Standard Heat Consumption Modelling Calculation and Operation Optimization of Boiler Steam Temperature System

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Abstract. The combination of neural network and genetic algorithm not only can improve the operating efficiency and economy of the boiler, but also give the recommended values of the operating parameters. Based on the power plant, the number of hidden layers, nodes and learning rate of the neural network modelling calculation are determined according to the data experiments. Taking the standard heat consumption as the target value, the adjustable and non-adjustable quantities of the input parameters are analysed, the parameters such as the crossover rate, the mutation rate and the GGAP suitable for the research object are selected, and the genetic algorithm is used for optimization. The results show that the standard heat consumptions of all the 100 groups of working conditions are reduced. The average reduction is 153.93 kJ/(kW•h). This indicates that by modelling and optimizing the parameters such as the superheater desuperheating water flow, it can provide operational guidance for actual production.

1. Introduction
Thermal power generation accounts for about 60% of China's total power generation capacity [1]. With the reform of China's power system and the introduction of policies such as plant-grid separation and price competition, an open and competitive regional power market pattern has gradually formed. Ensuring the safe and stable operation of the units and keeping them in the best condition for a long period of time, as well as minimizing the coal consumption rate are the realistic requirements for power plants in the market economy environment [2].

The thermal power plant steam temperature system is one of the important parts of the thermal power unit system, and its control effect directly affects the economy and safety of the entire unit production [3]. The main thermal process control systems in modern thermal power plants still use feedback control loops based on classical control theory, but for the nonlinear, large-inertia, and high hysteresis steam-temperature control systems, the conventional PID series control strategy has been difficult to meet the needs of the people [4].

In addition, the installed capacity of thermal power units is gradually increasing with the development of information technology and industrialization, the environmental protection and economic indicators are also rising, and the automation standards for thermal power plant control systems are also rising. Therefore, it is of great significance to identify the thermal object transfer function based on the field operation signal and the real-time measurement data of the actual production process, and to guide the control [5].
The rapid development of intelligent control technology, especially the advancement of neural networks, intelligent optimization algorithms and complex industrial models, provides a new and effective way to control thermal power plant systems [6]. The application of intelligent control to thermal power plant steam temperature control systems can fully compensate for the shortcomings of traditional control methods in terms of poor control performance and high hysteresis, and meet the needs of power plant unit steam temperature control [7].

This paper uses BP neural network and particle swarm algorithm to model and optimize the steam temperature control system in order to improve boiler operating efficiency, reduce operating costs, and achieve sustainable development, based on the Chibi 1000MW power plant unit.

2. Boiler steam temperature system object

The object of this study is the 1000 MW unit of Hubei Chibi Power Plant Phase II #3 unit. The boiler of this unit is an ultra-supercritical variable pressure direct current pulverized coal furnace manufactured by Shanghai Boiler Works Company Limited with the introduction of ALSTOM technology, model SG-3103/27.46-M536, type: single hearth, double-cut circle, primary intermediate reheat, balanced ventilation, open-arrangement, solid slagging, all-steel frame, full suspension structure, π-type direct current pulverized coal boiler; under BMCR condition, the main and reheat steam temperature is 605 ℃/603 ℃ and the main and reheat steam pressure is 27.46 MPa/5.86 MPa.

In the actual operation of the unit, there are a large number of parameters that affect the steam temperature characteristics, such as main steam temperature, main steam flow rate, main steam pressure, superheater desuperheating water flow rate, re-heat steam temperature, re-heat steam pressure, reheater desuperheating water flow rate, burner swing angle, super-heater flue gas baffle opening, reheater flue gas baffle opening, condenser A circulating water inlet temperature, blower inlet air temperature, excess air coefficient, the amount of fuel, etc.

The parameters are correlated with each other, which can affect the model accuracy if all of them are used as inputs. The parameters are fitted nonlinearly using the professional curve-fitting software 1stOpt, and the sensitivity factor for each energy consumption indicator is calculated, as shown in Table 1.

