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Modeling of Vertical Mill Raw Meal Grinding Process and Optimal Setting of Operating Parameters Based on Wavelet Neural Network

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Abstract—**The stability of vertical mill raw meal grinding process affect the yield and quality of cement clinker. Due to the nonlinear of grinding process, random variation of working conditions, and large lag of the offline index test, it is difficult to establish an accurate mathematics model, thus cannot collect the optimizing operating parameters of vertical mill in time. In this paper, based on the principal component analysis (PCA) for the related variables, a production index prediction model of vertical mill raw meal grinding process was established using wavelet neural network (WNN) and compared with the BP network model, and the validity of the novel model was verified. Then, based on the prediction model and related constraint conditions, the parametric optimization model was established, wherein, the optimal operating setting value under typical working conditions was obtained by using particle swarm optimization algorithm, and an optimal case base was established; through the case inquiry and revision, the optimal set points under the current conditions was obtained. The simulation results showed that, the novel wavelet neural network model and the parameter optimizing setting method could adapt to the changing of process indicators, and could provide optimal parameter value to make the production performance meet expectations, meanwhile achieved the optimizing goal.**

I. INTRODUCTION

RAW material grinding process is an important section of modern cement production, and the raw material quality and the stability of production process directly affect the yield and quality of the cement clinker. Vertical mill is a new type of grinding equipment, which combines multiple functions that include broken, grinding, drying, separating, and transporting, and is energy efficient grinding equipment [1]. Stability of the grinding pressure and suitable raw meal fineness are the key factors to determine the normal operation of the mill [2]. However, in the actual production, parameter is usually operated and adjusted manual according to the experience of the personnel, so the actual production is full of subjectivity and arbitrariness, and thus cause the production fluctuation and excess power consumption. At the same time, the vertical mill raw meal grinding process is a complex physical and chemical process, which has the characteristics of nonlinear, strong coupling, multi input; thus it's difficult to establish an accurate model according to the traditional method, and difficult to find rules from a large number of real time production data. Therefore, how to establish the vertical mill grinding raw material index model and to determine the optimal operating parameters to guide the production has become an urgent problem to be solved for all enterprises.

Artificial neural network has great advantages in solving non-linear problems, and the modeling method has been widely used. The literature [3] and [4] respectively established RBF neural network and Elman neural network model for the process of sugar clarification. A production index prediction model was established by GDFNN for sugar clarification in literature [5]. Wavelet neural network (WNN) is a feed-forward neural network based on wavelet analysis, in which the hidden activation function is replaced by wavelet function, and the scaling factor and the translation factor is introduced; the function has strong approximation ability and high prediction accuracy. The wavelet neural network was used to fault diagnosis for underwater vehicle in literature [6].

In this paper, the study begins from the mill process, using a large number of production data, by the method of Principal Component Analysis (PCA) to screen out the main factors which affect the operation stability of the grinding, then a wavelet neural network was used to establish the production index prediction model of the vertical mill raw material grinding; finally, the optimization model was made under this prediction model and relevant constraint conditions, and the optimal operation parameters under typical settings was obtained by a particle swarm optimization algorithm. The optimal case base was established, through case finding and correcting, and then got the optimal operation parameters value of the current condition.

II. DESCRIPTION OF VERTICAL MILL RAW MEAL GRINDING PROCESS

Vertical mill raw meal grinding process has four main steps: feeding, grinding, powder-selection, and dust collection.

The process is shown in Fig. 1. The material is transited through the conveyor belt, then enters and accumulates into the middle of the mill plate. The rotating disc drives the grinding roller rotates and the material moves to the edge of the grinding disc under the action of centrifugal force, and filled into the bottom of the grinding roller and was smashed. The material is crushed in the mill, and pushed to the disk edge, across the material barrier ring into the wind ring, taken up by high-speed stream; hot air drying is introduced at

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the same time, so large particles drop down back to the grinding disc, and small particles flow into a separator by the air flow for further separation. Coarse powder goes back to the grinding disc for regrind, and the qualified (fine powder) is collected outside of the machine as products by air flow. Under the stable production situation, the mill pressure difference is controlled between 4500-6500 kPa as usual, and the meal size is generally maintained at 80 μm for screen margin ≤25%, general controlled at 20%.

