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Nitrogen Oxides Emission Prediction & Optimization in Thermal Based Coal Power Plant Using Artifical Neural Network- A Review

Milind S.. Mankar

M.Tech. student, Thermal Engineering, Govt. College of Engineering, Amravati, (M.S.) India.

Abstract

Emissions observering is done by analytical instruments which are very costly to install and maintain.This paper describes nitrogen oxide formation mechanism,emission contol techniques and efficient approach to predict nitrogen oxides emission from thermal based coal power plant with optimised combustion parameter.

The oxygen concentration in flue gas,coal properties coal flow, boiler load, air distribution scheme, flue gas outlet, temperature and nozzle tilt were studied.

Artificial neutral network (ANN) used in broad range of applications including:pattern recognition, optimization, prediction, and automatic control. The coal combustion parameters used as input and nitrogen oxides as output of model. .

The optimum level of input operating conditions for low nitrogen oxides emission determined by simulated annealing (SA) approach.

The result indicates that combined approach used for reducing nitrogen oxides emission.

Keywords- NO_x emissions, ANN, SA, Thermal power plant

1.INTRODUCTION

Coal is the major source of engrgy in india. About 61%of the commericial 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 (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].

1.1 An overview of NOx formation mechanisms:

The formation and destruction of NOx is linked with the reactions of the other products of coal combustion. In particular, models for the combustion of volatiles and char are required to predict the oxygen available for the NOx reaction.

1.1.1 Coal combustion process: In the coal combustion process, many important reactions occur between the initial heating of the coal particle and the formation of fly-ash[3]

As the particle heats up, the volatile components of the coal will evaporate and diffuse into the gas stream, leaving a carbon-rich char particle. Once ignition temperature is reached, both volatiles and char will undergo combustion. The complex hydrocarbon volatiles will experience thermal cracking into simpler compounds or soot before oxidation, while the heterogeneous oxidation of char will eventually result in an ash residue.

1.1.1.1Devolatilisation: When a raw coal particle is subjected to high temperature, it will release a gaseous volatile compound. This is a multistage process, and is know as devolatilisation. The rate equations are of the Arrhenius type:

Reaction rate coefficient = $A\ exp(-E/RT)$ (1.1)

where R is the gas constant, E is the activation energy, T is the temperature, and A is some constant.

1.1.1.2Volatile combustion: The coal devolatilisation process can produce several hundred gaseous compounds.

Volatiles generally are composed of tars, hydrocarbon liquids, hydrocarbon gases, H2, H20, CO and CO2. Most of the compounds will continue to react in the vicinity of the char particles to produce successively lighter gases as the more complex molecules decompose, eventually forming CO2 and H20, provided that sufficient oxygen is available. If volatile combustion occurs at substoichiometric conditions, the heavier products (tars) may react to form soot.

The simplest overall reaction for the oxidation of hydrocarbon fuel is formulated as:

(R1) Fuel + O2 ~ CO2 d- H20;

and for the generalised single step hydrocarbon C_nH_m the reaction can be expressed as:(R2)

$$C_nH_m + \left(n + \frac{m}{4}\right) O_2 \rightarrow nCO_2 + \left(\frac{m}{2}\right) H_2O$$

with the generic single reaction rate expressed in (1.1).

1.1.1.3 Char combustion: Char is the residual mass after full devolatilisation of coal, and it is mainly composed of carbon and mineral matter with traces of hydrogen, sulphur and oxygen. The physical structure, or morphology, of char particles will vary depending on the speed of devolatilisation, ash content and structure of the raw coal. Char oxidation is a heterogeneous (solid/gas phase) reaction, where the gaseous oxygen diffuses into the particle, and is absorbed and reacts on the char surface. The reaction is much slower than the volatile combustion, and depends on various factors. Oxygen may react at the char surface or diffuse through the pores before reacting with the particles. Oxidation produces both carbon monoxide and carbon dioxide. CO may also be formed by the reduction of CO2 by the surface carbon of the char. However, given sufficiently fuel-lean combustion conditions, all carbon and CO will be oxidised to CO2.

