} \tag{7}$$

Where, N is the order of FIR filter, $h(k)$ is the kth coefficient. It is obvious that the function is a polynomial of z^{-1}, it has not zeros, and only has limited poles. So, FIR filter is usually very stable.

But, the precision of FIR filter with common design method is low, the error is large. FIR filter was optimized in this paper in order to reduce error and improve efficiency. The design steps after optimization are as following:

(1) Let ω_c is cutoff frequency of low-pass filter, its amplitude-frequency characteristic is:

$$h_d(k) = \frac{1}{2\pi}\int_{-\omega_c}^{\omega_c} e^{j\omega k} d\omega = \frac{\sin[\omega_c(k-\alpha)]}{\pi(k-\alpha)} \tag{8}$$

(2) To define the weighted error function as

$$E(\omega) = W(\omega)[H_d(\omega) - H(\omega)] \tag{9}$$

Where, $H_d(\omega)$ is the ideal amplitude function, $H(\omega)$ is the actual amplitude function, $W(\omega)$ is the weighted function. $H(\omega)$ can be identity deformed by trigonometric function as following

$$H(\omega) = Q(\omega)P(\omega) \tag{10}$$

Where, $Q(\omega)$ is the fixed function of ω, $P(\omega)$ is the linear combination of M cosine functions.

(3) To determine the expression of the above error function by Remez optimization algorithm.

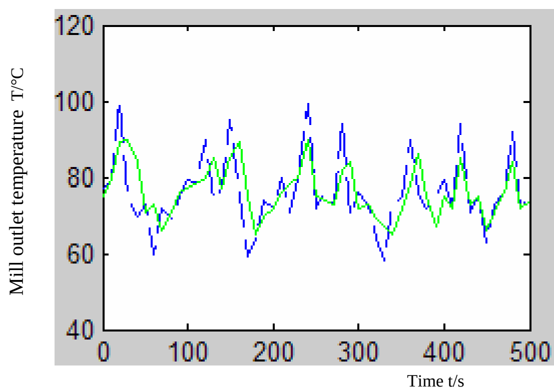
(4) To determine the window function $\omega(k)$ and window length N based on the constraint condition that the performance index and error is the least. Window length can be obtained by filter strips approximating to main-lobe width of window function.

(5) To get the unit impulse response of filter $h(k) = h_d(k)\omega(k)$.

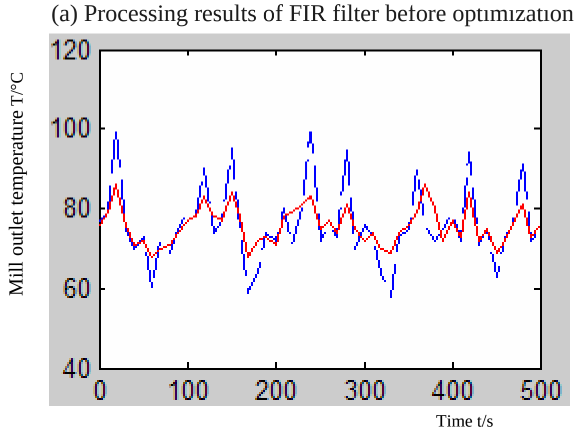
(6) To test the performance index of filter.

3.2 Simulation

The outlet temperature of duplex inlet and outlet ball pulverizer in a power plant was continuous sampled, and got one hundred series measured data. The one hundred series data was filter processed respectively by FIR filter and optimized FIR filter. The simulation results after filter processing are shown in Fig.1. The dotted line is measured value, and the solid line is the value after filter processing.



(a) Processing results of FIR filter before optimization



(b) Processing results of FIR filter after optimization

Figure 1: Simulation results comparison of FIR filter before and after optimization

By comparing (a) and (b) of Fig.1, we can know that the effect of optimization is better, and the error is relatively smaller. In the simulation results, error variances of FIR filter before and after optimization are respectively 0.325 and 0.127. The error decreases a lot more than before. It is illustrates that the optimization algorithm is feasible.

4. SOFT SENSOR MODELING OF MILL OUTPUT BASED ON FIR AND LS-SVM

The optimized FIR filter was combined with LS-SVM and formed a new soft sensor modeling method, FIR-LSSVM. Its structure is shown in Fig.2.

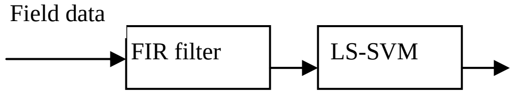


Figure 2: Structure of FIR-LSSVM

This method can better filter out the larger deviation data, reduce the error of LS-SVM and improve the training efficiency online.

4.1 Soft Sensor Modeling of Mill Output

Five influence factors of mill output are selected as input parameters. The five factors are sirocco door opening, mill current, mill outlet temperature, coal feeder speed and mill speed [15].

