MODELLING AND COMBUSTION OPTIMIZATION OF COAL-FIRED HEATING BOILER BASED ON THERMAL NETWORK

by

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Based on the thermal network and the MATLAB artificial intelligence toolkit, a combustion optimization hybrid modelling of a 300 MW coal-fired power station boiler is carried out. The boiler is optimized for combustion, and the weight coefficient method is used to convert the multi-objective optimization problem into a single-objective optimization problem. The results show that the relative error average absolute value of the boiler thermal efficiency and NO_x *emission mass concentration calibration samples are 0.142% and 1.790%, the model has good accuracy and generalization ability. The weight coefficient method can select the corresponding weight coefficient according to the actual situation, with the boiler thermal efficiency or* NO_x *emission mass concentration as the optimization focus, which has certain guiding significance for combustion optimization.*

Key words: *power station boiler, thermal network, combustion optimization,* NO_x *emissions, heating modelling, multi-objective optimization*

Introduction

The factors that affect the thermal efficiency and NO_x emissions of coal-fired power plant boilers are more complex. For a given boiler, factors such as boiler load, furnace oxygen content, furnace air distribution mode and coal feeder combination mode will affect boiler thermal efficiency and NO_x emissions, and these influencing factors mutual coupling presents a complex non-linear relationship, making it difficult to analyze boiler combustion data.

At present, intelligent algorithms are being vigorously promoted in the thermal efficiency and NO_x emission modelling of coal-fired power plant boilers. Some scholars have established prediction models of NO_x emission concentration and boiler thermal efficiency based on intelligent algorithms, using BP neural networks and support vector machines. Some scholars are based on nerves. The network established a hybrid model of boiler combustion, which realized the soft measurement of various parameters such as NO_x emissions, fly ash carbon content and boiler thermal efficiency. Some scholars realized the optimization of boiler combustion with the help of genetic algorithms. The aforementioned modelling and optimization many ideas and methods have their own characteristics and are worth learning from.

On the basis of previous studies, the author uses the operating data of a 300 MW coal-fired power station boiler, and based on the MATLAB artificial intelligence toolkit, the BP

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neural network is used to establish a BP neural network model for boiler combustion characteristics of boiler thermal efficiency and NO_x emission mass concentration [1]. On this basis, we use genetic algorithm (GA) to establish an optimization model for boiler combustion, and transform the multi-objective optimization problem of boiler thermal efficiency and NO_x emission mass concentration into a single-objective optimization problem through the weight coefficient method to transform the weight coefficient, thereby achieving boiler thermal efficiency and NO_x emission quality multi-objective optimization of concentration.

Research object

A 300 MW coal-fired power plant boiler is DG-1025/17.5-II4 type subcritical parameters, tangential combustion, natural circulation drum boiler. The boiler adopts a single furnace, open air lay-out, primary reheating, balanced ventilation, solid exhaust slag, full steel frame, full suspension structure, burning bituminous coal, with a metal rain cover on the top of the furnace [2]. The burner adopts a horizontal dense and light type direct current swinging pulverized coal burner, and two dense and light air and powder air-flow are injected from the four corners of the furnace. Each corner burner is arranged with 13 layers of nozzles, including five layers of primary air outlets (A, B, C, D, E) and eight layers of secondary air outlets (including one layer of overfire air (OFA) nozzles and seven layers of secondary air outlets (AA, AB, BC, CC, DD, DE, EE). The pulverizing system adopts a medium-speed coal mill, a cold primary fan, a positive pressure direct blowing pulverizing system, and is equipped with five coal mills (A, B, C, D, E).

