Cement Particle Size Modeling for Cement Combined Grinding System Based on LS-SVM

Yue Gong¹, Zhugang Yuan², Zhao Liu³ and Xianshen Du⁴

¹School of electrical engineering, University of Jinan 250022, China. m18366104460@163.com
²School of electrical engineering, University of Jinan 250022, China. cse_yzg@ujn.edu.cn
³School of electrical engineering, University of Jinan 250022, China. cse_liuz@ujn.edu.cn
⁴School of electrical engineering, University of Jinan 250022, China. mr_shen16696@163.com

Abstract. Aiming at the problem that the mechanism model of cement grinding process is difficult to be established due to its comprehensive complexity, a modeling method of cement particle size based on LS-SVM algorithm is proposed by analyzing its dynamic characteristic and manual operation mode. The model can reflect the relationship between mill load and particle size, reveal the dynamic change process of cement particle size, and lay a foundation for the optimal control of cement quality. The simulation results show that the model is reasonable and effective.

1. Introduction

As the last link in the process of cement preparation¹, the effect of cement grinding directly affects the final quantity and quality of cement production line. The operation in the grinding process largely depends on the manual experience. Due to the difference in the operator's experience level, sometimes it is unable to adjust the set value of the parameters timely and accurately, which makes the quantity and quality of cement fluctuate greatly. Under the condition of the existing grinding technology level, the key problem to be solved urgently is how to make full use of the state information in the process of cement grinding to obtain the best state parameters, so that the production process is in a good running state to achieve the goal of high quantity and quality. Therefore, in order to study the index optimization deeply to obtain the optimal process state parameters, establishing an accurate and reliable model is the foundation.

The industrial production process of the combined grinding system is a typical engineering system with serious nonlinear, strong coupling, and large time delay², therefore, the mechanism model is difficult to establish. For the modeling of complex industrial processes, the intelligent experimental modeling method has achieved remarkable results in industrial applications³–⁶, which provides a new idea and method for the model of cement grinding process. Literature [7] and [8] apply the least square method to grinding system identification, literature [9] proposes an extreme learning machine (ELM) online modeling method for combined cement grinding system. Literature [10] applies an
identification algorithm based on the least squares support vector machine (LS-SVM) to the modeling of the closed grinding process. Literature [11] proposes T-S fuzzy modeling by various working condition based on working condition template. The LS-SVM algorithm is used to model the pre grinding process in the literature [12]. However, the above literatures [7-11] all aim at controlling particle size and then establish models based on operating parameters and mill load or operating parameters and cement particle size. These models only consider keeping the mill load stable in the normal range, which can make the cement particle size reach the optimum, but they ignore the change of particle size caused by the change of mill load. And there is little research on the model of the relationship between the mill load and the cement particle size.

Based on this, the paper first analyzes the characteristics of the cement combined grinding process, and selects the state parameters which can not only reflect the state of the mill load but also closely relate to the cement particle size as an input. Then model is built using the cement particle size (<45 sieve residue) as the output and combining the LS-SVM algorithm. Finally, the simulation is carried out by MATLAB, and the result shows that the fitted model is reasonable and effective.

2. Analysis of combined grinding process

The combined grinding process is shown in Figure 1.

![Figure 1. Combined grinding process](image)

After mixing the cement clinker, limestone and citric acid residue through a certain proportion, then transport them through the belt conveyor to weighing bin, which has the effect of weighing and buffer, and there is a valve below the silo to control the number of large particles which are flow into the roller machine. The material is rolled and lapped in the roller press machine and raised by the hoist to the V classifier. The large particles selected by V classifier are crushed two times by the roller machine, and the finer particles are driven into the ball mill. After the grinding of the ball mill, the materials are lifted into the separator. The qualified material are transferred into the cement silo by a lifting machine, at the same time, the unqualified material are put into the ball mill again for regrinding.

