Predictive Modelling and Optimization of Power Plant Nitrogen Oxides Emission

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ABSTRACT

A predictive modelling of nitrogen oxides emission from a 210 MW coal fired thermal power plant with combustion parameter optimization is proposed. The oxygen concentration in flue gas, coal properties, coal flow, boiler load, air distribution scheme, flue gas outlet temperature and nozzle tilt were studied. The parametric field experiment data were used to build artificial neural network (ANN). The coal combustion parameters were used as inputs and nitrogen oxides as output of the model. The predicted values of the ANN model for full load condition were verified with the actual values. The optimum level of input operating conditions for low nitrogen oxides emission was determined by simulated annealing (SA) approach. The result indicates that the combined approach could be used for reducing nitrogen oxides emission.

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1. INTRODUCTION

Coal is the major fossil fuel in India and continues to play a pivotal role in the energy sector. Coal meets about 60% of the commercial energy needs and about 70% of the electricity produced in India comes from coal [1]. The coal combustion process produces various pollutants, such as oxides of carbon (COx), oxides of sulphur (SOx), oxides of nitrogen (NOx) and particulates. The acid rain and climate change are mainly due to pollutants like SO_2, NOx and CO_2 [2]. Most of the fly-ash (particulates entering the flue) can be removed by fitting electrostatic precipitators and over 90 per cent of SO_2 with the installation of a flue gas desulphurization plant. The best way to reduce CO_2 emissions is to improve power generation efficiency. However, no practical methods exist for reducing NOx to such a degree, leading to increased research into this area. During the combustion process in a coal-fired power plant, nitrogen from the coal and air is converted into nitric oxide (NO) and nitrogen dioxide (NO_2); together these oxides of nitrogen are commonly referred to as NOx. The methods for reducing NOx emissions in coal-fired power plants can be classified as either primary (or combustion modification) based technologies [3], which achieve reduction of NOx formation by limiting the flame temperature or the availability of oxygen in the flame; or secondary (or flue gas treatment) technologies.

NOx reduction by adding a reagent such as ammonia or urea into the flue gas is classified as a secondary technique. Installation of low-NOx burners and implementation of advanced boiler operation and control systems for NOx emission reduction would normally be classified as combustion modification technologies. Although low-NOx burners are usually sufficient to achieve the required target under current legislation, it is often at the expense of other important operational parameters such as incomplete combustion, steam temperature and boiler performance. This is one of the reasons why advanced operational and control systems in coal-fired boilers is so important [4]. Apart from the physical modification of boiler, researchers have tried to model and optimize boiler parameters for minimal emissions [5, 6]. The numerical simulation and three dimensional computer simulation models are useful tools to predict the behaviour of industrial pulverized coal furnaces and formation of nitric oxide in a tangentially fired boiler furnace [7 – 11]. However, these models tend to be really comprehensive to build and they are time consuming and also the appropriate parameters could not be determined immediately for changed operating conditions [12].

Researchers studied the non-linear problem for decades and many traditional and meta-heuristic techniques including artificial intelligence methods have been developed [13]. A machine-learning method for non-statistical model building, such as artificial neural networks (ANN), can be improved to attain the desired accuracy level by training it on experimental data [14,15]. An ANN is an information processing paradigm made up of a set of algebraic equations. The commonest type of artificial neural network's information-processing units (neurons) is organized in three groups, or layers: input, hidden and output [6]. Through the input layer, the normalized raw data is fed into the network. Activity of each unit of the hidden layer is determined by the activities of the input units and the weights on the connections between the input and the hidden units. Likewise, the behaviour of the output units depends on the activity of the hidden units and the weights between the hidden and output units. The inputs of each neuron in the hidden and the output layers are summed and the result is processed by an input–output function (transfer function). The behaviour of an ANN depends on both the weights and the transfer function specified for the units. Using the ANN as its fitness function, the optimization algorithm determines the optimum levels of coal combustion parameters for minimum NOx emission. ANN, in combination with optimization algorithm, has been used successfully in various studies to solve a variety of optimization problems, including problems where the objective function is discontinuous, non-differentiable, stochastic, or highly non-linear [16 – 20]. Here, the same combination is applied for NOx emission optimization.