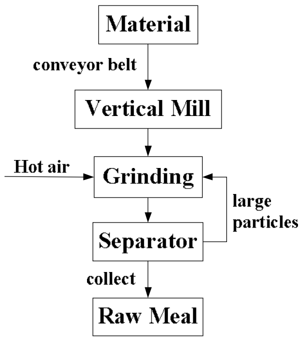

Fig. 1. Process of vertical mill raw meal grinding

According to the literature [1], the two main indicators which determine success or fail of the vertical mill production are the grinding pressure difference (i.e., vertical mill pressure between the inlet and the outlet) and grain size of the raw material, and the influence variables of these two indicator are feeding quantity, feeding air temperature, rotary speed of the separator, circulating air baffle opening, the grinding pressure etc..

III. Modeling of Production Indeices for Vertical Mill Raw Material Grinding Process

A. Wavelet Neural Network

Wavelet neural network (WNN) [7] is a feed-forward neural network which contains wavelet transform. As for single hidden layer neural network, the hidden layer activation function is replaced by the wavelet basis function which was positioned, and the alternative expansion factor and the threshold factor are replaced by the expansion factor and the translation factor based on wavelet, so the wavelet transform and the neural networks are connected through the mapping relationship between the layers. Multi input and multi output wavelet neural network model is shown in Fig. 2.

In which, $x_i(i=1,2,\cdots,M)$ is the input parameters of wavelet neural network, $y_i(i=1,2,\cdots,K)$ is the predicting output of the wavelet neural network, ω_{jk} and ω_{ij} is the connection weights of the wavelet neural network.

In this paper, we choose morlet wavelet as activation function in wavelet neural network hidden layer, and the mathematical expression is

$$\psi\left((x-b)/a\right)=\cos\left(1.75(x-b)/a\right)\exp\left(-0.5\left(x-b/a\right)^2\right) \quad (1)$$

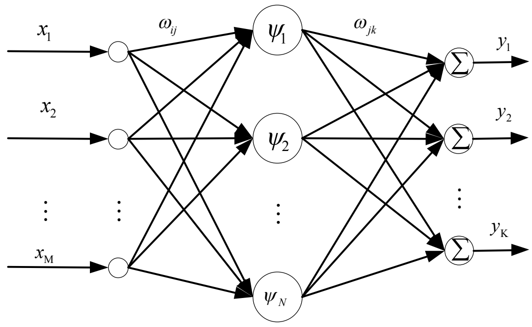

Fig. 2. The model structure of WNN.

where a, b are respectively the scale factor and shift factor of wavelet basis function.

While the input is $x_i\left(i=1,2,\cdots,M\right)$, the input of hidden layer is

$$H(j)=\sum_{i=1}^{M}\omega_{ij}x_i \quad (2)$$

where $j=1,2,\cdots N$, ω_{ij} is the connection weights from neuron i in the input layer to the neuron j in the hidden layer. The hidden layer output formula is

$$\psi(j)=\psi_j\left(\frac{H(j)-b_j}{a_j}\right) \quad (3)$$

where a_i, b_i are respectively the scale factor and shift factor of wavelet basis function $\psi(j)$, N is the number of neurons in the hidden layer of network.

The output expression of network output layer is as followed

$$y\left(k\right)=\sum_{j=1}^{N}\omega_{jk}\psi\left(j\right) \quad (4)$$

where $k=1,2,\cdots,K$, ω_{jk} is the weights of the output neurons from the j hidden layer neurons to the k output layer neurons, $\psi\left(j\right)$ is the j output of the hidden layer neurons, K is the number of output neurons.

