

# Realization of BP neural network modeling based on $\text{NO}_x$ of CFB boiler in DCS

Jianyun Bai, ZhuJun Zhu<sup>1</sup>, Qi Wang and Jiang Ying

Department of Automation, Shanxi University, Taiyuan 030013, China

<sup>1</sup> zzhu\_jun@163.com

**Abstract.** In the CFB boiler installed with SNCR denitrification system, the mass concentration of  $\text{NO}_x$  is difficult to be predicted by the conventional mathematical model, and the step response mathematical model, obtained by using the step disturbance test of ammonia injection, is inaccurate. This paper presents two kinds of BP neural network model, according to the relationship between the generated mass concentration of  $\text{NO}_x$  and the load, the ratio of air to coal without using the SNCR system, as well as the relationship between the tested mass concentration of  $\text{NO}_x$  and the load, the ratio of air to coal and the amount of ammonia using the SNCR system. Then it realized the on-line prediction of the mass concentration of  $\text{NO}_x$  and the remaining mass concentration of  $\text{NO}_x$  after reduction reaction in DCS system. The practical results show that the average error per hour between generation and the prediction of the amount of  $\text{NO}_x$  mass concentration is within  $10 \text{ mg/Nm}^3$ , the reducing reaction of measured and predicted hourly average error is within  $2 \text{ mg/Nm}^3$ , all in error range, which provides a more accurate model for solving the problem on  $\text{NO}_x$  automatic control of SNCR system.

## 1. Introduction

With the further improvement of the national environmental protection index, higher requirements have been put forward for the emission of  $\text{SO}_2$ ,  $\text{NO}_x$ , smoke and dust in coal-fired power plants. The  $\text{NO}_x$  emission of CFB boiler is much less than other boilers, and the temperature of cyclone separator is between  $800\text{--}900^\circ\text{C}$ , which is the suitable reduction reaction region of  $\text{NO}_x$  in the SNCR denitrification system<sup>[1-2]</sup>, therefore, CFB boilers generally use SNCR to reach the national emission reduction requirements.

The amount of  $\text{NO}_x$  generation in CFB boilers vary with combustion, operating condition, nitrogen content in coal and its conversion rate, it is difficult to use conventional mathematical formula to calculate the amount of  $\text{NO}_x$  generation; since the denitrification efficiency varies with the amount of the  $\text{NO}_x$  generation and ammonia injection, it is also difficult to obtain an accurate mathematical model for the step response test of ammonia injection. Liu Jizhen et al studied the least squares support vector machine (SVM) modeling of the boiler's  $\text{NO}_x$  emission, Niu Peifeng et al studied the support vector machine and drosophila optimization algorithm of the CFB boiler's  $\text{NO}_x$  emission characteristics<sup>[3-7]</sup>, most researchers just improve different methods for simulation and do not apply to the production site or the method is not easy to achieve in the production site, or some scholars like Olawoyin have used predictive models in other areas<sup>[8]</sup>, but the achievements of online forecasting  $\text{NO}_x$  applied to CFB boilers have not been reported in the public literature.

In view of this situation, this paper has selected BP neural network with the characteristic of self-learning, fault tolerance, nonlinear approximation, easy to implement and so on, which is trained by a



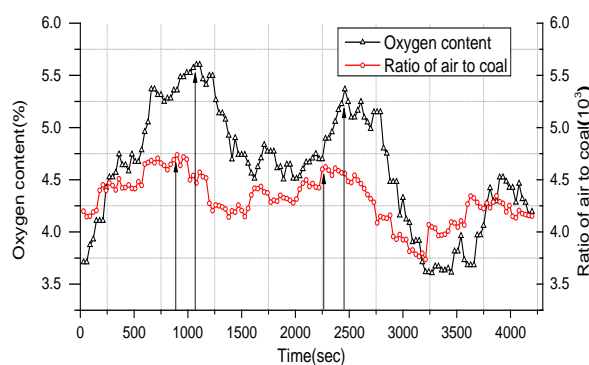
large number of historical data, and two kinds of BP neural network model is set up, the first model is to predict the mass concentration of  $\text{NO}_x$  generation, the second model is to predict the remaining  $\text{NO}_x$  mass concentration after reduction reaction. in order to apply the theory to practice, the concrete implementation method of BP neural network model in DCS is studied.

