Neural Network for Evaluating Boiler Behaviour

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Abstract
Fouling and slagging are some difficulties for the development of biomass as energy potential and to achieve the targets of renewable energy sources utilization. The proper technique to analyze the influence of fouling in a biomass boiler is to monitorize the evolution of heat absorption in heat transfer equipment. Traditional equation-based monitoring techniques have problems to tackle with this complex phenomenon. The objective of this paper is to present the methodology of Neural Network (NN) design and application for a biomass boiler monitoring and point out the advantages of NN in these situations. A combination of traditional methods aided with a NN structure to monitorize the boiler could completely solve the problem. NN monitorizing results show an excellent agreement with real data. It is also concluded that NN is a stronger tool for monitoring than equation-based monitoring. This work will be the basis of a future development in order to control and minimize the effect of fouling in biomass boilers.

Keywords: Monitorizing; Biomass Boiler; Simulation; Neural Network; Boiler Fouling.

1. INTRODUCTION
Renewable energy sources are essential paths towards sustainable development and CO₂ emission reduction. For example, the European Union has set the target of achieving 22% of electricity generation from renewable sources by 2010. Therefore, intensive research is carrying out in order to take advantage of biomass potential. Biomass characterization has been analysed in detail, and there is a great number of comprehensive studies of biomass combustion behaviour.

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Despite these developments, there is still a lack of knowledge about biomass boiler performance in special related with fouling. This is one of the keys to strengthen the technology and reach a wide development of biomass utilization. The fouling formation mechanisms in coal power plants has been widely analysed by several researchers [2-5], but the use of biomass has increase the numbers of variables affecting boiler fouling problem due to new components in ash chemistry [6]. The consequences of fouling includes a reduction in boiler and power plant efficiencies [7], higher CO2 emissions, losses of availability, and finally an uneven combustion with an increase in CO and NOx emissions [8].

Traditional methods for coal boilers to reduce boiler fouling (i.e. sootblowing) are not suitable without a proper boiler evaluation. In this case research has been focused in boiler monitoring by means of special measuring instruments and on-line calculations. Monitoring could be accomplished by means of standard and special power plant instrumentation or a combination of both techniques. In any case external software is required for simulation and calculations. Market has some examples of boiler monitoring, especially for fouling phenomena [8-10], but there is a lack of information about the internal behaviour of these applications.

Due to the inherent complexity of fouling, the use of experimental correlations of fouling probability depending on biomass characterization [11-12] or the use of selected biomass are not adequate approaches for general situations. The proper technique to analyze the influence of fouling in a biomass boiler is to monitorize the evolution of heat absorption in heat transfer equipment. The effect of fouling is a reduction of heat absorption, a boiler steam output reduction and a lost in thermal efficiency. Therefore monitoring techniques are fundamental tools for the study of boiler behaviour and fouling influence in biomass boiler. The present work is conceived as a contribution to this question.

The problem stems in combining these instrumentations, different software and the repeatability of plant data mainly caused by a variable feedstock and the uncertainty of fouling phenomena [13]. The main problems that monitoring techniques have to tackle with are: (i) a quick response for on-line monitoring, (ii) strong hardware and software to solve non linear mathematical operations, (iii) include several libraries and subroutines to calculate water, steam
and flue gases thermodynamics properties influences by, temperature, pressure and gas composition, (iv) finally, a data filtering to avoid wrong data inputs.

NN and Expert Systems has recently proved its availability to tackle with thermal engineering problems [14-16]. A monitoring technique based on Neural Networks (NN) allows all the previous circumstances to be taken into account and it could hand the complexity of the problem and actually provide an accurate boiler monitoring, avoiding all the problems presented above.

Moreover, the NN toughness tackles the problem of wrong values due to instrumentation system failure. NN have also been used in system modelling, control, robotics, pattern recognition, forecasting, power systems and optimisation [17-21]. NN have been also proposed to deal with biomass fouling [16, 22], but there are not a developed technique that completely solve the problem. Some examples are important revisions of the NN applications and references made in the field of energy [14, 22].

