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# Soft-sensing of NOx content in power Station based on BP Neural Network, RBF Neural Network and PCA-RBF Neural Network

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**Abstract.** The timely and accurate measurement of the NOx content of the power plant denitrification system is very important for the precise regulation of the amount of ammonia and the control of the NOx emission. In this paper, we use 660MW coal-fired units as the research object. Combined with consideration of the poor accuracy and hysteresis of NOx measurement, the prediction models are established respectively by using RBF neural network, BP neural network and PCA-RBF neural network. The PCA-RBF model is based on principal component analysis (PCA) and RBF neural network. In order to improve the accuracy of the NOx soft-sensing model, this paper simplifies the sample model by optimizing the data samples, reducing the redundant information, and using dynamic neural network to achieve more accurate and faster training model. The results show that RBF neural network is superior to BP neural network in prediction accuracy and speed, while the improved and optimized PCA-RBF model has better prediction accuracy than the RBF neural network model. At the same time, this paper provides a theoretical basis for the real-time and accurate measurement of NOx content in power station, and provides some reference for improving the measurement and control of NOx in the actual production process.

## 1. Introduction

China is a big power generation country. In 2014, coal-fired power accounted for 75.2% of the country's total electricity[1]. Coal-fired power generation will produce a large amount of harmful gases such as NOx and SOx, which will seriously affect the air quality and human health. Therefore, reducing NOx emissions is an important goal of thermal power plants. SCR denitration technology is widely used in China, but there are some problems such as non-linearity and large delay in the whole denitrification system. It is difficult to achieve steady-state control by directly using the inlet of the denitrification reactor obtained by the analyzer and the exit NOx control. Accurate measurement presents a severe test[2].

The core idea of soft measurement technology is to use computer language instead of hardware instrumentation to predict the predominant variables that are not measurable or have low measurement accuracy in real systems and establish the soft-sensing model with easily measurable process variables (auxiliary variables).And neural networks are well used in soft-sensing techniques[3].

Neural network algorithm has strong learning ability and non-linear fitting ability. BP neural network and RBF neural network can simply represent the complex relationship among various operating parameters and have achieved some results in the field of boiler combustion[4-5]. In order to realize the real-time and accurate measurement of NOx concentration, this paper determined the auxiliary variables by analyzing the various factors that generate NOx and established the soft-sensing model based on BP neural network and RBF neural network. A soft-sensing model for accurate NOx concentration was obtained by testing and comparing.

## 2. Sample data processing

Soft-sensing technology is mainly composed of auxiliary variable selection, data acquisition and processing, and soft-sensing model. The selection of auxiliary variables is very important for soft-sensing model.

### *2.1. Auxiliary variable selection*

The boiler system is a very complex system, which has the characteristics of multivariable and coupling. The factors that affect the NOx are more complex, and the appropriate auxiliary variables are the key factors that affect the accuracy and complexity of the model. Selecting the auxiliary variables should be based on the following two principles: First, the auxiliary variables must be the dominant factor affecting the dominant variables; Second, the auxiliary variables should be easily measured and acquired[6].

By analyzing the reaction mechanism of NOx generation and combining with the data, the main auxiliary variables that affect NOx concentration include unit load, total coal, total air volume, total secondary air, flue gas flow, flue gas temperature, flue gas oxygen content and A-F mill baffle opening.

### *2.2. Sample optimization*

The data used in this paper is obtained from the tangential coal-fired boiler in a power plant. There are many original data samples, and a large amount of sample data has some redundancy. The similarity between the sample data is very high. For the large-scale sample set optimization is crucial. In this paper, the original sample is optimized by the similarity between the sample data, so that the remaining data contain all the information of the data as much as possible and are more streamlined. The basic method of calculating the similarity is to find the distance between two vectors[7]. The smaller the distance, the greater the similarity. The general formula used to calculate the similarity is:

$$R_{ij} = \exp(-\frac{1}{\omega} \times \left\| x_i - x_j \right\|_2) \tag{1}$$

Where $\omega$ is the normalized parameter of the similarity function, $xi \in Rn, i = 1, 2, \cdots, m$ , $m$ is the number of samples, $n$ is the number of sample features, $R_{ij}$ represents the similarity between the $i$ th data sample and the $j$ th sample data sample. The criteria for sample optimization are as follows: To determine whether the similarity of the two groups of data functions is greater than the threshold, when the similarity is greater than the threshold, a set of redundant data is removed to optimize the input sample data. To reduce the principle of handling errors, generally selected normalization parameter $\omega$ ,

$$\omega = \sum_{i=1}^{m} \max D_i - \sum_{i=1}^{m} \min D_i \tag{2}$$

Where $D_i$ is the value of the $i$ feature of the sample, and $m$ is the dimension of the feature of the sample. Using the similarity function to optimize the sample data, the redundant information of training samples can be greatly reduced, the original data samples can be optimized, and the model can be simplified[8].

### *2.3. Feature extraction*

Feature extraction is to find a transform or mapping from n-dimensional original sample space to p-dimensional (low-dimensional) feature space. The purpose is to reduce the original information as much

as possible, reduce the dimension of feature space and simplify the feature space structure. Therefore, the feature extraction can be used to reduce the number of auxiliary variables, and the model structure complexity can be reduced under the condition of ensuring the accuracy of the model. PCA is an analytic, streamlined data set technology. The PCA technique transforms variables that may be initially relevant into a set of linearly independent variables by orthogonal transformation. PCA can save most of the important information while reducing the data set dimensions. In the process of predicting NOx emissions, PCA can remove duplicate information in source data, extract valid information, reduce the complexity of the model and improve the generalization ability of the model[9-10].

### *2.4. Sample data denoising and normalization*

Because the data collected from the scene is affected by instrument accuracy, measurement environment and reliability and other factors, will inevitably introduce a variety of errors. The low precision and failure of the measurement data caused by these errors will result in the decrease of measurement performance and may even lead to the output of the whole model becoming unwarranted. So, for the original data smoothing noise reduction is essential. In this paper, the smooth statement is used for smoothing denoising, so that some interference in useful information is removed to reduce the distortion of the data.

Only through the above data preprocessing process can we achieve accurate prediction of NOx and lay a solid foundation for the following modeling and prediction. The pre-processed data can effectively improve the accuracy of the prediction model and the convergence speed.

## 3. Neural network

### *3.1. BP neural network*

BP (Back Propagation) neural network is a multi-layer feedforward network with hidden layer trained by error inverse propagation algorithm. It uses the steepest gradient descent method, can learn and store a large number of input and output mode mapping, through reverse propagation to continuously adjust the network weights and thresholds, so that the sum of the square error of the network[11-12].

The BP network usually has one or more hidden layers. The neurons in the hidden layer are all S-shaped transfer functions, which can learn the linear and non-linear relationship between input and output. Output layer using a linear transfer function, which can broaden the network output, so that the output can take any value[13-14].

### *3.2. RBF neural network*

RBF neural network is a kind of forward neural network with local approximation of single hidden layer. It simulates the local biological network in the human brain which is adjusted locally and covers the domain of receptivity. Whether it is in approximation ability, classification ability and Learning speed and other aspects are better than the BP network. The RBF network has three layers. RBF network has a local approximation ability[15].

## 4. Establish a prediction model

Through the processing of the original data, the final data includes 14 auxiliary variables, which are used as input variables of the neural network model, and the NOx concentration is taken as the output to establish the soft measurement model.Style and spacing

### *4.1. RBF neural network modeling*

Since the input and output variables of the neural network are the row vectors, the data collected and processed before are the column vectors, so the input and output data should be transposed. Because there is a delay between the predicted value and the actual value of the neural network, about 40s, which has a great disturbance for the accurate prediction of the neural network. During the modeling process, the input and output variables are advanced by four shots and the experimentally proved fitting the best.

