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Modeling and coordinative optimization of NO_x emission and efficiency of utility boilers with neural network

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Abstract−An empirical model to predict the boiler efficiency and pollutant emissions was developed with artificial neural networks based on the experimental data on a 360 MW W-flame coal fired boiler. The temperature of the furnace was selected as an intermediate variable in the hybrid model so that the predictive precision of NO_x emissions was enhanced. The predictive precision of the hybrid model was improved compared with the direct model. Three optimal operational objects were proposed in order to minimize the fuel and environmental costs. Based on the neural network model and optimal objects, a genetic algorithm was employed to seek real-time solution every 30 seconds. Optimum manipulated variables such as excess air, primary air and secondary air were obtained under different optimal objects. The above algorithm interconnected with a distributed control system (DCS) formed the supervisory control and achieved real-time coordinated optimization control of utility boilers.

Key words: Coal Combustion, Efficiency, NO_x, Coordinative Optimization, Artificial Neural Networks, Genetic Algorithm

INTRODUCTION

Coal remains the main fuel of power stations in China. However because of mutable coal quality, rise of coal price, frequent retrofits and long interval between thermal tests, the operators have no reliance to adjust the boilers in time and the boilers have low efficiency and high pollutant emissions. Coal-fired boilers in China are in a dilemma to improve boiler efficiency and reduce pollutant emissions simultaneously. More and more attention is paid to optimal decision-making of high efficiency and low emissions.

Boiler retrofit is an effective way to reduce NO_x emissions, but it is costly and the unit has to be shut down during the retrofit. In recent years boiler unit optimal control has been an alternative way to improve combustion efficiency and reduce pollutant emissions. A model to predict the boiler operational property is the foundation and key to boiler unit optimal control.

Predictive models can be divided into three classes: mechanism models, empirical models and hybrid models. Computational fluid dynamics (CFD) is one of the mechanism models that can help designers to optimize the design or retrofit of boilers, but cannot meet the real-time demand of boiler optimization control because of complex mechanisms and time-consuming calculations [1-3]. The artificial neural network (ANN) model is an empirical model based on experimental data that has been widely used in system identification owing to its capability of good generalization, self-adaptation and self-learning [4-7]. The hybrid model is a synthesis of the mechanism model and empirical model. Theoretically speaking, it has the advantages of the former two models but its application is scanty.

The limitation on pollutant emissions is more and more stringent in China. If the emissions exceed the standard, power stations have to pay a penalty, so the economics has been affected. Therefore, the optimization objects should involve coordination between environment protections and economics [8]. In order to minimize the fuel and environmental costs, three optimal operational objects were presented to achieve the above objectives.

Based on the predictive model and optimal objectives, a genetic algorithm (GA) was applied to seek a real-time solution every 30 seconds. Optimum manipulated variables such as excess air, primary air and secondary air were obtained under different optimal objects. Optimization results were not only provided to operators as references but also connected with the unit DCS to achieve automatic closed-loop optimization control.

ARTIFICIAL NEURAL NETWORKS AND GENETIC ALGORITHM

1. ANN and Back Propagation Algorithm

An artificial neural network is composed of large amounts of artificial neurons simulating biological neurons interconnected. A back propagation (BP) network is one of feed forward neural networks. Fig. 1 is a sketch of a three-layer BP network, in which V_{ij} is the weighting vector between input layer and hidden layer and W_{jk} is the weighting vector between hidden layer and output layer. If the network output is not equal to the experimental data we get an error signal, which is used to amend the network weights. The error back propagation and network weights amending comprise the learning progress of a BP network until the expected error target or the predefined learning times are achieved.

Neural networks, with their remarkable ability to derive meaning from complicated or imprecise data, can be used to extract patterns and detect trends that are too complex to be noticed by either humans or other computer techniques. So they can be used to predict

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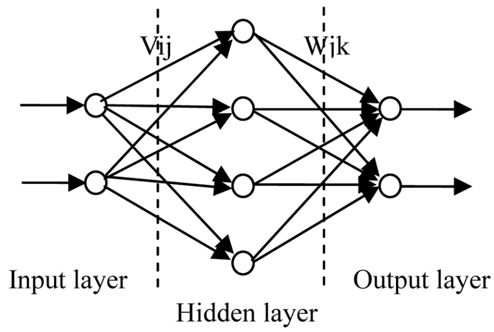

Fig. 1. Sketch of a three-layer BP network.

the combustion characteristics of boilers based on the experimental data. In engineering applications a BP network is usually employed because its learning algorithm is simple and convenient to realize by computers [9-13].