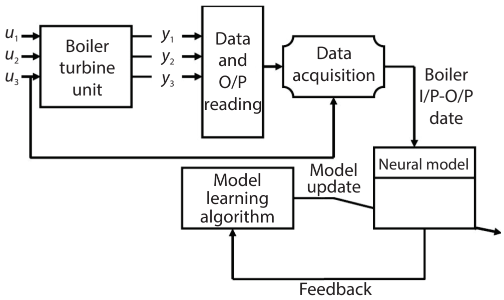

Figure 1. The BP neural network model of boiler combustion characteristics

The BP neural network model

Establish a BP neural network model

The paper uses the BP neural network to establish the boiler combustion characteristics BP neural network model of boiler thermal efficiency and NO_x emission mass concentration. The model has 20-dimensional inputs, including generator power, furnace oxygen content, primary wind speed, secondary air door opening and burnout air door opening and other parameters represent the influence of boiler load, excess air coefficient, primary and secondary air ratio, and over-fire air on the combustion characteristics of the boiler [3]. The schematic diagram of the model is shown in the fig. 1.

The working conditions selected for this modelling are all around the rated load of 300 MW, and the BP neural network model of boiler combustion characteristics is only for full load conditions. The test selects 100 sets of boiler operating data, of which 85 sets of data are used to train the BP neural network. Fifteen sets of data are used for verification. The sample data is shown in tab. 1, where ρ is the mass concentration of emission NO_x and η is the thermal efficiency of the boiler. When establishing the BP neural network model of the boiler's thermal efficiency and NO_x emission mass concentration, the network's training cannot be too saturated, that is, the network training error cannot be too low. Oversaturated network training will reduce the generalization of the network, and its training error should be controlled within a reasonable range [4]. For boiler thermal efficiency, due to its own variation range comparison. Therefore, the training error of its prediction should be controlled within 0.5%, the variation

Table 1. Test sample data

Serial number	Power [MW]	Wind speed of each primary wind [ms^{-1}]					Coal feed amount of each coal feeder [th^{-1}]				
		A	*B*	*C*	*D*	*E*	*A*	*B*	*C*	*D*	*E*
1	303.9	30.98	35.72	30.2	43.76	36.58	50	24.06	29.71	39.97	32.74
–	–	–	–	–	–	–	–	–	–	–	–
18	297	34.75	37.04	32.5	44.69	35	42	26.4	36.56	38	29.84
19	307.4	32.46	33.51	25.75	41.09	37.84	44	25.49	31.26	42.85	26.47
20	306.3	26.01	28.83	35.58	37.35	32.6	45	23.3	34.75	39.36	29.76
–	–	–	–	–	–	–	–	–	–	–	–
99	305	34.81	33.48	30.9	43.54	31.39	44	22.26	30.31	32.15	39.65
100	305.7	30.25	33.26	31.03	40.61	31.7	40	26.79	33.19	43.67	24.24

Serial number	Oxygen mass fraction [%]	Opening degree of each secondary air door [%]							Burnout throttle opening [%]	ρ [mgm^{-3}]	η [%]
		AA	*AB*	*BC*	*CC*	*DD*	*DE*	*EE*			
1	3.02	64.9	48.93	42.79	33.34	45.85	52.46	58.64	72.33	412.76	92.26
–	–	–	–	–	–	–	–	–	–	–	–
18	4.33	75.69	62.98	53.14	37.42	49.22	56.54	53.02	33.72	496.26	91.98
19	3.1	71.18	64.97	45.18	40.2	49.61	52.36	51.7	69.56	394.45	91.32
20	2.58	53.25	42.79	42.75	41.55	54.89	66.33	70.69	61.05	353.09	91.37
–	–	–	–	–	–	–	–	–	–	–	–
99	2.69	68.82	47.91	45.33	31.38	40.49	49.44	49.85	63.34	432.04	92.07
100	2.99	69.09	58.99	49.17	35.37	46.59	52.02	35.88	22.95	404.45	92.34

range of NO_x emission mass concentration is relatively large, and the training error should be controlled within 5%. When training the network, the training error should be compared with the calibration the errors are combined and compared, so that the BP neural network model of the boiler combustion characteristics meets both the training error requirements and the network generalization requirements.

