Research on Optimization of Boiler Air Distribution System based on Deep Neural Network

Jun Yuan¹², Xinyu Ren²*, Yingbai Xie² and Zhichao Li¹

¹ China Resources Power Technology Research Institute Co., Ltd, Shenzhen, China
² School of Energy, Power and Mechanical Engineering, North China Electric Power University, Baoding, China

*Corresponding author email: renxinyu8@crpower.com.cn

Abstract. The boiler air distribution system has an important influence on the stable operation of the thermal power unit. It directly affects the combustion efficiency, which in turn affects NOx emission of the boiler. However, boiler efficiency and NOx emission are a pair of contradictory goals, which will be one-sided if one is adjusted separately. In addition, thermal power units often face the impact of variable boundary conditions in operation. In this study, DNN-PSO modeling optimization was performed on air distribution system of a 1000MW double-tangential boiler. The deep neural network (DNN) is used to establish the boiler’s air distribution system model, and the particle swarm optimization algorithm (PSO) is used to optimize the opening of the secondary air baffle and the over fire air baffle. According to the on-site adjustment test based on the optimized guidance value, the NOx emission was reduced by 36.31mg/Nm³, and the boiler efficiency was increased by 0.09%, which proved the feasibility of using this model to guide the operation of the boiler air distribution system.

1. Introduction

At present, the operation of thermal power units are generally faced with the problems of variable coal types, variable unit load, variable environment and variable equipment, which brings new challenges to deep energy conservation research[1]. Especially under the variable boundary conditions, how to adopt an appropriate air distribution ratio to ensure efficient combustion and reduce the emission of NOx is an urgent problem to be solved.

The research on boiler air distribution system is mainly based on numerical simulation and field adjustment test. Sun [2] et al studied the influence of secondary air and over-fire air distribution ratio on boiler combustion characteristics and NOx emissions based on numerical simulations. Ma [3] and Yafeng Zhong [4] et al conducted a numerical simulation of the combustion process of the boiler and analyzed the influence of the temperature field distribution in the furnace, the operation of secondary air and over fire air on the generation of NOx. Shangda [5] et al analyzed the changes of NOx emission concentration and boiler efficiency under different operating conditions by adjusting the secondary air distribution ratio and OFA damper opening on site. J. Smrekar[6] and others built a nonlinear neural network model to predict the NOx emissions of coal-fired power plant boilers. The prediction results helped to achieve the effect of reducing NOx emissions and reducing maintenance costs.

There are many researches on low NOx emission and combustion optimization of boilers, but efficient combustion of boilers and low NOx emissions are a pair of contradictory goals, so an algorithm is needed to balance them [7]. This paper used deep neural network (DNN) to model the air distribution
system, combined with the particle swarm optimization algorithm (PSO) to optimize the opening of the air baffle of each floor in the air distribution system to obtain a reasonable air distribution plan. By conducting on-site adjustment tests through the guidance values predicted by the model, NOx emissions were significantly reduced, and boiler efficiency was also slightly improved.

2. Research Objects and Original Data

2.1. Research Objects
This paper focuses on the research of a 1000MW power plant boiler. The boiler is single-furnace, double tangential circle, single-reheat cycle, and balanced ventilation. The burners are arranged in front and back walls, a total of 6 layers, 8 burners per layer. Burners #1, #2, #3, #4 form an imaginary tangent circle rotating clockwise in the center of the left half of the furnace, #5, #6, #7, #8 form a counterclockwise in the center of the right part of the furnace Imaginary tangent to the circle. The combustion mode and burner layout are shown in figure 1.

Table 1. Main design parameters of boiler

| Parameter name                  | Unit   | Value  |
|--------------------------------|--------|--------|
| Superheated steam flow         | t/h    | 3103   |
| Superheated steam pressure     | Mpa    | 27.46  |
| Superheated steam temperature  | °C     | 605    |
| Reheat steam flow              | t/h    | 2590   |
| Reheat steam inlet pressure    | Mpa    | 6.06   |
| Reheat steam outlet pressure   | Mpa    | 5.86   |
| Reheat steam inlet temperature | °C     | 376    |
| Reheat steam outlet temperature| °C     | 603    |
| Feed water temperature        | °C     | 299    |
| Boiler efficiency(Qnet.ar)    | %      | 93.8   |
| Coal consumption              | t/h    | 390.8  |
| Exhaust gas temperature       | °C     | 129(124)|
| Excess air coefficient        | %      | 1.2    |