1.1.2Overview of NOx formation process: Although NOx refers to all oxides of nitrogen, during fossil fuel combustion, the major part of NOx emission has been found to be NO. There are three main sources of NO in combustion, namely thermal NO, prompt NO and fuel NO. Thermal NO results from the reaction of atmospheric nitrogen and oxygen at high temperature, prompt NO is formed by the reaction of nitrogen with hydrogen-derived radicals in the fuel-rich zone of combustion, whilst fuel NO results when nitrogen compounds present in the fuel are released and react with oxygen [4].

In coal-fired power plant, fuel NO is the major contribution to NOx emission, with some of the fuel NO being released from the devolitisation of the fuel and some from the oxidation of the char. The simplified NOx formation process associated with the combustion process of coal is briefly described in Figure 1.1

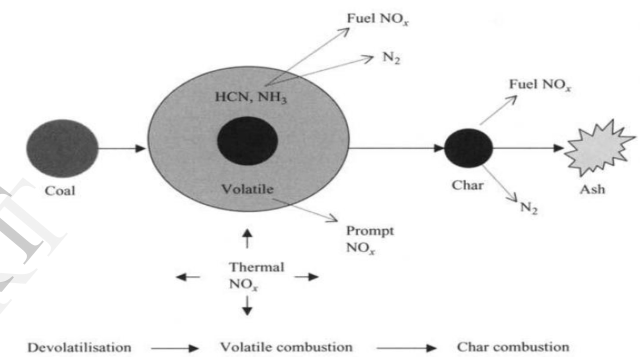

Fig.1. Simplified nitrogen oxides formation process

1.1.2.1Thermal NO FORMATION: High-temperature combustion causes atmospheric oxygen and nitrogen to react forming nitrogen oxide. The principal reactions:

(R3) $$N_2 + O \underset{k_{-1}}{\overset{k_1}{\Longleftrightarrow}} NO + N$$

(R4) $$N + O_2 \underset{k_{-2}}{\overset{k_2}{\Longleftrightarrow}} NO + O$$

(R5) $$N + OH \underset{k_{-3}}{\overset{k_3}{\Longleftrightarrow}} NO + H \quad \text{(for a fuel-rich mixture).}$$

The reaction rate coefficients (kl, k-l, k2, k-2, k3, k-3) for the forward reactions.

1.1.2.2Prompt NO formation: Prompt NO is formed by the reactions of N2 with fuel-derived radicals such as CH and CH2 in regions near the flame zone of a hydrocarbon fuel. Although its overall contribution can be small relative to the formation of total NO (less than 5 per cent), the concentration of prompt NO in fuel-rich zones can be significant. Additionally, in fuel-rich conditions of some low NOx burners, the proportion of prompt NO in the total NO formation may be greater.

1.1.2.3Fuel NO formation: Fuel NO is the main source of NOx emissions in fossil fuel combustion, and constitutes 70-90 per cent of the total NO [5]. Fuel NO is formed from the homogeneous oxidisation of nitrogen constitutes released during devolitisation. It is believed that the main gas species containing nitrogen produced during coal evolution are HCN and NH3. Once the fuel nitrogen is converted to HCN it rapidly decays to form various NH compounds (NHi), which react to form NO and N2.

1.1.2.4 NO2 formation: Formation and destruction of NO2 is believed to occur via the reaction of NO with 02, O, OH and HO2 in the flame. Chemical equilibrium considerations indicate that for temperatures greater than 1500 K the ratio of NO2 : NO is close to zero in the flame. However, significant NO2 concentrations have been measured in turbulent-diffusion flames near the combustion zone.