2. Genetic Algorithm

Genetic algorithm (GA) is a random optimization algorithm based on biological natural selection and inheritance mechanism, which presents the solution as chromosome survival of the fittest. Through the evolution of chromosomes including operations such as reproduction, crossover, mutation and selection generation by generation, GA ends up with the individual fittest environment, namely the optimal solution or the satisfactory solution. GA has been widely concerned in complex optimization problems because of concealed parallel properties and search in global solution space [14,15].

EXPERIMENTS AND DATA COLLECTION

We applied an orthogonal experiment design method to carry out the experiments on a 360 MW coal fired boiler which adopted a W-flame furnace [16-18]. There are 36 direct burners installed in the front and rear arch which eject to the centre of the furnace. The flame folds up at the furnace hopper and forms W type. Fig. 2 is

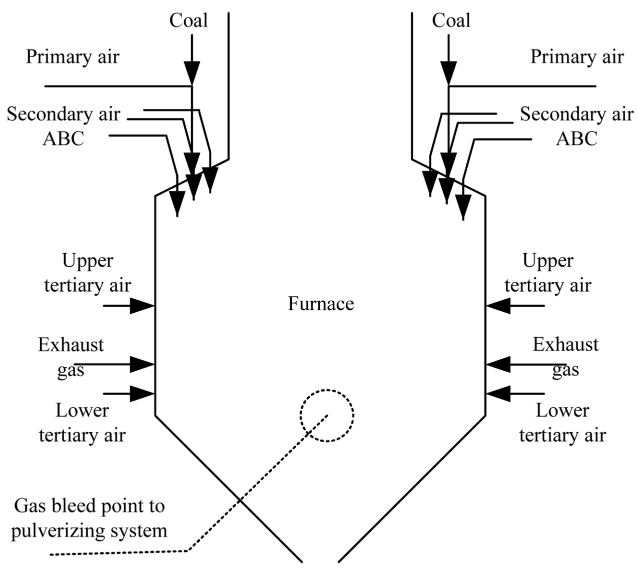

Fig. 2. Sketch of the boiler.

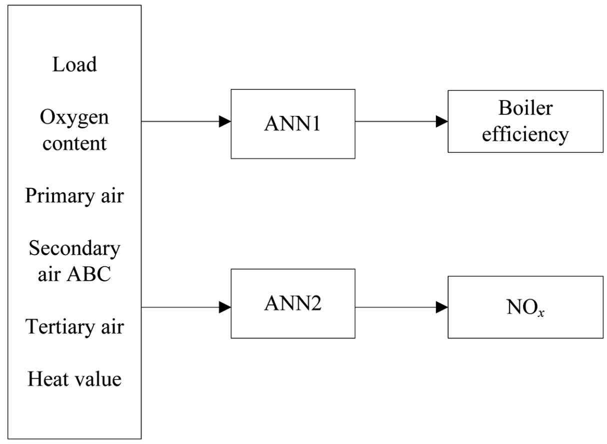

Fig. 3. Direct model of boiler efficiency and NO_x emission.

the sketch of the boiler. A ZWCT-1C type microwave carbon determination system was installed in each horizontal flue to measure carbon in ash (CIA) real time.

In order to study the combustion characteristics in a wide range of unit loads the experiments were made up of 54 groups: 1-18 under 100% load, 19-36 under 85% load and 37-54 under 70% load. Partial data are listed in Table 2.

RESULTS AND DISCUSSION

1. Direct ANN Modelling

Boiler NO_x emission and efficiency are influenced by several factors and the mechanism model could not meet the demand of real-time optimization, so we developed an ANN model to predict the boiler efficiency and pollutant emissions with the non-linear mapping property of a neural network.