## 2. Establishment of BP neural network model

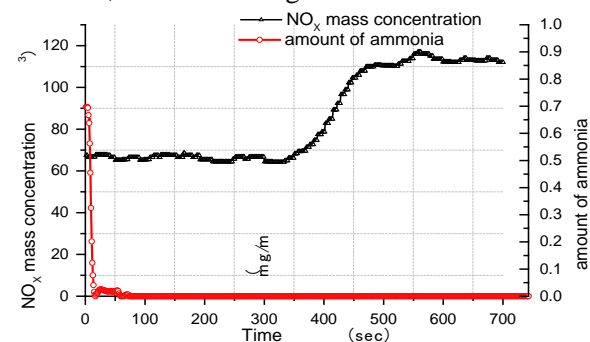
BP neural network modeling is to make use of the relationship between the easily measured process variables and the difficultly measured process variables, establishing the network model, the quantitative relationship between variables is hidden in weights and thresholds, and then through the network training, the network threshold and weight are corrected, and the indirect measurement of process variables is realized.

### 2.1. Selection of auxiliary variables in $\text{NO}_x$ model

① The change of CFB boiler load will affect the temperature of the furnace, the amount of flue gas and coal, the velocity of the flue gas. therefore, the change of CFB boiler load will directly affect the formation of the  $\text{NO}_x$  mass concentration. In the circulating fluidized bed combustion, the amount of  $\text{NO}_x$  generation will increase with the increasing oxygen content, but the fundamental reason for the change of oxygen content is the change of the ratio of air to coal, as shown in figure 1.



**Figure 1.** The tendency of the oxygen and air-coal ratio.



**Figure 2.** The step response curve

The figure 1 shows that the change tendency of the oxygen and the ratio of air to coal are similar, but the change of the ratio of air to coal than oxygen in advance, in the model one, the load and the ratio of coal to air are taken as auxiliary variables to predict the amount of  $\text{NO}_x$  generation earlier. therefore, the mode one can be used as a feedforward to optimize the control system.

② The mass concentration of the remaining  $\text{NO}_x$  after the reduction reaction is not only related to the amount of  $\text{NO}_x$  generation, but also is related to the amount of ammonia injection, so, in the model two, selecting the load, the ratio of air to coal and the reduction amount as auxiliary variables, a model for the mass concentration of remaining  $\text{NO}_x$  after reduction reaction is established. from the step response test of figure 2, we can see that there is at least four minutes of delay from reducing the amount of ammonia to the  $\text{NO}_x$  measurement change, while the model two can predict the  $\text{NO}_x$  content immediately after the change of reducing dose, so the mode two can be used as the object model, to solve the problem of large delay in SNCR denitration system, and improve dynamic characteristics.

## 2.2. Preprocessing of input and output data

The data collected in the production site inevitably have errors due to various disturbances, so it needs eliminate bad points. the dimension of various data is different, so after selecting the appropriate data, the data is normalized, at the same time, it is convenient to train the neural network by using MATLAB , the input and output data are converted to the [0-1] interval<sup>[9,10]</sup>.

Selecting one point every 10 seconds from the DCS history data, and eliminating the bad data, normalization processing and so on, finally getting 1300 valid data that need to be rearranged. the load, the ratio of air to coal, the amount of ammonia and the  $\text{NO}_x$  mass concentration before and after reaction should be unified to the same time coordinate, different load, different flow rate of flue gas will lead to different transmission time of  $\text{NO}_x$  mass concentration. therefore, the load is divided into 6 stages: 150MW, 180MW, 210MW, 240MW, 270MW and 300MW, different delay time are caused by different flow rate of flue gas under different loads, the data is adjusted to the ratio of air to coal for time points, other data will be unified to this time point.

