Improved Boiler Performance using Targeted Sootblower Activation

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Abstract: A novel, targeted approach to sootblower activation has been demonstrated recently at a large, T-fired, coal unit. Targeted sootblowing techniques are designed to activate blowers based upon the conditions of the boiler rather than a traditional time and/or sequence based approach. Various approaches have been used in the past to perform targeted sootblowing including neural network based models, cleanliness based approaches, expert systems, and performance calculations. Recently, we have combined all of these approaches to provide a new technique for targeted sootblowing.

At the core of this new approach is the use of neural network based models for predicting the changes in both the cleanliness factors and the heat duties of boiler heat transfer devices due to sootblower activation. To build such models, both the heat duty and cleanliness factor of each heat transfer surface in the boiler (i.e. division panels, final reheat, final superheat, etc.) are calculated using a series of performance calculations. Using the results of these calculations, a set of neural network based models are trained on historical data to predict the change in cleanliness factor and heat duty due to sootblower activation.

The resulting neural network models are used in an optimization scheme to control sootblower activation throughout the boiler. In this optimization scheme, a set of candidate sootblowers that are eligible for activation is identified. Given the set of eligible sootblowers, an expert system is used in combination with the neural network models to identify and activate (if necessary) the sootblower with the greatest impact on boiler performance. This technique has been shown to improve boiler performance at the demonstration site (i.e. desired steam temperatures, improvement of boiler efficiency, etc.) while at the same time reducing overall sootblower activations.

1.0: Introduction

Firing coal in a steam generating unit results in the buildup of soot and slag on the heat transfer surfaces which affects the overall performance of the boiler. Soot and slag accumulation affects overall performance by changing the distribution of the heat absorbed in various sections of the boiler. In addition, the accumulation of soot and slag affects furnace gas flows, metal temperatures (potentially resulting in hot spots), boiler efficiency, emissions, and temperatures and sprays in reheat and superheat sections.

To control soot and slag accumulation in boilers, various types of sootblowing devices are used throughout the boiler. Control of the activation of these devices is critical to governing the accumulation of soot and slag and thus also important to providing optimal boiler performance.

Traditional methods employed to remove soot and slag within boilers include manual, manual sequential, and time-based sequencing of soot cleaning devices. The soot cleaning devices are generally automated and are initiated by a master control device. In most cases, the soot cleaning devices are activated based on predetermined criteria, established protocols, sequential methods, time-based approaches, operator judgment, or combinations thereof. These methods have the potential to result in indiscriminate cleaning of the entire boiler or sections thereof, regardless of whether sections are already clean. Throughout the power generation industry, the traditional time-based methods are being replaced by criteria-based methods, such as the methods presented in this paper.

Intelligent sootblowing techniques are designed to activate blowers based upon the conditions of the boiler rather than a time and/or sequence based approach. Various approaches have been used to perform intelligent sootblowing including neural network based models, cleanliness based approaches, expert systems, and performance calculators. Recently, we have combined all of these approaches to provide a new technique for intelligent, targeted sootblowing. This approach has been demonstrated at large T-fired unit to provide better boiler performance while minimizing overall sootblower activations. The technique is described in detail next.

2.0: Modeling the Cleanliness Factor

At the core of the new approach is the use of neural network based models for the prediction of the effects of sootblower activation on heat transfer surfaces. To build such models, both the heat duty and cleanliness of each heat transfer surface in the boiler must be calculated.

The heat duties and cleanliness factors are computed using a series of performance calculations. First, the main steam and reheat steam flows are computed. Using these flows along with the steam pressure and temperatures at the inlets and outlets of various heat transfer surfaces, the amount of heat absorbed by the steam (the heat duty) for all sections of the boiler can be computed. At our demonstration site, the steam side heat duty was computed for the furnace water walls, division panels, superheat platen, final reheat, final superheat, low temperature superheat and the economizer.

The cleanliness factors are based upon the heat transfer coefficient associated with a heating surface. To compute the heat transfer coefficient, we need to compute the flue gas flow and flue gas enthalpy at inlet and outlet of heat transfer surfaces. To compute the flue gas flow, it is necessary to calculate the overall boiler efficiency. At our demonstration site, boiler efficiency was computed using the credit/losses approach outlined in ASME PCT 4.0 2008.

Given the boiler efficiency and the total overall steam side heat duty (computed by summing the individual heat duties of the heat transfer surfaces of the boiler), the total heat input from the coal was computed by dividing overall steam heat duty by efficiency. Given the total heat input, the overall flue gas flow was calculated using the methods of ASME PCT 4.0 2008.

