Neural Network Based Power Plant Coal Quality Analysis

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Abstract – Ash problems in coal-fired power plants result in decreases in efficiency, unscheduled outages, equipment failures, and cleaning. Assessing the potential impact of ash on power plant performance is extremely complex and difficult due to coal variability, the complexity of the ash behavior processes involved, and changing operating conditions. To predict the impact of ash on power plant performance, the impurities and mineral contents of coal have to be determined. Current coal quality evaluation methods are either inefficient or very expensive and time consuming. This paper develops a neural network which quickly determines the impurities and ash forming species in coal. The results are compared with those from computer-controlled scanning electron microscopy (CCSEM) methods. The developed model shows promise and has the potential to save coal-fired utilities millions of dollars in dealing with various coal ash problems.

Key Words: Power plants, Coal quality, Ash forming species, Neural networks.

1. Introduction

The cost of ash related problems at coal-fired power plants in the United States is significant. The ash issues are aggravated because the coal-fired power industry in the United States is faced with major changes in coal quality due to environmental regulations and economic constraints.

The impacts of ash on the overall performance of coal-fired combustion and gasification power plants may include fireside ash deposition, corrosion and erosion of boiler parts, slag flow maintenance, and production of fine particulates that are difficult to collect [1]. Ash deposits on fireside heat exchange surfaces of power plants significantly decrease plant efficiency and are aggravated by variability in coal quality (chemical and physical characteristics of inorganic materials), system operating conditions, and system design. These deposits require soot blowing and load shedding for removal, both of which decrease plant efficiency and availability. Ash accumulations on heat transfer surfaces also require annual or semi-annual shutdowns for cleaning which results in cleaning costs and more lost revenues from being off-line. Another major issue impacting wet-bottom boilers, cyclone-fired boilers, and entrained gasifiers, is maintaining slag flow. In some systems maintaining slog flow requires cofiring of other expensive fuels such as oil or adding fluxing agents and in some cases outages to remove frozen slag resulting in decreased efficiency and availability.

Effective management of ash behavior in coal-fired systems is extremely difficult because of the high variability and complex associations of the inorganic components (ash-forming constituents) in coal. The association and abundance of major, minor and trace-inorganic elements in coal is dependent upon coal rank and depositional environment.

Upon combustion, the inorganic components associated with coal are transformed to inorganic vapors, liquids and solids in the flame. The degree to which these transformations occur depends upon the characteristics of the conversion system and coal properties. The vapors, liquids, and solids are transported with the bulk gas flow through the system. During gas cooling, the vapors condense to form sub-micron particles on the surfaces of entrained ash particles and the liquid phases solidify to form solid particles. The state of the inorganic substances in the combustion system will dictate if it will end up in molten slag in wet bottom systems or entrained in the bulk gas flow. Partitioning of ash between slag, deposits, and entrained ash (fly ash) is extremely important in understanding the potential effects a coal may have on boiler performance [2]. Much work has been performed to determine the abundance and composition of vapor phase species as well as the size and composition of liquid and solid particles in coal [3].

Many of the above problems associated with coal ash are due to unforeseen excursions in the abundance of the ash-forming species in coal. The detrimental effects of inorganic species can be minimized through the use of an effective method to select, blend and forecast fuel quality. Currently, bulk coal analysis is performed and used by coal-fired power industry to determine the ash-forming species in the coal and to predict the ash behavior. This prediction, however, is severely limited because of the inadequacy of bulk coal analysis methods to determine the exact chemical and physical characteristics of the inorganic components in the coal . Improvements in determining the ash producing impurities and predicting ash behavior have been made through the use of computer-controlled scanning electron microscopy (CCSEM). Detailed CCSEM techniques determine the size, composition, and abundance of minerals in coal [4, 5]. CCSEM results are used to forecast the deposition tendency and slagging behavior of ash under various operating conditions of utility boilers by computing a set of performance indices. However, CCSEM based methods are rather time consuming. Thus, assessment techniques that can produce results similar to those from CCSEM methods and yet are inexpensive and efficient are highly desirable and sought by utility industry.

