Modelling and Optimization of Boiler Steam Temperature System Based on Neural Network and Genetic Algorithms

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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 for the boiler operation. Based on the field data from power plant, the errors of the 3 and 4-layer neural network were compared according to the data experiments. The 4-layer neural network was used to model the steam temperature system. Taking the standard heat consumption as the target value, the adjustable and non-adjustable quantities of the input parameters of the steam temperature system are determined, 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 maximum reduction of heat consumption is 186.88 kJ/(kW·h), and the average reduction is 153.93 kJ/(kW·h). This indicates that the combination of neural network and genetic algorithm can optimize the boiler steam temperature system by optimizing parameters such as superheater de-superheating water flow, superheater flue gas baffle opening and reheater flue gas baffle opening, which provides guidance for actual production.

1. Introduction

In the thermal control of thermal power plant, steam temperature is the most important output parameter of boiler, which has a significant impact on the safety and economic operation of power plant [1]. As an important loop in steam water system of thermal power unit, the main function of steam temperature system is to keep the steam temperature within the allowable range. If the steam temperature is too high, it will damage the metal part of the unit, shorten the service life of the equipment and increase the replacement cost of the equipment; if the steam temperature is too low, it will lead to the decrease of the thermal economy of the unit and affect the operation efficiency of the power plant [2]. Therefore, the steam temperature optimization of power plant boiler can improve the operation efficiency of thermal power unit and reduce the operation cost of the unit.

Fang Haiquan et al. used Bayesian neural networks (BNN) to model the boiler combustion system, and transformed it into a single objective problem by weight coefficient transformation method, and optimized the problem by genetic algorithm [4]. Lee et al. established a BP neural network for training by importing the historical data of the boiler plant, and then established the optimal combination of boiler parameters through genetic algorithm to optimize the boiler system [5]. Liu Binghan et al. obtained the optimal efficiency and minimum power supply coal consumption of coal-fired units through big data mining technology [6]. Ma Yunpeng used the extreme learning machine (ELM) to model the boiler combustion system, and used the teaching learning based optimization (TLBO) algorithm to optimize the combustion system [7].
At present, in the optimization of steam temperature system, normally only the specific target value is given. However, the specific operating parameters guiding the steam temperature optimization are rarely given. Therefore, this paper takes the actual 1000MW unit as the object, uses BP neural network and genetic algorithm to model and optimize the boiler steam temperature, which is used to guide the actual production.

In this paper, BP neural network is used to establish the model of steam temperature system, and the complex nonlinear relationship between boiler parameters and coal consumption is obtained. The structure parameters of BP neural network are designed, and the optimal structure parameters of neural network are obtained by comparing the experimental results, so as to improve the accuracy of boiler steam temperature model. The results can be used to guide the actual production.

2. Determination of structural parameters of neural network algorithm

2.1. Boiler steam temperature system object

The steam temperature system studied in this paper is a 1000MW unit of a power plant in Hubei Province. According to the actual operation data, the model is established, and more than 120000 samples are obtained for the operation of neural network.

According to the actual demand of the unit, 12 input quantities are determined, namely: main steam temperature (℃), main steam gas flow (t/h), main steam pressure (MPA), superheater desuperheating water flow (t/h), reheat steam temperature (℃), reheat steam pressure (MPA), reheater desuperheating water flow (T/h), burner swing angle (DEC), superheater flue gas baffle opening (%), reheater flue gas baffle opening (%), condenser A circulating water inlet temperature (℃), forced draft fan inlet air temperature (℃).

The output is the standard heat consumption, which is the target value of optimization.

2.2. Determination of structural parameters of neural network algorithm

To determine the structural parameters of neural network, we need to adjust the structure of neural network through many experiments, calculate the error of samples, select the structure corresponding to the optimal error, and finally determine the structural parameters of neural network. Most references [8, 9, 10] adopt 3-layer or 4-layer neural networks in consideration of the accuracy of calculation results and calculation time. Therefore, this paper first determines the number of layers of neural network.