At first we applied the direct model method to predict the boiler efficiency and NO_x emissions seen in Fig. 3. Although the direct model is simple to realize, the predictive precision is not satisfactory. The average relative error of boiler efficiency and NO_x emissions achieved 0.527% and 5.078% as seen in Table 1.

2. Hybrid ANN Modelling

In order to improve the predictive precision of the model, a hybrid ANN modelling method is proposed. According to the boiler combustion mechanism the boiler efficiency is mainly affected by carbon in ash and furnace temperature. The two variables are impacted by several operating parameters, such as primary air, secondary air, tertiary air and oxygen content in flue gas. From NO_x emission mechanism, we can see that NO_x emissions and boiler furnace temperature have strong direct relationships. An experimental

Table 1. Predictive precision comparison of two modeling methods

Items	Average predictive error of boiler efficiency (%)	Average predictive error of NO_x (%)
Direct model	0.527	5.078
Hybrid model	0.47	3.641
Improvement of precision	11.09	28.3

Table 2. Experimental data of thermal test

Case	Load (MW)	Coal property			Pressure of primary air (mbar)	The opening value of secondary air damp (%)			The opening value of tertiary air damp (%)		Oxygen content (%)	Temperature of furnace (°C)	NO_x ($mg \cdot Nm^{-3}$)	Carbon in ash (%)
		Volatile (%)	Sulphur (%)	Heat value ($kJ \cdot kg^{-1}$)		A	B	C	Upper	Lower				
1	347.84	9.97	4.25	21.70	3.57	53	22	43	33	33	1.805	1426.00	824.04	4.620
2	350.41	9.53	4.27	21.28	3.57	67	30	55	45	45	1.625	1391.46	825.69	4.270
3	347.79	9.50	4.36	21.11	3.57	74	30	66	57	57	2.575	1425.82	864.60	4.245
22	302.48	9.60	4.41	20.93	3.5	45.9	10	45.9	5	50	1.435	1411.98	693.31	6.000
23	296.88	9.67	4.26	19.96	3.5	60	20	55	15	65	1.315	1396.15	541.76	4.495
24	302.47	9.94	4.47	22.31	3.5	80	30	70	30	85	1.280	1385.77	460.91	4.130
45	254.55	9.96	4.59	21.7	3.1	30	5	30	10	20	3.345	1361.69	644.36	2.855
46	254.43	9.77	4.18	19.36	2.94	41	10	42	20	50	2.685	1280.34	608.84	5.975
47	255.28	10.06	4.49	22.08	3.1	50	20	55	50	100	3.500	1365.67	626.62	6.855

data correlation analysis also demonstrated that the boiler efficiency and NO_x emissions depended closely on the furnace temperature. Therefore, the temperature of the furnace was applied as the intermediate variable of the model. By combining the above mechanism analysis with the experimental data, the hybrid boiler combustion model can be established as:

$$
\begin{aligned}
T_F &= f_1(M_v, D_v) \\
C_{fh} &= f_2(M_v, T_F, D_v) \\
NO_x &= f_3(M_v, T_F, D_v) \\
\eta &= f_4(M_v, T_F, C_{fh}, D_v)
\end{aligned} \tag{1}
$$

M_v is a manipulated vector composed of oxygen content in flue gas, primary air, secondary air, and tertiary air. D_v is the disturbance vector composed of LHV (low heat value), ash, volatile content of coal and load. T_F is the temperature of furnace predicted, C_{fh} is predicted carbon in ash, NO_x is NO_x emission predicted, f_1, f_2 and f_3 are ANN models to predict the temperature of furnace, CIA and NO_x emissions, f_4 is the function to calculate the boiler efficiency, η is the boiler efficiency predicted.

