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A study on a new algorithm to optimize ball mill system based on modeling and GA

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ABSTRACT

Aiming at the disadvantage of conventional optimization method for ball mill pulverizing system, a novel approach based on RBF neural network and genetic algorithm was proposed in the present paper. Firstly, the experiments and measurement for fill level based on vibration signals of mill shell was introduced. Then, main factors which affected the power consumption of ball mill pulverizing system were analyzed, and the input variables of RBF neural network were determined. RBF neural network was used to map the complex non-linear relationship between the electric consumption and process parameters and the non-linear model of power consumption was built. Finally, the model was optimized by genetic algorithm and the optimal work conditions of ball mill pulverizing system were determined. The results demonstrate that the method is reliable and practical, and can reduce the electric consumption obviously and effectively.

1. Introduction

Ball mill pulverizing system is widely used in power generation unit. It is one of the major auxiliary equipment and electric power consumer in power plants. By statistic, the proportion of electric power consumed by pulverizing system is up to 15–25% of the whole electric consumption in power plant. Therefore, it is very important to enable pulverizing system work in efficient and optimal conditions. Conventionally, the economical index of pulverizing system is calculated and evaluated by the electric consumption of per ton qualified coal powder. Because the ball mill pulverizing system is a non-linear and strong coupling system, which results in the conventional linear mathematic models described the system have some disadvantages. The traditional optimization method for ball mill pulverizing system is based on performance experiments basically [7,10]. The approach has to conduct experiments under many different work conditions. Obviously, the disadvantage of this method is the test cost is high, the workload is heavy. So this method can not be employed usually. It is necessary to research a novel optimization method for ball mill system.

In practical operation of ball mill system, a very important monitoring parameter and control variable is the coal powder level in the tube, which is defined fill lever of ball mill. It is critical to the production capability and energy efficiency of the ball mill. But as the work condition of ball mill is complicated and limitation of measure method, fill level is difficult to measure directly up to now. In practice, the mills have to run at low load in order to avoid over-loading which causes mill blockage. As a result, the efficiency is low and electricity consumption of ball mill is high.

In this paper, we preliminarily focus on the optimization operation for ball mill pulverizing system in power plant. The non-linear model of electric consumption is built based on RBF networks. Then, the model is optimized by genetic algorithm. So, we can obtain the optimal work conditions and parameters for ball mill pulverizing system. The organization of this paper is as follows: the experiments and measurement of fill level based on vibration signals of mill shell was introduced in Section 2. The electric consumption modeling based on improved RBF was given in Section 3. In Section 4, the optimization of electric consumption model based on genetic algorithm was proposed. Finally, in Section 5, the conclusions of the paper were summarized.

2. Measurement for fill lever based on vibration signals of mill shell

2.1. Measurement of fill lever

The work principle of ball mill pulverizing system is described as follows: ball mill is fed with raw coal. At the same time, the hot air and recycle air are blown into the ball mill to dry and deliver the coal powder. After pulverizing, the coal powder is transferred into the coarse classifier and fine classifier. The unqualified powder is fed back into the ball mill for further pulverizing while the qualified powder is stored in the pulverized coal bunker finally. The schematic representation of a ball mill pulverizing system is shown in Fig. 1.

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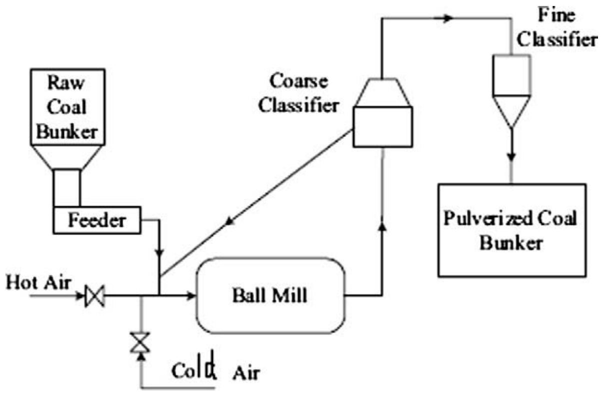

Fig. 1. Schematic representation of a ball mill pulverizing system.