The paper uses the feedforward net function that comes with the BP neural network to create the BP neural network, using a three-layer network, the hidden layer is set to one layer, and the trainlm function is used as the training function of the network. The transfer function and the learning rate are the default of feedforwarded function. After setting, the training effect is best when the number of hidden layer nodes is 24.

Effectiveness verification of BP neural network model

In order to observe and compare intuitively, the paper sorts out the 2-D output of the BP neural network model (*i.e.*, boiler thermal efficiency and NO_x emission mass concentration), respectively, and compares the training effects and relative results of 85 sets of training samples and 15 sets of calibration samples for boiler thermal efficiency [5]. The errors are summarized separately in the same figure, and the training effects and relative errors of the NO_x emission mass concentration are summarized and sorted. The results are shown in figs. 2-5.

Figure 2 shows the training effect of boiler thermal efficiency. Figure 3 is the relative error diagram of boiler thermal efficiency samples. From fig. 3, the maximum absolute relative

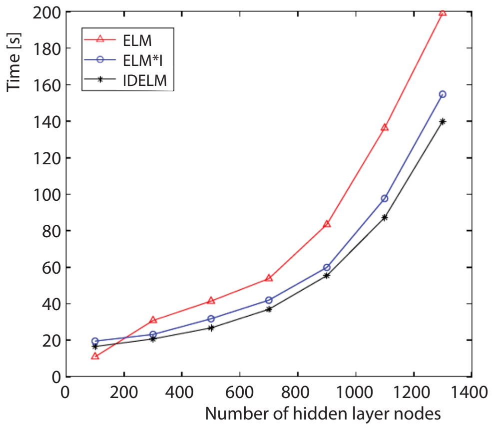

Figure 2. Training effect of boiler thermal efficiency

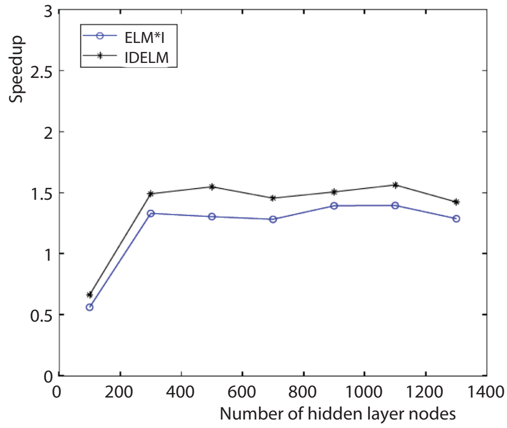

Figure 3. Relative error of boiler thermal efficiency sample

error of boiler thermal efficiency training samples is 0.176%. The training accuracy meets the requirements and has high generalization.

Figure 4 shows the training effect of the emission mass concentration of NO_x. Figure 5 is the relative error graph of the emission mass concentration sample of NO_x. From fig. 5, the maximum relative error of the training sample NO_x emission mass concentration is 3.312%, relative the average absolute value of the error is 0.469%. The accuracy of training and calibration meets the requirements.

The ELM*I refers to a feedforward artificial neural network algorithm, ID-ELM refers to the improved classification algorithm of extreme learning machines, and ELM refers to the extreme learning machine algorithm.