1.2 ARTIFICIAL NEURAL NETWORK (ANN):

An ANN is represented as a non-linear interconnected layer of processing nodes which are normally referred to as neurons, a term borrowed from neurobiology. It is an information processing paradigm made up of a set of algebraic equations. The most common class of ANN is the multilayered feedforward network which primarily consists of input layer, one or more hidden layer and an output layer [6]. Through the input layer, the normalized raw data is fed into the network. The input layer holds the data and distributes them into the network via interconnections to neurons in the hidden layer(s) where they are processed by the activation function to obtain the output signal. 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 as in Figure 2.

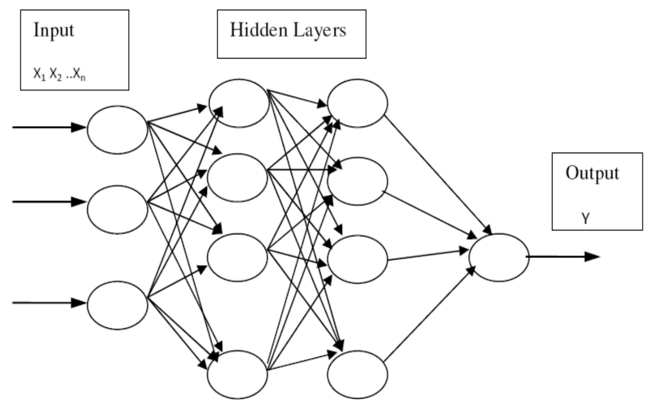

Fig. 2 ANN architecture for NOx prediction

It constitutes flavonoids, uranoflavonoids, and furan derivatives and is used in treating skin diseases and in bio pesticide. The meal cake can be used as fertilizer, pesticide and used for organic farming. Seed shells can be used as combustibles.

1.2.1Backpropagation Neural Network (BPNN): Using the ANN as its fitness function, the optimization algorithm determines the optimum levels of coal combustion parameters for minimum NO_x 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 [7,8].

The backpropagation neural network however has been widely used to develop soft sensors for prediction of NO_x [9]. The main advantage of ANN is the ability to model a problem by the use of data associated with process, rather than analysis of process by some standard numerical methods.

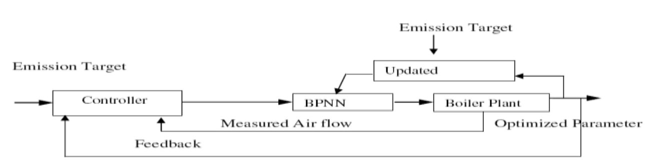

Fig. 2 Block diagram for Boiler with BPNN

1.3 Simulated annealing(SA):

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' [10].

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

2 LITERATURE REVIEW

Several works have been done to develop predictive systems for industrial emissions.

1) T. Faravelli , L. Bua , A. Frassoldati , A Antifora , L. Tognotti, E. Ranzi(2001): The main objective of this paper is to illustrate flow and temperature fields within the furnace, obtained through CFD codes. The papers describe both kinetic and fluid dynamic aspects during combustion.

The kinetic model based on (a) non-equilibrium radical concentrations make ineffective simplified approaches; (b) large fuel-rich regions are produced as in the case of the reburning technique. Detailed kinetic models are able to predict minor species whose concentrations range from ppbs to a few ppms.

In this paper uses the SFIRN (Simplified Fluid dynamic by Ideal Reactor Network), is based on a two-step procedure. Starting from the complex flow, temperature and stoichiometry fields computed by means of the 3D CFD simulation.

The paper shows comparison under several operating conditions between computed results (SFIRN & CFD) and experimental measurements at the gas/oil-fired 75 MW Plant.

Scope for future work as this approach can become an interesting tool to optimize the furnace design and to attain the stringent law requirements for the pollutant emissions from thermal processes.

2) S. Thompson and K. Li: In this chapter describes the emission reduction method in pulverized fuel plant& nitrogen oxides emission models.

Nitrogen oxides emission model are classified as

1) Black Box methods
    - ANN model
    - Identification model
2) Grey-box model
    - Grey-box mode
3) White box methods
    - CFD model

This chapter gives an overview of NO_x formation mechanisms. this paper shows each type of model has its particular advantages and disadvantages. Neural network and Identification model are easier and quicker to build.