Along with the rotating of mill, steel balls and coal particles in the ball mill are brought to a certain height by the centrifugal force of the ball mill and friction, then fall along the parabolic trajectory under the effect of gravity. In the course of falling, the part of impact energy of steel balls is absorbed by coal particles to realize the grinding and comminuting of coal. Another part of impact energy is delivered to the mill shell and causes the vibration of the shell, and then this part impact energy is further transmitted to the front and rear bearing housings of the mill to cause the vibration of bearing housings. When the coal load is higher in mill, the more impact energy of steel balls is absorbed by coal powder, and the lower impact energy reaches the mill shell and bearing housings to cause relatively small vibration, and vice versa. So the vibration strength of the mill shell and the bearing housings to some extent can reflect the level of fill level. Because the accelerometer can be mounted easily on the front and rear bearing housing, the traditional vibration methods measured the fill level based on vibration signals of the bearing housings. At present among these methods, some characteristic values of the fill level, such as amplitude [1,5], energy [9], power [8] and vibrated root mean square (RMS) of vibration signals [4,11], are extracted from vibration signal of the bearing housings to monitor the fill level.

However, there are many reasons and vibration sources to cause the vibration of bearing housings. In addition to the impact of steel balls, there are still some other vibration sources, such as transmission system vibration, foundation vibration, vibration caused by the moment of asymmetry and installation error. These vibration sources will affect characteristics of the time and frequency domain of vibration signals for the bearing housings. Furthermore, vibration transmission path and sound radiation of structural vibration also have a certain impact for vibration signals of bearing housings. So vibration signals of the bearing housings can not very accurately reflect the collision condition of steel balls in the mill and the fill level information. According to the analysis of different transducer positions, the vibration signal of mill shell was more sensitive to mill fill lever than vibration signal of bearing housing [2,3]. Due to the difficulties of accelerometer installation and vibration data transmission, in addition high cost of vibration data acquisition system, at present there is little work for measuring the fill level by vibration signals of the mill shell. In the research, experiments were operated at an industrial ball mill in coal-fired power plant and vibration signals were collected from the impact region of steel balls on the mill shell. The fill lever is represented by the vibration signal of ball mill shell. The vibrated root mean square (RMS) of vibration signals are extracted as the monitoring parameter.

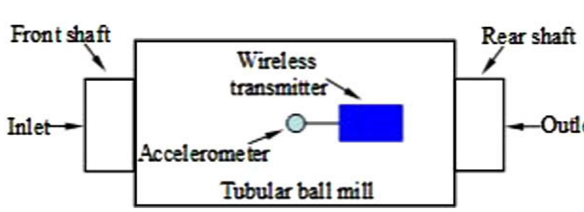

Fig. 2. Schematic diagram of fixed position of sensor and wireless transmitter.

2.2. Experiment interpretation

For acquiring the vibration signal of mill shell, the experiments were performed on a ball mill of a 135 MW generation unit in a power plant. The experimental ball mill had a diameter of 3.5 m and a length of 6.0 m, and driven by a motor (YTM630–6). The revolving rate of ball mill was 17.57 rpm. The ball mill was operated with a combination of three different diameter balls: 40, 50 and 60 mm corresponding to 40%, 40%, 20% mass ratio, respectively. In the experiments process, the total ball charge was approximate 35 ton.