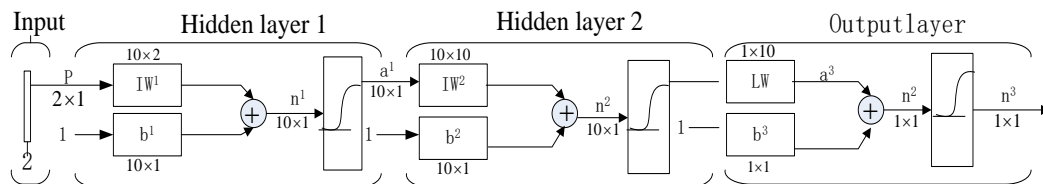
## 2.3. Establish BP neural network model

### (1) the selection of network layer number

Before establishing BP neural network, the number of layers in the network must be determined, in order to obtain a higher accuracy model, when the two models are built, the amount of data is large, so, the single hidden layer can not meet the needs after the experiment. therefore, the neural network modeling with two hidden layers is selected.

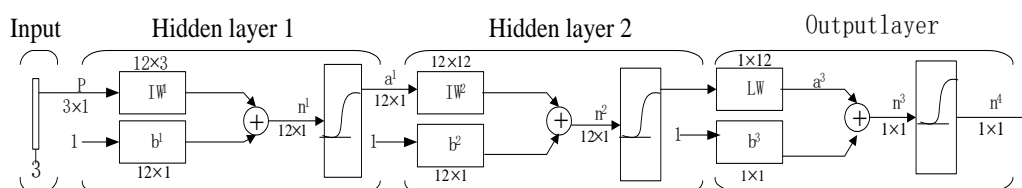
### (2) selection of nodes in each layer

In the establishment of the first model, the load and the ratio of wind to coal are selected as the main influencing factors, and the  $\text{NO}_x$  mass concentration is the predicted value, therefore, the input node is two, and the network output node is one. the experiment selected one thousand groups of data, the number of hidden layer nodes is selected and network is trained according to many times experiment, it is found that the number of nodes in two hidden layers is ten and ten respectively, the training effect is better. at the same time, the network transport functions are all logsig, and finally the neural network structure as shown in figure 3 is constructed.



**Figure 3.** The neural network model one.

In the second model, the load, the ratio of air to coal and the amount of ammonia are selected as the main influencing factors, the  $\text{NO}_x$  mass concentration after the reduction reaction is the predicted value, therefore, the input node is three, and the network output node is one. the experiment selected one thousand groups of data, the number of hidden layer nodes is selected and network is trained according to many times experiment, it is found that the number of nodes in two hidden layers is twelve and twelve respectively, the training effect is better. at the same time, the network transport functions are all logsig, and finally the neural network structure as shown in figure 4 is constructed.



**Figure 4.** The neural network model two.

(3) selection of training algorithms

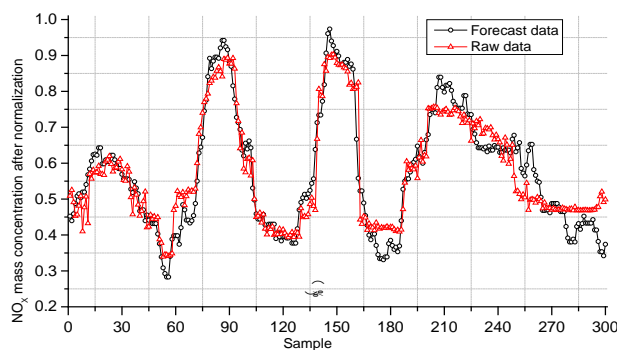
In this paper, the two models are trained by LM algorithm, and the LM algorithm, like Newton method, is designed to avoid the computation of the Hessian matrix, when the approximate two order training rate is corrected<sup>[11]</sup>.