For the three-layer neural network, 10000 groups of samples are selected for training, and 500 groups of samples are selected for error prediction among the remaining samples, and the training times are 500. The final error is shown in Table 1.

| Number of hidden layer nodes | Learning rate |
|-----------------------------|---------------|
|                             | 0.01 | 0.02 | 0.03 | 0.04 | 0.05 | 0.06 | 0.07 | 0.08 |
| 18                          | 0.6915 | 0.5813 | 0.6674 | 0.8154 | 0.7058 | 0.5625 | 0.6494 | 0.6210 |
| 19                          | 0.6679 | 0.8045 | 0.5957 | 0.6231 | 0.5713 | 0.8820 | 0.5699 | 0.9570 |
| 20                          | 0.5863 | 0.8607 | 0.6939 | 0.5515 | 0.8364 | 0.6531 | 0.7127 | 0.7618 |
| 21                          | 0.7073 | 0.5427 | 0.5484 | 0.6879 | 0.5769 | 0.5631 | 0.8687 | 0.7953 |
| 22                          | 0.6137 | 0.6690 | 0.6210 | 0.7010 | 0.6331 | 0.6087 | 0.6111 | 0.6844 |
| 23                          | 0.6002 | 0.6894 | 0.7138 | 0.7035 | 0.5326 | 0.6364 | 0.7923 | 0.7517 |
| 24                          | 0.7642 | 0.8005 | 0.6212 | 0.7049 | 0.5533 | 0.6137 | 0.7197 | 0.5459 |
| 25                          | 0.7504 | 0.8361 | 0.6720 | 0.6516 | 0.6915 | 0.7325 | 0.5742 | 0.6937 |
| 26                          | 0.6146 | 0.6626 | 0.6105 | 0.7779 | 0.6544 | 0.7063 | 0.7989 | 0.6611 |
| 27                          | 0.7100 | 0.6465 | 0.7276 | 0.6718 | 0.7268 | 0.5710 | 0.5827 | 0.8820 |

For the 4-layer neural network, the same number of samples as the three-layer neural network is selected for training and error prediction. Firstly, the error test of the node number change of the hidden layer of the middle two layers is carried out, as shown in Table 2.
### Table 2. Error test of the number of nodes in different hidden layers

| Number of hidden layer nodes | 18   | 19   | 20   | 21   | 22   | 23   | 24   | 25   | 26   | 27   |
|------------------------------|------|------|------|------|------|------|------|------|------|------|
| 18                           | 0.4423 | 0.4873 | 0.4354 | 0.4454 | 0.4112 | 0.4379 | 0.4164 | 0.4592 | 0.4545 | 0.5665 |
| 19                           | 0.4487 | 0.4328 | 0.4809 | 0.4720 | 0.5365 | 0.4832 | 0.4609 | 0.4953 | 0.5364 | 0.4695 |
| 20                           | 0.4575 | 0.4354 | 0.4077 | 0.4288 | 0.4847 | 0.4121 | 0.4809 | 0.4301 | 0.5044 | 0.5392 |
| 21                           | 0.4166 | 0.4237 | 0.4703 | 0.4588 | 0.4979 | 0.4563 | 0.4914 | 0.4676 | 0.5366 | 0.4973 |
| 22                           | 0.4569 | 0.4642 | 0.4523 | 0.4748 | 0.4383 | 0.4231 | 0.4308 | 0.5140 | 0.5020 | 0.5517 |
| 23                           | 0.4568 | 0.5079 | 0.4303 | 0.4787 | 0.5331 | 0.5048 | 0.4935 | 0.4758 | 0.5222 | 0.4446 |
| 24                           | 0.4278 | 0.4850 | 0.4630 | 0.4411 | 0.4257 | 0.4224 | 0.4977 | 0.4896 | 0.4657 | 0.4484 |
| 25                           | 0.4708 | 0.4380 | 0.4512 | 0.4139 | 0.4516 | 0.4591 | 0.4943 | 0.4260 | 0.4969 | 0.4568 |
| 26                           | 0.4178 | 0.4205 | 0.5009 | 0.4756 | 0.4465 | 0.4609 | 0.4546 | 0.4598 | 0.5081 | 0.4670 |
| 27                           | 0.4602 | 0.4174 | 0.5103 | 0.4713 | 0.5019 | 0.4483 | 0.4889 | 0.4795 | 0.4835 | 0.4570 |