The objective of this paper is to present the application of NN for a biomass boiler monitoring. This paper proposes the use of an Artificial Feedforward Neural Networks Based Model in order to evaluate the biomass boiler fouling. NN have been developed using the data provided by a traditional thermal model (theoretical equations based). Validation shows an excellent agreement between NN outputs and real data obtained from a biomass boiler. Undoubtedly, the capability of artificial NN as a tool in energy monitoring and boiler behaviour evaluation becomes clear.

2. METHODOLOGY
2.1 Description of the boiler

Originally the boiler analysed used coal as fuel, but a fuel change was introduced with a strong refitting in the eighties. Nowadays, the boiler uses biomass fed with a moving inclined grate. It produces a steam output of 74.6 t/h with clean surfaces. The actual fuel is a mix of different types of biomass (bark and wood of indeterminate species) with 48.5% of moisture, 3% of ash and an average heating value of 8.5 MJ/kg. The boiler includes furnace, two superheaters, two convective evaporators and two economizers. The steam output temperature
from the first superheater is 276 °C and the steam output temperature from the final superheater is 475 °C. Other relevant operation values of the boiler are listed in table 1.

2.2. Monitoring

One of the main barriers to biomass technology includes boiler fouling and slagging with a reduction of boiler efficiency. Intensive research is needed to solve the effect in boiler output. Boiler monitoring provides the opportunity to know the fouling effect in the boiler and to solve the efficiency reduction.

Traditionally, boiler monitorizing includes the on-line evaluation of heat transfer coefficient in heat exchangers. Since overall heat transfer coefficients reduce during boiler operation, the comparison between them and the values obtained with clean surfaces allows the boiler fouling to be evaluated. There are two remarkable techniques that could be used to develop an accurate boiler monitoring: theoretical thermal modelization and Neural Networks simulation. The first technique requires strong hardware and software to solve non-linear mathematical operation in real time, a specific software to calculate different boiler variables, libraries or subroutines to calculate water, steam and flue gas thermodynamic properties and finally, a data filter to avoid wrong inputs to be used or mistake outputs to be generated. However, Neural Networks (NN) simulation technique is able to deal with complex calculations, obtaining accurate results without needing of high developed software. Negative aspects of NN include that it is not possible to calculate intermediate values of a problem (for example heat in each exchanger.) One of the contributions of this paper is to use data provided by theoretical modelization in the NN training with the aim of improving monitoring techniques.

Figure 1 shows the architecture of a traditional equations-based monitoring system (theoretical modelization). First, fuel composition has to be calculated in order to know the flue gas composition into the boiler. Due to the flue gas path, the equations take into account the combustion chemical relations, paying special attention to the exit gas composition in the stack and to the initial fuel moisture.

Once exhaust gases properties in the boiler are known, available temperature and pressure signals in the steam and gas sides allow the heat transferred in the boiler to be
calculated by means of mass and energy balances in every exchanger. Although the main
result of the previous calculation is the heat transferred section by section, a great number of
secondary variables are also obtained, (i.e. intermediate exhaust gas temperatures or steam
flows in the exchangers). Obviously heat absorbed in the exchangers not only depends on
surfaces fouling or slagging, but also on operational strategies. Therefore, to avoid all the
unwanted influences an overall heat transfer coefficient (UA) is calculated in every section.
These values are corrected in order to eliminate the load influence. Finally, a comparison
between corrected UA and a UA value taken as reference (UA corresponding to clean
exchanger conditions) supplies a significant index of the fouling/slagging level. A theoretical
thermal modelization has been developed based in this scheme.

The validation of this traditional equation based model has been accomplished by the
comparison between a real data of the Steam Output (a main boiler variable taken from the
historical data) and the result of adding all the heat transferred values obtained by the
monitoring system from a section-per-section calculation. Results, figure 2, show a perfect fitting
between the theoretical model and real data.

The main advantage of this modelization is the capability to reproduce satisfactorily the
boiler behaviour, providing important values as heat transferred in each boiler section or the
fouling index. Therefore, these data are going to be used as training data to develop a NN.

2.3 Neural Network architecture

The final aim of the developed NN is to reproduce the value of fouling index obtained by
the theoretical model used for monitoring and steam output obtained by real data. By this way,
the NN monitoring system follows the behaviour of the traditional equation-based monitoring
system. However, it introduces important advantages such robustness not dependent of data
validation, a quick response to be used in on-line monitoring and accuracy obtained without the
use of external programming and libraries of fluid properties.