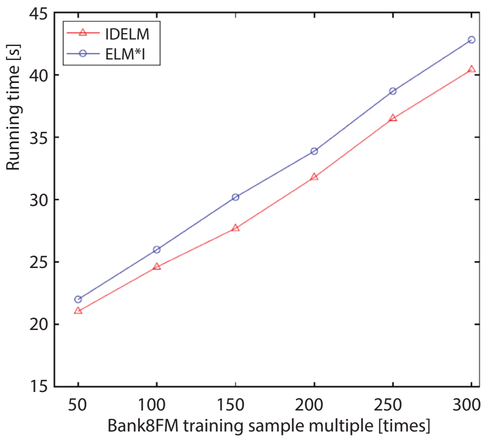

Figure 4. Training effect of NO_x emission mass concentration

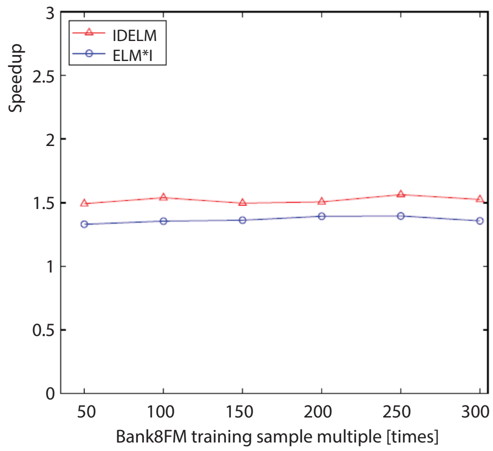

Figure 5. A relative error of emission mass concentration samples

Boiler combustion optimization model based on genetic algorithm

Establishment of combustion optimization model

Based on the established BP neural network model of boiler thermal efficiency and NO_x emission mass concentration boiler combustion characteristics, the paper establishes a genetic algorithm-based boiler combustion optimization model [6]. The fitness function in the optimization model is replaced by the BP neural network model, and BP neural the network model is used to evaluate the optimization effect. The optimization goals are boiler thermal efficiency and NO_x emission mass concentration. This problem essentially belongs to the category of multi-objective optimization. The author gives a weight coefficient to the two objectives to be optimized, and linearly adds them to convert the multi-objective optimization problem into a single-objective optimization problem. Adaptation of genetic algorithm the degree function can be expressed:

$$\min F(x) = a(-\eta) + \beta\rho + 1 \tag{1}$$

where α and β are the weighting coefficients of boiler thermal efficiency and NO_x emission mass concentration, α takes the commonly used coefficients 0.3, 0.7, 0.4, 0.6, 0.5, 0.5, 0.6, 0.6. Then take the commonly used coefficients 0.4, 0.7, 0.3 for β to perform calculation analysis and research, and the last item plus 1 is to ensure that the fitness value is always positive.

The population individuals are all binary coded, the total population individuals' number is set to 50, the binary digits of each variable are 20, a total of 20 dimensions. We set the maximum number of iterations as 60. In order to ensure the rationality of the optimization results, the variables of each individual in the population, that is, the boiler combustion parameters, should be constrained within a certain range [7]. The constraint range is determined based on the actual operating experience of the power plant, that is, the decimal system represented by the binary code of each variable parameter constraints are within a certain range, which can narrow the optimization range and improve the feasibility of the optimization results. The parameter constraints are shown in tab. 2.

Table 2. Parameter constraint range

Parameter	Wind speed of each primary wind [ms^{-1}]	Coal feed amount of each coal feeder [th^{-1}]	Opening degree of each secondary air door [%]	Burnout throttle opening [%]	Oxygen mass fraction [%]
Bound range	25-45	0-50	20-100	20-100	2-5.5

Optimization results

The optimization results of boiler thermal efficiency and NO_x emission mass concentration under different weighting coefficient ratios is shown in figs. 6-10. In order to better compare the optimization results, tab. 3 lists two groups of boiler original operating data and five groups of different weighting coefficient ratios [8]. The optimization results. The first and second groups of data are the original operating data. The third to seventh groups correspond to the weighting coefficient ratios of boiler thermal efficiency and NO_x emission mass concentration of 0.3, 0.7, 0.4. Optimized results at 0.6, 0.5, 0.5, 0.6, 0.4, and 0.7, 0.3. The first set of data is 0.3 and the second set of data is 0.7, 0.4 is the original operating data. Optimizing the results of the first set of data is 0.6, 0.5, the results of the second set of data are 0.5, 0.6, 0.4, and finally calculated as the ratio of the first set of data to the second set of data is 0.7, 0.3.