In this work, the parametric field experiments to obtain the relationship between the operating parameters and NOx emission concentration in flue gas are introduced. The ability of ANN to model the NOx pulverized coal combustion characteristics of a 210 MW thermal power plant under full load condition is demonstrated. The relationship of the NOx combustion characteristics with the coal properties and combustion conditions are obtained using ANN.

Recently meta-heuristic approaches such as simulated annealing (SA), tabu search (TS), genetic algorithms (GA), and evolutionary programming (EP) have been used to develop advanced on-line and real-time combustion optimization software package in modern power plants. This article emphasizes the effectiveness of Simulating Annealing (SA) combined with artificial neural networks (ANN) to determine the optimal combustion parameters for minimum NOx emission. SA is employed to perform a search to optimize the input space of the neural network model to determine the low NOx emissions level to meet the requirement. Neural network modelling and Simulated Annealing described in this study are implemented in Matlab R2011a (MathWorks, Inc.) and run under the Microsoft Windows 7 environment.

The paper is organized in the following way. In Section 2, the experimental details are presented with collected data. Subsequently, in Section 3, the predictive modelling of NOx emission using ANN is presented. Section 4 summarizes the fundamentals of simulated annealing technique. Finally, the results obtained from the combined approach of ANN with SA for full load condition are presented in Section 5 and the conclusions reached in this study is discussed in Section 6.

2. RESEARCH METHOD

2.1. Experiments

The experiments are carried out in a 210 MW tangentially fired dry bottom boiler with a large furnace. The tilting fuel and combustion air nozzles including six primary air burners and seven secondary air burners are located in each corner of the furnace. All nozzles can be tilted in vertical direction over about 30^o from the horizontal axis, both upwards and downwards. The burners on A–F levels were put into operation under the rated load. The coal pulverisers are employed to supply the coal–air mixture to the burners on the corresponding levels. The tangential firing system is employed to combust bituminous coal. The arrangement of the burners is illustrated in Figure 1.

In total, 35 tests have been performed on this boiler, changing the boiler load, primary air, secondary air distribution pattern, nozzles tilting angle, respectively, to analyze the characteristics of the NOx emission of the tangentially fired system. Out of which, 12 test data pertaining to full load condition (210 MW), are used for this present study.

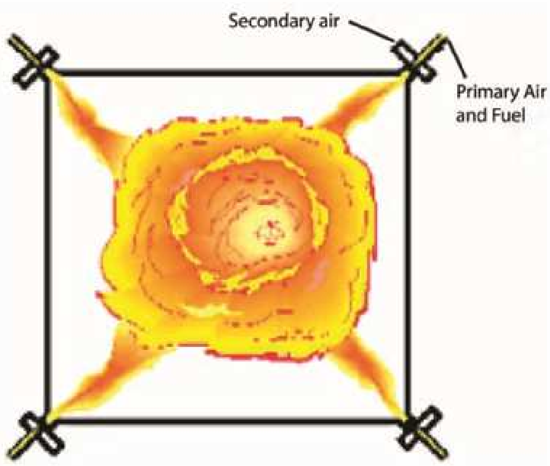


Figure 1. The arrangement of the burners

2.1.1 The NOx emission characteristics

During all the experiments, the fineness of the coal is kept constant. During all the measurements, NOx and O_2 concentrations are monitored continuously in the boiler outlet prior to the air heater. Fly ash samples are withdrawn from the flue gas by a constant rate sampling probe. The NOx concentrations reported in this work are average values over several hours of stable operation, and they are obtained under dry gas conditions. The test data under full condition is provided in Table 1 and 2. The measured NOx emissions for full load condition are summarized in Table 3.

