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Artificial Neural Network Model for Emissions from Cofiring of Coal and Biomass in A Travelling Grate Boiler in India

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Abstract: Concerns regarding the potential global environmental impacts of fossil fuels used in power generation and other energy supplies are increasing worldwide. One of the methods of mitigating these environmental impacts is increasing the fraction of renewable and sustainable energy in the national energy usage. A number of techniques and methods have been proposed for reducing gaseous emissions of NOx, SO2 and CO2 from fossil fuel combustion and for reducing costs associated with these mitigation techniques. Some of the control methods are expensive and therefore increase production costs. Among the less expensive alternatives, cofiring has gained popularity with the electric utilities producers. This paper discusses about the emission model for cofiring of coal and biomass using Artificial Neural Network. The model uses an Elman network which is trained and simulated using back propagation algorithm. The ANN model was constructed and trained with experimental data got when biomass was cofired in 18.68 MW power plant with bituminous coal in 3 proportions of 20, 40 and 60% by mass. Bagasse, wood chips (Julia flora), sugarcane trash and coconut shell are the biomass fuels cofired with coal in this study. The impacts of mixing ratio and bed temperature on the emissions were considered. The model predicted emissions were consistent with experimental data.

Key words: Cofiring, biomass, NOX,SO2,CO2, ANN network and BP Algorithm

INTRODUCTION

With the present major worldwide agenda to reduce greenhouse gas emissions, the emphasis is on conventional coal-fired utilities to burn renewable fuels such as biomass residues or energy crop-derived biomass fuels as a low-cost option for reducing greenhouse gas emissions[1-4]. The need for finding new renewable sources of energy together with the necessity of searching new technologies to reduce the negative impact of waste accumulation has led to the possibility of using biomass as an alternate fuel. Most of the industrial sources of pollution come from coal fired power plants which necessitate the need to find ways to decrease the greenhouse gas emissions from these sources. Also, the ratification of the Kyoto Protocol would need countries to implement measures to meet Kyoto standards by 2008. One of the options that need to be considered is the application of cofiring technologies to coal fired power plants[5,6].

Cofiring is the simultaneous combustion of a supplementary fuel with a base fuel. Selectively, utilities and independent power producers have used biofuels, particularly wood waste to generate electricity in small stand alone generating stations with less than 50 MWe capacity. In more recent years, utilities have become interested in cofiring biofuels with coal and other fossil fuels, applying wood wastes and other solid forms of biomass to high efficiency, higher capacity generating plants. Initially, cofiring was seen as a means for reducing greenhouse gas emissions from fossil energy generation. Biomass cofiring with coal is proving to be the cheapest method for generating green power in utility plant demonstrations[1,7-12]. Those savings come not only from replacement of coal, but also from displacement of materials being sent to landfill, that ultimately decompose and form both CO_2 and another more powerful greenhouse gas: namely methane. The potential for expanding the use of Biomass Energy Technologies (BETs) for energy generation is vast in India and awaits further exploitation.

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Table 1: Proximate and ultimate analysis of fuels on % weight basis

S. No.	Parameter	Bituminous coal%	Wood chips %	Sugarcane trash%	Coconut shell%	Bagasse%	Lignite%
1	Moisture	5.55	7	4	6.5	50	48.5
2	Ash	34	0.37	1.75	6.50	1.5	7.0
3	Carbon	44.14	48.80	49.00	49.75	23.5	29.06
4	Fixed Carbon	34.5	38.11	38.27	38.85	18.35	22.69
5	Hydrogen	3.23	6.37	5.89	5.8	3.25	2.35
6	Sulphur	0.59	0	0	0.05	0	0.5
7	Oxygen	11.58	44.4	43.36	36.7	21.75	12.31
8	Nitrogen	0.91	0	0	1.2	0	0.28

In this context, biomass cofiring and its applicability to Indian power production, will be a great boost to the power producers, environmentalists and all concerned. The present work carried out, proposes a three layer Feed Forward Neural Network (FFNN) to predict the gaseous emissions and particulate matter, when a 18.68 MW traveling grate boiler is used to cofire a combination of coal and different types of biomass.