It shows the defined target error function as follow

$$E=\frac{1}{2}\sum_{p=1}^{P}\sum_{k=1}^{K}\left(d_k-y_k\right)^2 \quad (5)$$

where d_k is the expected network output, y_k is the actual network output, $P\left(p=1,2,3,\cdots,P\right)$ is the output signal number of samples, $K(k=1,2,3,\cdots,K)$ is the output neurons number of the network.

The network weights and the parameters of wavelet basis function were adjusted according to the parameter weights error function. We substitute improved weight adjustment algorithm for original static optimization algorithm based on steepest descent. We superpose a part of last weight adjustment quantity at the weight adjustment quantity calculated according to error of this time, then using it as actual weight adjustment quantity of this time, that is

$$\Delta W(t) = -\eta \nabla E(t) + \alpha \Delta W(t-1) \quad (6)$$

$$\nabla E(t) = \partial E / \partial W(t-1) \quad (7)$$

where α is the momentum factor and η is the learning rate; here $\alpha \in (0,0.9)$ and $\eta \in (0.001,10)$. The momentum factor α can reduce oscillation trend during learning process and improve convergence. In the same way, we can get $\Delta a(t)$ and $\Delta b(t)$ as follow

$$\Delta a(t) = -\eta \nabla E(t) + \alpha \Delta a(t-1) \quad (8)$$

$$\nabla E(t) = \partial E / \partial a(t-1) \quad (9)$$

$$\Delta b(t) = -\eta \nabla E(t) + \alpha \Delta b(t-1) \quad (10)$$

$$\nabla E(t) = \partial E / \partial b(t-1) \quad (11)$$

where $\Delta a(t)$, $\Delta b(t)$ are respectively the scale factor adjustment quantity and the shift factor adjustment quantity.

B. Modeling Data Preprocessing

The original data collected from the actual grinding process cannot be used directly, so it must be preprocessed. on the one hand, these original data contain gross errors caused by human factors, and the random errors due to measurement noise contaminated signals; on the other hand, in order to analyze the grinding process, the collected data may exist redundancy, and also there may be missing data, which will result in the inconsistent between the model and actual process, thus make the index prediction inaccessible.

Therefore, in the process of data preparation, additional work must be done. Firstly, gross error must be eliminate, according to the variable in the practical production operation range, by using the method of limiting culling to exclude the data which is not within the range, when the deviation between the data sample and the average value is greater than 3 times of the standard deviation the data must be eliminated; Secondly, the random error must be decreased, the data were smoothed using Seven Point Linear Smoothing Method commonly used in project so as to eliminate the random noise. This method is a data remedial measures to make the original data filling and smooth; Finally, using the method of Principal Component Analysis (PCA) [8], [9] to compress the data and reduce the dimension.

The 281 groups online and offline production index data of a vertical mill was obtained by using the method mentioned above from a large cement factory at Shandong province. The results of principal component analysis are listed in Table I.

TABLE I
THE OUTCOME OF PRINCIPAL COMPONENT ANALYSIS

Variables	Contribution rate	Cumulative contribution rate
Feeding quantity	42.3937%	42.3937%
Grinding temperature	37.5704%	79.9641%
Rotary speed of the separator	12.7185%	92.6826%
Circulating air baffle aperture	7.3199%	100.0000%

As shown in Table I, we simply select the 3 principal component variables which can reflect the information of the original variables 92.6826%. We therefore chose the feeding quantity, grinding temperature, and rotary speed of the separator as input variables, meanwhile, mill pressure difference and raw meal fineness as output variables.

C. Simulation Results and Analysis

The processed data were divided into two parts: 200 groups of randomly selected data as network training data, and the remaining 81 groups of data as network test data. The WNN adopted 3-30-2 structure. The generalization performance is shown in Fig. 3 and Fig. 4.