Selecting the radial basis function which has the better generalization ability as kernel function:

$$K(x_i, x) = \exp\left[-\frac{|x - x_i|}{2\sigma^2}\right] \tag{11}$$

Where, σ is the kernel width.

The selection of three parameters is very important when establishing the LS-SVM model of mill output, there are normalization parameter γ, kernel width σ and insensitive coefficient ε. The value of parameter γ is related to tolerable error. The bigger value of C allows the smaller error, and the smaller value allows bigger error. The kernel width σ is related to the input space range of study sample. The input space range is bigger, the value of σ is bigger also. The parameter ε is determined by prior estimation noise level.

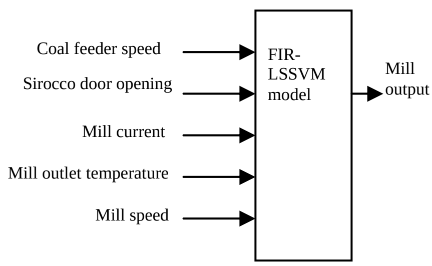


Figure 3: FIR-LSSVM soft sensor model of mill output in pulverizing system

FIR-LSSVM soft sensor model of mill output is black-box model. Its input data was processed by improved FIR filter, and the nonlinear relationship of input and output was realized by LS-SVM. The soft sensor model is shown in Fig.3. Its input is all sorts of secondary variables and output is mill output.

4.2 Experiments

Because there is not field value of mill output as a reference, we cannot identify the measurement accuracy of soft sensor model. As we all know, the mill output of direct-fired system is balanced with coal feed amount under the steady-state condition. So, in order to test the rationality of soft sensor model, we sequentially sample the steady-state condition after running a period and suddenly change the coal feed amount. The coal feed amount was changed from 40t/h to 50t/h. Then the mill output was measured online respectively using LS-SVM and FIR-LSSVM soft sensor model. The normalization parameter and kernel width is respectively selected $\gamma=102$, $\sigma=1.3$. The parameter ε is taken for 10^{-4}, and set to stop training when the value less than 10^{-5}.

The measurement results of mill output are shown in Fig.4.

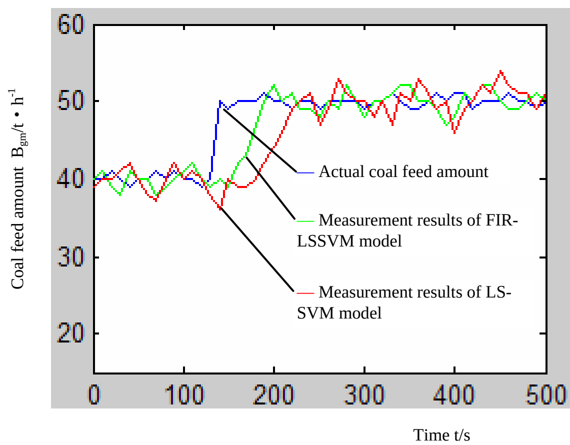


Figure 4: Measurement results with two models

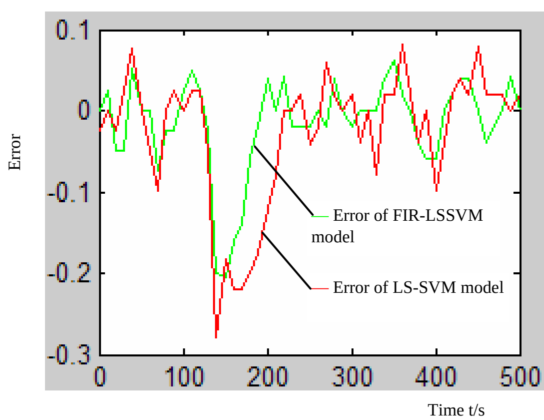


Figure 5: Comparison of error with two models

Fig.4 is the measurement results of mill output respectively using LS-SVM and FIR-LSSVM model. In Fig.4, the blue line expresses actual coal feed amount, the red line expresses measurement results of LS-SVM model, the green line expresses measurement results of FIR-LSSVM model. Fig.5 is the error comparison of two models. The statistical results of error are shown in table 1.

Table 1 :Statistical results of error with two models

	Maximum absolute error	Average relative error	Mean square error
LS-SVM	8	0.076	0.0346
FIR-LSSVM	5	0.0207	0.0216

The following conclusions can be obtained by analyzing the above simulation results:

(1) The measured values of mill output by two methods can basically reflect the actual output also when changing coal feed amount after running a period. It is illustrates that the two soft sensor methods are all feasible.

(2) The training speed of FIR-LSSVM model is faster. In Fig.4, when changing the coal feed amount, the measured values of LS-SVM may be delayed 120s can track real output, while FIR-LSSVM model only delays about 60s.