Artificial neural networks (ANNs) have been used in various segments of industry to solve several problems [6]. For example, ANN have been used to detect and locate faults on power system transmission and distribution lines [7] and to identify and eliminate bad data that are telemetered to the energy control centers of the electric utilities [8]. For a partial list of ANN applications in electric power industry the reader is referred to [9]. To a limited degree, feed-forward backpropagation ANNs have also been used to predict ash behavior in power plants. There are several publications on this subject and the results show promise [10-12]. However, an ANN system specifically designed for predicting the CCSEM based analysis results has not been developed to predict the quality of coal.

This paper describes an ANN which takes the utility based bulk coal/ash analysis results and accurately and quickly determines detailed CCSEM type of results. The developed ANN can be integrated with other ash analysis programs to quickly compute the boiler performance indices. Using this integrated system, the analysis will be fast and inexpensive. Thus the developed ANN has the potential to save the coal-fired utility industry millions of dollars and aid in the development of advance power systems through matching fuel quality to power plant design and optimization of operating conditions in order to minimize ash-related problems. ANNs can be used to forecast ash problems based on coal shipments allowing operations staff to change operating conditions and coal blends to alleviate those problems.

The second section of the paper describes the structure and other details of the developed neural net. The third section presents a practical test case. The final section gives some concluding remarks.

2. Approach

In order to make the presentation of the developed ANN more meaningful, a brief description of neural network concepts is in order.

2.1 Artificial Neural Networks

ANNs represent a set of new and advanced information and data processing systems. They provide a means to perform tasks such as pattern matching and classification, linear and multidimensional nonlinear function approximation, complex optimization, vector quantization, and data clustering, while traditional computer techniques are inefficient at most of these tasks. However, conventional computers are faster in algorithmic computational tasks and precise arithmetic operations.

ANNs are generally formed by interconnecting a number of simulated neurons in a similar way that natural neurons of human brain are connected. The main objective of the ANN technology is to mimic the brains approach to processing data and information. Specifically, an ANN consists of a large number of simple processing elements called neurons, units, cells, or nodes. Each neuron is connected to other neurons by means of directed communication links, each with an associated weight or strength. The weights represent information being used by the net to solve a problem. These weights are determined and fixed during the learning or training stage of the network. To train a neural net, a number of examples of a particular problem are given (shown) to the net. The net learns and makes adjustments to its weights from these examples in much the same way that people learn through experimentation and interaction with their environment.

Models of ANNs are specified by three basic entities: models of the neurons themselves, models of the interconnection links among neurons, and the training or learning rules for determining the connecting weights.

Each of the neurons of a net is characterized by what is known as its activation function. The activation, which is a function of the inputs the neuron receives, determines the internal state or the activity level of the neuron. Typically, a neuron sends its activity level as a signal to other neurons connected to it. Figure 1 shows the mathematical model of a neuron known as the McCulloch and Pitts neuron. In this model, the ith neuron computes a weighted sum of its inputs and produces an output signal (firing) or a zero (not firing) according to whether this weighted input sum is above or below a certain threshold θ_i :

$$\mathrm{f_i} = \sum_{\mathrm{j}=1}^{\mathrm{m}} \mathrm{W_{ij} X_j(t)} - \theta_\mathrm{i} \tag{1}$$

$$\mathrm{Y_i(t+1) = A(f_i)} \tag{2}$$

where the activation function $\mathrm{A(f_i)}$ could be any of the so called sigmoid functions.