Plant description: A study to measure cofiring emission characteristics is done in a 18.68 MW power plant, situated in Virudachalam district of Tamilnadu, the southern most state of India. This plant is a cogeneration plant, attached to the sugar mill. The plant has been generating power to meet its own requirements and the rest is being given to the main grid. The boiler is provided with two fuel feeder routes, one each for coal and biomass. Coal feeding is done from a height of 8 m and biomass from a height of 9.8 m above the base. The maximum amount of steam generation from the plant has been kept at 70 tonnes/hour for the tests conducted. The generated steam has a maximum temperature and pressure of 485°C and 65 kg /cm^2.

Boiler specifications: The pressure and temperature rating of our boiler is as follows :

- Design pressure of boiler : 51 kg/cm^2(g)
- Working pressure of boiler : 42 kg/ cm^2 (g)
- Boiler temperature : 256°C
- Boiler super heater outlet steam temperature : 410 +/- 15°C
- The Total heating surface of our boiler : 3396 m^2.
- The size of the travelling grate is 3842mm wide x 5664mm long: 2 No's.
- The speed of the travelling grate : 0.027 rpm to 0.27 rpm.

Fuel characterization: Bituminous coal, lignite, bagasse, wood chips, sugarcane trash and coconut shell are the fuels used for the tests. The proximate and ultimate analyses were carried out for all the fuels and the results are presented in Table 1. It should be noticed that, in comparison to the primary fuel (coal), biomass contains much less carbon and more oxygen. With regard to the ash content, values for biomass are much lower that for coal. Bituminous coal, which costs Rs.3000/tonne, was mixed with lignite abundantly available in the state of Tamilnadu, but inferior quality than bituminous coal. Biomass materials which were required for cofiring tests, were procured from the neighboring areas, whose cost varies from Rs.700 to Rs.900 per tonne.

Cofiring tests: Cofiring tests were conducted in the plant, with various combinations of biomass fuels in different proportions (K.V Narayanan, E Natarajan 2006). The results have been used to model the neural network.

Elman network architecture: Elman networks are two-layer back propagation networks, with the addition of a feedback connection from the output of the hidden layer to its input (Fig. 1). This feedback path allows Elman networks to learn to recognize and generate temporal patterns, as well as spatial patterns. The Elman network commonly is a two-layer network with feedback from the first-layer output to the first layer input. This recurrent connection allows the Elman network to both detect and generate time-varying patterns. The Elman network has tansig neurons in its hidden (recurrent) layer, and purelin neurons in its output layer. This combination is special in that two-layer networks with these transfer functions can approximate any function (with a finite number of discontinuities) with arbitrary accuracy. The only requirement is that the hidden layer must have enough neurons. More hidden neurons are needed as the function being fit increases in complexity. Note that the Elman network differs from conventional two-layer networks in that the first layer has a recurrent connection. The delay in this connection stores values from the previous time step, which can be used in the current time step. Thus, even if two Elman networks, with the same weights and biases, are given identical inputs at a given time step, their outputs can be different due to different feedback states. Because the network can store information for future reference, it is able to learn temporal patterns as well as spatial patterns. The Elman network can be trained to respond to, and to generate, both kinds of patterns.

