Overall optimization of operation cost of the boiler and SCR in coal-fired power plants

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Abstract. Coal-fired power plants are usually equipped with selective catalytic reduction (SCR) systems to reduce nitrogen oxides (NOx) emissions. In this paper, we considered both the denitrification cost of the SCR system and the coal burning cost of the boiler to develop an operation cost model. Furthermore, the genetic algorithm was proposed to minimize the total operation cost by optimizing the feature parameters, including the primary air pressure, secondary air volume, overheated air volume, and NH₃ injection volume. Simulation experiments were performed based on the operating data of a 1000 MW coal-fired power plant, with results showing that the total operating cost of the boiler and SCR was lowered.

1. Introduction
The nitrogen oxides (NOx) emissions from coal-fired power generation are one of the main constituents of air pollution. In recent years, the government has set increasingly strict requirements for NOx emissions from coal-fired power plants. In order to reduce NOx emissions, most of the domestic currently running and newly built large coal-fired power plants have installed the flue gas denitrification devices. Among the denitrification technologies, selective catalytic reduction (SCR) has become the main choice for coal-fired power plants due to its high denitrification efficiency and mature technology [1-4]. The SCR system needs to continuously consume the reducing agent NH₃; at the same time, the operation of the dilution fan and NH₃ production equipment will also bring additional power loss, which has a certain impact on the operating costs of power plant units.

Researchers have proposed combustion optimization technology to reduce NOx emissions. The NOx emissions from coal-fired boilers are influenced by parameters. Thus, artificial intelligence (AI) techniques can be used to develop a model between NOx emissions and operating parameters of the boiler and achieve NOx reduction in the flue gas. This method has been widely used because it does not require to promote equipment or modify the structure of the boiler. For example, some research proposed to use methods such as artificial neural networks (ANN) and support vector machines (SVM) to build NOx emissions models based on historical operating data of the power plant [5, 6]. Based on the NOx emission prediction model, intelligent algorithms such as the genetic algorithm (GA) and particle swarm optimization (PSO) algorithms were used to optimize adjustable parameters to achieve NOx emissions...
reduction [7]. However, if only the reduction of NOx emissions generated during the combustion of the boiler is considered, operating conditions can deviate from the design value, further leading to a reduction in boiler efficiency and an increase in coal consumption. In view of this, Gu et al [8] simultaneously established the models of NOx emissions and boiler efficiency, and optimized NOx emissions and boiler efficiency respectively. Yang et al [9] established the economic operation model of the denitrification system by considering the boiler efficiency, the cost of NH3 injection of the SCR system and the sewage charges. However, in the actual power generation process, the denitrification operation cost cannot be simply measured by the sewage charges. If the NOx concentration in the flue gas exceeds the emission limit, the unit will not be allowed to keep running. Based on the above research, this paper considers both the NOx denitrification cost and the coal cost of the boiler to develop an operation cost model by using ANN. Furthermore, GA is applied to optimize the parameters to achieve the minimization of the overall operation cost.

2. Boiler and SCR operation cost model

2.1. Boiler and SCR operation cost model
The structure of the overall operation cost model is shown in Figure. 1. The entire model consists of three sub-models, namely the boiler combustion model, the SCR system model and the cost calculation model. The parameters related to the combustion characteristics of the boiler are selected as the input of the combustion model, including unit load, coal-feed rate, total air rate, the primary air pressure, the secondary air rate, and overfire air (OFA) rate. The SCR inlet flue gas flow, flue gas temperature, NOx concentration and coal consumption are selected as the model output. Collecting data samples from the historical operation database of the power plant, back-propagation (BP) neural network is used to build the boiler combustion model. Similarly, the parameters that affect the SCR reaction characteristics are selected as the input of the SCR system model, including the SCR inlet NOx concentration, flue gas flow, flue gas temperature, and NH3 injection, and model output are NH3 slip and NOx emissions at the outlet. The SCR system model is constructed by using the BP neural network. Then the coal consumption (the power consumption of the SCR system is also included in the coal consumption) and the amount of NH3 injection per unit load is multiplied by the corresponding price to obtain the overall operation cost. Based on which, the cost calculation model is constructed. It can be seen that the proposed model considers both the economics of the boiler and the economics of the SCR system. The primary air pressure, secondary air rate, OFA rate, and the NH3 injection of the model input variables are used as adjustable parameters, the GA algorithm is used to optimize them to minimize the overall operation cost.