It can be seen from Table 2 that when the number of nodes in both hidden layers is 20, there is a minimum error. But in Table 2, the learning rate of each layer is the same, so we continue to study whether the error can continue to decline under different learning rates. Table 3 shows the test error of 4-layer neural network with different learning rate.

### Table 3. Error test in different learning rates

| Level 1-2 learning rate | Level 2-3 learning rate | Level 3-4 learning rate 0.01 | 0.02 | 0.04 | 0.06 | 0.08 |
|-------------------------|-------------------------|--------------------------------|------|------|------|------|
| 0.01                    | 0.4210                  | 0.4044                         | 0.04 | 0.06 | 0.08 |
| 0.02                    | 0.4597                  | 0.4876                         | 0.4863 | 0.4952 | 0.4011 | 0.4537 |
| 0.04                    | 0.4103                  | 0.4797                         | 0.5287 | 0.4693 | 0.5035 |
| 0.06                    | 0.3976                  | 0.4217                         | 0.5687 | 0.6061 | 0.5554 |
| 0.08                    | 0.4224                  | 0.4077                         | 0.6322 | 0.5654 | 0.4917 |
| 0.04                    | 0.4274                  | 0.4468                         | 0.4972 | 0.6245 | 0.485 |
| 0.06                    | 0.4165                  | 0.3821                         | 0.4908 | 0.4512 | 0.4635 |
| 0.08                    | 0.4563                  | 0.6122                         | 0.4789 | 0.6393 | 0.4494 |
| 0.06                    | 0.4266                  | 0.4617                         | 0.6288 | 0.6886 | 0.5931 |
| 0.02                    | 0.3967                  | 0.4875                         | 0.4659 | 0.5628 | 0.6232 |
| 0.04                    | 0.4405                  | 0.4698                         | 0.4653 | 0.5251 | 0.6459 |
| 0.06                    | 0.4399                  | 0.4848                         | 0.5083 | 0.5565 | 0.5396 |
| 0.08                    | 0.4022                  | 0.4447                         | 0.5643 | 0.5611 | 0.7970 |
| 0.02                    | 0.4202                  | 0.4514                         | 0.5814 | 0.7865 | 0.4794 |
| 0.04                    | 0.4278                  | 0.4652                         | 0.5077 | 0.5283 | 0.5182 |
| 0.06                    | 0.4664                  | 0.4964                         | 0.5396 | 0.5783 | 0.6281 |
| 0.08                    | 0.4212                  | 0.5685                         | 0.4721 | 0.5787 | 0.5478 |
| 0.08                    | 0.4263                  | 0.4822                         | 0.5165 | 0.7226 | 0.4915 |
| 0.02                    | 0.3922                  | 0.4450                         | 0.5119 | 0.6255 | 0.5353 |
| 0.04                    | 0.4155                  | 0.3894                         | 0.4961 | 0.3858 | 0.6448 |
| 0.06                    | 0.4277                  | 0.4508                         | 0.4497 | 0.4904 | 0.4470 |
| 0.08                    | 0.5041                  | 0.4272                         | 0.4445 | 0.6734 | 0.4854 |
After the test, it can be found that there is a smaller error. Compared with the middle two hidden layers, the change of learning rate of output layer has a greater impact on the error. This is because the transfer function of the hidden layer of the middle two layers of the 4-layer neural network is log sigmoid function, while the transfer function of the output layer is linear function. The function of log sigmoid function is to rearrange and distribute the data in the (0, 1) interval, enlarge the data close to the origin, and compress the data far away from the origin [11]. Therefore, compared with the linear function, the change of the weight threshold has less influence on the output, while the learning rate of the output layer is larger, which will have a greater impact on the accuracy, so a smaller learning rate should be selected.