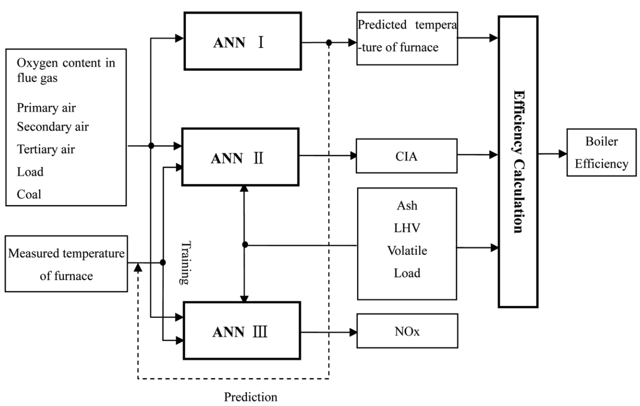

Fig. 4. Hybrid model of boiler efficiency and NO_x emission.

A hybrid model of boiler efficiency and NO_x emission can be established as Fig. 4. During the model application the furnace temperature was predicted by ANN I, then it was passed as the input to ANN II and III to predict the CIA and NO_x emissions seen as the dashed line in Fig. 4. Whereas, during model training in order to improve the ANN precision of models II and III, the measured temperature of the furnace was used as the input of ANN II and III. The boiler efficiency was obtained through further calculation based on CIA predicted and coal type etc.

During the model training the experimental data are normalized first so that the input components have the same dimension from the beginning of model training. Then 47 groups are randomly selected as the training set to train the network and the others as the test set to check the generalization ability of the network. The hidden layer and the output layer both employ sigmoid activation function. A BP algorithm was applied to train the network and end when the test error was less than 0.01. Table 3 is the comparison between measured values of test set and the predict values, from which we can see that the model can predict the NO_x emission characteristics in real time and exactly. The results in Table 4 show that the model can predict the boiler CIA in time and satisfy the need for combustion optimization. Boiler efficiency can be calculated based on CIA predicted. Table 1 lists the predictive precision of two modelling methods, from which we can see that the hybrid model has greatly improved the predictive precision.

3. Optimization Objects

Boiler efficiency is the concentration of power stations, and vari-

Table 3. Comparisons between predicted NO_x emissions and real NO_x emissions

Case	1	2	3	22	23	24	45	46	47
NO_x real value ($mg \cdot Nm^{-3}$)	824.04	825.69	864.60	693.31	541.76	460.91	644.36	608.84	626.62
NO_x predicted ($mg \cdot Nm^{-3}$)	823.41	839.08	895.09	712.95	567.02	478.46	648.05	598.76	644.60
Relative error*100 (%)	−0.076	1.622	3.526	2.833	4.663	3.808	0.573	−1.656	2.869

Table 4. Comparisons between predicted CIA and real CIA

Case	1	2	3	22	23	24	45	46	47
Real CIA (%)	4.620	4.270	4.245	6.000	4.495	4.130	2.855	5.975	5.490
CIA predicted (%)	4.570	4.969	4.064	5.430	4.202	4.190	2.974	5.717	4.709
Relative error*100 (%)	−1.082	16.370	−4.264	−9.500	−6.518	1.453	4.168	−4.318	−12.796

ous means have been tried to improve the efficiency. At present, pollutant control is attracting more and more attention in China and if pollutant emissions exceed the standard power stations will pay plenty of penalty. According to the charge standard for disposing of pollutants promulgated by the State Environmental Protection Administration NO_x emission was charged 0.075 dollars per pollutant equivalency after July 1, 2004 [19]. The calculation of atmosphere pollutant equivalency is

$$\text{pollutant equivalency quantity}=\frac{\text{pollutant emissions (Kg)}}{\text{pollutant equivalency (Kg)}}$$

(pollutant equivalency of NO_x is 0.95 kg)

Thus, we cannot ignore the importance of emission control and must balance the efficiency and NO_x emissions to minimize the fuel and environmental costs. So three optimal objects are proposed:

• Maximum the efficiency precondition that NO_x emission not exceed the standard

$$\begin{aligned}&\max\ \eta\\&\text{s.t. } T_F=f_1(M_v, D_v)\\&\quad C_{fh}=f_2(M_v, T_F, D_v)\\&\quad NO_x=f_3(M_v, T_F, D_v)\\&\quad \eta=f_4(M_v, T_F, C_{fh}, D_v)\\&\quad [M_v]_{min}\le M_v\le [M_v]_{max}\\&\quad NO_x\le [NO_x]_{max}\end{aligned}\tag{2}$$