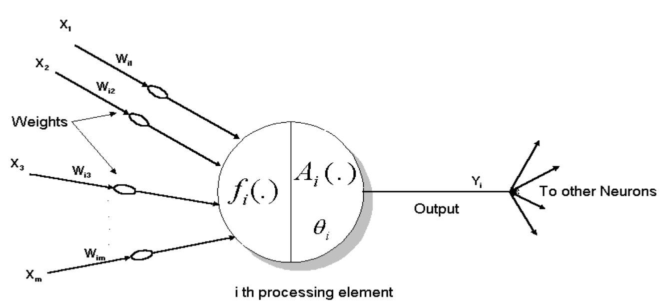

Figure 1: Diagram of a typical neuron

A popular activation function is known as the logistic sigmoid function (an S-shaped curve) and is defined by:

$$\mathrm{A(f)} = \frac{1}{1+\exp(-\mathrm{f}\lambda)} \tag{3}$$

where f is defined as in Equation (1) and λ determines the steepness of the activation function. Figure 2 shows a typical sigmoid function for various values of λ. The choice of λ depends on the problem and the data being analyzed.

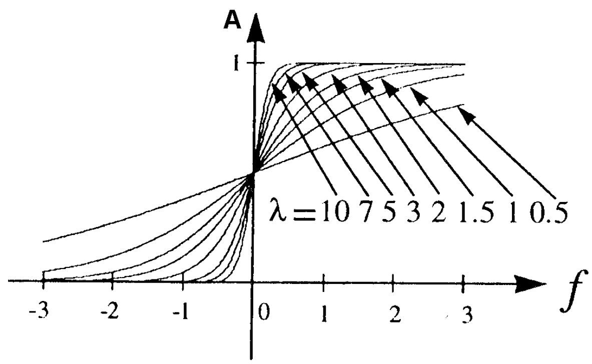

Figure 2: A typical logistic sigmoid function

Depending on the way that neurons are organized and the connection geometry among them, there are several structures (or architectures) of ANNs. One of these structures, known as the feed-forward ANN, is designed such that a layer of input neurons is connected to one or more layers of neurons called hidden layers. The hidden layers are then interconnected to the next layer of neurons called the output layer of the net. These interconnected input, hidden, and output layers now form a multilayer feed-forward neural network. The input layer typically performs no function other than buffering of the input signal. The outputs of the net are generated from the output layer. A net is said to be fully connected if every output from one layer is connected to every neuron in the next layer. A fully connected multilayer feed-forward ANN is generally called a multilayer perceptron (MLP). A MLP with two hidden layers of neurons is shown in Figure 3.

One of the most critical and important factors in the design of ANNs is their training. In general, there are three categories of ANN training or learning methods: supervised learning, reinforcement learning, and unsupervised learning. Experience and tests indicate that supervised learning is the most suitable method of training for the network of this project. In a supervised training method, the designed net is presented with several input-output pairs of examples. Each time an input is presented, the net produces an output. The produced output is then compared with the corresponding desired output. If there is a discrepancy, the net computes the error and makes corrections to the weights of the links connecting the neurons together. When the entire set of the input-output training pairs are presented, the net randomly reshuffles the pairs and then starts over again at the beginning of the reorganized training set. This training process is repeated several hundreds, thousands, or more times until the output errors become small and the net outputs are within a user-specified tolerance level for all the input-output training pairs. One of the well-known methods that is used to minimize the output errors of the net during its training is the backpropagation technique. Depending on the computer speed, the training process can be very slow and may take up to several hours, days, or even weeks to complete. Details about the training issues are discussed elsewhere in the ANNs literature.

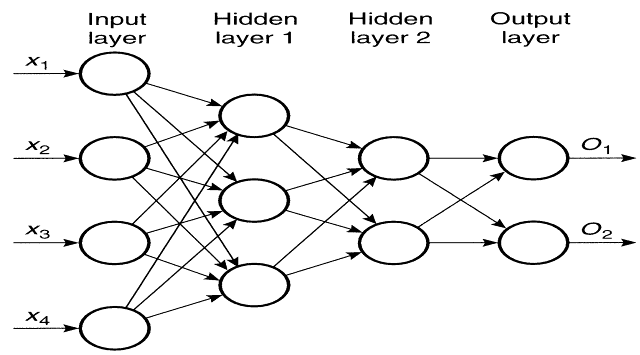

Figure 3: A multilayer perceptron

Once a net is successfully trained and tested (i.e., the net produces answers that are within the user-specified tolerance), the user may wish to reduce the error tolerance and continue training the net in order to achieve a higher level of accuracy in the predictions of the net. The ultimate accuracy of the net predictions, however, highly depends on the accuracy of the input-output training pairs. Furthermore, an over trained NN memorizes its training sets and thus will not be able to generalized and produce accurate outputs to the inputs it has not seen before.

