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Nitrogen Oxides Emission Prediction in Coal Based Thermal Power Plant using Artificial Neural Network

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Abstract— This paper describes systematic approach to predict of nitrogen oxides emission from 270 MW coal fired thermal power plant with the help of artificial neural network. The NO_x formation mechanism and NO_x emission control techniques also describe. The oxygen concentration in flue gas, coal properties coal flow, boiler load, air distribution scheme, flue gas outlet, temperature and nozzle tilt were investigated through field experiment. The predicted values of ANN model for different load condition were verified with the actual values. These parameters help us to ensure to complete combustion and less emission with increased boiler life.

Keywords—Artificial neural network,prediction,nitrogen oxides emission,thermal power plant

I. INTRODUCTION

Now a day every country is moving towards development and this development is mostly signified by technology development and power generation. The energy source harnessed to turn the generator varies widely. It depends chiefly on which fuels are easily available, cheap enough and on the types of technology that the power company has access to. Most power stations in the world burn fossil fuels such as coal, oil, and natural gas to generate electricity, and some use nuclear power. There are different types of power plants but major part of power generated is from Coal fired power plant. Coal is the major source of energy in India. About 61%of the commercial energy needs and about 72%of the electricity produced in India comes from coal [1]. The coal combustion process produces various pollutants, such as oxides of carbon (CO_x), oxides of sulphur (SO_x), oxides of nitrogen (NO_x) and particulates. The acid rain and climate change are mainly due to pollutants like SO_2, NO_x and CO_2 [2]. A. NO_x formation mechanisms: During the combustion process of hydrocarbons with air there is the possibility of forming, among many other pollutants, oxides of nitrogen in the exhaust. These oxides might be nitric oxide (NO), nitrous oxide (N_2O) or nitrogen dioxide (NO_2), and they are collectively called with the generic term of NO_x. Theoretically, the formation of NO_x can take place in every part of the furnace, but often it is produced only in certain parts of the flame, and over 80% of the NO_x might be produced in only 10% of the flame volume. Nitrogen emitted at the stack. The largest fraction is by far composed by NO. Typically, N2O is not significant in the case of coal combustion and also NO2 only represents a small fraction of the oxides of in the atmosphere most of the NO is then converted into NO2.The amount of NOx formed depends on a variety of factors which include the fuel burned, the stoichiometry, the temperatures, the mixing and the residence time. The three main mechanisms of NOx formation in the gas phase are: thermal NOx, fuel NOx and prompt NOx [3]. Fuel NO is formed from the nitrogen contained in the fuel, and in the case of coal it can account for 60-80% of the total NO formed [3]. It is formed more readily than thermal NO as the bonds of nitrogen with coal or in the molecules emitted from coal (mainly HCN and ammonia) are much weaker than the triple bond of the molecular nitrogen present in the gas stream. Therefore the formation of fuel NO can be considered almost temperature independent. Fuel bound nitrogen is normally emitted as molecular nitrogen, ammonia or HCN. Especially the last two species are the most significant, and their amount in the gas stream is a strong function of the kind of fuel [4]. In general high rank coals tend to emit most of their nitrogen as HCN, while low rank coals has also a significant fraction of ammonia [4]. Thermal NOx originates from the reaction of oxygen in the gas stream with nitrogen at high temperatures [3]. This pathway has a very strong dependence on the temperature and on the oxygen concentration. This pathway can be described by the widely accepted two-step Zeldovich mechanism:

$$N_2 + O \Leftrightarrow NO + N \qquad (R1)$$

$$N + O_2 \Leftrightarrow NO + O \qquad (R2)$$

$$N + OH \Leftrightarrow NO + H \qquad (R3)$$

The third reaction is particularly important under rich flame conditions where the OH radicals are present in higher concentrations than atomic hydrogen or oxygen. At mean temperatures below 1800 K, thermal NO formation is very slow [3]. In the case of prompt NO_x, nitric oxide can be formed when hydrocarbons resulting from volatilization process attack molecular nitrogen near the reaction zone of the flame [3]. The main reaction in this process is:

$$N + CH \rightarrow HCN + N_2 \qquad (R4)$$

Then HCN reacts with oxygen to create NO. Prompt NO is more significant in fuel rich flames since it needs hydrocarbon to initiate the chain of NO formation [3].