(4) the creation and training of BP neural networks

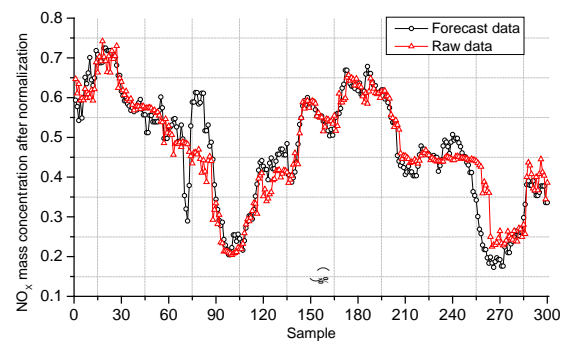
The processed data is imported into the MATLAB and the BP neural network is created, and the appropriate weights and thresholds are finally obtained by iterative training.

(5) validation of network models

In addition, the three hundred groups of data in other time periods are tested on the two kinds of trained neural networks, and the results are shown in figure 5 and figure 6.



**Figure 5.**Actual data and the forecast data comparison of model one.



**Figure 6.**Actual data and the forecast data comparison of model two.

After verification of the model, it is found that the predictive output of the two kinds of neural networks are similar to the target value, the average error is within 2%, and it is in the acceptable error range, therefore, the two kinds of neural network model structure and training weights and thresholds are obtained, which provides a theoretical basis for the actual operation of DCS in production site.

### 3. Implementation of BP neural network model in DCS

#### 3.1. Forward propagation mechanism of BP neural network

Taking the first BP neural network model as an example, the forward propagation mechanism of BP algorithm is introduced in detail. the network structure is shown in figure 7. the input layer has  $M$  ( $m=1,2$ ) input signals, any of which is represented by  $m$ , and the first hidden layer has  $I$  ( $i=1,2,\dots,10$ ) neurons, any of which is expressed by  $i$ ; the second hidden layer has  $J$  ( $j=1,2,\dots,10$ ) neurons, any of which is expressed by  $j$ ; the output layer has one neuron, and the output is represented by  $y$ . the weight between the input layer and the first hidden layer are represented by  $W_{im}$ , and the weight between the first hidden layer and the second hidden layer is expressed by  $W_{ji}$ , and the weight between the second hidden layer and the output layer is expressed by  $W_{pj}$ . the output of the first hidden layer is represented by  $U_i$ , and the output of the second hidden layer is represented by  $V_j$ . the output layer is represented by  $y$ . the thresholds are  $b_1, b_2, b_3$ , and the output of the BP neuron is obtained by the following formula:

(1) first output of hidden layer

$$u_i = f\left(\sum_{m=1}^M w_{im}x_m + b^1\right) \quad (1)$$

(2) second output of hidden layer

$$v_j = f\left(\sum_{i=1}^I w_{ji} u_i + b^2\right) \quad (2)$$

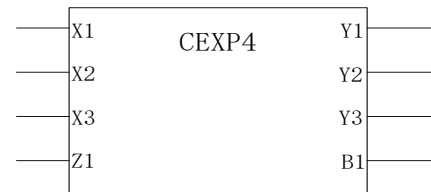
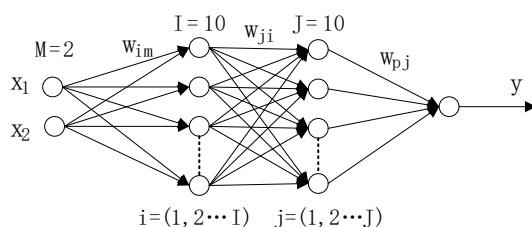
(3) output of the output node

$$y = f\left(\sum_{j=1}^J w_{pj} v_j + b^3\right) \quad (3)$$

$$\text{and } f(x) = \frac{1}{1 + e^{-x}} \quad (4)$$

### 3.2. DCS platform for implementing BP neural network model

In the DCS of the xinhua OnXDC2.2 version, there is a functional block - C expression one (CEXP4), which can be programmed in C language, it provides a platform for the implementation of BP neural networks. the configuration diagram is shown in figure 8.