2.2 Designed Neural Network

Several multilayer perceptron architectures with various numbers of hidden layers and hidden processing elements (PEs) were developed and tested for this project. The number of input and output PEs was determined and fixed by the size of each input (bulk ash) and output (CCSEM) samples provided by a utility. The size of each bulk ash sample was 10 and the size of each of the corresponding desired CCSEM samples was 18. Tables 1 and 2 list the input bulk ash components and the corresponding desired CCSEM output results. Given the bulk ash analysis results, the neural net should be able to predict the CCSEM results that are critical in predicting ash behavior.

After several trails, the required ANN was designed as shown in Figure 4. This ANN has 32 neurons (PEs) and 112 synapse

Table 1: Typical Weight Percent of Input Bulk Ash on a Mineral Basis

Mineral	% Weight
%Ash (dry basis)	6.95
Na_2O	1.21
MgO	7.4
Al_2O_3	23.88
SiO_2	47.29
P_2O_5	0.97
K_2O	0.41
CaO	15.46
TiO_2	1.18
Fe_2O_3	2.2

Table 2: Typical Weight Percent of Desired CCSEM Output Results on a Mineral Basis

Mineral	%Weight			
	1.0 - 4.6	4.6 - 22.0	22.0 - 46.0	46.0 - 100.0
Quartz	8.8	10.3	3.7	1.0
Kaolinite	25.9	24.2		1.0
Montmorillonite	0.9	0.4		0.0
K Al-Silicate	2.5	1.5		0.0
Pyrite	2.9			
Total	47.2	49.3		3.5

connections (weights). The best value of these weights were determined by training the net a number of times.

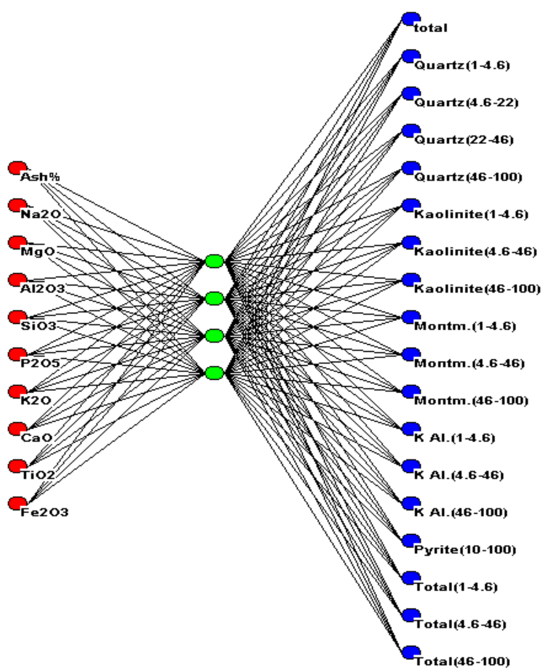

Figure 4: Designed ANN for CCSEM Prediction

To train the net, an enhanced variant of back propagation technique known as the momentum learning method was used for both the hidden and the output layers. The value of each of the parameters of the learning rule were determined by several trail and error efforts as there are no fast and deterministic rules available for this. These parameters highly depend on the data to be analyzed and require some degree of experience and insight into the problem to be solved. The value of the design parameters determined for this work are summarized in Tables 3 and 4.

Table 3: Design Parameters

Layer	Learning Method	PE Nonlinearity
Hidden	Momentum	Sigmoid
Output	Momentum	Sigmoid

Table 4: Learning Parameters

Layer	Step Size (Learning Rate)	Momentum Rate
Hidden	0.5	0.7
Output	0.08	0.7

The net was trained in a batch mode for fifty (50) times each with 10,000 epochs. The output results are discussed next.