Prompt NO_x is normally most significant in the case of clean fuels (that contain no nitrogen). In the case of coal combustion it is normally ignored [3].

B. NO_X Control Technologies:

In coal-fired boilers, thermal NO_x typically represents about 25 % of the total NO_x formed.

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The quantity of thermal NO_x depends primarily on the combustion: temperature, time and turbulence. NO_x control technologies are categorized in two broad categories [5]:

1) pre-combustion techniques,
2) post-combustion techniques

The pre-combustion modifications provide the NO_x control by reducing the temperature of combustion. The most effective pre-combustion control techniques are:

i) Low NO_x burners – lower maximum flame temperature, control of the mixing,

ii) Overfire air – OFA nozzles, air is injected above the normal combustion zone,

iii) Reburning – part of the boiler heat input is added in a separate reburning zone,

iv) Flue gas recirculation – FGR – part of the flue gas is mixed with the combustion air,

v) Operational & construction modifications – changing the boiler operational parameters.

The post-combustion NO_x control is primarily accomplished by reacting ammonia with nitrogen oxides, forming nitrogen and water vapour. Two basic variations exist, using thermal energy or a catalyst:

i) Selective non-catalytic reduction – SNCR – typically ammonia/urea is injected into the boiler above the combustion zone

ii) Selective catalytic reduction – SCR – a catalyst vessel is installed downstream of the boiler, catalysts can
be made inactive by ash

iii) Hybrid process – SNCR and SCR can be used in conjunction with each other.

Several works have been done to develop predictive systems for industrial emissions. One of the earlier ideas was presented by S.S.S Chakravarthy, A.K Vohra and B.S Gill [6] has developed a predictive emission monitors for industrial process heaters. They have used heuristic optimizer genetic algorithm (GA) to tune the NO_x kinetic parameters. L. Zheng, S. Yu, M. Yu [7] used generalized regression neural network (GRNN) to establish a non-linear model between the parameters of the boiler of 300MW steam capacity and the NOx emissions. Researchers studied the non-linear problem for decades and many traditional and meta-heuristic techniques including artificial intelligence methods have been developed [8]. 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 [9]. T. Faravelli , L. Bua , A. Frassoldati, A Antifora , L. Tognotti, E. Ranzi is to illustrate flow and temperature fields within the furnace, obtained through CFD codes[11]. A.T.C. Goh and C.G. Chua describes the study deals with Back-propagation neural network & Bayesian neural network[11]. 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 270 MW thermal power plant under full load condition is studied. Artificial neural network modelling described in this study are implemented in Matlab 6.5.0 (Math Works, Inc.) and run under the Microsoft Windows 8 environment.

This paper is organized as follows: Section 2 presents a brief literature on artificial neural network and Back propagation neural network (BPNN). Section 3 describes the modeling background in terms of the parameters used, case study of coal fired 270MW power plant and the dataset used. Section 4 presents the results and analysis obtained from the approach of ANN for full load condition and Section 5 gives a brief conclusion reached in this study.

II. ARTIFICIAL NEURAL NETWORK (ANN)

Artificial neural networks are inspired by the systems of nerve cells in the brain. ANNs accurately estimate nonlinear relationships between inputs and outputs by imitating the complex processes of the brain. Although brain activities are tremendously complicated, modeling of a nerve cell known as neuron gives detailed information about biochemical reactions. ANNs provide sufficient structure for the neural system to understand biological processing of neurons. This structure has huge numbers of processing units and interconnections between them. Each unit or node is a simplified model of a biological neuron which receives input signal from the previous linked neurons and sends off output signals to subsequent linked neurons. The general mathematical description of a neuron is defined as follows:

$$y(x) = f\left(\sum_{i=0}^{n} w_i x_i\right) \qquad (1)$$

Where, x is a neuron with n input dendrites (x_0,…...,x_n) and one output axon *y(x)* and where (w_o,….,w_n) are weights defining how much the inputs should be weighted.

The simple processing unit of neural network is shown in Figure 1. On the left side inputs are connected to neuron j and each connection has an associated weight given as w_{ij}. Neuron *j* computes its output by performing a differentiable transfer function "*f*" on weighted sum of inputs plus a bias term "b". The bias term allows us to compensate errors for the data. This output value is sent along all the output connections shown at the right.