Table 2: Comparison of ANN model results with reference to the experimental data given for training

No of hidden units	No of input data sets	No. of simulation data sets	CPU time for training	Trainingfn/learning fn/ transfer fns	Error Min	Error Max
24	100	50	116.1250	Traingdx/Learngdm/Tansig-atlins	0.05	-0.058
24	100	50	196.3590	Traingdx/Learngdm/Tansig-purelin	0.8	-0.45
6	51	50	16.8440	Trainlm/Learngdm/Tansig-satlins	0.041	-0.034
6	100	50	538.1240	Trainlm/Learngdm/Tansig-satlins	0.038	-0.042
12	51	50	8.4680	Trainlm/Learngdm/Tansig-satlins	0.05	-0.032
12	100	50	35.422	Trainlm/Learngdm/Tansig-satlins	0.04	-0.07
18	51	50	42.8410	Trainlm/Learngdm/Tansig-satlins	0.038	-0.042
18	100	50	149.8960	Trainlm/Learngdm/Tansig-satlins	0.072	-0.038
24	51	50	58.8750	Trainlm/Learngdm/Tansig-satlins	0.048	-0.032
24	100	50	241.20	Trainlm/Learngdm/Tansig-satlins	0.028	-0.030

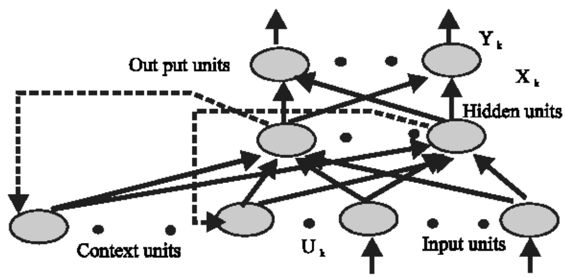

Fig. 1: Elman network architecture

Creating an elman network (newelm): An Elman network with two or more layers can be created with the function newelm (Math works tool box,7.1). The hidden layers commonly have tansig transfer function, so that is the default for newelm. Purelin is commonly the output-layer transfer function. The default back propagation training function is trainbfg. One might use trainlm, but it tends to proceed so rapidly that it does not necessarily do well in the Elman network. The backdrop weight/bias learning function default is learngdm and the default performance function is mse. When the network is created, each layer's weight and biases are initialized with the Nguyen-Widrow layer initialization method implemented in the function initnw.

Training: An Elman network can be trained with either of two functions, train or adapt. When using the function train to train an Elman network the following occurs, at each epoch: the entire input sequence is presented to the network and its outputs are calculated and compared with the target sequence to generate an error sequence. For each time step, the error is backpropagated to find gradients of errors for each weight and bias. This gradient is actually an approximation since the contributions of weights and biases to errors via the delayed recurrent connection are ignored. This gradient is then used to update the weights with the backprop training function chosen by the user. The function traingdx is recommended The function learngdm is recommended. Elman networks are not reliable as some other kinds of networks because both training and adoption happen using an approximation of the error gradient. For an Elman to have the best chance to learning a problem it needs more hidden neurons in its hidden layer than are actually required for a solution by another method. The function trains an Elman network to generate a sequence of target vectors when it is presented with a given sequence of input vectors . Train takes these vectors and intial weights and biases of the network, trains the network using back propagation with m omentum and adaptive learning rate and returns new weights and biases.

Simulation: Simulation is actually an application of the inputs on to the network and thus causing the network to produce outputs. In MATLAB simulation can be done using the function sim which takes the network 'p' and the network object 'net' and returns the network output 'a'.

RESULTS AND DISCUSSION

ANN model (an Elman network) is created, trained and simulated for various data sets and the results are compared in Table 2. For a set of 50 data the training graph is shown in Fig. 2 and the corresponding error profile is shown in Fig. 3. The ANN model was trained for the values that are inferred from experiments conducted for various combinations of coal and biomass and for various proportions of fuel mix. The ANN model responded very closely to the desired output parameters as shown in Fig. 4. Hence this ANN model can predict the various output parameters such as SO_2, NO_x and SPM for different combinations and proportions of fuel mix. One such output for a combination of coal: Coconut shell, which shows a variation of output parameters like SO_2, NO_x and SPM with respect to mixing ratio and bed temperature, is shown in Fig. 5-7.