• Minimum NO_x emissions precondition that efficiency be not lower than the predefined value

$$\begin{aligned}&\max\ NO_x\\&\text{s.t. } T_F=f_1(M_v, D_v)\\&\quad C_{fh}=f_2(M_v, T_F, D_v)\\&\quad NO_x=f_3(M_v, T_F, D_v)\\&\quad \eta=f_4(M_v, T_F, C_{fh}, D_v)\\&\quad [M_v]_{min}\le M_v\le [M_v]_{max}\\&\quad \eta\ge [\eta]_{min}\end{aligned}\tag{3}$$

• Balance the efficiency and NO_x emissions to minimize the fuel and environmental costs

Coal used for generating per kWh electricity can be decided by

$$B_j=\frac{3600}{\eta_t\cdot\eta\cdot Q_{dw}}[\text{kg/kWh}]\tag{4}$$

Coal cost per 1 kwh

$$M_c=p_c*B_j\ [\$/\text{kWh}]\tag{5}$$

Theoretical air needed per kg coal [20]

$$V_0=0.0889(C+0.375S)+0.265H-0.0333O\ [\text{Nm}^3/\text{kg}]\tag{6}$$

At $\alpha=1$, Combustion products per kg coal, such as the volume of RO_2, H_2O, N_2 in flue gas

$$V_{RO_2}=1.866\frac{C+0.375S}{100}[\text{Nm}^3/\text{kg}]\tag{7}$$

$$V_{N_2}=0.79V_0+0.8\frac{N}{100}[\text{Nm}^3/\text{kg}]\tag{8}$$

$$V_{H_2O}=0.111H+0.0124W+0.0161V_0[\text{Nm}^3/\text{kg}]\tag{9}$$

At $\alpha=1$, Volume of flue gas per kg coal

$$V_y^0=V_{RO_2}+V_{N_2O}+V_{H_2O}[\text{Nm}^2/\text{kg}]\tag{10}$$

At $\alpha>1$, Volume of flue gas per kg coal

$$V_y=V_y^0+(\alpha-1)V_0+0.0161(\alpha-1)V_0\ [\text{Nm}^3/\text{kg}]\tag{11}$$

Volume of flue gas per kWh electricity

$$V=V_y*B_j\ [\text{Nm}^3/\text{kWh}]\tag{12}$$

NO_x emissions per kWh electricity

$$V_{NO_x}=NO_x*V\ [\text{mg/kWh}]\tag{13}$$

NO_x emission penalty per kWh electricity

$$M_p=0.075*\frac{V_{NO_x}}{0.95*10^6}[\$/\text{kWh}]\tag{14}$$

Fuel and environmental costs per kWh electricity

$$M=M_c+M_p=\frac{3600}{\eta_t\cdot\eta\cdot Q_{dw}}\left(\frac{0.075V_y}{0.95*10^6}\cdot NO_x+p_c\right)[\$/\text{kWh}]\tag{15}$$

Balance pollutant emissions and boiler efficiency to minimize the fuel and environmental costs

$$\begin{aligned}&\min\frac{3600}{\eta_t\cdot\eta\cdot Q_{dw}}\left(\frac{0.075V_y}{0.95*10^6}\cdot NO_x+p_c\right)\\&\text{s.t. } T_F=f_1(M_v, D_v)\\&\quad C_{fh}=f_2(M_v, T_F, D_v)\\&\quad NO_x=f_3(M_v, T_F, D_v)\\&\quad \eta=f_4(M_v, T_F, C_{fh}, D_v)\\&\quad [M_v]_{min}\le M_v\le [M_v]_{max}\end{aligned}\tag{16}$$