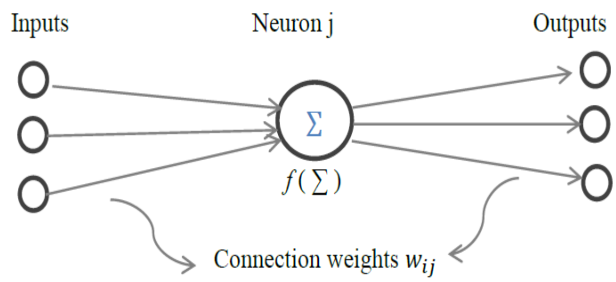

Figure1: Neuron Model

A. Backpropagation Neural Network (BPNN):

The back propagation neural network however has been widely used to develop softsensors for prediction of NOx [12]. However, BPNN has some weaknesses, including the need for numerous controlling parameters, difficulty in obtaining a stable solution and the danger of overfitting. The solution shown by Zheng et al [13] points to the fact that BPNN is unreliable even if all of the network objects are predetermined.

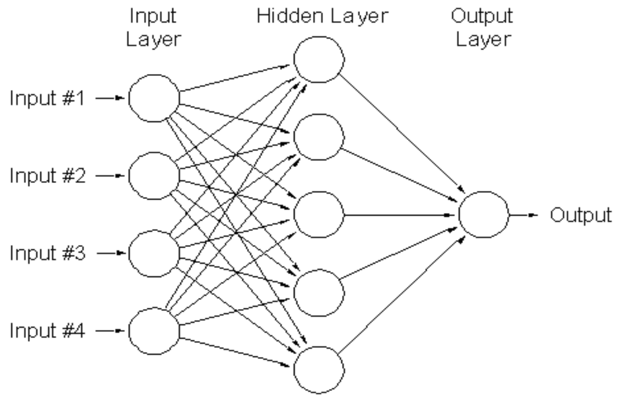

Figure 2: Typical Back propagation Neural Network

The Performances of the Models are Gauged using Standard performance Functions in the form of Correlation Factor(R) and Root Means Square Error (RMSE):

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(\hat{X}_i - X_i)^2} \tag{1}$$

$$R = \frac{\sum_{i=1}^{n}(X_i - \overline{X})(\hat{X}_i - \overline{\hat{X}})}{\sqrt{\sum_{i=1}^{n}(X_i - \overline{X})^2 \sqrt{(\hat{X}_i - \overline{\hat{X}})^2}}} \tag{2}$$

Where, *Xi is* the Predicted Value, *Xi* is the True Value and *n* is the Number of Testing Samples.

III. RESEARCH METHOD

A. Experiments:

The experimentation is carried out in a 270 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 degree from the horizontal axis, both upwards and downwards. The burners on A, B, C, D, E, 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 3.

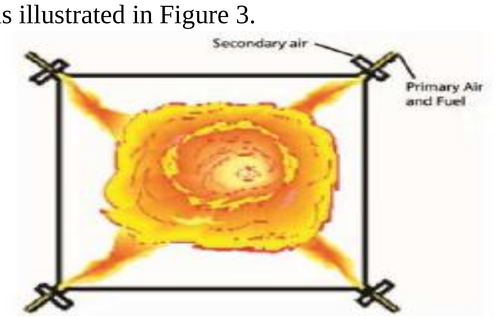

Figure 3: The Arrangement of the Burners

Tangential firing helps in keeping the temperature of the furnace low so that NO_x emission is reduced considerably and over fire air is provided which is used as combustion process adjustment technically for keeping the furnace temperature low and thereby low NO_x formation. Tangential firing helps in keeping the temperature of the furnace low so that NO_x emission is reduced considerably and over fire air is provided which is used as combustion process adjustment technically for keeping the furnace temperature low and thereby low NO_x formation. Each corner of the burner wind box is provided with two numbers of separate over fire air compartments, kept one above the other and the over fire air is admitted tangentially into the furnace. The over fire air nozzles has got tilting arra ngement and compartment flow control dampers for working in unison with the tilting tangential type burner system for effective control of NO_x formation. The primary air system delivers air to the mills for coal drying and transportation of coal powder to furnace.

In total, 30 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 NO_x emission of the tangentially fired system. Out of which, 10 test data pertaining to full load condition, are used for this present study.

B. the NO_x Emission Characteristics:

During all the experiments, NO_x 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. Selected 10 sets of test data under full condition is provided in Table 1,2,3 and Table 4. The measured NOx emissions for full load condition are summarized in Table 5 and 6.