3) Preeti Manke, Sharad Tembhurne (2013): This paper describes an efficient approach to predict nitrogen oxides emission from a 500 MW coal fired thermal power plant with optimized combustion parameters.

This paper has brought to focus the ability to model the NO_x emission from a 500 MW tangentially fired boiler under full load condition. Their 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. Combined with simulated annealing, the optimum operating parameters can be achieved to decrease the NO_x emission.

Scope for future work as hybrid model that involves both neural network and support vector machines will be developed in order to further improve the predictive accuracy and computational efficiencies.

4) Hao Zhou, Kefa Cen, Jianren Fan (2001): The paper presented an approach to predict NO_x emission of large capacity pulverized coal fired boiler with ANN. The experimental results an ANN was used to model NO_x emission and carbon burnout characteristics.

GA(Genetic algorithm) employed to perform a search to determine optimum solution of the ANN model, determining the optimal set points for current operating conditions to decrease NO_x emission. Comparison with ANN CFD approach, the modeling process using ANN is much easier and direct. Verifying with experimental results, show that ANN approach is accurate and give general and suitable way to predict NO_x emission under various condition and burning different coal.

5) A.T.C. Goh and C.G. Chua (2004): The paper describes the study deals with Back-propagation neural network & Bayesian neural network. Bayesian inference procedure that provides good generalization and a statistical approach to deal with data certainty.

This method over the conventional back-propagation method is that the algorithm is able to provide assessments of the confidence associated with the network's Predictions.

This paper demonstrates the robustness of the Bayesian neural network approach to model complicated nonlinear relationships.

3. A SCHEMATIC POWER PLANT DIAGRAM:

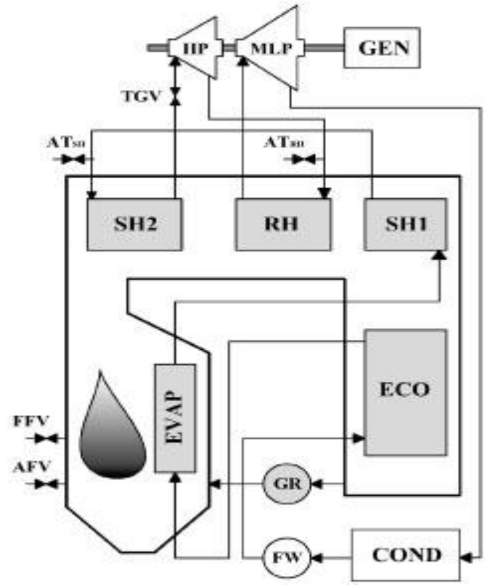

Fig. 3 A schematic power plant diagram

AAV-air flow valve FFV-flue flow valve FW-feed water ECO-economizer COND-condenser EVAP-evaporator SH-superheater HP-high pressure turbine TGV-turbine governor valve GEN-generator RH-reheater MLP-medium low pressure turbine

4. RESULT:

Many researcher developing NO_x predictive models and compare to each other and they found some result as

- A static neural network gives the worst overall performance, though widely used in industry.
- Introducing input dynamics (dynamic feedforward ANN model) gives improved overall prediction performance. However, the best recurrent neural network does not necessarily produce a better overall performance than a dynamic feedforward ANN model.
- By comparison with the CFD approach, ANN model is much easier and direct.

5. CONCLUSION: It is concluded that a combined approach of artificial neural network and SA for predicting and optimizing NOx emission using back propagation-feed forward neural network method is accurate. It can always give a general and suitable way to predict NOx emission under various operating conditions and burning different coal.

The combined approach of ANN and SA, the optimum operating parameters can be achieved to decrease the NO_x emission.

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Author profile

Milind S.Mankar student
M.Tech(Thermal Engg) final year in
Govt. College Of Engineering Amaravati
(M.S) India