Where $[M_v]_{min}$, $[M_v]_{max}$ are the constraints of manipulated variables which are decided by boiler operational characteristics, $[NO_x]_{max}$ is the limitation of NO_x emissions which differs from emission standards, $[\eta]_{min}$ is the lowest boiler efficiency permitted, which is decided by boiler conditions, η_t is the efficiency of turbulence, Q_{dw} is the heat value of coal, C, H, O, N, S are W the carbon, hydrogen, oxygen, nitrogen, sulphur and water content of coal, B_j is coal used per kWh electricity, p_c is coal price, α is excess air coefficient, V_0 is theoretical air needed per kg coal, V_{RO_2}, V_{N_2}, V_{H_2O} are combustion products per kg coal, such as the volume of RO_2, N_2, H_2O in flue gas, V_y^0, V_y are volume of flue gas per kg coal when $\alpha=1$ and $\alpha>1$, V is the volume of flue gas per kWh electricity, VNO_x is the volume of NO_x emissions per kWh electricity, M_c, M_p and M are the coal cost, emission penalty and total cost per kWh electricity.

Based on the hybrid model and the optimization objects we can seek the optimal manipulated variables such as primary air, secondary air, tertiary air and oxygen content in flue gas.

4. Realization of Supervisory Control

The above optimization problem contains a non-function model, which classical optimization methods fail to solve. GA is employed to solve the problem because of its advantages such as hidden parallelism and global search in solution space. So we can obtain the optimal operational parameters under different objects through GA optimization based on the above model.

Based on the neural network model developed and the optimization object to balance economics and environment, all unit states and parameters are obtained from DCS and GA is employed to seek the optimal operation parameters which feedback to DCS every 30 seconds. The above algorithm formed the supervisory control and achieved real-time coordinated optimization of utility boilers.

Supervisory control can work on two modes as seen in Fig. 5.

• Adviser mode

The optimization results from supervisory control are provided to operators, then input to DCS after being affirmed by the operators manually.

• Close-loop mode

Supervisory control delivers the optimization results to DCS directly to realize automatic close-loop optimization.

The supervisory control would not influence the safety of a unit because the system only adds a bias to the set point of manipulated variables and the bias can be constrained according to the operation condition. When the supervisory control is brought into service the system can work on optimization-adviser mode first, and after long-time operation the system can adopt close-loop mode. In this way the unit safety is guaranteed and the operation optimization is achieved too.

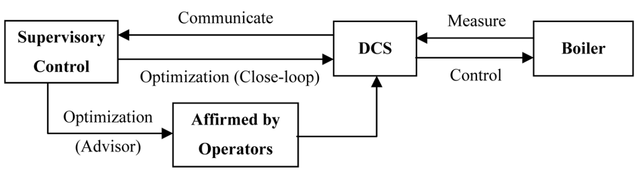

Fig. 5. Realization of supervisory control.

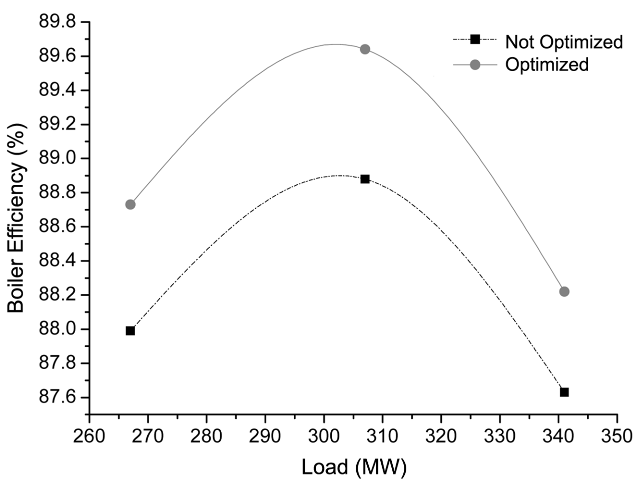

Fig. 6. Comparison of boiler efficiency optimized and not optimized.