Table 1. The Important Boiler Operating Parameters

Sr. No.	LOAD	FG Temp at ECO. O/L(deg)		Total Air Flow
	MW	L	R	T/Hr
1	270	334	331	979
2	265	339	334	985
3	268	339	334	985
4	272	340	335	998
5	275	340	335	993
6	260	329	325	924
7	250	327	322	907
8	240	325	325	906
9	225	322	317	884
10	200	320	316	832

Sr. No .	O_2 (%)		Windbox Pr(mmWC L)		Furnace Windbox DP(mmWC L)	
	L	R	L	R	L	R
1	4.7	4.6	66	91	88	88
2	5.1	5.2	68	95	90	90
3	5.1	5.1	67	93	91	91
4	5	4.9	70	97	92	92
5	5	4.9	67	94	91.5	91.5
6	4.8	4.0	67	67	85	85
7	4.8	5.1	61	61	72	72
8	4.8	5.1	62	62	73	73
9	5.9	5.1	69	69	78	78
10	6.9	6.1	52	52	60	60

Table 2. The Important Boiler Operating Parameters

Table 3 The Important Boiler Operating Parameters

Sr. No.	Coal Flow	Feedrate of Mills in service(T/Hr)					
	T/Hr	A	B	C	D	E	F
1	156	40	17	37	37	23	0
2	157	40	17	37	39	23	0
3	161	41	17	37	40	24	0
4	161.5	41	17	37	40	23	0
5	161.9	41	17	37	40	23	0
6	149	39	0	40	39.7	26	0
7	142	38	0	39	38	25	0
8	142	38	0	39	38	25	0
9	141	37	0	39	38	25	0
10	125	35	0	34	32	23	0

Table 4 The Important Boiler Operating Parameters

Damper openings at Elevations (%)											
AA	A	AB	B	BC	C	CD	D	DE	E	EF	F
50	19	11	5.8	11	18.3	11	18	11	9.5	11	0
50	20	11	5.8	11	18.8	11	19	11	9.9	11	0
50	20	11	5.8	11	18.6	11	20	11	9.9	11	0
50	20	11	5.8	11	18.8	11	20	11	9.9	11	0
50	20	11	5.8	11	19	11	20	11	9.9	11	0
50	20	11	6	11	19	11	20	12	10	12	0
50	21	10	6.2	12	19	12	20	11	10.5	12	0
50	21	11	6	11	18.3	12	21	12	10	11	0
50	21	10	6	12	18.3	11	21	12	10.6	11	0
50	21	11	6	11	18.8	11	20	11	10	11	0

Table 5 The NOx emission under above operating condition and predicted NOx (ppm)

Sr.No	1	2	3	4	5
Measured NO_x	119	119	119.6	119.6	119.6

Table 6 The NOx Emission Under Above Operating Condition And Predicted NOx (ppm)

Sr. No.	6	7	8	9	10
Measured NO_x	143	153	150	163	166

C. Predictive Modelling of NO_x Emission:

The model is developed in MATLAB By following steps:

- Step1: Variable selection
- Step2: Data collection
- Step3: Data preprocessing
- Step4: Training, testing, and validation sets
- Step6: Evaluation criteria
- Step7: Neural network training
- Number of training iterations
- Learning Rate
- Step8: Implementation

The model is developed as a benchmark using BPNN. The optimal network parameters are chosen by varying the number of layers and number of hidden neurons per layer. The parameter that gives the best performance is chosen and shown below:

- Number of layers = 2
- No of neurons (hidden layer) = 10
- Transfer functions (input layer) = tan-sigmoid
- Transfer function (hidden layer) = linear
- Training algorithm =Lavenberg-Marquat
- Training:70%
- Testing:15%
- Validatition:15%

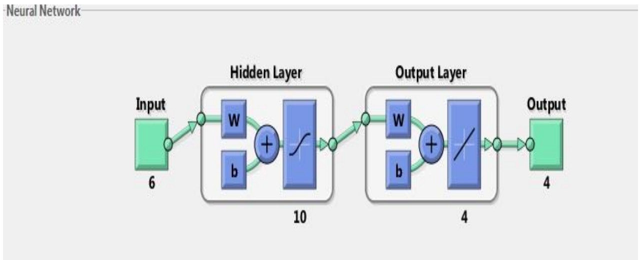

Figure 4. The Schematic Diagram of a Feed Forward-Back Propagation Network

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 [14].