This vibration data acquisition system is comprised of two major components: a high resolution accelerometers and a wireless transmitter unit mounted directly to the mill shell. See Fig. 2 for more details. Since the vibration amplitude of the mill shell is far greater than that of bearing housings of the mill, the accelerometer (PCB Piezotronics Inc., USA) that has a large measurement range is chosen. The amplitude range and sensitivity of the accelerometer are in the range of ±100 g and 50 mv/g, respectively. This sensor was located in the middle of the mill shell (see Fig. 2). Firstly, a small metal plate was welded on the mill shell. Then the sensor was screwed on the metal plate. It should be noted that the sensor has to be screwed on after welding the metal plate. Otherwise the sensor may get damaged by the high welding current. The sensor that was installed on the mill shell will rotate together with the rotation of the ball mill, which is not the same as the traditional vibration method that the sensor can be directly connected with data acquisition computer by the cable. In order to realize the wireless transmission of vibration data, our laboratory has developed a set of wireless transmitter device that was connected with sensor by the sensor cable on the mill shell (see Fig. 2), and this device can transmit the vibration signals that are collected by the vibration sensor to the data acquisition computer by the way of wireless. And some sampling commands, such as command of sampling frequency, command of sampling point and sampling angular position, were sent to the wireless transmitter device by

Fig. 3. Installation image for the wireless transmitter device mounted on the mill shell.

the data acquisition software of the data acquisition computer to collect vibration data. The method of fixing the wireless transmitter has a certain similarity with that of sensor. Firstly, a metal supporting plate was welded on the mill shell. Then the wireless transmitter device was mounted on this supporting plate by six screws, and Fig. 3 is a real photo of mounting in the spot.

Because the range of impact frequency response on the mill shell that is caused by the impact of steel balls is relative wider, the sampling frequency needs to set up a large and appropriate value to fully capture the original vibration information. In this research the sampling frequency was set at 40 kHz after several experiments that were operated at different values of sampling frequency. Due to the limitation of hardware of data acquisition system, the sampling point was set at 4096 points.

3. Modeling of electric consumption

3.1. BRF neural networks

Artificial neural networks (ANN) is widely accepted as a technology offering an alternative way to simulate complex and ill-defined problems. They have been used in diverse applications in control, robotics, pattern recognition, forecasting, power systems, manufacturing, optimization, signal processing, etc., and they are particularly useful in system modeling. A neural network is a computational structure, consisting of a number of highly interconnected processing units called neurons. The neurons sum weighted inputs and then applies a linear or non-linear function to the resulting sum to determine the output and the neurons are arranged in layers and are combined through excessive connectivity.

Radial basis function neural network (RBFNN) is a typical ANN that has been widely used in many research fields. RBFNN are composed of simple elements operating in parallel. These elements are inspired by biological nervous systems. As in nature, the network function is determined largely by the connections between elements (neurons). Commonly RBFNN are adjusted, or trained, so that a particular input leads to a specific target output. Moody and Darken [6] defined a learning rule as a procedure for modifying the values of the connections (weights and biases) between neurons for a RBFNN. The design of a RBFNN in its most basic form consists of three separate layers: input layer, hidden layer and output layer. The hidden layer contains a number of RBF neurons, and each of them represents a single radial basis function. The output layer provides the response of the network to the activation patterns applied to the input layer. The architecture of the RBFN is shown in Fig. 4.

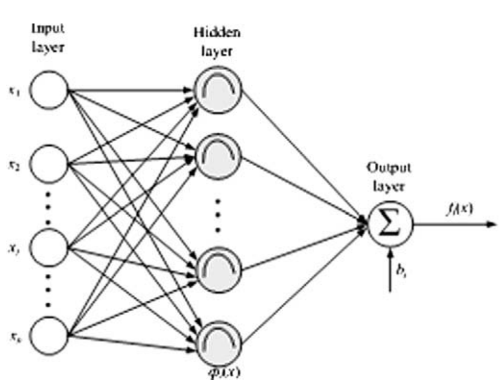

Fig. 4. Architecture of the radial basis function network.