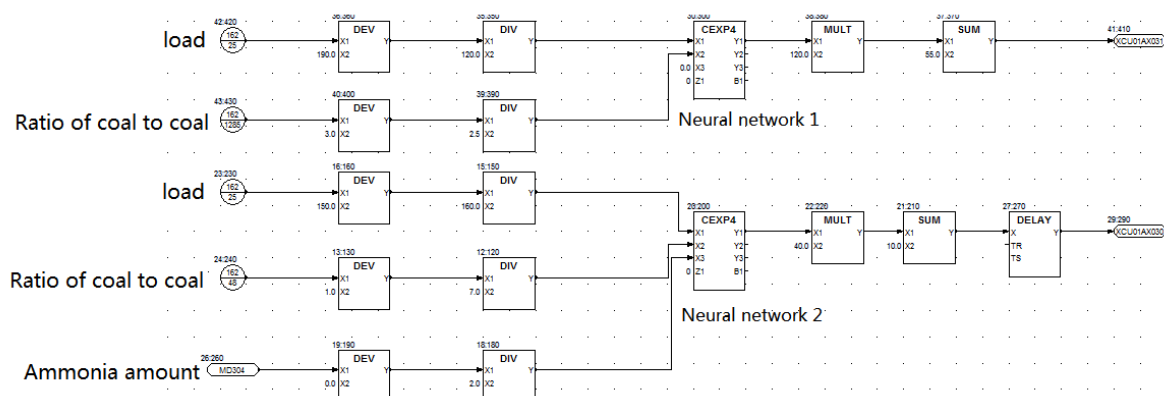


**Figure 7.** The BP neural network structure.

**Figure 8.** Xinhua special function block.

In function blocks, the X1, X2, and X3 are used as input signal, and Y1 is used as the output of the signal. within the functional module, you can write the program by C language<sup>[12]</sup>.

In the second part of this paper, through the network construction and training, we have got the trained weights -  $W_{im}$ ,  $W_{ji}$ ,  $W_{pj}$  and thresholds -  $b^1$ ,  $b^2$ ,  $b^3$ , according to the formula of 3.1 BP neural network model (1)–(4), the training weights and thresholds are written into C language expressions, by normalizing the real time input signal into X1, X2, X3 and according to the formula, we can get real-time value of Y1, and finally through the inverse normalization, the actual  $\text{NO}_x$  mass concentration prediction is obtained. the DCS configuration diagram of the two models is shown in figure 9.