In this process, the mill is used as the core equipment in the combined grinding system. The mill load restricts the production efficiency of the process and affects the quality and output of the cement. Through experience and a large amount of data analysis, the state parameters that can well represent the mill load include the mill current, the out-mill elevator current and feedback of cement. The combination of the three to determine the state of the mill load is an effective method to increase the efficiency of grinding. Next, three state parameters are described in more detail.

1) Ball mill is one of the most important equipment in the combined grinding system. The operating state of the equipment directly affects the efficiency and stability of the whole system. The low current of the mill indicates that the material in the mill is too large, so that the material in the mill can't be fully lapping, the qualified law of the fineness of the grinding material is reduced, the feed volume is increased, the grinding efficiency is reduced, and the extreme grinding condition of "full grinding" is serious. On the other hand, the mill current is too high, indicating that the material in the
mill is too small, which can not give full play to the effect of the mill and reduce the production efficiency.

2) Out-mill elevator current can accurately reflect the state of the load in the mill. The rise of the current indicates to some extent that the load inside the ball mill is increasing. On the contrary, it shows that the load in the mill is decreasing.

3) Feedback of cement refers to the unqualified material sent to the ball mill after sorting through the separator. It not only affects the grinding effect of the ball mill, but also restricts the pre grinding process, so it has an important influence on the quality and production of cement.

In order to verify the correctness of the mechanism analysis, the sample data of the 2000 combined grid was selected to plot the corresponding relationship between the mill current, the out-mill elevator current, feedback of cement and the particle size. Table 1 shows the original sample statistics for each factor, and Figure.2, Figure3, and Figure4 show a partial enlarged view of the correspondence relationship for the 2000 data. Among them, it is worth noting that, according to the actual production of a cement plant, the particle size data is expressed as a percentage of the particle size of less than 45μm. In order to clearly analyse their relationship, the cement particle size in Figure 2 is shifted upward by 110 units, the cement particle size in Figure 3 is shifted upward by 60 units, the cement particle size in Figure 4 is shifted downward by 40 units.

Table 1. Initial data statistics for variables

| Variable               | Max   | Min   | Average |
|------------------------|-------|-------|---------|
| Mill current           | 208.145 | 197.392 | 203.594 |
| Out-mill elevator current | 155.618 | 144.381 | 150.394 |
| Feedback of cement     | 51.192  | 47.187 | 48.991  |
| <45um sieve residue    | 89.726  | 80.035 | 82.445  |

Figure 2. Mill current and <45μm

Figure 3. Out-mill elevator current and <45μm
From Figure 2 to Figure 4, mill current and out-mill elevator current have a significant positive correlation with particle size, while feedback of cement has little correlation. In order to further determine the influence degree of each influencing factor on the particle size, 300 sets of data were selected to be filtered by a moving average filtering method, and the correlation coefficient between the three factors and the particle size was calculated using the formula shown in Formula 1, represent 300 groups of actual values of influencing factors and particle size, respectively, and $r$ is a correlation coefficient. The calculation results are shown in Table 2.

$$r = \frac{\sum_{i=1}^{n}(x_i - \bar{x})(y_i - \bar{y})}{\sqrt{\sum_{i=1}^{n}(x_i - \bar{x})^2 \cdot \sum_{i=1}^{n}(y_i - \bar{y})^2}}$$

Table 2. Correlation coefficient between factors and <45um sieve residue

| Factor                | Correlation coefficient |
|-----------------------|-------------------------|
| Mill current          | 0.33776                 |
| Out-mill elevator current | 0.427527              |
| Feedback of cement    | 0.130097                |

According to the analysis results, the correlation between feedback of cement and the particle size was the smallest, only 0.13, the correlation between the out-mill elevator current and the particle size is the largest, which is 0.43. Therefore, the ball mill current and out-mill elevator current with large correlation with particle size are selected as the input of the model, select <45um particle size as the output of the model and build the model.

