A State Monitoring Method for Coal Mill Grinding Roller Base On Wavelet Multi-Scale Decomposition

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Abstract

To realize the wear condition of grinding roller of coal mill in power plant and improve the reliability of the equipment, it is essential to build a monitoring model with high accuracy for grinding roller wear state. In this paper, through collecting field historical operation data, the current model of coal mill is built by double hidden layers BP (Back Propagation) neural network to predict the wear state of grinding roller. The predicted value of the model and the actual value can form a residual, and the low frequency component obtained by wavelet multi-scale decomposition is used to characterize the wear state trend of grinding roller. The validity of the proposed method is verified by real data of a certain unit. The simulation shows that double hidden layers BP neural network can achieve high prediction accuracy so as to provide basis for the follow-up wavelet multi-scale decomposition of the constructed residual error, which can well reflect the changing trend of roller wear state after wavelet optimal scale decomposition. The proposed method has a certain engineering practical significance.

Keywords

Coal mill; BP; Multi-scale decomposition; Wear state.

1. Introduction

With the development of power market, improving the competitiveness of thermal power has become the goal of the industry. It is necessary to improve the safety and stability of equipment operation, develop monitoring and diagnosis technology and carry out state maintenance. In the national guidance on "Internet +" action, big data and intelligent technology are advocated to maintain the predictive status of equipment. Coal mill is an important auxiliary equipment in thermal power plant. Its working condition has important influence on the safety and economy of the whole power plant system. Due to wear of the coal mill is a slow process, the device has the characteristics of big inertia, large delay, and is a multi-input nonlinear system, the mechanism of the conventional modeling is complex and difficult, so using the huge amounts of data of power plant's SIS(Supervisory Information System) to build an accurate model has important practical significance. In this paper, a large amount of historical operation data of a coal mill in the power plant is collected to establish the current monitoring model of double-hidden layers BP neural network, which provides a theoretical analysis basis for the monitoring of wear condition of the grinding roller, The residual formed by the model is decomposed by wavelet optimal scale, and the low-frequency component obtained by the decomposition is used to represent the wear trend of the grinding roller, so as to monitor the wear state of the grinding roller of the coal mill.

2. Methods

In this paper, the power plant normal operation historical data which consisted of 10080 sets as training samples with a sampling interval of 1min. After processing, 3200 groups of samples were finally selected for training, and 100 groups of samples were used to test the prediction effect of the model.

2.1 BP Modeling

BP neural network is a multi-layer feed forward network which has hidden layers using error back propagation .Neural network has good nonlinear fitting ability and is suitable for complex objects modeling [1,2]. The mechanism model analysis of literature [3] showed that the coal mill current is affected by many variables, due to the restriction of site factors, only some variables can be measured accurately, through the screening of large amounts of data, this paper established a current neural network model which adopting the capacity of coal mill, air volume of coal mill, primary air temperature of coal mill, differential pressure between outlet pressure and primary air as the inputs of model, and the current of coal mill as the output of model[3,4]. Compared with single hidden layer, double hidden layers BP network can improve the performance error and gradient error of the network, so as to improve the prediction accuracy of the model and improve the network performance[5]. So the 8 inputs required for modeling include the current data and the previous data. Double hidden layers network structure is: 8-10-1-1. In the training model, the learning rate was set at 0.05, the learning times were 1000, and the learning target value was 1e-5. The accuracy of modeling can be reflected by the mean square error (MSE).The prediction results of the model are described in figure 1 with the MSE is 0.977[5].

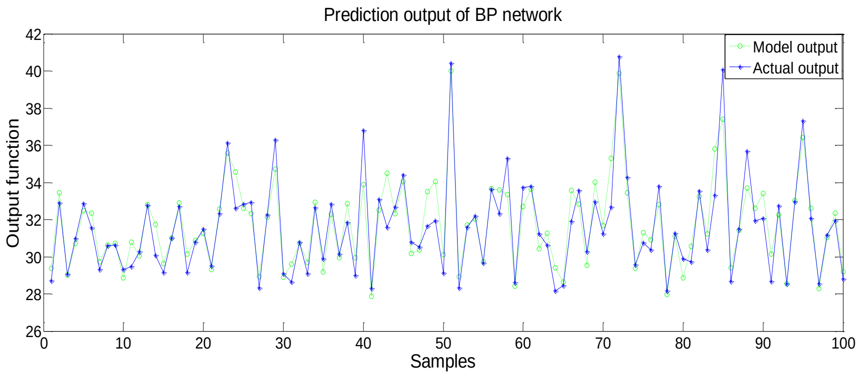

Fig.1 8-10-1-1 network prediction output diagram of double hidden layer

2.2 Basic Principle of Wavelet Transform

Wavelet analysis is developed on the basis of Fourier analysis. Wavelet transform has the characteristics of multi-resolution, which can decompose the signal into simple branches carrying information of different frequency bands with little loss of energy. Therefore, it is suitable for multi-scale analysis of thermal signals [6, 7]. As a time-frequency analysis method, wavelet analysis has made many essential advances. It provides an adaptive time-domain and frequency-domain localization analysis method, which can focus on any details of signal time period and frequency band, thereby it is called mathematical microscope [7]. For a finite energy function $f(t)$, if it satisfied as $f(t) \in L^2(R)$, its continuous wavelet transform is described in Equation (1):