Table 1. Sensitivity Factor Calculation Results

| Energy consumption indicators                  | Sensitivity factor (%) | Energy consumption indicators                  | Sensitivity factor (%) |
|-----------------------------------------------|------------------------|-----------------------------------------------|------------------------|
| Main steam temperature                        | -0.6327                | Re-heater desuperheating water flow            | 0.4712                 |
| Main steam flow                               | 0.3218                 | Burner pendulum angle                          | 0.3978                 |
| Main steam pressure                           | -0.4932                | Super-heater flue gas baffle opening           | -0.5672                |
| Super-heater desuperheating water flow         | 0.4721                 | Re-heater flue gas baffle opening              | -0.5721                |
| Reheat steam temperature                      | -0.5832                | Condenser A circulating water inlet temperature| 0.6282                 |
| Environmental temperature                     | 0.1512                 | Fuel amount                                    | 0.2541                 |
| Reheat steam pressure                         | -0.3782                | Blower inlet air temperature                   | 0.5425                 |

Based on the results of the sensitivity analysis in Table 1, the steam temperature, main steam flow rate, main steam pressure, superheater desuperheating water flow rate, reheat steam temperature, reheat steam pressure, reheater desuperheating water flow rate, burner swing angle, super-heater flue gas baffle opening, reheater flue gas baffle opening, condenser A circulating water inlet temperature, and blower inlet air temperature were determined as the input quantities.

The equivalent heat loss, which is the sum of the turbine heat loss rate and the boiler heat loss rate, is used as the output of the neural network model, which is the target value for optimization. The equivalent heat consumption represents the energy consumption of the steam temperature control system of the thermal power plant.

The above model was developed based on actual operational data, from which more than 150,000 samples were obtained for calculation and analysis.
3. Neural network models

3.1. BP Neural Networks

Artificial Neural Network (ANN), often referred to as a neural network, is a data processing model that draws on biological neural networks.

As shown in Figure 1, a neural network consists of a large number of artificial neurons (nodes) connected for computation, which change their structure according to the information provided by the outside world, i.e., they adjust the weights between the nodes to model the input data and finally solve the problem [8].

The design of a BP neural network includes several aspects such as the number of layers, the number of neurons in each layer, the transfer function between the layers, and the learning rate [9].

3.2. Determination of Structural Parameters of Neural Networks

To determine the structural parameters of the neural network, it is necessary to continuously adjust the structure of the neural network through several experiments, calculate the error of the sample, select the structure corresponding to the optimal error, and finally determine the structural parameters of the neural network. Most of the literature uses a 3- or 4-tier neural network after considering the accuracy of the calculation results and the time required for the calculation.

In this paper, a four-layer neural network is used and the number of nodes in the middle two implicit layers is 20, and the learning rates between the layers are 0.02, 0.06, and 0.02, respectively.

4. Particle Swarm Algorithms

4.1. Introduction to Algorithms

The particle swarm optimization algorithm starts from a random solution and evaluates the solution from the adaptation degree by iterative search.

At first, it starts with a group of random particles in the solution space, evaluates the target according to the adaptation function, and then makes each particle move with velocity $V$ in the solution space and follows the optimal particle to search for the optimal solution after many iterations.

In each iteration, the particle swarm algorithm updates its velocity and position as follows.

$$
\begin{align*}
 v^{(t+1)} &= w v^{(t)} + c_1 r_1 (p(t) - x^{(t)}) + c_2 r_2 (p_g^{(t)} - x^{(t)}) \\
x^{(t+1)} &= x^{(t)} + v^{(t+1)}
\end{align*}
$$

where $t$ is the current iteration number, $v^t$ is the velocity of the particle at the $t$-th iteration, $x^t$ is the position of the particle at the $t$-th iteration, $w$ is the inertia factor, the value interval is $[0, 1]$, $c_1$ and $c_2$ are acceleration constants, the value interval is $[0, 4]$, usually $c_1$ and $c_2$ take the same value, $r_1$ and $r_2$ are random numbers, $p(t)$ is the current best position, $p_g$ is the global best position.
4.2. Combination of Neural Networks and Particle Swarm Algorithms

Figure 2 shows the flow of BP neural network modelling and particle swarm algorithm optimization. In the figure, not only the parameters of the neural network influence the calculation results, but also the parameters of the particle swarm have a great influence. In particular, in the particle swarm algorithm, the inertia factor $w$ and the learning factors $c_1$ and $c_2$ have a great influence on the optimization performance of the algorithm, usually, $c_1$ and $c_2$ take the same value.