In this paper, the newrb function is used to create a RBF neural network. The expansion speed of this function is experimentally repeatedly to determine the optimal value of 22 and the maximum number of neurons to be 101. Alternating gradient algorithm is used to optimize output layer weight and its function center and standard deviation of RBF neural network model. In sample training, the center and width of the network are fixed first, and the output layer weights are trained. The two processes are trained alternately until the required accuracy is achieved. The real value and the predicted value of NOx emission concentration were compared by using the established RBF neural network. It can be seen from Figure 1 that the actual value of the RBF neural network model is very close to the predicted value, indicating that the RBF neural network model has a good prediction effect.

The results of RBF model showed that the root mean square error (RMSE) is 3.6059%, the absolute mean error (AME) is 2.3702% and the average percentage error is (MAPE) 0.059%. The prediction residuals shown in Figure 2.

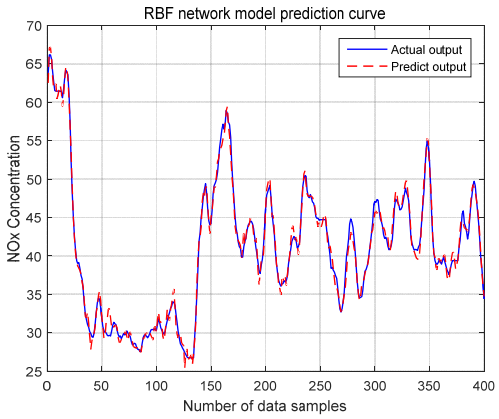


Figure 1. Prediction and actual value curve of RBF Neural Network.

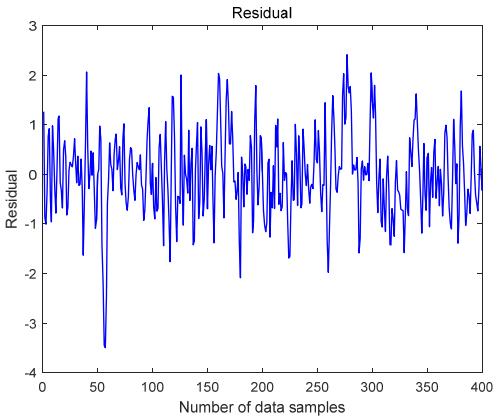


Figure 2. RBF neural network prediction residual.

*4.2. BP neural network modeling*

Train the network with the same input and output data as the RBF network. BP neural network uses Newff function. In this paper, the hyperbolic tangent S-type transfer function (tansig) is adopted in the hidden layer and output layer using a linear transfer function (purelin);. Train the forward trainlm function using the Levenberg-Marquardt rule. After debugging, get the best forecast result. BP neural network prediction results shown in Figure 3, the prediction residuals shown in Figure 4.

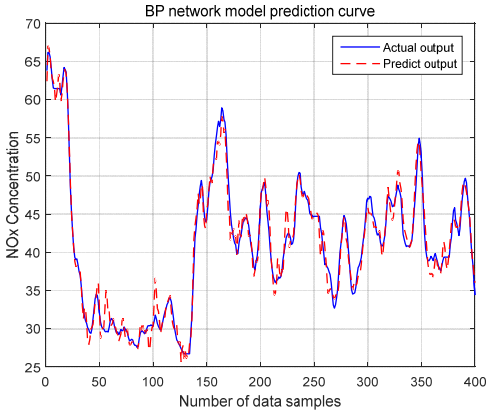


Figure 3. Prediction and actual value curve of BP neural network.

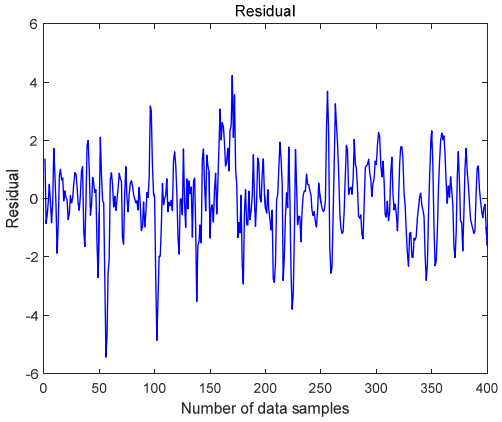


Figure 4. BP neural network prediction residual.