Figure 1. Combustion method and burner arrangement

2.2. Raw Data
The data in this paper is the historical data of the unit's operation for one year selected from the SIS system of the power plant. The start and end time of the data is from November 1, 2018 00:00 to
November 1, 2019 00:00, and the sampling period is 30s. This data is the original data of the operation of the unit. It is pre-processed to remove outliers that do not meet the test, including: (a) over temperature and over limit (main steam temperature exceeds 615 °C); (b) exceeds environmental indicators (SO2 less than 35mg/Nm³, NOX less than 50mg/Nm³ (after denitration treatment); (3) Flue gas dust concentration is less than 10mg/Nm³); (4) Large fluctuations in operating conditions (main steam temperature fluctuation exceeds 10°C, main steam pressure Fluctuation exceeding 1Mpa, flue gas outlet oxygen fluctuation not exceeding 1.5%). Then divide the boundary conditions according to the unit load, ambient temperature and coal types information, and filter out the data under stable working conditions. The total data sample is about 120,000.

3. DNN-PSO Modeling and Optimization Method

3.1. DNN-PSO Model Optimization Process

The DNN algorithm is a neural network with multiple hidden layers. For the modeling and analysis of high dimensions and large amounts of data, the model expression effect is more excellent[8]. Particle Swarm Optimization algorithm (PSO) is widely used in thermal power technology. Particle swarm optimization evaluates the quality of particles through fitness function. Therefore, the choice of fitness value determines the search direction of the algorithm. The optimization process of the DNN-PSO model is to establish the relationship of the boiler air distribution system model through the deep neural network. When optimizing the parameters of the boiler air distribution system, the parameters are divided into operational adjustable parameters and non-adjustable parameters, and the adjustable parameters are adjusted as the optimization variables of the PSO algorithm, and the non-adjustable parameters are used as the restriction constraints. The established DNN model was used as the fitness function evaluation standard, and PSO was used to optimize the adjustable parameters. The optimization process is shown in figure 2.

![Figure 2. Schematic diagram of DNN-PSO model optimization process](image)

3.2. DNN Neural Network Model Design

The input parameters for the boiler air distribution system are selected as follows: unit load, coal-feed of each layer of coal pulverizer, total air volume, the opening of the secondary air baffle and the over fire air baffle, pressure difference between secondary air box and furnace, burner tilt, a total of 35 parameters. The goal of the air distribution system optimization is to make the unit obtains both high-efficiency combustion and low NOX emissions. The output parameter of the DNN model is expressed by the comprehensive optimization value of air and coal powder, and the calculation formula is as follows:
In formula (1), $Q_i$ is the heat loss of solid incomplete combustion, %; $NO_X$ is the average value of NOX concentration at the inlet of SCR reactor; $Q_{fan, forced}$ is the equivalent heat loss of the electrical consumption of the forced draft fan, and $C_1$ and $C_2$ are the correction coefficients. The establishment of the formula for the comprehensive optimized value of the air and coal powder comprehensively considers the influence between the air distribution and the emission of $Q4$, $NO_X$ and the current of the blower, so as to model it, and the model can better reflect the actual operation of the unit.

4. Model Optimization and Discussion of Test Results

4.1. Selection of DNN Deep Neural Network Model Parameters

The structure of the neural network was continuously adjusted to select the parameters corresponding to the smallest errors were selected. By selecting 5000 samples as the training set, 200 samples as the test set for error prediction, the training times is 3000.

First, select the number of hidden layers of the neural network. The optimal number of neural network hidden layers is 3-4. For the neural network with 3 hidden layers, after 3000 training times, the relative error table of the output parameters is shown in table 2.