D. Performance of network:

Figure 5 shows a network stopping after the error stopped improving. Therefore, while training the ANN, the maximum epoch is fixed to a high value that will not likely be reached (1000) to give training enough trials to converge. Best validation performance is 1.7405 at epoch 166 of ANN network.

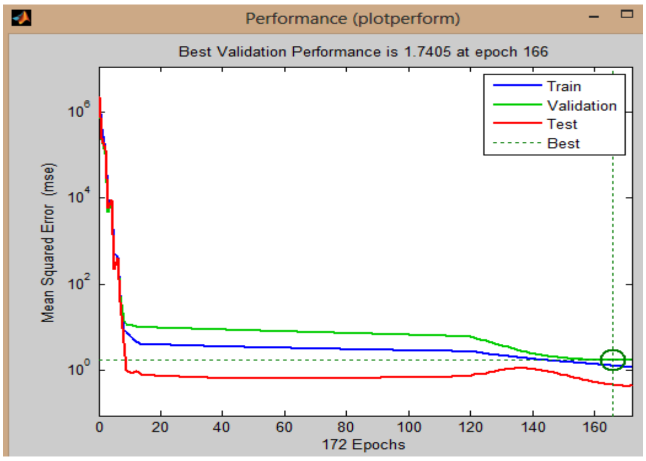

Figure 5. Training Stopping Due to Convergence

Training:

These are presented to network during training and the network is adjusted according to its error. The Graph of predicted values versus experimental values and Regression coefficient of network for the full load condition of training is shown in Figure 6.

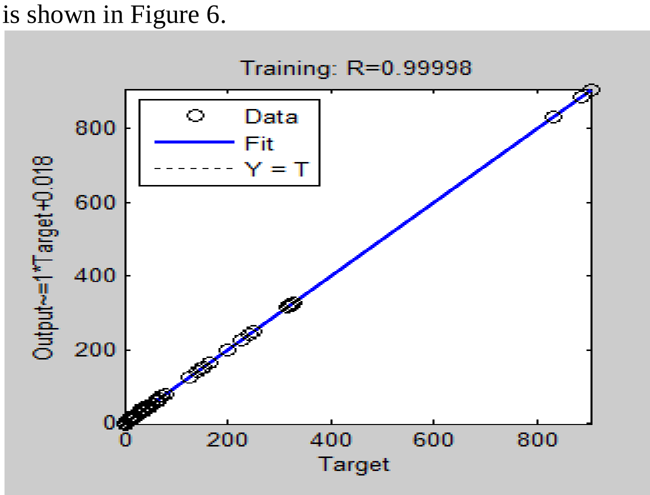

Figure 6. Regression Coefficient of Network for Training Validation

These are used to measure network generalization and to halt training when generalization stops improving. The Graph of predicted values versus experimental values and Regression coefficient of network for the full load condition of validation is shown in Figure 7.

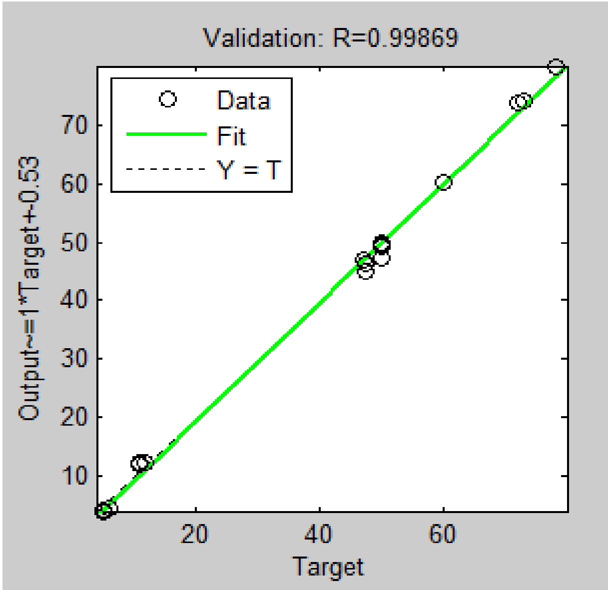

Figure 7 Regression Coefficient of Network for Validation

Testing:

These have no effect on training and so provide an independent measure of network performance during and after training. The Graph of predicted values versus experimental values and Regression coefficient of network for the full load condition of testing is shown in Figure 8.