Table 1. The boiler operating condition for full load condition

Case	O_2 %	Total air flow (ton/hr)	Total coal flow (ton/hr)	Feeder speed (ton/hr)					
				A	B	C	D	E	F
1	4.03	766.79	105.66	27.19	0.00	26.78	25.69	26.77	0.00
2	2.24	628.6	99.55	24.86	0.00	25.04	25.26	25.12	0.00
3	3.85	687.25	99.58	25.12	0.00	24.90	24.96	24.83	0.00
4	4.22	749.01	101.98	24.80	0.00	23.10	27.45	27.13	0.00
5	5.01	782.32	105.04	24.69	0.00	22.90	29.46	28.31	0.00
6	6.52	898.23	112.40	28.19	0.00	28.59	30.01	28.18	0.00
7	4.42	784.21	100.93	0.00	0.00	25.25	24.82	25.16	26.24
8	4.31	786.13	102.45	0.00	0.00	25.54	25.24	25.50	26.80
9	4.43	792.00	102.07	0.00	0.00	25.45	25.10	25.41	26.56
10	5.12	733.69	101.03	0.00	0.00	25.88	26.49	23.85	25.55
11	4.24	749.80	95.07	0.00	0.00	24.03	23.72	23.82	24.18
12	3.54	701.17	96.20	0.00	0.00	24.23	23.84	23.97	24.45

Table 2. The boiler operating condition for full load condition (Contd.)

Case	Damper opening position (%)			Burner tilt		FG Temp at LTSH O/L		Load	
	AB	BC	CD	DE	EF	FF	Degree	(°C)	MW
1	24.98	25.09	24.83	25.37	24.97	0.15	9.08	416.75	210
2	0.45	0.26	0.16	0.25	0.15	0.27	28.48	433.26	210
3	11.48	11.02	11.48	11.02	11.50	0.27	-9.59	429.68	210
4	23.28	23.38	23.19	23.34	22.94	0.00	8.09	458.98	210
5	26.99	27.08	26.99	27.08	27.11	0.00	28.96	456.05	210
6	57.44	57.65	57.40	57.79	57.43	0.00	5.10	430.66	210
7	0.00	31.36	31.40	31.48	31.59	31.49	28.86	433.26	210
8	0.00	45.72	45.29	45.44	45.30	45.64	28.81	442.14	210
9	0.00	89.35	89.40	89.30	89.48	89.23	28.79	445.96	210
10	0.00	14.90	15.23	14.90	15.24	15.15	28.28	417.32	210
11	0.00	27.43	27.56	27.28	27.59	27.33	7.46	414.71	210
12	0.00	12.50	12.21	12.52	12.21	12.52	28.59	453.77	210

Table 3 The NOx emission under various operating conditions

Load (MW)	NOx (ppm)											
	1	2	3	4	5	6	7	8	9	10	11	12
210	326	276	356	345	416	429	515	520	537	437	385	398

2.2. Predictive modelling of NOx emission

Artificial Neural Network (ANN) is widely accepted as a technology offering an alternative way to simulate complex and ill defined problems. They are used in diverse applications in control, robotics, pattern recognition, forecasting, power systems, manufacturing, optimization, signal processing, etc., and they are particularly useful in system modelling. ANNs are well-known tools among artificial intelligence techniques, which are able to reproduce the relationships existing between input and output variables of highly nonlinear systems [13]. Up to now, there are many research works that focused on applying neural-networks to pollutants emissions modelling.

ANN architecture mimics the learning process of human brain. The basic architecture of ANN involves interconnected neurons, which are defined in three distinct categories: input layer neurons, output layer neurons and hidden layer neurons as shown in Figure 2.

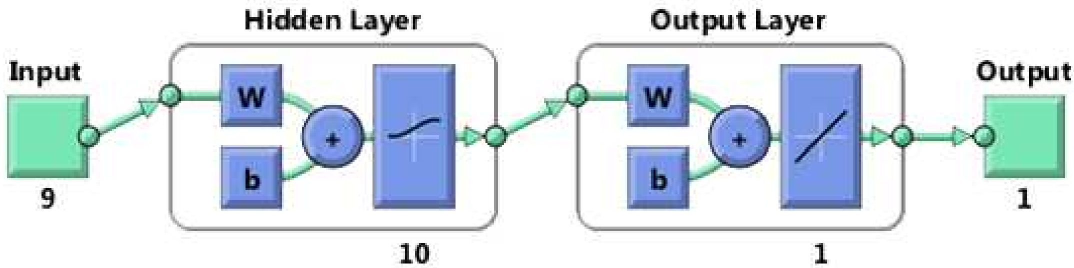


Figure 2 The Schematic diagram of a feed forward-back propagation network

The input data are presented through input layer neurons, and the response of the input data is presented at output layer neurons. Neurons are connected by scalar functions known as weights that take part in the learning process of networks. In back propagation algorithm, which is widely used in training of ANNs, a series of input and output data is presented to the system. Each hidden layer neuron and output layer neuron process this input data by multiplying its corresponding weights, and using a transfer function.