3. Results

A total of 200 input/output sample pairs of bulk ash and CCSEM results were used to train the network. Out of these 200 samples, 11 were used for cross validation, 2 were used for testing purposes, and the remaining 187 were used to actually train the network. After training, the net was tested a couple of times. One of the test results is reported here. The values in Tables 1 and 2 were not included in the training set. Instead, they were used to test the network. The actual test results (the results predicted by the network) are shown in Table 5.

Table 5: Weight Percent of Actual CCSEM Output Results on a Mineral Basis

Mineral	%Weight			
	1.0 - 4.6	4.6 - 22.0	22.0 - 46.0	46.0 - 100.0
Quartz	8.7	10.2	3.8	1.4
Kaolinite	15.6	19.6		2.2
Montmorillonite	3.3	3.2		0.9
K Al-Silicate	1.6	1.7		0.9
Pyrite	3.0			
Total	48.3	48.4		6.8

A Comparison of the values in Table 2 and Table 5 indicates a close match between the majority of what is desired and what is actually predicted by the net. The variations in some of the results are somewhat statistically insignificant and it is expected that with additional samples and more training the discrepancies will become even smaller and eventually disappear.

4. Conclusions

A neural network model has been developed that determines the impurities and ash-forming species in coal. Results from the model can be used and further analyzed to accurately select, blend, and forecast fuel quality in power plants. Compared to conventional techniques, the method of this paper is quick, efficient, and economical. It can save utilities millions of dollars in their costs dealing with various coal ash problems.

References

[1]. S. A. Benson, E. A. Sondreal, and J. P. Hurley, "Status of Coal Ash Behavior Research," Elsevier Journal of Fuel Processing Technology, Vol. 44, Nos. 1-3, 1995, pp. 1-12.

[2]. J. P. Hurley and S. A. Benson, "Ash Deposition at Low Temperatures in Boilers Burning High-Calcium Coals. 1. Problem Definition, *Energy & Fuels*, Vol. 9, 1995, pp. 775-781.

[3]. S. A. Benson, J. P. Hurley, C. J. Zygarlicke, E. N. Steadman, and T. A. Erickson, "Predicting Ash Behavior in Utility Boilers," *Energy & Fuels*, Vol. 7, 1993, pp. 746-754.

[4]. C. J. Zygarlicke and E. N. Steadman, "Advanced SEM Technologies to Characterize Coal Minerals," Scanning Electron Microsc., Vol. 4, No. 3, 1990, pp. 579-590.

[5]. L. Kong, C. J. Zygarlicke, and S. A. Benson, "Computer Controlled SEM Analysis of Minerals in Coal," Proceedings of the Thirteenth Annual International Pittsburgh Coal Conference, September 3-7, 1996, Pittsburgh, PA.

[6]. S. Haykin, *Neural Networks - A Comprehensive Foundation*, New York: IEEE Press and Macmillian, 1995.

[7]. L. Fausett, *Fundamentals of Neural Networks*, New Jersey: Prentice-Hall, 1994.

[8]. C. Lin and G. Lee, *Neural Fuzzy Systems*, New Jersey: Prentice-Hall, 1996.

[9]. M. Kezunovic and I. Rikalo, "Detect and Classify Faults Using Neural Nets," IEEE Computer Applications in Power, Vol. 9, No. 4, 1996, pp. 42-47.

[10]. H. Salehfar and R. Zhao, "A Neural Network Preestimation Filter for Bad-Data Detection and Identification in Power System State Estimation," Journal of Electric Power System Research, Vol. 34, 1995, pp. 127-134.

[11]. P. E. Keller, "Neural Network Applications in the Electric Power Industry," World Wide Web URL at: http://www.emsl.pnl.gov:2080/docs/cie/neural/bib/power.html.

[12]. D. J. Wildman, J. M. Ekmann, and S. M. Smouse, "Prediction of Pilot-Scale Coal Ash Deposition: Comparison of Neural Network and Multiple Linear Regression Techniques," Engineering Foundation Conference on Impact of Ash Deposition on Coal-fired Plants, Solihull, England, 1993.

Biographies

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