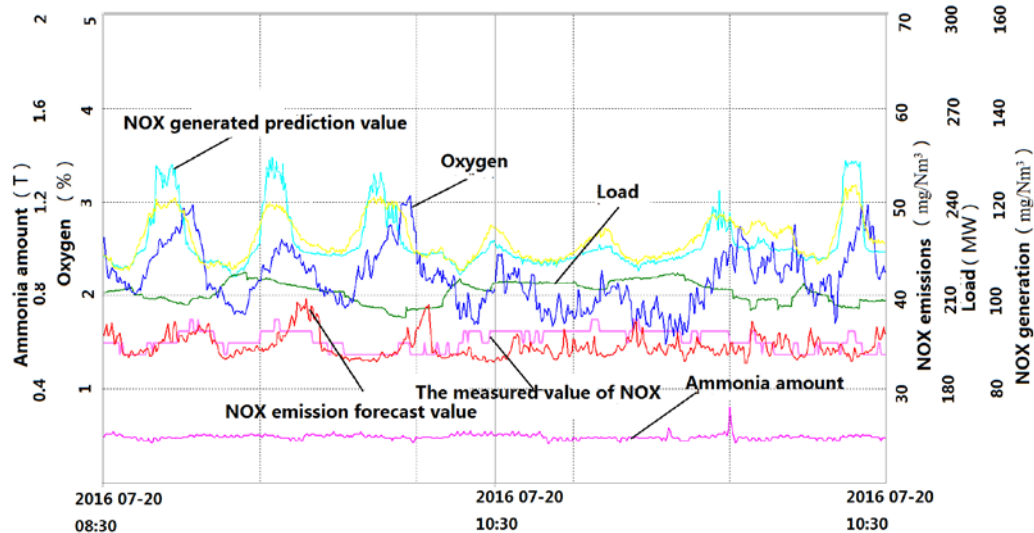


**Figure 9.** Application configuration diagram.

The first two modules in figure 9 are normalized, and middle module is made up of BP neural network module, the latter two modules are processed by inverse normalization, and the second models are added with pure delay, its purpose is to coincide with the actual measured value, so that it is easy to observe.

#### 4. Actual operation effect and analysis

After running the configured neural network model for a period of time, the  $\text{NO}_x$  prediction curve is obtained, as shown in figure 10.



**Figure 10.** Prediction curve.

From the prediction curve, the first neural network model can predict the mass concentration of  $\text{NO}_x$  better. the training data is environmental indicators of  $\text{NO}_x$  within  $200\text{mg}/\text{Nm}^3$ , then CFB boilers do not need to install the SNCR system, but now, the EPA has proposed ultra-low emission environmental indicators and require that the amount of  $\text{NO}_x$  emission is not higher than  $50\text{mg}/\text{Nm}^3$ . So, CFB boilers now must be add reductant to reduce  $\text{NO}_x$  emission, so the data could not be verified directly, but from the change of oxygen content and the normal running situation, it shows the reliability of the predicted values, it is estimated that the average error between the  $\text{NO}_x$  generation and the predicted value is within  $10\text{mg}/\text{Nm}^3$ . since it is much earlier than that obtained by  $\text{NO}_x$  sensor, therefore, the first kind of BP neural network model can be used as feedforward in the automatic control system to achieve more accurate lead regulation and improve the dynamic characteristics of the system

The second neural network models predict the mass concentration of the remaining  $\text{NO}_x$  after the reduction reaction. in the second model configuration, pure delay is applied to fit the measured value. the pure delay time varies with the flow velocity under different loads. as shown in figure 10, the curve fitting degree is higher, and the  $\text{NO}_x$  prediction value is close to the measured value, the average error of the measured value and the predicted value is within  $2\text{mg}/\text{Nm}^3$  by calculation, which meets the needs of the actual controlled object model. therefore, the model can be used as the controlled object model of automatic control to solve the large delay problem in SNCR denitrification system.

#### 5. Conclusions

Because the unpredictable quantity of  $\text{NO}_x$  generation and the large time delay, it is difficult to realize the automatic control of  $\text{NO}_x$  with conventional PID in SNCR system, in order to help it to achieve automatic control and provide the conditions for optimal control, this paper establishes two kinds of BP neural network model, the first model is to predict the mass concentration of  $\text{NO}_x$ . the second model is the remaining mass concentration of  $\text{NO}_x$  after the reduction reaction. in order to apply the theory to practice, the forward propagation mechanism of BP neural network is introduced in detail, and the concrete method of implementing BP neural network in DCS of xinhua OnXDC2.2 version is studied. when the trained network model is written into the DCS configuration program, it is found that the mass concentration of  $\text{NO}_x$  and the remaining mass concentration of  $\text{NO}_x$  after the reduction reaction can be accurately predicted in the actual operation. therefore, the realization of the two kind



of BP neural network models in DCS play an important role in optimizing the automatic control of NO<sub>x</sub> in the SNCR denitrification system.

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