The learning of the network is carried out through adjusting the weights by continuous iterations and minimizing the error between experimentally measured response and ANN model- predicted response [21]. Mean square error (MSE), Sum of square error (SSE), and determination coefficients (R^2) are used to evaluate ANN-GA performance. When the MSE / SSE are at the minimum, and 'R' value closer value to 1 represents high performance and perfect accuracy [22]. The network performance during the training till the final adaptation for full load condition is shown in Figure 3. The Graph of predicted values versus experimental values and Regression coefficient of network for the full load condition is shown in Figure 4.

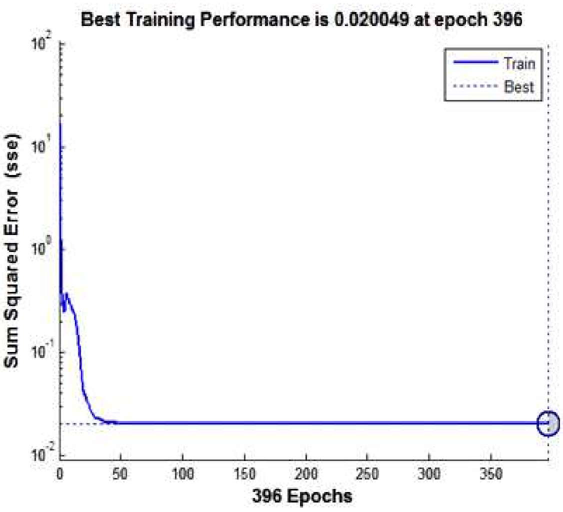


Figure 3. Network performance for full load condition

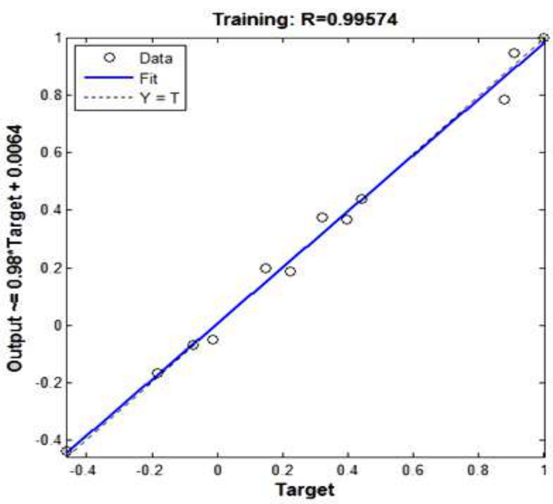


Figure 4. Regression coefficient of network for full load condition

ANN model can be combined with the optimizing algorithms. Using the ANN, the fitness function between the input operating parameters and the NOx emissions can be obtained. Because the ANN may be considered simply as a nonlinear input–output mapping, such a mapping is so quick and it is suitable to be used as the fitness (or objective) function for the optimization algorithms. The optimum operating parameters can be found employing the searching ability of optimization algorithms.

2.3. Optimization method

In this study, SA is employed to optimize the NOx emissions. Prior to application, a brief description of the optimization approach is presented in the following subsection.

2.3.1. Simulated annealing

The simulated annealing models the process of annealing in solids. Essentially, the SA method generates a sequence of solutions, which are successively modified until a stopping criterion is satisfied. A temperature parameter is used to control the acceptance of modifications. Initially, the temperature is set to a high value and is decreased over iterations. If the modified solution has better fitness value than the current solution, it replaces the current solution. If the modified solution is less fit, it is still retained as current solution but with a probability condition. As the algorithm proceeds, the temperature becomes cooler, and it is then less likely to accept deteriorated solutions. In each iteration, the process of generating and testing a new trial solution is repeated for a specified number of trials, to establish the 'thermal equilibrium' [18].

The last of the accepted solution becomes the initial solution for the next iteration, after the temperature is reduced, according to the 'annealing schedule'. Thus the main features of the SA process are: the transition mechanism; and the cooling scheme. The transition mechanism consists of three components:

Step (a): Generation of candidate solution by perturbing the current solution according to a probabilistic distribution function.