Multilayer Feedforward NN is the structure used in this work. Its principal characteristic
is that the information goes from the input to the output throughout intermediate layers in an
unidirectional way, without connections with neurons of the previous layers. Intermediate layers
contain sigmoid neurons to easily reproduce non-lineal behaviour, but the output layer is built with lineal neurons because they must simulate functions without discontinuities. Feedforward NN have been chosen for the great process capacity [17] and the subsequent robust performance [20]. It is also possible to build up “grey box” models with them. These models are intermediate between “black box” models (where any relation between inputs and outputs is ignored) and “white models” (where the connection between inputs and outputs could be expressed using equations, for example the traditional equation-based model) [23]. The “grey box” models allow theoretical information to be introduced but no in a traditional sense. In this case, this information has been chosen to be introduced in the selection of the architecture of the global NN. Therefore, special attention has been paid in inputs selection since irrelevant inputs have been reported of causing over fitting in the NN [23-26].

The methodology applied to develop NN could be theoretically divided in four stages: structure or architecture design, training, validation and use. Independent resolution of each one is impossible in practical terms. Conclusions extracted in advanced stages about how to improve the NN often indicate the necessity of changing parameters of previous stages. Definitively, this operation causes an exhaustive iterative work before establishing the definitive parameters of the NN. However, despite of this complex development, the developed set of NN obtains quick and robust responses, and attractive benefits can be obtained from its industrial application.

As said previously, this set of NN tries to be a grey model of the boiler behaviour. In order to obtain this characteristic the theoretical knowledge is introduced in a non traditional way in the structure design stage. Instead of building up an only Feedforward NN with a lot of neurons in the intermediate layer to simulate accurately the wanted results, a more complex structure of Feedforward NN has been preferred. In this case, three sets of simple Feedforward NN connected also with a Feedforward style imitates exactly the traditional calculation way showed in figure 1. The advantages of this architecture are evident:

- Each NN set is very simple, and the relationship between inputs and outputs are clear.
- As in the traditional simulation, intermediate values are able to be obtained.
- The reduction of input variables is undoubted. The clear relations avoid circumstantial influences to be taken into account.

As thermal modelization, the architecture is built up with three NN: a combustion flue gases composition NN, a heat transferred section-by-section NN and finally a fouling/slagging evolution index NN.

The attention paid in the input selection should be pointed out. To avoid an excessive subjectivity of the researcher in the problem, the selection of the inputs has been made only using tools related with NN. Starting with the 23 available inputs, the NN is training and the mean square error (MSE) is registered. After that, each variable is eliminated and MSE is also registered and compared with the first value. The higher the influence of the absent input in the training is, the more increased the MSE value is, and more important the eliminated input variable is to solve the problem [27]. The analysis of the influence of the inputs is time-consuming and iterative, but it can be made using the own NN procedures. It is verified that this analysis produces a selection of input variable logically related with the real thermo-physical relations. For example, to calculate the exhaust gases composition, input variables related with exit gases composition in the stack and the moisture in the boiler have been selected, but those related with temperature and pressure signals have been rejected.

Figure 3 shows the final structure of the monitorizing NN. Although it has been said that the connection between the three sets follows a Feedforward style, it must be pointed out that it exist an intralayer connection between the heat transferred in the furnace and the heat transferred in the evaporators. From a NN point of view, the only way to obtain acceptable results for the heat transferred in the evaporators has been reached adding the heat transferred in the furnace to the inputs. Historical data show that fouling in the furnace surface causes a heat transfer diminution in this zone, higher flue gas temperature and obviously, a steam output decrease. At the same time higher temperature in the flue gases entering in the evaporators section causes a heat transfer augmentation and an increase in the steam output in this section. Therefore from a thermo-physical point of view, this dependence is logically accepted. Since the NN is developed only to obtain on-line fouling index, regardless intermediate variables, the structure could be simplified.
2.4 Neural Network Training

Training is a fundamental stage in the NN development. This stage stores in NN the implicit knowledge about the process. The recommended training method for Feedforward NN is called Backpropagation.

