Implementation of Artificial Neural Networks (ANN) modelling in Power Plant operation optimisation

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Abstract. Artificial Neural Networks (ANN) consist an alternative method of solving complex problems. They operate as a “black box” model learning from examples, which is capable of dealing with non-linear problems and predicting results at high speed. An advantage of using ANN is their ability to handle large and complex systems with many interrelated parameters. They seem to simply ignore excess data that are of minimal significance and instead they concentrate on the more important input data.

The application reported in the present paper considers the implementation of ANN models for the prediction of particulate emissions and ash characteristic temperatures from a Power Plant by taking into consideration main operating parameters and fly ash composition, respectively. This can demonstrate the suitability of Artificial Neural Networks as a tool for Electrostatic Precipitator (ESP) and boiler operation optimisation.

Keywords: Artificial Neural Networks, Power Plants, optimization, Electrostatic precipitator

1. INTRODUCTION

Efficiency monitoring in existing coal-fired Power Plants consists a very important operational aspect and becomes even more crucial in the framework of the energy market liberalization. The information provided by such systems can contribute towards efficiency improvement, reduction of emissions as well as in the decision making process regarding the operating condition and maintenance requirement of the equipment. In general, efforts in efficiency monitoring and optimization employ either Artificial Neural Network (ANN) modeling, or linear and non-linear programming approaches.

Over the past years, ANN modeling has successfully been implemented in several industrial applications as well as in energy production systems with encouraging results [8], [9]. In the literature, there are available solutions based on ANN modeling that combine dynamic and steady state non-linear models as well as a closed-loop control based on Model Based Predictive
Control (MBPC). There are several applications of ANN modelling in the field of energy production [3], [4], [6].

An alternative approach which is available in the literature is the non-linear mathematical programming. Mathematical programming has been used successfully over the past decade in energy production and distribution problems. The main idea is the mathematical modeling of the problem as well as the behavior of the system through sensitivity analysis.

In the 1980s the “Interior Point Algorithm” was developed [7] for linear and non-linear problems opening new horizons in the solution of linear problems [1]. More recently, a new class of algorithms (Exterior Point Algorithm) has been developed to deal with the general linear problem [2], [10], and which have become more efficient over the years [11].

ANN is an adaptable system that can “learn” relationships through repeated presentation of data and is capable of generalizing to new, previously unseen data [5]. Most networks are supervised, in that a human determines what the network should learn from the available data. In this case, the network is provided with a set of input data and corresponding desired outputs, and the network tries to learn the input-output relationship by adapting its free parameters.

In the present research work, the ability of ANN modelling to perform Electrostatic Precipitator operation optimization as well as prediction of Ash Fusion Temperatures and Coal Heating Values through composition is investigated.

2. OPTIMISATION OF ELECTROSTATIC PRECIPITATOR (ESP)

Electrostatic precipitation (ESP) is a technology that controls particulate emissions from coal-fired power plants for more than 70 years and is the most effective fly ash removal system. ESPs that were built in the 1930s achieved efficiencies near 95%. By the 1950s, guarantees were being made for efficiencies of 97%-98%. By the 1970s, the efficiency of ESPs approached values above 99.5%. Nowadays ESPs are designed for efficiencies greater than 99.9%. It should be noticed that 0.1% rise in ESP efficiency from 99.8% to 99.9% corresponds to double amount of particles emitted.

The process of electrostatic precipitation consists of four distinct phases:

1. Ionization of flue gases flowing between electrodes
2. Collection of the particles on oppositely charged plates
3. Knocking the particles off the plates and into hoppers

The efficiency of an ESP mainly depends on the temperature of the flue gas (the higher the temperature the lower the efficiency), amount of fly ash, velocity of flue gas, quality of fly ash and the condition of the precipitator.

All the aforementioned parameters should be taken into account in order to be able to predict the efficiency of an ESP. Artificial Neural Networks (ANN) offer the possibility to perform predictions of particle emissions for several cases as well as to accomplish optimization of the ESP operation by implementing scenarios in a safe mode.
For the present analysis, the main operating conditions such as power output, consumed lignite, O\textsubscript{2} concentration, combustion air flow, flue gas temperature and efficiency of ESP, have been measured for a full scale Power Plant Unit.

A database of 562 measurements (from January 2005 to June 2005) was utilised. The measured values as well as the measured range are listed in Table 1. Only a set of 450 measurements were employed for model training and the remaining 112 measurements were used for the evaluation of the results. From the collected data only the Unit Power Output, the Oxygen Concentration, the Lignite Flow, the ESP Power Consumption and the ESP Opacity were used since the rest of the data (i.e. SuperHeater Pressure) do not present significant changes during the operation of the Unit or do not affect the ESP efficiency.