![Figure 2](image)

**Figure 2.** The optimization flow of the BP neural network particle swarm algorithm.

5. Vapour Temperature System Optimization

The goal of steam temperature control system optimization in thermal power plants is to reduce the equivalent heat consumption of the unit. The adjustable and non-adjustable operating parameters are determined according to the actual situation, and the adjustable operating parameters are adjusted as optimization variables for the gravity search algorithm, while the non-adjustable operating parameters are used as limiting constraints.

The optimization is carried out under the same sample condition, and the mean solution set of the optimal solutions obtained experimentally for each parameter combination in Figure 2 is shown in Table 2.
Table 2. Optimal equivalent thermal depletion with different parameters in the particle swarm algorithm.

| $c_1$ | 0.1 | 0.2 | 0.3 | 0.4 | 0.5 | 0.6 | 0.7 | 0.8 | 0.9 | 1.0 |
|-------|-----|-----|-----|-----|-----|-----|-----|-----|-----|-----|
| $c_2$ |  0.5|  0.5|  0.5|  0.5|  0.5|  0.5|  0.5|  0.5|  0.5|  0.5|
|       |  0.7|  0.7|  0.7|  0.7|  0.7|  0.7|  0.7|  0.7|  0.7|  0.7|
|       |  0.9|  0.9|  0.9|  0.9|  0.9|  0.9|  0.9|  0.9|  0.9|  0.9|
|       |  1.0|  1.0|  1.0|  1.0|  1.0|  1.0|  1.0|  1.0|  1.0|  1.0|

Therefore, by comparing the optimal solution obtained from the inertia factor $w$ and the learning factors $c_1$ and $c_2$ in Table 2, the smallest equivalent heat loss is selected from them, as shown in Figure 3. As shown in Figure 3, the smallest value of equivalent heat dissipation is obtained when the inertia factor $w$ and learning factors $c_1$ and $c_2$ are 0.6, 3.0, and 3.0, respectively, which can be considered as the best parameters of the particle swarm algorithm for this problem.

![Figure 3](image)

Figure 3. Comparison of optimal equivalent heat loss for different parameters of the particle swarm algorithm.

Table 3. Comparison of parameters before and after optimization

| Operating Volume          | Original condition | Optimization of working conditions |
|---------------------------|--------------------|-----------------------------------|
| Super-heater desuperheating water flow (t/h) | 71.29              | 65.92                             |
| Re-heater desuperheating water flow (t/h)    | 0                  | 0                                 |
| Burner Pendulum Angle (DEC)                 | 70                 | 68.95                             |
| Super-heater flue gas baffle opening (%)    | 70                 | 73                                |
| Re-heater flue gas baffle opening (%)       | 50                 | 47                                |
| Standard heat consumption (kJ/kW·h)         | 797.94             | 788.37                            |

Table 3 compares the values of the relevant operating quantities before and after optimization. From Table 3, it can be seen that after optimization, the equivalent heat loss is reduced by 95.7 kJ/(kW·h), and the equivalent heat loss rate at this condition is reduced by 1.2%.

6. Conclusion

In this paper, BP neural network and particle swarm algorithm are used for modelling and optimization of boiler steam temperature system, taking Hubei Chibi Power Plant Phase II #3 1000MW unit as the target, and the following conclusions are obtained.

1) For the subject of this paper, according to the results of the sensitivity analysis, determine the steam temperature, main steam flow rate, main steam pressure, superheater desuperheating water flow rate, re-heat steam temperature, re-heat steam pressure, reheater desuperheating water flow rate, burner swing angle, super-heater flue gas baffle opening, reheater flue gas baffle opening, condenser
A circulating water inlet temperature and blower inlet air temperature as input quantities, and select the equivalent heat loss as output.

2) The parameters of the neural network and the particle swarm algorithm have a great influence on the optimization results. In this paper, a 4-layer neural network is used, and the number of nodes in the middle two implicit layers is 20, the learning rates between the layers are 0.02, 0.06, and 0.02, respectively. An analysis of inertia and learning factors in the particle swarm algorithm is presented.

3) After optimization, the equivalent heat dissipation is reduced by 95.7 kJ/(kW·h). In the particle swarm algorithm with inertia factor $w$ and learning factors $c_1$ and $c_2$ of 0.6, 3.0, and 3.0, respectively, the value of equivalent heat dissipation is the smallest. The equivalent heat dissipation rate is reduced by 1.2% under this condition.

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