Step (b): Acceptance test for the solution based on better objective values or a probability of acceptance in case of higher values

Step (c): Iterative procedure.

In the last component, the first and the second components are used to produce a chain of tested candidate solutions. The last accepted solution becomes the initial solution of the next iteration. The procedure by which the control temperature parameter is reduced is called the cooling (annealing) schedule.

3. RESULTS AND ANALYSIS

The main objectives for boiler combustion optimization are to help the operators to perform clean and efficient utilization of coal. Thus the NOx optimization objective function was derived from the weights and biases of the trained feed forward back propagation neural network [23].

Weights and biases of all layers of neurons were combined with transfer functions of ANN model to achieve an ANN equation pattern as the following steps.

- The 9 input layer nodes with the 1st bias node connected to 10 nodes of hidden layer. Thus, there are 90 values of weights and 10 values of biases on the layers between input and hidden layer. On the hidden layer, the ‘tansig’ transfer function is used to calculate the sum of the 90 weighted inputs ($W_{i,j}$) and the 10 biases (b^t_j). The sum of weights and biases in hidden layer is displayed on Eq. (1).

$$Z_j = f^t(W_{i,j} X_i + b^t_j), \ i = 1,2,3,4,5,6,7,8,9 \ j = 1,2,3,\ldots,10 \quad (1)$$

where, Z_j is the 10 outputs of hidden layer
f^t is the ‘tansig’ transfer function of hidden layer
$W_{i,j}$ is the weights from input layer i to hidden layer j
X_i is the 9 inputs of input layer
b^t_j is the 10 biases of hidden layer

- The 10 nodes of hidden layer connected to one node of output layer. It means the layers between hidden layer and output layer have 10 values of weights rows and one value of bias. On the output layer, the ‘purelin’ transfer function is used to calculate the sum of the 10 weighted inputs (Wj) and one bias (b^p). The sum of weights and bias in output layer is displayed on Eq. (2).

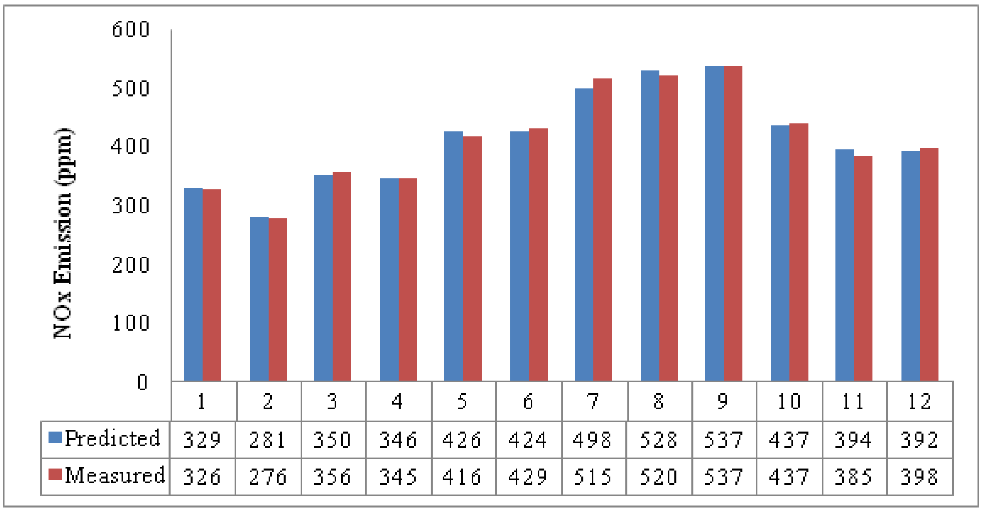
$$Y = f^p(W_j Z_j + b^p), \ j = 1,2,3,\ldots,10 \quad (2)$$

where, Y is the output – NOx emission
f^p is the ‘purelin’ transfer function of output layer
W_j is the weights from hidden layer j to output layer

Z_j is the 10 inputs of hidden layer
b^p is the bias of output layer

The ANN is used to train the operating parameters by considering the experimental data from Table 1 and Table 2. It determines the weights between processing elements in the input and hidden layer and between the hidden layer and output layers which minimize the differences between the network output and the measured values. The experimental data stated above are used to find the relation between the operational parameters and the NOx emission concentration in flue gas under full load condition. The trained network achieved highest R^2 and lowest SSE (R=0.99574; SSE=0.02004) using trial-and-error procedure. The measured and predicted NOx emission concentration in flue gas shown in Figure 5, indicates that the trained network is performing reasonably good in prediction.