| Hidden layer nodes | Learning rate |
|--------------------|---------------|
|                    | 0.0 | 0.0 | 0.025 | 0.030 | 0.035 | 0.045 | 0.050 | 0.055 |
| 15                 | 1.3  | 0.8  | 1.1  | 2.4  | 0.9  | 1.7  | 0.9  | 0.8  |
| 20                 | 84   | 29   | 53   | 65   | 85   | 02   | 50   | 36   |
| 25                 | 1.0  | 0.9  | 0.7  | 2.3  | 1.1  | 2.0  | 1.2  | 1.0  |
| 30                 | 98   | 46   | 91   | 66   | 75   | 60   | 14   | 71   |
| 35                 | 1.5  | 1.4  | 0.9  | 0.7  | 1.4  | 0.8  | 1.5  | 1.5  |
| 40                 | 15   | 98   | 48   | 62   | 91   | 97   | 69   | 91   |
| 45                 | 1.2  | 0.8  | 0.7  | 1.2  | 1.1  | 0.8  | 1.1  | 1.3  |
| 50                 | 58   | 24   | 87   | 19   | 22   | 74   | 18   | 15   |
| 55                 | 0.9  | 0.8  | 0.7  | 0.9  | 1.4  | 1.2  | 1.0  | 0.9  |
| 60                 | 49   | 96   | 88   | 53   | 56   | 44   | 95   | 07   |
| 65                 | 0.8  | 0.8  | 0.9  | 1.5  | 0.8  | 1.3  | 1.0  | 1.4  |
| 70                 | 90   | 28   | 91   | 41   | 21   | 36   | 77   | 98   |
| 75                 | 0.9  | 0.6  | 0.7  | 1.0  | 0.8  | 0.8  | 0.9  | 1.1  |
| 80                 | 18   | 73   | 87   | 84   | 12   | 97   | 88   | 10   |

It can be seen from table 2 that the minimum training error is 0.673%, the corresponding number of hidden layer nodes is 21, the learning rate is 0.02, and the model's performance on the test set is shown in figure 3.

Similarly, the same test was performed on the neural network model of the four hidden layers. After 3000 training times, a smaller training error of 0.59% was obtained. The optimal hidden layer node is
selected as 20, the optimal learning rate is 0.02. The model was tested on the test set, and the
correlation between the final predicted value and the true value is shown in figure 4.
Figure 4 shows that the actual value of the neural network model using four hidden layers is basically
consistent with the predicted value. The reason is that the same activation function is used for the same
set of data. When the neural network minimizes the loss function, the update range of the weight and
threshold is small, but the four hidden layers neural network has calculated the characteristics of the
input samples many times, and achieved better prediction results, indicating that the model has higher
reliability.
In summary, this paper selects a neural network with four hidden layers for modeling the boiler air
distribution system. The number of nodes in each hidden layer is 20, and the learning rate is 0.02.

![Figure 3. Neural network prediction graph of three hidden layers](image)

![Figure 4. Neural network prediction graph of four hidden layer](image)

4.2. Discussion of Results before and after Model Optimization
The real-time data of the operation of the unit was transferred to the DNN-PSO model for optimization,
and the optimization adjustment test was carried out according to the optimization guidance value of
the model. The optimization process is shown in figure 5.
The prediction result of the model is consistent with the theory of low NO\textsubscript{X} emissions of air staged combustion reduction technology, and field adjustment experiments were carried out accordingly. The optimization results are shown in table 4.

The test data in table 4 shows that, after optimization and adjustment, the comprehensive optimization value of the air and coal power of the boiler was reduced by 0.16, the NO\textsubscript{X} emission concentration was reduced by 36.31\text{mg/Nm}^3, and the boiler thermal efficiency was increased by 0.09\%.

The optimization results were basically consistent with the above theoretical analysis, which shows that the optimization and adjustment not only ensures the boiler efficiency, but also reduces the NO\textsubscript{X} emissions, which further proves the reliability of the model.

5. Conclusion
In order to solve the problem of variable boundaries during the actual operation of thermal power units and the contradiction between NO\textsubscript{X} emissions and boiler efficiency, this paper proposed the use of DNN deep neural network modeling technology to model the boiler air distribution system, combined with particle swarm optimization algorithm to optimize the opening of the secondary air baffle and over fire air baffle of each layer to guide the boiler air distribution. The conclusions are as follows:

(1) After data preprocessing, the data under stable boundaries were selected to model the air distribution system. The relative error of the neural network model reached 0.59\%, indicating that the model has high reliability;

(2) Through the on-site adjustment test of the boiler, the optimization results show that: the comprehensive optimization value of the air and coal power was reduced by 0.16, the thermal efficiency of the boiler was increased by 0.09\%, and the NO\textsubscript{X} emission was reduced by 36.31\text{g/Nm}^3, indicating that the optimization model has a guiding role in the actual operation of the unit;

(3) The opening of the separated overfire air (SOFA) baffle has a significant effect on reducing NO\textsubscript{X} emissions.
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