Given the overall flue gas flow, the economizer exit gas temperature, and the heat extracted by each of the heat transfer devices, a series of backward chaining calculations were used to determine the enthalpy (as well as total heat and temperature) at the inlets and outlets to the various heat transfer sections including the inlets and outlets of the division panels, super heat platen, final reheat, final superheat, low temperature superheat and the economizer. Finally, given the flue gas flow, inlet and outlet flue gas enthalpies, the steam flows, and the input and outlet steam enthalpies of all sections, the heat transfer coefficient for each heat transfer surface was computed.

The calculations described above were used to compute the heat transfer coefficients at our demonstration site which is a large T-fired unit. Figure 1 shows the layout of the heat transfer surfaces between the furnace and air preheater at the demonstration site.

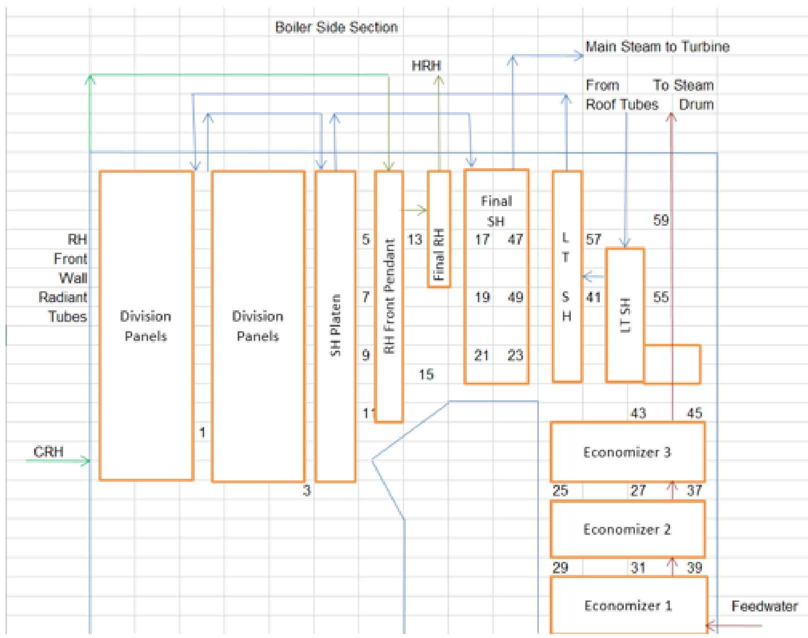

Figure 1: Boiler side section view of the heat transfer surfaces (after the furnace and before the air preheater) at our demonstration site. The identification number of each of the sootblowers is also shown.

At the core of our approach to intelligent sootblowing, we are interested in modeling the effects of activations of the sootblowers on the heat transfer coefficients (or cleanliness factors as described below). Figure 2 shows a typical neural network model used to predict the heat transfer coefficient. Using historical data over typically a three month period, we train a neural network to predict the heat transfer coefficient as a function of the time since the last activation of the sootblowers that affect the heating surface.

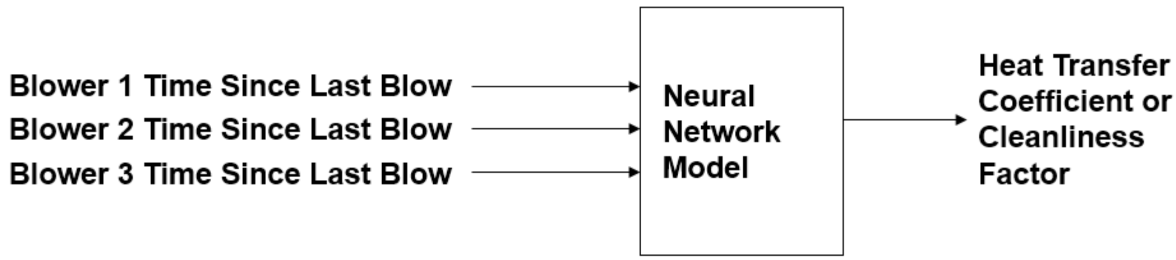

Figure 2: Neural network model for predicting the heat transfer coefficient or cleanliness factor. In this case, the neural network model uses the time since the last blow of the sootblowers that affect the heat transfer surface of interest.

Figure 3 shows a specific implementation of the neural network model used at our demonstration site for modeling the Division Panel section. The Division Panels are affected by three sootblowers. A neural model was trained to predict the heat transfer coefficient based upon the time since last blow of these three sootblowers. Figure 3 shows the predicted and actual value of the heat transfer coefficient over one day. It can be observed that the model predicts that different sootblowers will have different effects on the heat transfer coefficient.