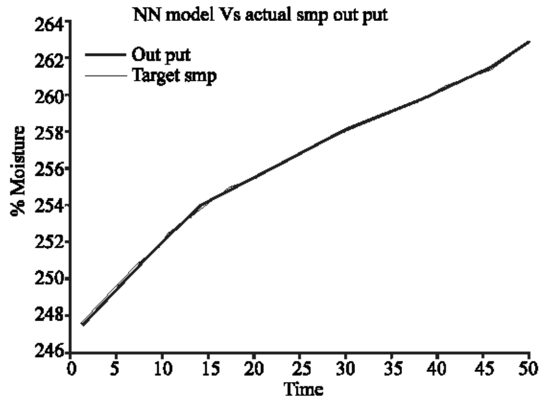

Fig. 2: Comparison of ANN output vs the target to the data sets

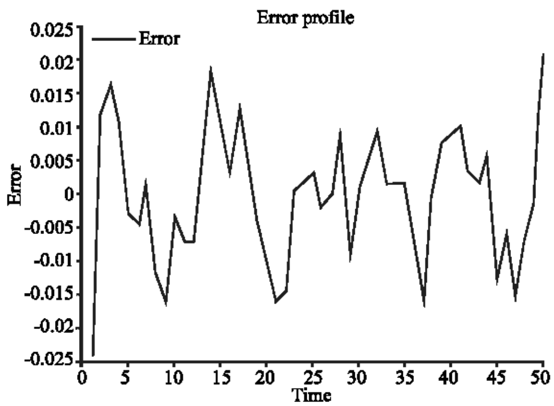

Fig. 3: Variation of training error with respect to output for SPM

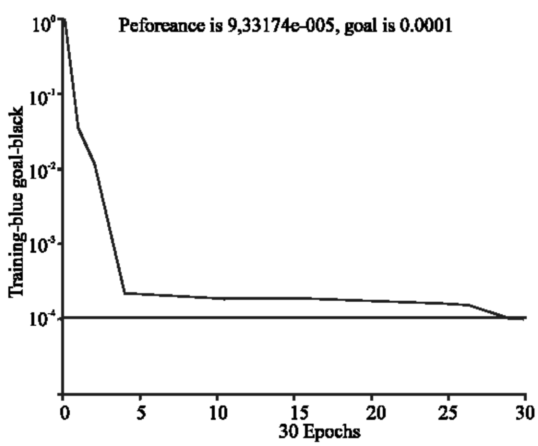

Fig. 4: Training graph for the given data sets

Specifications of the concluded result:

Training Function: trainlm

Transfer function: Tansig (input layer) Satlins (hidden layer)

Goal: 0.0001

Fig. 5: Variation of Stack emission SPM for different mixing ratios and temperatures for coal:coconut shell cofiring

Fig. 6: Variation of Stack emission SO_2 for different mixing ratios and temperatures for coal:coconut shell cofiring

Fig. 7: Variation of Stack emission NO_x for different mixing ratios and temperatures for coal:coconut shell cofiring

Learning Function: learngdm
No. of epochs: 30
No. of hidden units: 24
No. of training data sets: 50
No. of simulation data sets: 50

CONCLUSION

The future of coal and biomass blend cofiring in utility boilers looks very bright. Based on th positive results of recent cofiring studies conducted across the globe, coupled with more strict environmental regulations and associated penalties, utilities are seriously considering cofiring locally available biomass fuels with coal in their boilers. In addition, many countries like United States, Denmark, U.K have made using a percentage of biomass mandatory for electric utilities.

Cofiring biomass fuels with coal has the capability to reduce both NO_x and SO_2 levels from existing pulverized coal fired power plants. In addition, overall CO_2 emissions can be reduced because biomass is a CO_2 neutral fuel. However, cofiring technology faces some technological problems.

The outcome of the present work can be summarized as follows:

- Within the range of experimental conditions tested, it has been observed that, the ANN model gave predictable results with respect to the experimental results.
- Apart from the experiments that can be conducted to arrive at the optimal fuel combination and proportion, it has been felt that the ANN model could help the power producers benefit largely, by simulating such experiments thus finding the best optimal choice for cofiring in their plant.

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