The SA is employed to search the optimum solution of Eq. (2) to determine the optimum operating parameters like the flue gas oxygen, nozzle tilt, flue gas outlet temperature and secondary air burner damper opening position for minimum NOx emission. The other input parameters, such as pulverizer feeder opening value, air flow rate through the pulverizer and wind box differential pressure are usually not considered as adjustable factors for combustion optimization purpose. These parameters can also be optimized with the same method if necessary. The NOx emission concentration calculated by SA under various generations is shown in Figure 6.



	1	2	3	4	5	6	7	8	9	10	11	12
Predicted	329	281	350	346	426	424	498	528	537	437	394	392
Measured	326	276	356	345	416	429	515	520	537	437	385	398

Figure 5. Measured versus predicted NOx emission concentration in flue gas

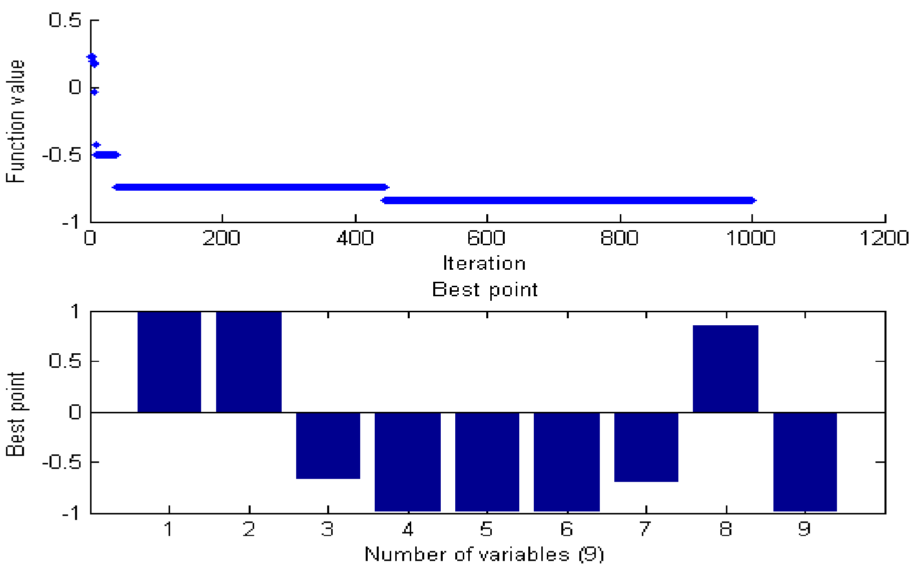


Figure 6. Best fitness function value and best individual operating parameters in SA

The graph illustrates that the search process is progressive and the rate of convergence is very fast, consuming a few minutes of CPU time on a modern desktop computer. The reduced NOx emission concentration and optimum operating parameters such as the flue gas oxygen, nozzle tilt, flue gas outlet temperature and secondary air burner damper opening position for full load condition are listed in Table 4. The optimized results agree well with the experimental experience, leading to low NOx emission in full load condition.

Table 4. Optimum operating parameters and NOx emission concentration for full load condition (210 MW)

Damper Opening Position (%)						Burner Tilt	FG Temp at LTSH O/L	O_2	NOx
AB	BC	CD	DE	EF	FF	Degree	^oC	%	ppm
100	17	0	0	0	15	29	454	2	208

4. CONCLUSION

It is concluded that a combined approach of artificial neural network and SA for predicting and optimizing NOx emission from a 210 MW tangentially fired boiler under full load condition, is developed and verified. The results show that the back propagation-feed forward neural network method is accurate, and it can always give a general and suitable way to predict NOx emission under various operating conditions and burning different coal. Combined with SA, the optimum operating parameters can be achieved to decrease the NOx emission. The results proved that the proposed approach could be used for generating feasible operating conditions.

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