The results of BP model showed that the root mean square error (RMSE) is 3.9869%, the absolute mean error (AME) is 3.0551% and the average percentage error is (MAPE) 0.0766%.

*4.3. PCA-RBF neural network*

In the previous analysis, a total of 14 auxiliary variables are obtained, which makes the input variables of neural network have a high dimension, which not only affects the speed of model prediction but also affects the prediction accuracy. PCA dimensionality reduction is used to extract the features, and then the extracted variables are taken as input variables of neural network. Based on the previous RBF neural network model, the optimization is optimized and the PCA-RBF neural network model is established.

The real value and predicted value of NOx emission concentration in PCA-RBF neural network model are obtained. It can be seen from Figure 5 that the fitting of the actual value and the predicted value curve is very good, which shows that the PCA-RBF neural network model has a good prediction effect. The prediction residuals are shown in Figure 6.

The PCA-RBF model predicts that the root mean square error RMSE is 2.8336%, the absolute mean error AME is 2. 1579% and the average percentage error (MAPE) is 0.056%.

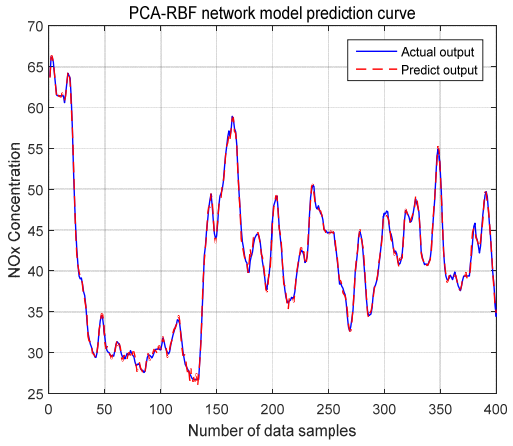


Figure 5. Prediction and actual value curve of PCA-RBF neural network.

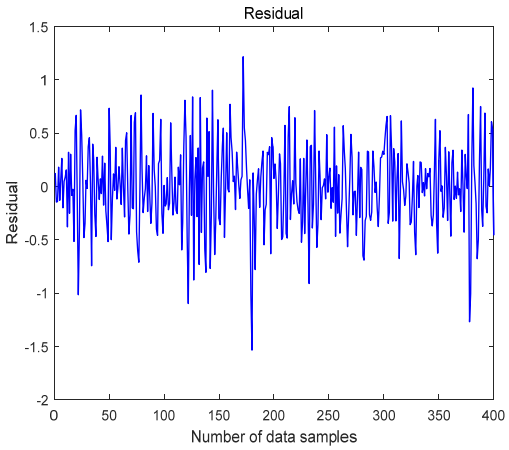


Figure 6. PCA-RBF neural network prediction residual.

*4.4. Model comparison*

The prediction results of different models are compared and the results are shown in Table 1.

Table 1. Comparison of different models.

| | RMSE/% | AME/% | MAPE/% | Time/s |
|---|---|---|---|---|
| **BPNN** | 1.143 | 0.285 | 0.286 | 0.593 |
| **RBFNN** | 1.143 | 0.285 | 0.067 | 0.796 |
| **PCA-RBF** | 2.571 | 0.109 | 0.600 | 0.439 |

Table 1 shows:

- The prediction accuracy of RBF neural network model is higher than BP neural network model;
- RBF neural network model is faster than BP neural network;
- Compared with RBF neural network model without feature extraction, PCA-RBF neural network has higher prediction accuracy, faster convergence rate and shorter training time.

## 5. Paper submission

Based on BP neural network, RBF neural network and PCA-RBF neural network respectively, this paper establishes a prediction model of NOx concentration in power station boiler. The prediction results show that the prediction accuracy and speed of the RBF neural network are better than that of the BP neural network. In addition, the RBF neural network model has stronger simulation and generalization ability, robustness and strong self-learning ability than the BP neural network model. However, the improved PCA-RBF has higher prediction accuracy than the RBF neural network, and the prediction time is shorter and the prediction performance is better after feature extraction. It provides some reference for NOx measurement and control in the actual production process.

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