Data is obtained in the traditional physical equation boiler monitoring based on real data. Data is filtered following severe criteria due to only maximum load is required whatever fouling effect it may be: incomplete data, short periods with partial load, and transitory periods between different loads are eliminated. A total of 4595 monitored real data remains, 3000 are used to train and 1595 are reserved to validate. The training data are randomly chosen to avoid circumstantial control strategies that could influence any outputs. Consequently not only the training data set, but also the validation set are more representative and the validation range is optimum.

In this stage the number of neurons is chosen. Trainings are repeated reducing the number of neurons up to MSE variation can not be assumed. All NN has a number of neurons inferior to six. That means a easily generalized relation between inputs and outputs.

2.5 Neural Network Validation

Every NN has been individually validated during the training stage. The validity of the proposed NN scheme is tested under two strategies. The former compares equation-based monitorizing data and NN results for the 330 set of data used to train (this validation is called resubstitution test). The latter compares the 1495 set of data reserved for final validation (this validation is named resistance test). In both cases, NN results validation considers the differences that appear between the real outputs and the simulated ones.

The aim of the double validation strategies is to reject overfittings in the NN. The low average error values shown in the tables 2, 3 and 4 evidence the accuracy of the NN developed. Exhaust flue gas properties results are showed in table 2. Despite a low number of neurons, results form resubstituion and resistance validation are excellent. These values clearly show a non-overfitting NN with excellent predictions.
Table 3 shows the results of the second NN set, predicting the heat recovered in boiler equipment. The number or neurons slightly increases and real data and NN results are in good agreement. Heat recovered in evaporator (furnace wall and convective equipment) needs a large number of neurons and results do no fit as close as other equipment data. This deviation was expected from real boiler behaviour experience due to a lack of representative data set.

Finally, table 5 summarizes the main results to monitorize boiler fouling. Neuron number increased up to 6 for economizer. Obviously this is not a large number but it was expected due to economizer is the final equipment and its behaviour is influenced by all the previous equipment. In spite of this inconveniences and the particular boiler configuration, results are excellent. All predictions are into or close to a deviation of 2.0%. Figure 4 shows graphically a comparison between equation-based monitoring and NN results for furnace fouling index. The data obtained from the traditional equation-based monitorizing are represented in the abscised axis, while the output generated by the NN are represented in ordinate axis. Closer the points are to the identity line, more accurate is the monitorizing.

Finally, to strength the qualities of NN a sensitivity analysis shows the advantages of NN opposed as equation-based monitoring. Table 5 shows an example of results from a sensitivity study based on instrumentation uncertainty. It is clearly shown that the sensitivity using NN is reduced and the average error obtained form NN validation is below the sensitivity values, pointed out the excellent NN results. It should be concluded that the influence of uncertainties are lower for NN than for physical equations model.

CONCLUSIONS

There are some difficulties for the biomass utilization. In particular, biomass combustion produces fouling in boiler heat transfer equipment causing a reduction of steam output and boiler efficiency. In order to strengthen this technology a set of NN for fouling and biomass boiler monitorizing has been developed. The NN can predict a set of operational variables and the fouling state of the boiler. All the results have been validated with real and equation-based monitoring data. Agreement between data and NN results is excellent. It is also pointed out the NN is a stronger tool for monitoring than equation-based monitoring.
However, more research is required to minimize the effect of fouling once it has been detected. A new set of NN to predict fouling and boiler behaviour evolution is needed. Also a set of fuzzy logic rules based in the real data and the results from these NN could optimize boiler cleaning cycles and fouling evolution. The knowledge acquired in developing this set of NN will serve as the groundwork for the future development and validation of NN + Fuzzy Logic software to minimize the effect of fouling in biomass boilers.

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REFERENCES.