3. LS-SVM algorithm

Suppose a given set of samples is $D = \{(x_i, y_i) | i = 1, 2, ..., l\}, x_i \in \mathbb{R}^n$ is a sample input for dimensions, and the $y_i \in \mathbb{R}$ is the sample output. The principles of the LS-SVM algorithm are as follows:

$$\min \frac{1}{2} \|W\|^2 + \frac{C}{2} \sum_{i=1}^{l} e_i^2$$

s.t. $y_i = W^T \varphi(x_i) + b + e_i$

Where $e_i \in \mathbb{R}$ is error variable, b is the bias term, and C is the regularization parameter. Solving this optimization problem by Lagrange method, we get the Lagrange function:

$$L(W, b, e, \alpha) = \frac{1}{2} \|W\|^2 + \frac{C}{2} \sum_{i=1}^{l} e_i^2 - \sum_{i=1}^{l} \alpha_i (W^T \varphi(x_i) + b + e_i - y_i)$$
\[ \alpha = [\alpha_1, \alpha_2, \ldots, \alpha_r]^T \]

where \(\alpha_i\) is the Lagrange multiplier.

Under optimal conditions in
\[ \frac{\partial L}{\partial W} = 0, \frac{\partial L}{\partial b} = 0, \frac{\partial L}{\partial \epsilon_i} = 0, \frac{\partial L}{\partial \alpha_i} = 0 \]

Can get the equation conditions
\[ W = \sum_{i=1}^{\infty} \alpha_i \varphi(x_i) \]
\[ \sum_{i=1}^{\infty} \alpha_i = 0 \]
\[ \alpha_i = C \epsilon_i \]
\[ W^T \varphi(x_i) + b + \epsilon_i - y_i = 0 \]

According to the condition of the existence of the optimal solution, we get the matrix equation:
\[ \begin{bmatrix} 0 & 1 & \cdots & 1 \\ 1 & K(x_i, x_i) + C^{-1} & \cdots & K(x_i, x_j) \\ \vdots & \vdots & \ddots & \vdots \\ 1 & K(x_i, x_j) & \cdots & K(x_j, x_j) + C^{-1} \end{bmatrix} \begin{bmatrix} \alpha_1 \\ \alpha_2 \\ \vdots \\ \alpha_n \end{bmatrix} = \begin{bmatrix} 0 \\ b \\ \vdots \\ y_j \end{bmatrix} \]  

(7)

Where \(K(x_i, x_j) = \varphi(x_i) \varphi(x_j)\) is a symmetric function that satisfies the Mercer condition called a kernel function.

Thus, the regression function can be determined:
\[ f(x) = \sum_{i=1}^{\infty} \alpha_i K(x, x_i) + b \]  

(8)

4. LS-SVM model simulation

4.1 Kernel function selection

The choice of different kernel functions will result in different LS-SVM models. There are three types of commonly used kernel functions:

1) Polynomial function:
\[ K(x_i, x_j) = (x \cdot x_i + 1)^d \]

where \(d\) is the order.

Polynomial kernel functions can be used to map low-dimensional input spaces to high-latitude feature spaces. However, polynomial kernel functions have many parameters. When the order of polynomials is high, the element values of nuclear matrices tend to be infinite or infinity. The complexity will be too large to calculate.

2) Radial basis function (RBF):
\[ K(x_i, x_j) = \exp \left[ -\frac{(x - x_i)^2}{2\sigma^2} \right] \]

where \(\sigma\) is the nuclear width.

The Gaussian radial basis function is a locally strong kernel function that maps a sample to a higher-dimensional space. The kernel function is one of the most widely used. It has good performance regardless of large samples or small samples, and it has less parameters than polynomial kernel functions. Therefore, in most cases, the Gaussian kernel function is used preferentially when it is not known what kernel function to use.
3) sigmoid function:

\[ K(x, x_i) = \tanh(\beta x_i + b) \]  

(11)

where \( \beta \) is a scalar, \( b \) is the displacement parameter.

Sigmoid kernel functions come from neural networks and can only be used if their parameters meet certain conditions.