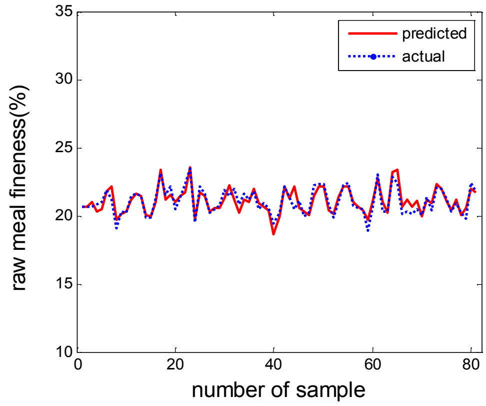

Fig. 3. The generalization curve based on raw meal fineness in WNN

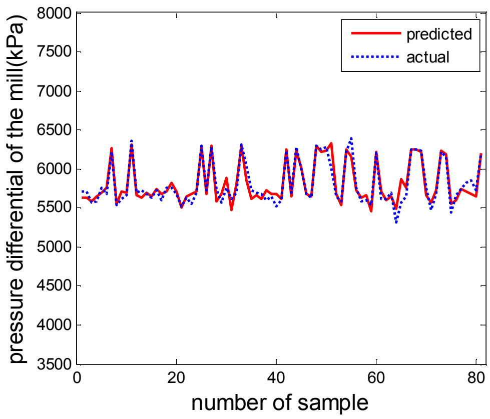

Fig. 4. The generalization curve based on grinding pressure difference in WNN

In order to verify the validity of the model, the same training data and test data were used to establish the BP network prediction model. The BP network also adopted 3-30-2 structure, training 2000 times, and the learning rate was 0.01. The generalization results of BP network is shown in Fig. 5 and Fig. 6.

Through the comparison between WNN and BP, we can see clearly that the WNN forecasting model is effective, and has smaller error and shorter training time than those based on BP. Performance comparison of the two kinds of prediction model are shown in Table Ⅱ.

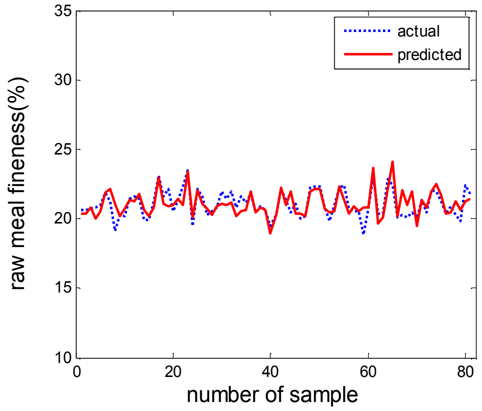

Fig. 5. The generalization curve based on raw meal fineness in BP

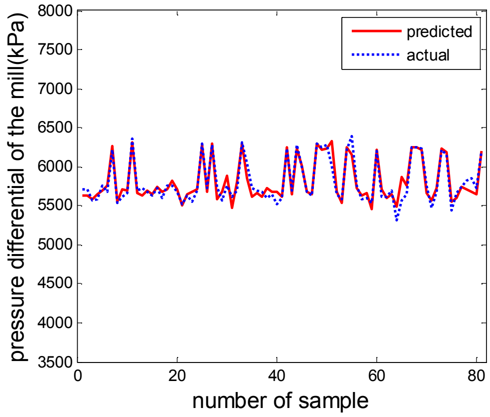

Fig. 6. The generalization curve based on grinding pressure difference in BP

TABLE II
THE PERFORMANCE COMPARISON OF WNN AND BP MODEL

Items	WNN	BP
RMSE of raw meal fineness	0.0106	0.0135
RMSE of grinding pressure difference	1.7845	2.5753
Training time	1.44s	4.84s
Number of iterations	38	374

IV. INTELLIGENT OPTIMAL SETTING METHOD OF OPERATING PARAMETERS

A. *Description of Intelligent Optimal Setting Method*

In this paper, an intelligent optimal setting method on vertical mill operating parameters of raw meal grinding process was done, based on the production index prediction model and the particle swarm optimization(PSO) algorithm. The diagram of optimizing setting method of grinding process is shown in Fig. 7.