[1]


**Figure 1.** Boiler monitoring system scheme
Figure 2. Validation. Steam output from available data versus heat transferred obtained from thermal model
Figure 3. Relation between variables of the three NN sets
Figure 4. Furnace Fouling Index validation
<table>
<thead>
<tr>
<th>Parameter</th>
<th>Value</th>
<th>Parameter</th>
<th>Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Fuel Flow</td>
<td>29.60 tons/h</td>
<td>Grate surface</td>
<td>64.3 m²</td>
</tr>
<tr>
<td>Steam mass flow</td>
<td>74.6 tons/h</td>
<td>Grate load</td>
<td>1037 kW/m²</td>
</tr>
<tr>
<td>Final steam temperature</td>
<td>475 ±10ºC</td>
<td>Furnace load</td>
<td>70104 kW</td>
</tr>
<tr>
<td>Drum pressure</td>
<td>61.9 bar</td>
<td>Total air flow</td>
<td>88000 Nm³/h</td>
</tr>
</tbody>
</table>

**Table 1.** Boiler operation values
<table>
<thead>
<tr>
<th>Monitorized Variable</th>
<th>Neurons number</th>
<th>Resubstitution average error</th>
<th>Resistance average error</th>
</tr>
</thead>
<tbody>
<tr>
<td>Gases mass flow</td>
<td>1</td>
<td>0.01%</td>
<td>0.01%</td>
</tr>
<tr>
<td>% CO₂ Gases</td>
<td>2</td>
<td>0.15%</td>
<td>0.58%</td>
</tr>
<tr>
<td>% H₂O Gases</td>
<td>3</td>
<td>0.10%</td>
<td>0.67%</td>
</tr>
<tr>
<td>% N₂ Gases</td>
<td>3</td>
<td>0.49%</td>
<td>0.43%</td>
</tr>
</tbody>
</table>

*Table 2* Training and validation error values of the exhaust gases properties monitoring NN
<table>
<thead>
<tr>
<th>Monitorized Variable</th>
<th>Neurons number</th>
<th>Resubstitution average error</th>
<th>Resistance average error</th>
</tr>
</thead>
<tbody>
<tr>
<td>Furnace heat</td>
<td>2</td>
<td>1.77%</td>
<td>1.84%</td>
</tr>
<tr>
<td>SH 2 heat</td>
<td>2</td>
<td>0.79%</td>
<td>0.75%</td>
</tr>
<tr>
<td>SH 1 heat</td>
<td>2</td>
<td>1.64%</td>
<td>1.68%</td>
</tr>
<tr>
<td>Evaporator heat</td>
<td>4</td>
<td>3.41%</td>
<td>3.65%</td>
</tr>
<tr>
<td>Economizer heat</td>
<td>2</td>
<td>0.95%</td>
<td>0.92%</td>
</tr>
</tbody>
</table>

Table 3 Training and validation error values of the heat transferred monitorizing NN
<table>
<thead>
<tr>
<th>Monitorized Variable</th>
<th>Neurons number</th>
<th>Resubstitution average error</th>
<th>Resistance average error</th>
</tr>
</thead>
<tbody>
<tr>
<td>Furnace fouling I.</td>
<td>3</td>
<td>1.03%</td>
<td>1.01%</td>
</tr>
<tr>
<td>SH 2 fouling I.</td>
<td>4</td>
<td>1.60%</td>
<td>1.54%</td>
</tr>
<tr>
<td>SH 1 fouling I.</td>
<td>3</td>
<td>1.08%</td>
<td>1.09%</td>
</tr>
<tr>
<td>Evaporator fouling I.</td>
<td>4</td>
<td>2.35%</td>
<td>2.36%</td>
</tr>
<tr>
<td>Economizer fouling I.</td>
<td>6</td>
<td>0.86%</td>
<td>0.88%</td>
</tr>
</tbody>
</table>

Table 4 Training and validation error values of the fouling index monitorizing NN
<table>
<thead>
<tr>
<th>Error</th>
<th>SH 1 Fouling Index</th>
<th>Evaporators Fouling Index</th>
</tr>
</thead>
<tbody>
<tr>
<td>Equation-based monitorizing</td>
<td>9.11%</td>
<td>17.63%</td>
</tr>
<tr>
<td>NN monitorizing</td>
<td>7.53%</td>
<td>9.77%</td>
</tr>
<tr>
<td>Validation average error</td>
<td>1.09%</td>
<td>2.36%</td>
</tr>
</tbody>
</table>

*Table 5. Validation average error comparison with the monitorizing sensitivity.*