Table 3. Comparison of operating parameters before and after optimization

Serial number	Power [MW]	Wind speed of each primary wind [ms^{-1}]					Coal feed amount of each coal feeder [th^{-}]				
		A	*B*	*C*	*D*	*E*	*A*	*B*	*C*	*D*	*E*
1	297.67	30.45	33.79	30.73	38.69	34.36	47	24.16	33.65	27.14	35.84
2	305.07	32.6	35.31	32.96	42.99	34.74	49	27.49	39.49	28.97	27.51
3	300	26.67	26.93	26.6	33.16	30.2	39.49	36.63	33.43	30.82	27.31
4	300	27.51	27.49	28.57	32.25	29.88	38.11	33.39	30.69	36.42	28.87
5	300	27.98	28.92	27.26	34.87	31.96	35.67	32.83	35.42	30.69	32.85
6	300	28.57	29.31	28.12	33.11	30.41	34.33	30.22	34.53	33.19	34.24
7	300	28.17	29.51	29.13	35.66	31.96	32.96	30.02	34.2	33.21	35.21
Serial number	Oxygen mass fraction [%]	Opening degree of each secondary air door [%]							Burnout throttle opening [%]	ρ [mgm^{-3}]	η [%]
		AA	*AB*	*BC*	*CC*	*DD*	*DE*	*EE*			
1	2.73	70.6	44.99	44.19	35.46	34.83	52.25	46.32	69.76	489.84	92.129
2	3.19	65.55	49.87	40.33	39.62	40.51	56.98	49.16	70.46	429.19	90.96
3	2.59	34.06	44.2	58.56	73.84	45.23	56.43	51.43	71.15	316.77	92.3
4	2.73	36.45	46	62.79	70.83	49.54	53.92	53.51	61.56	361.68	92.75
5	2.95	45.55	35.18	63.26	68.28	46.08	56.38	51.07	55.82	379.04	93.37
6	3.28	51.97	61.83	49.63	63.02	53.07	46.19	55.01	50.24	423.94	93.71
7	3.54	49.19	59.57	55.47	65.21	65.18	51	56.23	42.18	477.5	93.96

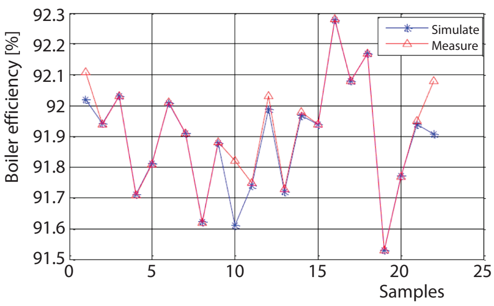

Figure 6. Optimization results when $\alpha = 0.3$ and $\beta = 0.7$

When $\alpha = 0.3$, $\beta = 0.7$, see fig. 6, the weighting coefficient ratio of the boiler thermal efficiency is 30%, and the weighting coefficient ratio of the emission mass concentration of NO_x is 70%, more attention should be paid to the emission quality of NO_x. At this time, the emission mass concentration of NO_x is reduced to 316.77 mg/m^3, which is nearly 28% lower than the average emission mass concentration of NO_x (440 mg/m^3) of the 100 operating data sets. The optimization effect of the emission mass concentration is significant [9]. At the same time, the boiler thermal efficiency is increased to 92.3%, which is 0.6% higher than the average value of boiler thermal efficiency (91.7%) of the 100 sets of operating data. Compared with the operating data, the optimized combustion parameters of the boiler show that the amount of coal fed to each layer is more uniform, and the air distribution form is the lower anoxic combustion method, and the boiler thermal efficiency and NO_x emission mass concentration have been improved.

When $\alpha = 0.4$ and $\beta = 0.6$, see fig 7, the weight coefficient ratio of boiler thermal efficiency is 40%, and the weight coefficient ratio of NO_x emission mass concentration is 60%, the more attention is paid to the emission mass concentration of NO_x, The mass concentration of emission NO_x was reduced from the average to 361.68 mg/m^3, a decrease of about 18%. The optimization effect of mass concentration of emission NO_x was more significant; at this time, the boiler thermal efficiency increased from the average to 92.75%, an increase of 1.05 %, the optimization effect is more obvious than when $\alpha = 0.3$ and $\beta = 0.7$.