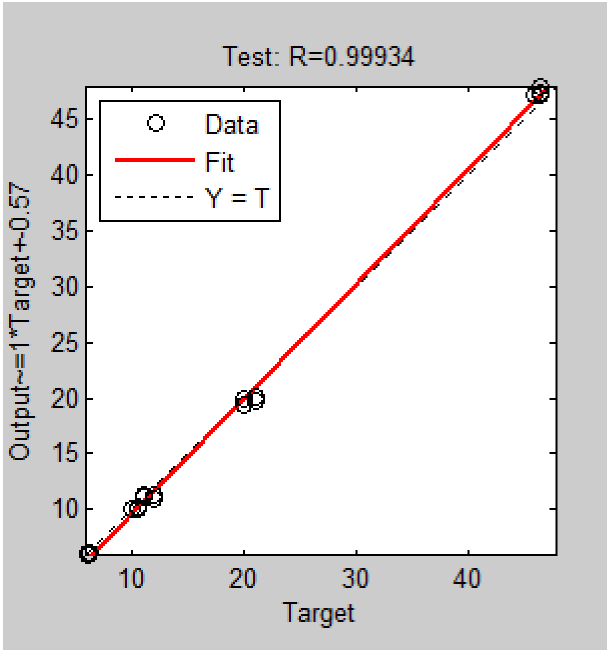

Figure 8. Regression Coefficient of Network for Test

IV. 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 NO_x optimization objective function was derived from the weights and biases of the trained feed forward back propagation neural network. Weights and biases of all layers of neurons were combined with transfer functions of ANN model to achieve using 60% training and 40% testing for better prediction result. On the output layer, the 'purelin' transfer function is used to calculate the sum of the weighted inputs and bias. Then sum of weights and bias in output layer is displayed. 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 NO_x emission concentration in flue gas under full load condition. The trained network achieved highest R² and lowest SSE (R=0.9998; SSE=$1.23e^{-1}$) using trial-and-error procedure. The measured and predicted NO_x emission concentration in flue gas shown in Figure 9 and table 7, 8 indicates that the trained network is performing reasonably good in prediction.

Table 7&8 The NOx Emission Under Above Operating Condition and Predicted NOx

Sr. No.	1	2	3	4	5
Measured NO_x	119	119	119.6	119.6	119.6
Predicted NOx	126.84	117.71	121.34	122.52	121.59

Sr. No.	6	7	8	9	10
Measured NO_x	143	153	150	163	166
Predicted NO_x	140.94	152.9	149.85	163.0 2	165.81

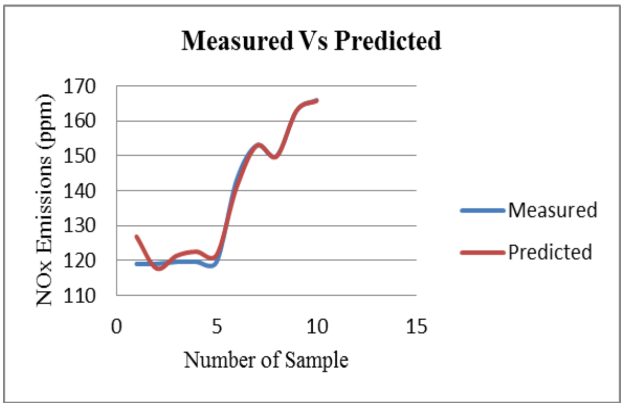

Figure 9 Measured versus predicted NOx emission concentration in flue gas

Average performance of BPNN is given in Table 4.

Training Data	MSE	R
Set 1	$1.23e^{-0}$	$9.9998e^{-1}$
Set 2	$207.10e^{-0}$	$9.8176e^{-1}$

The measured and predicted NOx emission concentration in flue gas shown in table and Figure 7 indicates that the trained network is performing reasonably good in prediction.

V. CONCLUSIONS

This paper has brought to focus the ability to model the NO_x emission from a 270 MW tangentially fired boiler under full load condition. It is developed and verified with working parameters. 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 NO_x emission under various operating conditions and burning different coal. The results proved that the proposed approach could be used for generating feasible operating conditions. The result of ANN are very sensitive to number of neurons. Increasing number of neurons in hidden layer decrease the number of calculation steps with decrease in sum squared error.

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