(3) The error of FIR-LSSVM model is less. The difference between LS-SVM measured values and coal feed amount is large, its maximum absolute error is 8, average relative error is 0.076, and mean square error is 0.0346. While, when using the FIR-LSSVM model, the maximum absolute error is only 5, average relative error is 0.0207, and mean square error is only 0.0216. There are all reduced than LS-SVM model.

5. CONCLUSIONS

LS-SVM algorithm lacks sparseness. The training time is longer. So, it goes against online realization. According to the multivariable, strongly nonlinear, large time delay and difficult to direct measurement system of industrial process, a new soft sensor method, FIR-LSSVM, was proposed in this paper. This method is a combination of LS-SVM and optimized FIR filter. FIR filter was optimized by Remez algorithm. The simulation results show that the optimization effect is better. Then, FIR-LSSVM was used in the direct-fired system with duplex inlet and outlet ball pulverizer in power plant. The analysis of field experiment shows that the learning speed of FIR-LSSVM is faster and the error is smaller. So, it is more suitable to study online. It has laid a good foundation for online optimization control of mill system.

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LIST OF SYMBOLS

- x_i, y_i : input and output ;
- L : training sample number ;
- w : weight vector ;
- e_i : error variable

- $h(k)$: the kth coefficient ;
- γ , σ , ε : kernel parameters ;
- α_i : lagrange multiplier ;
- b : deviation ;
- $H_d(\omega)$: ideal amplitude function ;
- $H(\omega)$: actual amplitude function ;
- ω_c : cutoff frequency of low-pass filter ;
- $W(\omega)$: weighted function.

REFERENCES

[1] WANG Dong-feng, SONG Zhi-ping, A study on the soft-sensing of coal load in ball mill tube of pulverized system based on neural networks, *Proceeding of the CSEE*, vol. 21, n.12,2001, pp. 97-104.

[2] Vapnik V, *The Nature of Statistical Learning Theory*, New York：Springer, 1995.

[3] YAN Wei-wu, SHAO Hui-he, WANG Xiao-fan. Soft sensing modeling based on support vector mchine and Bayesian model selection, *Computers & Chemical Engineering*, vol. 28, n.8, 2004, pp.1489-1498.

[4] Kiran D, Yogesh B, Sanjeev S. Tambe, Bhaskar D. Kulkarni, Soft-sensor development for fed-batch bioreactors using support vector regression, *Biochemical Engineering Journal*, vol. 27, n.3, 2006, pp. 225-239.

[5] Suykens J A K, Vandewalle J, Least squares support vector machine classifiers, *Neural Processing Letters (S1370-4621)*, vol. 9, n.3, 1999, pp.293-300.

[6] Suykens J A K, Lukas L, Van Dooren P, De Moor B, Vandewalle J, Least square support vector machine dassifiers: a large scale algorithm, *Proceedings of the European Conference on Circuit Theory and Design(ECCTD'99)*, Stresa, Italy,1999, vol. 9, pp.839-842.

[7] Suykens J A K, Lukas L, Vandewalle J, Sparse least squares support vector machines, *ESANN'2000*, Bruges, Belgium, 2000:37-42.

[8] Muhsin T G, Murat U, Prediction of flashover voltage of insulators using least squares support vector machines, *Expert Systems with Applications*, vol. 36, n.7, 2009, pp.10789-10798.

[9] Jong-Jy Shyu, Soo-Chang Pei, A generalized approach to the design of variable fractional-delay FIR digital filters, *Signal Processing*, vol. 88, n.6, 2008, pp.1428-1435.

[10] Mohammed A Z, Qassem A Z, A novel algorithm for the design of selective FIR filters with arbitrary amplitude and phase characteristics, *Digital Signal Processing*, vol. 16, n.3, 2006, pp.211-224.

[11] YAN Wei-yong, Kok L T, Optimal finite-precision approximation of FIR filters, *Signal Processing*, vol. 82, n.11, 2002, pp.1695-1705.

[12] LAI Xiao-ping, An OPRemez Approach to the Design of FIR Digital filters, *5th International Conference on WCCC-ICSP2000*, Beijing, China. 2001, pp. 438-441.

[13] WANG Hu, LI En-ying, LI Guang-yao, The least square support vector regression coupled with parallel sampling scheme metamodeling technique and application in sheet forming optimization, *Materials and Design*, 2009, pp.1468–1479.

[14] LI Yan-kun, SHAO Xue-guang, CAI Wen-sheng, A consensus least squares support vector regression (LS-SVR) for analysis of near-infrared spectra of plant samples, *Talanta*, vol. 72, 2007, pp.217–222.

[15] FENG Lei-hua, GUI Wei-hua, YANG Feng, Soft sensor modeling for mill output of duplex inlet&outlet ball pulverizer system based on an improved grey relational analysis, *Chinese Journal of Scientific Instrument*, vol. 31, n.9, 2010, pp.2062-2067.