Taking into account the advantages of RBF kernel function with good performance and few parameters, in this paper, the kernel function is chosen as the radial basis kernel function, and thus formula (8) is transformed into formula (12), which is the LS-SVM model.

\[ f(x) = \sum_{i=1}^{l} \alpha_i \exp\left[-\frac{(x - x_i)^2}{2\sigma^2}\right] + b \]  

(12)

4.2 Model parameter optimization

In the previous section, we chose the RBF function as the kernel function of the model. The main parameters of the LS-SVM model based on the RBF kernel function include the regularization parameter \( C \) and the width \( \sigma \) of the kernel function. Both determine the learning and generalization capabilities of the model. Selecting different \( C \) and \( \sigma \) results in different model error accuracy. The simulation training continuously adjusts the values of \( C \) and \( \sigma \) for testing, and selects the cross validation method to solve the optimal parameter values. By comparison, the final test fitting curve error is the smallest when \( C=30 \) and \( \sigma=0.3 \).

4.3 Training and testing

This section uses the actual sample data obtained after preprocessing, according to the formula (8) for sample training, compare the actual value and the model output value. The first 120 sets of data were selected for training, and the training results, namely the training and training errors charts of the actual output values and model output values are shown in Figure 5 and Figure 6. It can be seen that the fitting accuracy between the model output value and the actual value is very high, and the absolute value of error is within 0.4. Root mean square error (RMSE) of training is 0.1285. The value of the Lagrange multiplier obtained by the model training is the coefficient of formula (8), as follows: \( \alpha_1 = -1.4513, \alpha_2 = -0.187 \ldots, \alpha_{119} = 1.5147, \alpha_{20} = 0.1301, b = -0.1046 \).

![Figure 5. Training curve](image-url)
Another 60 sets of sample data were used to test the training model. The curves and error curves of the model test output and actual values are shown in Figure 7 and Figure 8. From Figure 7 and Figure 8, it can be seen that the actual value and the model predictive value have a high degree of fit, the absolute value of error is within 0.6, root mean square error (RMSE) of the test is 0.1306. Therefore, the established LS-SVM model can reflect the changing state of cement particle size to some extent, and has certain reliability.

5. Conclusions
This paper studies the model of cement particle size based on LS-SVM algorithm, which solves the problem of difficult to establish mechanism model for cement combined grinding process. The network is trained by training samples and is verified by test data. The simulation results show that the cement particle size model based on LS-SVM is accurate and can be a foundation for the realization of index optimization.

Acknowledgment
This work is supported by the Project of Shandong Province Higher Educational Science and Technology Program (J17KA046), the Science Foundation for Post Doctorate Research from the University, and Independent Innovation and Achievements Conversion of Shandong Province under Grant (2015ZDXX0101F01) to Z.G. Yuan.
References

[1] Z Wang, R Zeng. Cement grinding technology, 281 (2008)
[2] X Wang, H Xie, S Jing, Z Yuan. CCC C, 3, (2008)
[3] K. Chan, T. Dillon, C. Kwong. IEEE Tran. J, 7, 11, (2011).
[4] W. Wang, W. Chen, Y. Ye, Z. Xu, B Jia. Iron Steel Res., Int. J, 41, 3, (2016).
[5] Safwan Altarazi; Maysa and Ammouri Ala Hijazi. Mat. Sci. J, 153, 9, (2018)
[6] N Wang. D, Shanghai Jiao Tong University, (2009).
[7] C Zhou. D, University of Jinan, (2012).
[8] Z He. D, University of Jinan, (2016).
[9] H. Liu, Z. Yuan, Q Zhang, Z. Su. CIA C, 5, (2015).
[10] Z. Yuan, X. Zhang, Q. Zhang, Z. Su. IEEE, C, 5, (2015)
[11] X Zhang. D, University of Jinan, (2015).
[12] Benzer H, Ergün L, Öner M, Mine. Engi. J, 14, 10, (2001)
[13] Z Zhou, Y Li. Mathematical statistics, 315, (1987).