Based on the above data experiment, a 4-layer neural network structure is finally chosen. The number of nodes in the middle two hidden layers is 20, and the learning rate between each layer is 0.02, 0.06, and 0.02, respectively.

3. Optimization of steam temperature system

The objective of boiler steam temperature system optimization is to reduce the standard heat consumption of the unit. According to the actual situation, the adjustable operation parameters and non-adjustable operation parameters are determined. The adjustable operation parameters are adjusted as the optimization variables of genetic algorithm, and the non-adjustable operation parameters remain unchanged as constraints.

In the training of BP neural network, there are 12 inputs, including 5 operable variables, which are: superheater desuperheating water flow, reheater desuperheating water flow, burner swing angle, superheater flue gas baffle opening, reheater flue gas baffle opening. According to the boiler operating condition samples, the range of the operable quantity is determined, as shown in Table 4.

| Operable quantity       | upper limit | lower limit |
|-------------------------|-------------|-------------|
| superheater desuperheating water flow (t/h) | 120 | 60 |
| reheater desuperheating water flow (t/h)     | 50 | 0 |
| burner swing angle (DEC)       | 70 | 50 |
| superheater flue gas baffle opening (%)     | 100 | 20 |
| reheater flue gas baffle opening (%)     | 100 | 20 |

Table 5. Optimal Solution for Different Parameters in Genetic Algorithms

| Crossover rate | Mutation rate | 0.1 | 0.2 | 0.3 | 0.4 | 0.5 | 0.6 | 0.7 | 0.8 | 0.9 |
|----------------|--------------|-----|-----|-----|-----|-----|-----|-----|-----|-----|
| 0.4            | 0.0001       | 7897.7 | 7899.4 | 7937.0 | 7907.0 | 7913.0 | 7917.7 | 7906.6 | 7903.5 | 7920.6 |
|                | 0.001        | 7900.0 | 7902.7 | 7886.0 | 7898.8 | 7886.7 | 7866.4 | 7884.8 | 7883.2 | 7882.9 |
|                | 0.01         | 7894.0 | 7884.3 | 7882.4 | 7881.8 | 7881.7 | 7881.7 | 7881.7 | 7881.7 | 7881.7 |
|                | 0.1          | 7895.3 | 7888.8 | 7884.0 | 7884.0 | 7883.5 | 7882.7 | 7884.6 | 7883.3 | 7882.3 |
| 0.6            | 0.0001       | 7916.4 | 7906.9 | 7891.0 | 7900.7 | 7910.0 | 7912.2 | 7902.3 | 7989.2 | 7926.7 |
|                | 0.001        | 7898.2 | 7889.2 | 7885.1 | 7885.8 | 7884.9 | 7881.8 | 7882.7 | 7885.3 | 7883.7 |
|                | 0.01         | 7888.4 | 7882.6 | 7884.7 | 7881.9 | 7881.7 | 7881.7 | 7881.7 | 7881.7 | 7881.7 |
|                | 0.1          | 7912.1 | 7886.2 | 7886.7 | 7883.7 | 7884.2 | 7882.9 | 7883.0 | 7883.3 | 7882.3 |
| 0.8            | 0.0001       | 7914.1 | 7898.7 | 7888.0 | 7901.2 | 7898.8 | 7896.6 | 7886.6 | 7889.5 | 7886.8 |
|                | 0.001        | 7902.9 | 7899.8 | 7891.4 | 7888.7 | 7883.2 | 7888.1 | 7882.8 | 7882.6 | 7881.8 |
|                | 0.01         | 7899.0 | 7882.2 | 7882.4 | 7881.9 | 7881.8 | 7881.9 | 7881.7 | 7881.6 | 7881.7 |
|                | 0.1          | 7895.7 | 7888.9 | 7886.2 | 7884.0 | 7884.3 | 7883.2 | 7883.0 | 7882.7 | 7883.5 |