2.2. BP neural network modeling theory
Collecting \( n \) samples from the operation data of the power plant, the input \( \mathbf{x} = [x_1, x_2, \ldots, x_p]^T \) of each sample contains \( p \) variables and the output \( \mathbf{y} = [y_1, y_2, \ldots, y_q]^T \) contains \( q \) variables. We consider a three-layer neural network, consisting of an input layer, a hidden layer, and an output layer, where the input layer contains \( p \) nodes, the hidden layer contains \( h \) nodes, and the output layer contains \( q \) nodes.
Each node in the input layer is weighted and accumulated before entering the hidden layer, then the result adds an offset to obtain the output through the excitation function; that is:

\[ net_k = f^1 \left( \sum_{i=1}^{p} w_{ki} x_i + b^1_k \right) \]  

\[ y_j = f^2 \left( \sum_{k=1}^{h} w_{jk} net_k + b^2_k \right) \]  

where \( i = 1, \ldots, p \), \( j = 1, \ldots, q \), \( k = 1, \ldots, h \). The above formula can be written in a matrix form:

\[ y = f^2 (w^2 f^1(w^1 x + b^1) + b^2) \]  

where \( w^2 \in \mathbb{R}_q \times h \) and \( w^1 \in \mathbb{R}^{h \times p} \) are weights, \( b^1 \in \mathbb{R}^h \) and \( b^2 \in \mathbb{R}^q \) are offsets, \( f^1(\cdot) \) and \( f^2(\cdot) \) are usually calculated by using linear and sigmoid functions.

The weights \( w^1 \) and \( w^2 \) in the BP neural network are determined by the back-propagation algorithm. The input value of the data reaches the hidden layer through the operation of weights and offsets, and the obtained hidden layer data reaches the output layer similarly. If the output value deviates from the actual value, the output layer error is used to calculate the hidden layer error, and then to calculate the input layer error. The error of the output performance is transmitted step by step in a direction opposite to the input, and the connection weight of each layer is modified one by one. The error is reduced to the allowable range by iterating this process continuously.

### 2.3. Construction of operation cost model

Considering the unit load \( r_{load} \), coal-feed rate \( r_{coal} \), total air rate \( r_{ta} \), primary air pressure \( p_a \), secondary air rate \( s_A, s_B, s_C \) (here we consider three-layer secondary air), and OFA rate \( s_{OFA} \) as input variables, the SCR inlet flue gas flow \( q_g \), flue gas temperature \( t_g \), coal consumption \( r_{nc} \), and SCR inlet NOx concentration \( \rho_{NOx,g} \) as model outputs, the boiler combustion model is developed as follows:

\[ [q_g, t_g, r_{nc}, \rho_{NOx,g}] = F_1 (r_{load}, r_{coal}, r_{ta}, p_a, s_A, s_B, s_C, s_{OFA}) \]  

where \( F_1(\cdot) \) is a three-layer BP neural network function with 8 inputs and 4 outputs.

Selecting the SCR inlet flue gas flow \( q_g \), flue gas temperature \( t_g \), SCR inlet NOx concentration \( \rho_{NOx,g} \), and NH\(_3\) injection \( r_{NH_3} \) as model inputs, the outlet NOx emissions \( \rho_{NOx_{out}} \) and NH\(_3\) slip \( \rho_{NH_3} \) as model outputs, we can build the SCR system model below:

\[ [\rho_{NOx_{out}}, \rho_{NH_3}] = F_2 (q_g, t_g, \rho_{NOx,g}, r_{NH_3}) \]  

where \( F_2(\cdot) \) and \( F_3(\cdot) \) is a three-layer BP neural network function with 4 inputs and 2 outputs.

The parameters related to economical operation mainly consist of coal consumption and NH\(_3\) injection. The two items are multiplied by the corresponding prices to obtain the total operating cost to construct the cost calculation model. The boiler is usually equipped with SCR devices on both sides, for simplicity, it is assumed that the SCR devices on both sides have the same characteristics. The cost calculation model is given as follows:

\[ c = c_{coal} + c_{NH_3} \]  

\[ c_{coal} = r_{nc} \cdot p_{coal} \]  

\[ c_{NH_3} = \frac{2r_{NH_3}}{r_{load}} \cdot p_{NH_3} \]  

where \( p_{coal} \) and \( p_{NH_3} \) are the costs of coal and NH\(_3\) per ton, respectively, and the unit is yuan \( \cdot t^{-1} \). The formulas (6)-(8) characterize the cost calculation model that includes the coal consumption of the boiler and the cost of reducing agent NH\(_3\) of SCR system; that is to say, the economy of the boiler combustion and SCR operation is considered at the same time. Thus the results obtained have more practical significance.
2.4. Optimization of operation cost by GA

The economic operation of the boiler and SCR is to minimize the total cost, which can be regarded as an optimization problem with the objective of minimizing the operation cost function. GA is one of the fundamental evolutionary stochastic optimization algorithms. GA can obtain the solution based on a natural selection process and it has become one of the most widely used evolutionary optimization algorithms. Thus, GA is used to optimize the adjustable parameters.