Firstly, we established the optimization model based on the production index prediction model and variable constraint range; then, solved the optimization model according to the typical working conditions and expected production index; finally, gave the optimal operation parameters under typical conditions, and both into the case base. In the current working condition, firstly, go through the query case library and give the preset point of the operating parameters; then, put the preset points into the production index prediction model to get a forecast index. If the errors between the forecast indexes and the expected index meet the allowable range, the preset point is put into the controller as the final point to guide production, and is stored in the optimization model base; Otherwise, the preset points are modified by the expert rules and the data is used and stored until the error range meets the need.

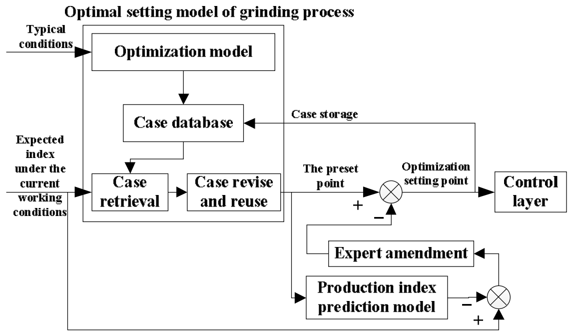

Fig. 7. Diagram of intelligent optimal setting method

B. *The application of intelligent optimization setting method*

1) The establishment of optimization model and the solving of optimal operation parameters: According to the established index prediction model above, we determine the granularity of raw material y_1 and grinding pressure difference value y_2 as expected production index.

$$y_1 = 20.7, y_2 \leq 5700 \tag{12}$$

where, the recommended value range of raw meal fineness y_1 is 18% to 22%,, and the grinding pressure difference value y_2 is controlled under 5700 KPA. Accordingly, the optimization model is established for each typical working conditions, as follows

$$\begin{cases} \min\ f_1 = |y_1 - 20.7| \\ \min\ f_2 = y_2 - 5700 \end{cases} \tag{13}$$

$$s.t. \begin{cases} 135 \leq x_2 \leq 185, 37 \leq x_3 \leq 41 \\ (y_1, y_2) = F(x_1, x_2, x_3) \end{cases} \tag{14}$$

Where, x_1 is the feeding quantity, x_2 is the grinding temperature, and x_3 is the rotary speed of the separator.

The particle swarm optimization (PSO) [10] was used for each condition; the whole procedure is as follows:

a. Initialization, we set the population size is 20, the maximum number of iterations is 100, learning factor $c_1 = c_2 = 2$, and restrict the search speed of particle in the in-flight space.

b. Among the randomly generated 200 particles in the range of particle position and velocity, the fitness value of each particle was calculated. According to the fitness function, we calculated the optimal fitness value of individual particle, and the corresponding fitness value of the global optimum location.

c. For each particle in the population, we compared its fitness value with the current optimum value and global optimum value, and then we continued to guide the particle flying towards the optimal direction.

d. Updated the position and velocity of the particle.

e. Check whether the maximum number of iterations was reached, if not, transfer to c. to continue the optimizing, otherwise, output and store the optimal value as the optimization value.