When $\alpha = 0.5$, $\beta = 0.5$, see fig. 8, the boiler thermal efficiency and the weighting coefficient ratio of the emission mass concentration of NO_x are the same, the two attention levels are also the same, and the emission mass concentration of NO_x decreases from the average to 379.04 mg/m^3, a reduction of about 14%. Boiler thermal efficiency increased from the average to 93.37%, an increase of 1.67%, compared to the current status of boiler thermal efficiency, its optimization effect is significant, and this weighting coefficient ratio is also the majority power plants tend to be more in-depth research under this weighting coefficient ratio.

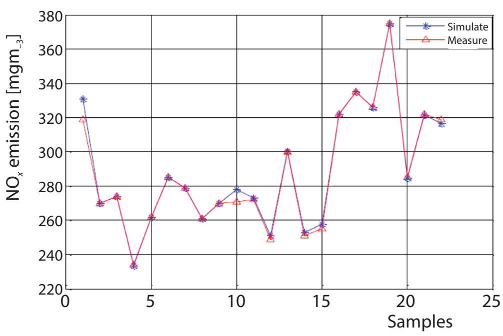

Figure 7. Optimization results when $\alpha = 0.4$ and $\beta = 0.6$

When $\alpha = 0.6$, $\beta = 0.4$, see fig. 9, the weighting coefficient ratio of the boiler thermal efficiency is 60%, and the weighting coefficient ratio of the emission mass concentration of NO_x is 40%, the boiler thermal efficiency is more concerned, hope further improve the thermal efficiency of the boiler. At this time, the emission mass concentration of NO_x is reduced to 423.94 mg/m^3, which is nearly 4% lower than the average value [10]. The optimization effect is significantly worse than the previous weight coefficient ratio (70%, 60%, and 50%). The thermal efficiency of the boiler has increased from the average value to 93.71%, an increase of 2.01%, and its optimization effect is significant, but this is based on the premise of sacrificing a certain NO_x emission mass concentration.

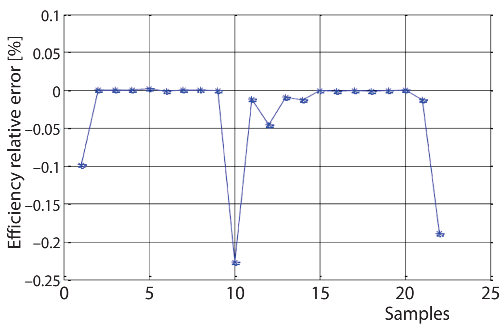

Figure 8. Optimization results when $\alpha = 0.5$ and $\beta = 0.5$

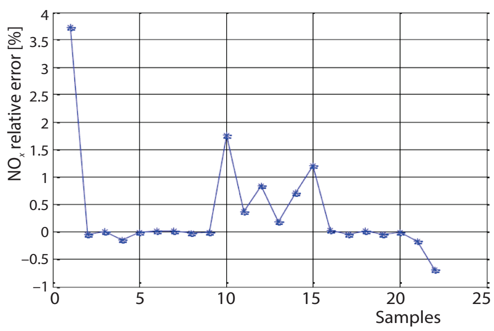

Figure 9. Optimization results when $\alpha = 0.6$ and $\beta = 0.4$

Conclusion

The average absolute value of the relative error of the test sample is 1.790%, which can meet the requirements. The optimized primary wind speed is lower than the original operating data under the premise of ensuring the transportation of pulverized coal. The coal feed rate of each layer is basically uniform and burning anoxic combustion in the lower part of the device and increasing the amount of burn-out air are beneficial to inhibit the formation of NO_x, while a proper increase in the oxygen mass fraction and the use of equal air distribution are beneficial to improve the thermal efficiency of the boiler.

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