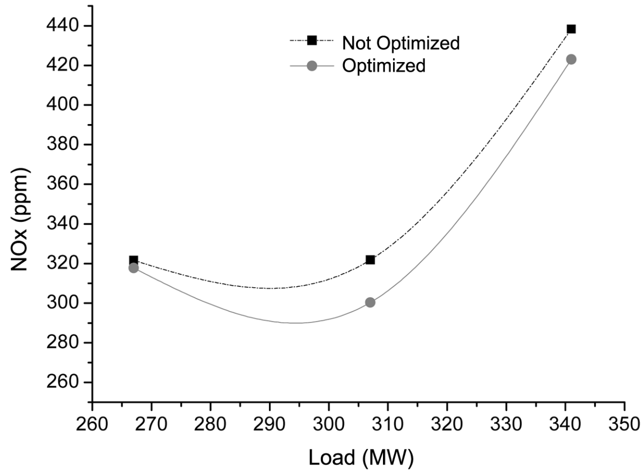

Fig. 7. Comparison of NO_x emissions optimized and not optimized.

5. Optimization Results

A validation experiment was performed by the authoritative party at three typical loads. From Figs. 6 and 7, we can get the following conclusions. Supervisor control can improve the boiler efficiency 0.69% on average under three typical cases. The NO_x emissions level is lowered about 13.53 ppm. Meanwhile, the supervisory control system does no harm to the safety of the boiler.

CONCLUSIONS

A hybrid ANN model based on the experimental data was successfully applied on a 360 MW coal fired boiler. The model to predict the combustion characteristics based on experimental data was consistent with the actual operational characteristics and satisfied the request of supervisory control.

In order to minimize the fuel and environmental costs, three optimization objects were proposed which accord with the demand for high efficiency and low pollutions at present. GA was employed to seek optimal solution every 30 seconds under different objects. The example demonstrated that the algorithm has good convergence and stability.

The above algorithms interconnected with DCS formed the supervisory control and achieved real-time coordinated optimization of utility boilers. The supervisor control system can improve the boiler efficiency 0.69% under three typical cases and do no harm to the safety of the unit.

REFERENCES

1. M. Xu, J. Azevedo and M. G. Carvalho, *Fuel*, **79**, 1611 (2000).
2. J. M. Miller and C. T. Bowman, *Prog Energy Combust Sci.*, **15**, 287 (1989).
3. F. Marias, J. R. Puiggali, M. Quintard, et al., *Korean J. Chem. Eng*, **19**, 28 (2002).
4. H. Zhou, K. F. Cen and J. B. Mao, *Fuel*, **80**, 2163 (2001).
5. H. Zhou, X. P. Qian et al., *Fuel Processing Technology*, **85**, 113

(2003).
6. C. W. Moreno and S. B. Yunker, *Proceedings of conference on expert system applications for the electric power industry*, Phoenix (1993).
7. W. K. Song and V. I. Kouprianov, *International Journal of Thermal Sciences*, **42**, 889 (2003).
8. V. I. Kouprianov, *Renewable and Sustainable Energy Reviews*, **9**, 474 (2005).
9. K. Li and S. Thompson, *Proceedings of the 3rd World Congress on Intelligent Control and Automation*. 992 (2000).
10. X. T. Fang and N. Y. Ye, *J. Huazhong Univ. of Sci. & Tech.* (*Nature Science Edition*), **12** (2003).
11. H. Zhou, K. F. Cen and J. R. Fan, *Energy*, **29**, 167 (2004).
12. L. Q. Han, *Theory, design and application of artificial neural networks*, Chem industry Press (2002).
13. K. F. Reinschmidt and B. Ling, *Proceedings of the American Power Conference*, 354 (1994).
14. L. Wang, *Intelligent optimization algorithms and applications*, Tsinghua Univ. Press (2004).
15. P. H. Wang, L. L. Li, et al., *Power Engineering*, **24**, 466 (2004).
16. L. J. Fang, Z. Y. Gao, et al., *Proceedings of the CSEE*, **8**, 211 (2003).
17. K. T. Fang, *Orthogonal and uniform experiment design*, Beijing, Science Press (2001).
18. D. H. Chung, J. B. Yang, D. S. Noh, et al., *Korean J. Chem. Eng*., **16**, 489 (1999).
19. State Development Planning Commission and ministry of finance, Criterion management regulation promulgated. Attachment: Charge criterion and calculation of pollutant discharge (2003).
20. J. K. Feng and Y. T. Shen, *Boiler principle and calculation*, Science Press (1992).