2) Determination of the preset operation parameters value: Each of the typical conditions in F and the obtained optimal operation parameters J_2 are combined into a typical case $C=\{F,J\}$, and the typical case was stored in the case database. When a new condition F' comes, we check the query case library; if the conditions are the same, we directly call the corresponding operation parameters as the optimal setting points; if the conditions are different, we find out the two most similar conditions of F_1, F_2 and the corresponding operation parameter J_1, J_2, and calculate the preset points of the operating parameters as follow

$$J'=\left(\sum_{k=1}^{2} sim(F',F_k)\times J_k\right)\Big/\sum_{k=1}^{2} sim(F',F_k) \quad (15)$$

where, J' is the preset point of operating parameter of condition F'. $sim(F',F_k)$ is the similarity between the current working condition F' and the query conditions F_k, as follows

$$sim(F',F_k)=\sum_{i=1}^{2}\omega_i sim(f_i',f_{i,k})\Big/\sum_{i=1}^{8}\omega_i \quad (16)$$

$$sim(f_i',f_{i,k})=1-\left(\left|f_i-f_{i,k}\right|\right)\Big/\max(f_i,f_{i,k}) \quad (17)$$

where, f_i' and $f_{i,k}$ are characteristics of working conditions of F' and F_k, ω_i is determined by the experience of the expert.

Put the preset point into the production index prediction model, if the forecast indexes meet the expectations, there is no need to correct; otherwise, the preset value must be modified due to the expert experiences until the result is satisfied, and then choose the correction value as the optimal operating parameters of current condition and assign the value to the controller.

C. *The Effect of Optimization*

Using the intelligent optimization method mentioned above, we optimized the operation parameters under each working conditions of the vertical mill raw material grinding. Fig. 8 and Fig. 9 respectively show the changes of the two production indexes about the raw meal fineness and grinding pressure difference after artificial adjustment and optimization setting while the working conditions vary.

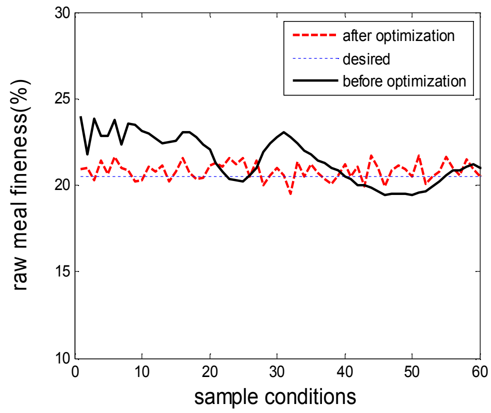

Fig. 8. Distribution curve of raw meal fineness values before and after optimization

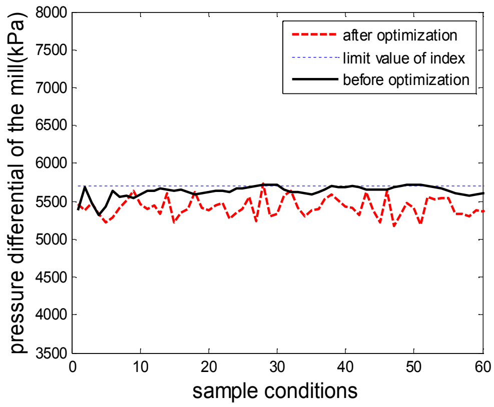

Fig. 9. Distribution curve of grinding pressure difference before and after optimization

From Fig. 8 and Fig. 9 we can see that, through the optimization of operating parameters, the raw material granularity and the mill pressure difference can still close to or meet the expecting production index under random working conditions, and achieve better production results than that get from artificial operating parameters.

V. CONCLUSION

This paper focused on the problems of strong nonlinearity of vertical mill raw meal grinding process, complex characteristics of strong coupling, and the lack of accurate mathematical model, arbitrariness of artificial parameter setting in the actual production process, so we built a production index prediction model of vertical mill raw material grinding using wavelet neural network, and compared the results with those collected in the BP neural network model. Then, based on the prediction model and the constraint conditions, the index optimization setting model of grinding process was established, and realized the function of providing the optimal setting values under continuous changing working conditions. The simulation results showed that, the established wavelet neural network model in this paper has higher generalization accuracy and smaller root mean square error than the BP model. The intelligent optimal setting method could avoid the subjectivity and arbitrariness artificial setting to some extent; so it has certain reference meanings in optimizing the industrial production process with the similar complex characteristics.

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