The model output is the prediction of the Flue Gas Opacity. The opacity of each ESP, expressed as a percentage, corresponds to a specific ash concentration in Flue Gas (gr/Nm\textsuperscript{3}). High Opacity percentage corresponds to high ash concentration. The standard deviations of the results are 10.1% and 9.0% for left and right ESP respectively. The range of deviation is 72.9% and 78.6% for left and right ESP respectively. These deviations are quite high and the model can not be used as a reliable prediction tool. The reason for high deviation is the partial incorporation of the ash quality properties through the input data. The input data are only capable of introducing a rough estimation of the coal quality. This is achieved by the ratio of Lignite Flow to Power Output and the higher the ratio, the lower the coal quality. Lower coal quality corresponds to higher ash content in coal and lower ESP efficiency. In order to achieve better model accuracy new measured data have to be added in order to incorporate further ash quality characteristics (i.e. CaO content). Such measurements are not available in standard Unit measurement configuration.

3. OPTIMISATION OF BOILER OPERATION THROUGH THE PREDICTION OF TENDENCY FOR SLAGGING AND FOULING

The efficiency of steam boilers depends (among others) on the Slagging and Fouling tendency of fly ash. Low fly ash fusion temperature results in high accumulations in heat transfer areas (reduced efficiency and longer shut down periods for cleaning). Therefore the Slagging and Fouling potential of fly ash is very important to Power Plant operators since it provides a tool for ash behaviour prediction during combustion as well as the effect of adding minerals (i.e. CaO). Ash characteristic temperatures (IDT, ST, HT, FT) are determined by the chemical composition [15], [16]. There are several experimental techniques for estimating the ash characteristic temperatures (i.e. ASTM method) but in contrast very few theoretical models are in existence and which rely mainly on statistical correlations between chemical composition and characteristic temperatures [13], [14].
<table>
<thead>
<tr>
<th>Measured Value</th>
<th>Unit</th>
<th>Range</th>
</tr>
</thead>
<tbody>
<tr>
<td>Unit Power Output</td>
<td>MW&lt;sub&gt;el&lt;/sub&gt;</td>
<td>0-300</td>
</tr>
<tr>
<td>Oxygen Concentration</td>
<td>%</td>
<td>0-21</td>
</tr>
<tr>
<td>Lignite Flow</td>
<td>%</td>
<td>0-80</td>
</tr>
<tr>
<td>ESP Power Consumption</td>
<td>kW</td>
<td>0-1000</td>
</tr>
<tr>
<td>SuperHeater Steam Flow</td>
<td>t/h</td>
<td>0-960</td>
</tr>
<tr>
<td>SuperHeater Steam Pressure</td>
<td>Kg/cm²</td>
<td>0-175</td>
</tr>
<tr>
<td>Combustion Air Flow</td>
<td>Nm³/h x 10³</td>
<td>0-1000</td>
</tr>
<tr>
<td>Flue Gas Temperature before ESP</td>
<td>°C</td>
<td>0-250</td>
</tr>
<tr>
<td>ESP Opacity</td>
<td>%</td>
<td>0-100</td>
</tr>
</tbody>
</table>

Table 1. Measured values for ESP optimization modelling

The present paper demonstrates the ability of ANN to predict the ash Slagging and Fouling tendency by estimating the ash characteristic temperatures. The ANN model is trained with several data (ash chemical analysis) from the literature and from existing Greek Power Plants. The database used consists of 182 samples of coal and biomass ashes. Validation of the model is performed on data that were not used during training.

Figure 1 represents the predicted results for Ash Fusion Temperatures for two randomly selected samples, using the developed ANN model and formulas from the literature. Tables 2 and 3 include the composition of the 2 samples as well as the experimental and predicted by ANN model values.

The largest deviation (using the ANN model) exists for the estimation of F.T. for the Greek Ash sample and is 73°C. It should be noticed that the reproducibility of the ash fusion temperatures determined within one laboratory, using the same operator, procedure and equipment is 30 – 40°C, and between different laboratories is about 50 – 70°C, [13].