The RBFN has been defined, and the equation of the conventional RBFN forms given:

$$\begin{cases} f(x) = \sum_{i=1}^{n} w_i \phi_i(x) + b \\ x = [x_1, x_2, \ldots, x_p]^T \\ w = [w_1, w_2, \ldots, w_n]^T \end{cases} \tag{1}$$

where ϕ is the non-linear activation function, x the column vector of design variables, p the total number of the design variables, j the index of the design variables, w the column vector of weights of activation function, b the basis of the output layer neuron, and n is the total number of the weights.

The Gaussian function is usually chosen as the activation function by a center (μ) and a width (σ^2). Therefore, the non-linear transformation function of the ith class of RBF is given as follows:

$$\phi_i(x) = e^{-\frac{\|x-\mu_i\|^2}{2\sigma_i^2}} \tag{2}$$

where e is the exponential function, μ_i the ith RBF center, σ_i the widths of the ith RBF input patterns, and x is the input vector.

Hence, the output function of the RBFN is also the linear combination of Gaussian functions. The output layer transfer function is linear, and given as follows:

$$f_j(x) = \sum_{i=1}^{n} w_{ji}\phi_i(x) + b_j = \sum_{i=1}^{n} w_{ji} e^{-\frac{\|x-\mu_i\|^2}{2\sigma_i^2}} + b_j \tag{3}$$

where $f_j(x)$ Output of the jth output layer neuron.

3.2. Structure of RBF neural networks

Based on the systematic characteristic of pulverizing system and analytical results above, the input variables of RBF neural networks were determined. The pulverizing capability is reflected by the mill fill level, operation current of ball mill and coal feed. Desiccation capability could be represented by outlet temperature. Ventilation capability was represented by inlet negative pressure, the difference between inlet and outlet negative pressure and current of pulverized coal powder exhauster. The output variable of the neural network was electric consumption. The structure diagram of RBF neural network was presented in Fig. 5.

At the steady work condition of coal feed was 45 ton/h; 50 group data were collected continuously. The data of operation parameters were recorded by the distributed control system (DCS) in engineering station and the vibration signal of mill shell were sampled in spot simultaneously. The sampling method was introduced in part 2. The front 40 group data were used to train the RBF neural network and the last 10 group data were utilized to test the generalization ability of the neural networks. Before modeling, all the data were normalized to the closed interval [0, 1].

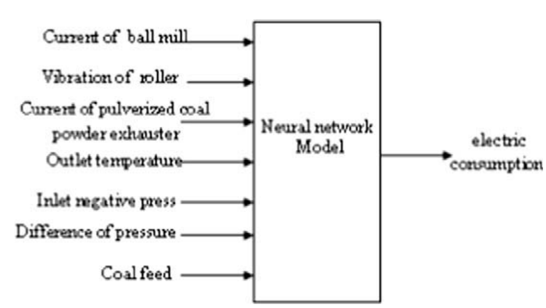

Fig. 5. Structure diagram of the electric consumption non-linear model.

Table 1
Comparison between practical value and model value.

Practical value (kW h/t)	25.40	25.70	25.69	25.36	25.90	26.01	25.72	25.58	25.27	25.28
Model value (kW h/t)	25.41	25.64	25.61	25.42	25.83	25.94	25.74	25.57	25.35	25.37
Relative error (%)	0.05	0.22	0.33	0.24	0.25	0.25	0.08	0.06	0.32	0.37

3.3. Modeling results

Model values of electric consumption and practical values were compared in Table 1.

Table 1 shows that the maximum of relative error is 0.37%; the accuracy of model is very high. The modeling results demonstrate the built RBF neural networks model have good generalization ability.

4. Optimization of electric consumption based on GA

4.1. Optimization objective function

In part 3, the non-linear mathematic model between the electric consumption and the affect factors was built based on RBF networks. Here, the model is optimized based on genetic algorithm in order to obtain the optimum operation parameters. The objective of optimization operation is to minimize the electric consumption based on the premise that all constrains are satisfied. The Optimization objective function of electric consumption is as follows:

$$\begin{cases} \min & \hat{y} = f(X_i) \\ \text{s.t.} & X_i \in E_i \end{cases} \tag{4}$$

where E_i is constrain of ith input variable, $\hat{y}$ is output of neural network. X_i is ith input of neural network.