By using GA, the following optimization problems are solved to minimize the running cost:

$$\min c = r_{nc} \cdot p_{coal} + \frac{2r_{NH_3}}{\eta_{load}} \cdot p_{NH_3}$$

subject to:

$$\rho_{NOx_{out}} < \delta_{NOx}$$

$$\rho_{NH_3} < \delta_{NH_3}$$

where the vector $[p_a, s_A, s_B, s_C, s_{OFA}, r_{NH_3}]^T$ is to be optimized, $\rho_{NH_3}$, $\rho_{NOx_{out}}$ and $r_{nc}$ are calculated by formulas (4) and (5), and $\delta_{NOx}$ and $\delta_{NH_3}$ are NOx and NH3 emissions limits.

3. Experimental results and discussion

3.1. Data preparation

We investigate an ultra-supercritical 1000 MW boiler and SCR system in a coal-fired power plant. This power plant boiler has three secondary air rate and one OFA. To meet environmental protection requirements, low-nitrogen combustion technology and two SCR devices are used, which are equipped over the air preheater on both sides of the boiler. The two SCR systems share a set of NH3 storage and transportation system. In order to simplify the calculation, the A-side SCR system model is established, and the B-side SCR system is considered to have the same characteristics. Operating data are taken from the samples in the power plant database, including unit load, total coal feed rate, total air volume, primary air pressure, AB, CD, EF three-layer secondary air rate, OFA rate, NH3 injection, SCR inlet flue gas flow, flue gas temperature, flue gas NOx concentration, coal consumption, NH3 slip, SCR outlet NOx emissions. Data samples were collected with a running time span of two weeks, with a total of about 4,000 data samples. After the removal of outlier samples and steady-state screening, a total of 1,420 samples are obtained. These data are divided into two sets: 1220 samples (training set) to build the model and 200 samples (testing set) to test the prediction accuracy of the model. For training samples and test samples, optimization of adjustable parameters is implemented by using GA to obtain the optimal overall operation cost.

3.2. Prediction results

Based on the training samples, we use BP neural network to construct the boiler combustion model. This model is used to calculate the flue gas flow $q_g$, flue gas temperature $t_g$, NOx concentration $\rho_{NOx_{ag}}$, and coal consumption $r_{nc}$. For similarity, we only analyze the prediction results of flue gas flow and temperature, which are shown in Figures 2 and 3.

![Figure 2. Prediction results of flue gas flow.](image1)

![Figure 3. Prediction results of flue gas temperature.](image2)
Figures 2 and 3 show that the prediction errors of the boiler combustion model in the training set are very small. The predicted values of flue gas flow, flue gas temperature almost coincide with actual values, which indicates that the model has a good approximation capability. Moreover, the prediction accuracy of the boiler combustion model in the testing set is also acceptable. For example, when predicting the flue gas temperature, the prediction error of most test samples is within 2 °C. It can be seen that the model also has better prediction accuracy for new operating conditions, indicating that the boiler combustion model has a good generalization capability.

In addition, BP neural network is used to construct the SCR system model, which is used to predict the outlet NOx emissions and NH3 slip. The prediction results are shown respectively in Figures 4 and 5. We can find a small deviation exists between the predicted values of the NOx and the NH3 slip from the actual measured values in the training and testing sets, showing that the model has better approximation and generalization capabilities. Therefore, the constructed SCR system model can realize the accurate prediction of NOx emissions and NH3 slip.

3.3. Model optimization

Based on the outputs of the boiler combustion model and the SCR system model, and considering the cost of coal and NH3, the operation cost model is constructed by Equation (6). The coal consumption is converted to coal consumption with a calorific value of 5,500 kcal, which corresponds to the coal price of 680 yuan · t⁻¹ and the liquid NH3 price of 3400 yuan · t⁻¹. Taking the overall operation cost as the objective function, an optimization model is obtained as shown in Equation (9). GA is used to optimize the adjustable parameters, including the primary air pressure, secondary air rate of the AB, CD, and EF layers, the OFA rate and the NH3 injection. Optimizing results of all samples in the training and the test sets are shown in Figure 6. Considering a typical operating condition the figure, the objective function can converge to 0.212; that is, the optimal operation cost is 0.212 yuan · (kWh)⁻¹, whereas the operation cost before optimization was 0.222 yuan · (kWh)⁻¹, with 4.5% cost reduced. Meanwhile, the SCR outlet NOx emissions and NH3 slip can meet the emission requirements. Figure 5 also shows that for most operating condition data, after GA optimization, the operation cost can be obviously reduced.

Figure 4. Prediction results of NOx emission at the SCR outlet.

Figure 5. Prediction results of NH3 at the SCR outlet.

Figure 6. Comparison of the operation cost before and after the optimization.
4. Conclusion
Considering the cost of the coal consumption and the SCR system, the parameters including unit load, total coal feed rate, total air volume, primary air pressure, secondary air rate, OFA rate, and NH$_3$ injection are used as inputs to construct the operation cost model of the boiler and SCR system based on the BP neural network. In addition, the adjustable operating parameters are optimized by using GA. The real operating data of a 1000 MW coal-fired power plant are investigated, and experiment results show that the operation cost of the unit can be obviously reduced by after optimization.

5. References
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