$$WT(a,\tau) = \frac{1}{\sqrt{a}} \int_{-\infty}^{+\infty} f(t)\psi\left(\frac{t-b}{a}\right)\mathrm{d}t \tag{1}$$

where a is the scale to control the expansion and contraction of the wavelet function, b is the translation quantity, which controls the translation of the wavelet function. $\psi_{a,b}(t)$ is wavelet basis function. Through the change of scale factor a, translation factor b, the wavelet window moves along the time axis, subsequently the function in the whole time is analyzed on different scales. It uses scale function to analyze data, which makes wavelet transform has multi-scale characteristics and time-shifting. The scaling detailed signals can be observed on different scales [8]. Since wavelet transform can realize multi-scale decomposition and reconstruction of signals on the premise of little energy loss. Therefore, in this paper adopts Mallat algorithm of binary discrete wavelet transform based on multi-resolution analysis. The discrete wavelet transform is used to decompose coal mill time series into several components which have more stationary On the basis of analyzing the optimal wavelet basis, the original signal is successively decomposed into the low-frequency and high-frequency components in different scales [8]. Because the wear trend of grinding roller is mainly contained in its low-frequency component, the low-frequency component is extracted as wear index by using the multi-resolution characteristic of wavelet analysis, and the wear state of grinding roller can be monitored by the low-frequency reconstruction signal. By analyzing the reconstruction ability of low frequency signals with different wavelet basis functions to residual signals, and combining with early warning time, further simulation is carried out to find out a more suitable wavelet basis.

3. Multi-Scale Simulation Analysis

It has been found that Haar wavelet, Daubechies wavelet, Coiflets wavelet and Symlets wavelet are all suitable for analyzing residual sequences. After experimental screening, Haar wavelet basis, db3 wavelet basis, coif1 wavelet basis and sym3 wavelet basis are selected for wavelet multi-scale decomposition respectively in this paper. Using wavelet analysis toolbox with repeated experimental analysis, when the optimal decomposition scale is 8, the low-frequency component of the residual corresponding to each wavelet basis has obvious change trend after wavelet multi-scale decomposition, which can well characterize the wear state of coal mill grinding roller, thus guiding power plant operation management personnel to realize predictive maintenance. After decomposition at level 8, the original signal can be decomposed by the following equation (2): S represents the original signal, a is approximate signal (i.e., low-frequency parts) and d is detailed signal (i.e., low-frequency parts).

$$S=a8+d8+ d7+ d6+ d5+ d4+ d3+ d2+ d1 \tag{2}$$

The detailed decomposition results are described in the following Figures 2-6:

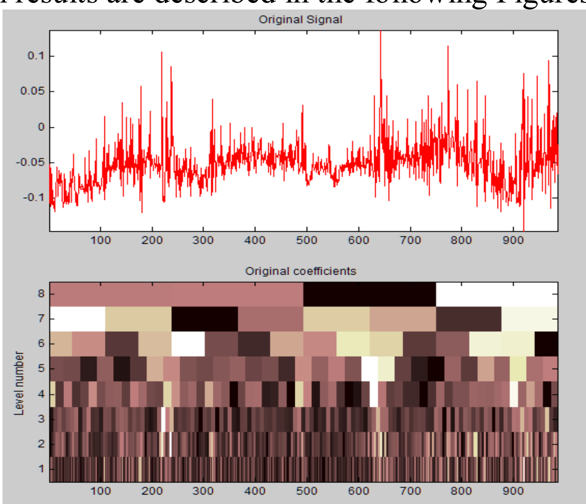

Fig.2 Multi-scale time-frequency decomposition diagram of the residual

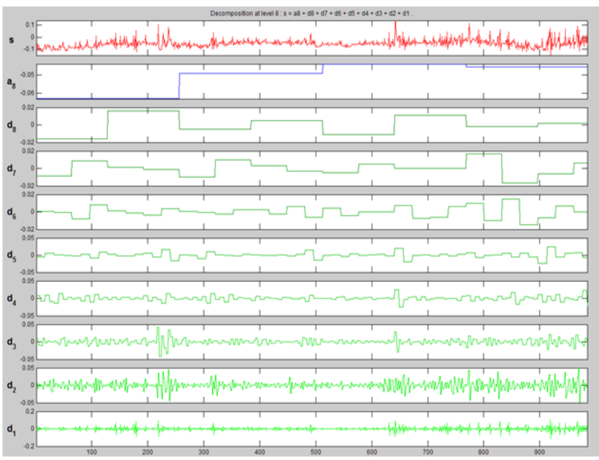

Fig. 3. Decomposition diagram of Haar wavelet based on scale 8

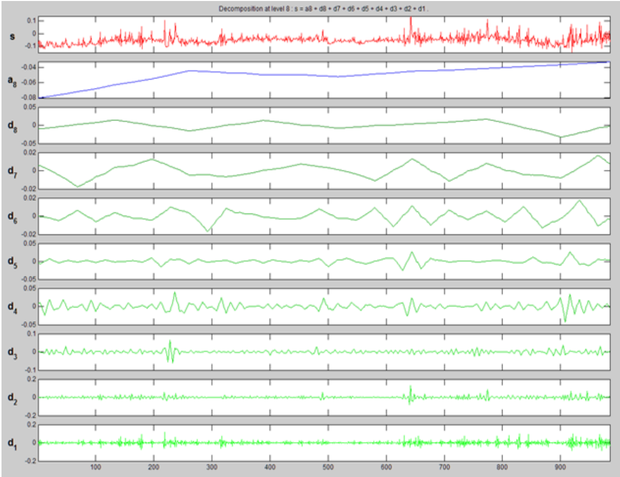

Fig. 4. Decomposition diagram of db3 wavelet based on scale 8

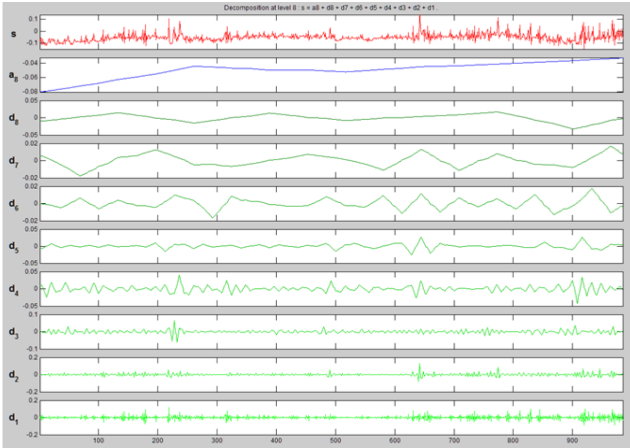

Fig. 5. Decomposition diagram of sym3 wavelet based on scale 8

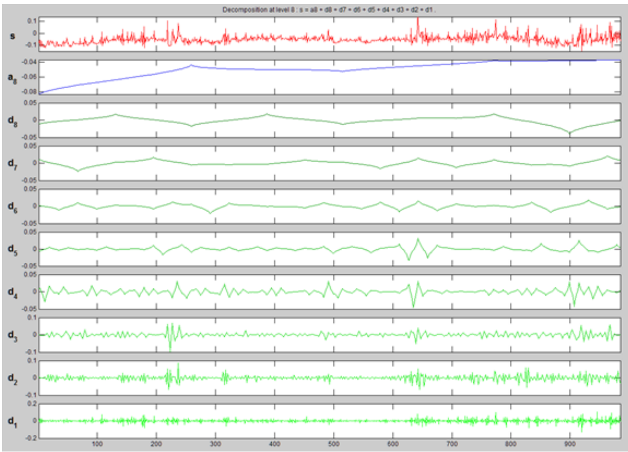

Fig.6. Decomposition diagram of coif1 wavelet based on scale 8

As can be seen from Figure 3 to Figure 6, the following facts can be observed. When the optimal scale is 8, the low-frequency component a8 corresponding to each wavelet t basis shows a gradual upward trend on the whole. The rising trend indicates that the wear degree of the grinding roller gradually increases, which plays an early warning role. Among them, the a8 low-frequency component of db3 and sym3 show an obvious upward trend at the moment of sample 100, which can play an early warning role. The a8 low-frequency component of Haar wavelet shows an obvious rising upward at the moment of sample 250, while the low-frequency component of coif1 wavelet a8 shows an obvious rising trend changing faster than others during all the time. Therefore, coif1 wavelet basis is selected for multi-scale transformation. According to Figure 11, as time goes on, the residual of the low-frequency signal obtained by decomposing coif1 wavelet basis at scale 8 increases with time, indicating that the wear degree of the grinding roller is gradually increasing, which is consistent with the actual running state of the grinding roller of the coal mill. Therefore, the a8 low-frequency component obtained from the residual signal of coal mill current after the multi-scale transformation of coif1 wavelet can be used to characterize the wear state of the grinding roller, which can be adopted as the result of the wear state monitoring of the coal mill grinding roller in power plant. Hence, the proposed method plays an early warning role in advance to achieve the predictive maintenance of the grinding roller in the power plant at the site.

4. Conclusion

This paper presents a model for monitoring the wear state of coal mill based on BP neural network and wavelet multi-scale decomposition. The experimental results show that the model has a higher prediction accuracy, and the residual signal obtained by using coif1 wavelet as the basis function and scale 8 as the optimal decomposition scale shows an increasing trend with the increase of time. The change trend is consistent with the actual operation state of the coal mill in the power plant. It can be used as a reference for power plant workers to realize predictive maintenance of grinding rollers. The method provides an effective modeling method for monitoring the wear state of grinding roller of coal mill in power plant, and provides technical basis for the maintenance and repair of grinding roller for the staff of power plant.

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