4.2. Genetic algorithm

Genetic algorithm was presented by J. Holland who was inspired by biological evolutionism in 1975. Genetic algorithm is a parallel random adaptive algorithm that is based on "survival of the fittest". The GA repeatedly modifies a population of individual solutions. At each step, the GA selects individuals at random from the current population to be parents and uses them to produce the children for the next generation. In GA optimization, the factors involved are: the size of the initial population, the crossover factor, the mutation factor, and a fitness function. A fitness function is used to evaluate individuals, since reproductive success varies with fitness. The advantage of the GA approach lies in the ease with which it can handle arbitrary kinds of constraints and objectives. And allow the decision maker to select the best alternative.

The optimization parameters of ball mill pulverizing system are the input variables of the neural networks. And all of the process parameters vary within a known range and encoded as a binary string (chromosome). We use 10-bit encoding which results in an 80-bit chromosome for each parameter. Set the GA's operating parameters: the generation size is set to 200, the size of the initial population is set to 100, the crossover and mutation factors are set to 0.6 and 0.1, respectively. Because the objective of optimization is to minimize the electric consumption, the fitness function is chosen the electrical consumption which was calculated by the neural networks.

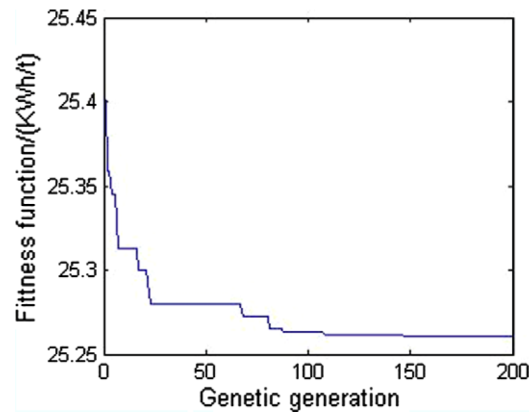

Fig. 6. Evolution of generations for electric consumption optimization.

$$Fit(f(x)) = f(x) \tag{5}$$

where $Fit(\cdot)$ is fitness function.

4.3. Optimization results

The optimization results were listed in Table 2, for the sake of comparing; the process parameters with minimal electric consumption in practical operation were also listed in Table 2. The convergence of fitness function in the optimization process was shown in Fig. 6.

The optimization results by GA in Table 2 shows that the electric consumption obtained by the algorithm decreased 0.01 kW h/t comparing to the minimal consumption in practical operation. By calculation, the optimized electric consumption decreased 0.51 kW h/t comparing to mean value in practical operation. According to the algorithm, the optimal operation conditions were determined. The results show that optimization method is feasible and effective. The method can be used as guidance for practical operation in power plants.

5. Conclusions

In this paper, a new optimization method for ball mill pulverizing system is proposed. We analyze the process factors which affect of electric consumption and import the vibration of ball mill shell to represent the mill fill level which is difficult to measure directly. Based on RBF neural networks optimization model of electric consumption is built. For the sake of optimization, GA optimal algorithm

Table 2
Optimization results based on GA algorithm.

Process parameters	Coal feed (t/h)	RMS of shell vibration (m/s^2)	Current of ball mill (A)	Current of pulverize coal exhauster (A)	Inlet negative press (Pa)	Outlet temperature (°C)	Difference of press (kPa)	Electric consumption (kW h/t)
Optimized value	46.01	49.56	77.26	54.7	207.63	71.58	1.94	**25.26**
Practical value	45.98	55.7	77.44	54.1	208.53	72.46	1.82	**25.27**

is used to optimize the model. And the optimal work conditions of ball mill pulverizing system are determined. This approach is practical and simple. It can be utilized as guidance in practical operation for power plant to improve the economy and efficiency.

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