In order to further cross validate the results of the ANN model, 36 samples were randomly removed from the training data and used as testing data. Using the remaining 146 samples as input training data for the ANN model the standard deviation for the above mentioned 36 samples are 33°C, 27°C, 36°C and 46°C for the temperatures IDT, ST, HT and FT respectively.
Figure 1. Experimental and calculated data for Ash Fusion Temperatures (Black Thunder Coal and Greek Lignite)

<table>
<thead>
<tr>
<th></th>
<th>SiO₂ [%]</th>
<th>Al₂O₃ [%]</th>
<th>TiO₂ [%]</th>
<th>Fe₂O₃ [%]</th>
<th>CaO [%]</th>
<th>MgO [%]</th>
<th>K₂O [%]</th>
<th>P₂O₅ [%]</th>
<th>Na₂O [%]</th>
<th>SO₃ [%]</th>
<th>Mn₃O₄ [%]</th>
</tr>
</thead>
<tbody>
<tr>
<td>Black Thunder Coal</td>
<td>30.7</td>
<td>16.5</td>
<td>1.29</td>
<td>5.10</td>
<td>21.3</td>
<td>4.80</td>
<td>0.35</td>
<td>0.92</td>
<td>1.43</td>
<td>17.7</td>
<td>0.00</td>
</tr>
<tr>
<td>Greek Lignite</td>
<td>38.7</td>
<td>15.7</td>
<td>0.30</td>
<td>3.70</td>
<td>30.0</td>
<td>2.12</td>
<td>1.34</td>
<td>0.00</td>
<td>0.91</td>
<td>6.53</td>
<td>0.00</td>
</tr>
</tbody>
</table>

Table 2. Composition of Black Thunder Coal and Greek Lignite
4. ESTIMATION OF FUEL HEATING VALUE THROUGH ARTIFICIAL NEURAL NETWORK (ANN) MODELLING

In the literature, there exist very few formulas for solid fuels Lower and Higher Heating Value estimation. The usual procedure is experimental with sample combustion and measurement of the released heat. ANN modelling can avoid this time consuming procedure and provides reliable results.

For the creation of the ANN model a data base of 86 samples was developed. In Table 4 the composition of two randomly selected samples are listed as well as the range of composition for all samples included in the data base. Although the range of components in the data base is not quite large it covers almost all Greek coals.

Two parallel models were developed for the estimation of LHV and HHV from Proximate and Ultimate analysis. Table 5 includes the results of the ANN model as well as experimental measured values and values extracted from formulas in the literature [17].

<table>
<thead>
<tr>
<th>Ultimate Analysis [%]</th>
<th>Proximate Analysis [%]</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>H₂O</td>
</tr>
<tr>
<td></td>
<td>H₂O</td>
</tr>
<tr>
<td>Range</td>
<td>48.9 – 55.6</td>
</tr>
<tr>
<td>Sample N° 1</td>
<td>54.0</td>
</tr>
<tr>
<td>Sample N° 2</td>
<td>49.8</td>
</tr>
</tbody>
</table>

Table 4. Range and composition Greek Lignite (sample N° 1 and N° 2)
<table>
<thead>
<tr>
<th></th>
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<tbody>
<tr>
<td></td>
<td>1519</td>
<td>1481</td>
<td>1401</td>
<td>1894</td>
<td>1857</td>
<td>1692</td>
</tr>
<tr>
<td>Sample No 2 (Proximate Analysis)</td>
<td>1151</td>
<td>1258</td>
<td>1590</td>
<td>1519</td>
<td>1630</td>
<td>1925</td>
</tr>
<tr>
<td>Sample No 1 (Ultimate Analysis)</td>
<td>1177</td>
<td>1179</td>
<td>N/A</td>
<td>1561</td>
<td>1559</td>
<td>N/A</td>
</tr>
<tr>
<td>Sample No 2 (Ultimate Analysis)</td>
<td>1547</td>
<td>1515</td>
<td>N/A</td>
<td>1917</td>
<td>1888</td>
<td>N/A</td>
</tr>
</tbody>
</table>

Table 3. Results from experiments and ANN modeling

Figure 2 depicts the results extracted from experiments and calculated from the ANN model and formulas from the literature [17].

4. CONCLUSIONS

In the present paper, preliminary results have been presented regarding Power Plant Optimization through individual processes ANN modeling. ANN can be used as a tool for optimization of individual processes and consequently for the whole Unit operation. ANN modelling for ESP optimization does not generate very optimistic results mainly due to the fact that parameters of ash quality cannot be integrated with the measurement configuration of the Unit under investigation. However with the current measurement a standard deviation of approximately 10% is achieved.

Heating Value and Ash Fusion Temperature estimation from ash and coal composition respectively provides very promising results. ANN modeling can be used for bypassing ash and coal laboratory analysis saving man-hours and time (for immediate evaluation of Unit operating condition).
Fig.2. Experimental and calculated data for Greek Lignite

References