Through the genetic algorithm, we hope to get the optimal solution and its corresponding optimal operation quantity. Therefore, by comparing the optimal solutions obtained by different crossover rate,
mutation rate and generation gap, the minimum standard heat consumption and its corresponding parameters are selected as the optimal parameters of the genetic algorithm. Set the number of individuals as 200 and the maximum genetic algebra as 500. Select one of the samples to optimize. The solution set of the optimal solution obtained by experiment is shown in Table 5.

It can be seen from the above table that no matter what kind of value of crossover rate and generation gap is taken, the optimal solution will always get the minimum value when the variation rate is 0.01; the influence of crossover rate is more obvious, and the greater the crossing rate is, the smaller the optimal solution will be; and the influence of generation gap is related to the mutation rate. When the mutation rate is small, the smaller generation gap is easier to approach the ideal optimal solution, that is, to keep fewer parents. When the mutation rate is large, more parents are reserved to approximate the ideal optimal solution.

The optimized operation capacity and the comparison of standard heat consumption with the original working condition can be seen in Table 6.

Table 6. Comparison of parameters before and after optimization

| Operable variables                          | Original working condition | Optimized working condition |
|---------------------------------------------|---------------------------|-----------------------------|
| superheater desuperheating water flow (t/h) | 71.29                     | 64.37                       |
| reheater desuperheating water flow (t/h)    | 0                         | 0                           |
| burner swing angle (DEC)                   | 70                        | 68                          |
| superheater flue gas baffle opening (%)    | 70                        | 25                          |
| reheater flue gas baffle opening (%)       | 50                        | 24                          |
| standard heat consumption (kJ/kW·h)        | 7839.15                   | 7639.80                     |

It can be seen from the table that the standard heat consumption has been significantly reduced after optimization, and the heat consumption rate has been reduced by 2.5% under this condition.

100 groups of working conditions are optimized in the same way, as shown in Figure 1. It is found that the standard heat consumption after optimization is lower than that before optimization, and the average standard heat consumption is reduced by 153.93 kJ / (kW · h). The maximum standard heat consumption can be reduced by 199.34 kJ / (kW · h).

![Figure 1. Comparison of standard heat consumption before and after optimization of 100 sets of samples](image)

4. Conclusion
In this paper, BP neural network and genetic algorithm are used to model and optimize the boiler steam temperature system for a 1000MW unit, and the following conclusions are as follows:

1) For the research object of this paper, through comparing the error test of 3-layer and 4-layer BP neural network, the final choice is 4-layer BP neural network with 20 nodes in the middle and learning
rate of 0.02, 0.06 and 0.02 respectively. The error between the actual output and the ideal output is 0.36\%, and the maximum relative error of the sample is 1.22\%.

2) Through the comparative calculation of three kinds of crossover rate, four kinds of mutation rate and nine kinds of generation gap, the optimal parameters of genetic algorithm are determined as follows: crossover rate 0.8, mutation rate 0.01, and generation gap 0.8.

3) By changing the parameter ranges of superheater desuperheating water flow, superheater flue gas baffle opening, and reheater flue gas baffle opening, the standard heat consumption after optimization of all 100 groups of working conditions is lower than that before optimization. On average, the heat consumption rate of the unit can be reduced by 1.96\%, that is, the standard heat consumption can be reduced by 153.93 kJ/(kW·h). The maximum standard heat consumption can be reduced by 199.34 kJ/(kW·h).

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