Establishing high quality neural models of cleanliness can be difficult due to other factors affecting heat transfer besides blower activations. These factors are generally described as ‘disturbances’, and can either be measured or unmeasured. Our approach addresses both types of disturbances by (1) allowing for additional inputs to the neural models to account for measured disturbances, and (2) using an advanced neural training technique which uses the temporal arrangement of training data to minimize the impact of unmeasured disturbances.

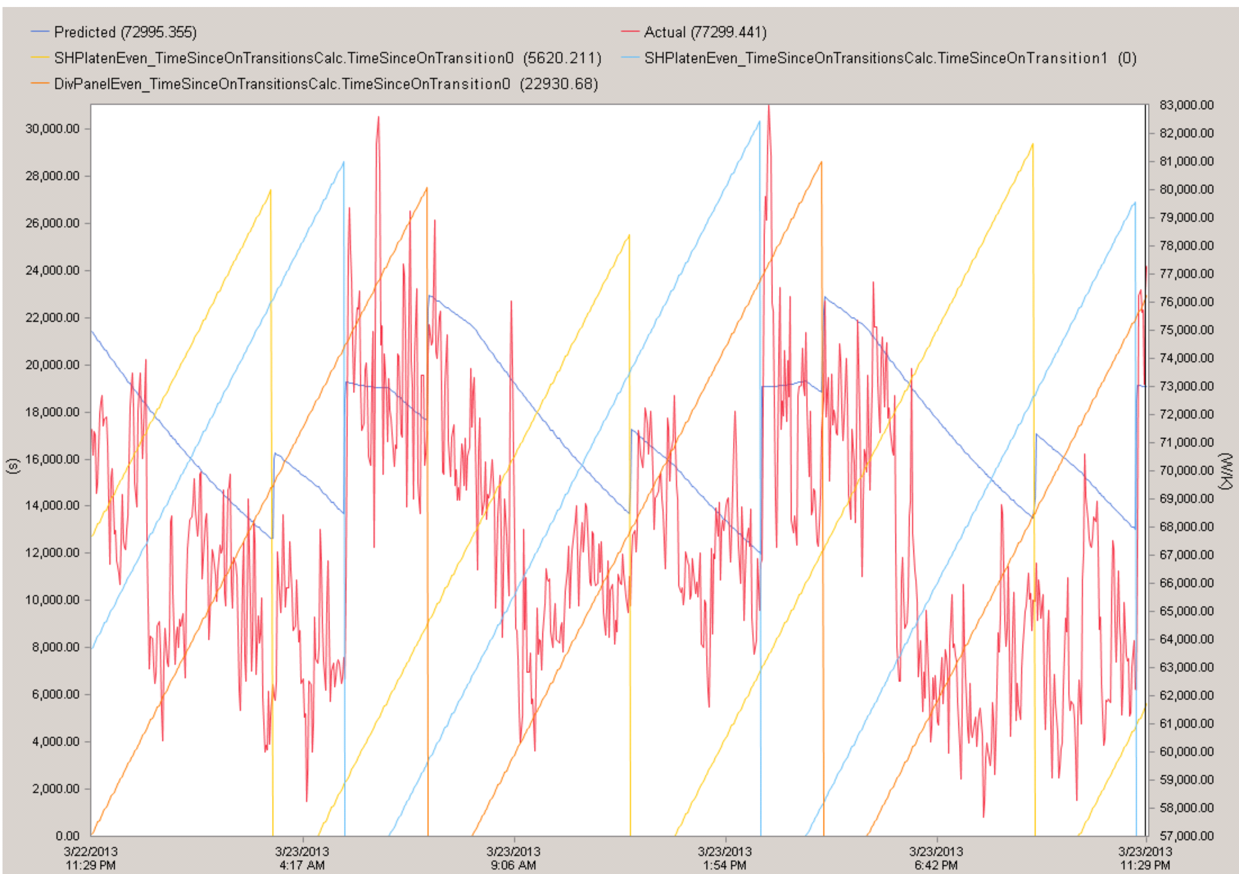

Figure 3: Heat transfer coefficient for the division panel section shown in red for a one day period. The yellow, light blue and orange lines show the time since last activation for three blowers that affect the Division Panel section. (When a sootblower is activated, the time since value drops to zero.) The navy blue line shows a neural network model prediction of the change in heat transfer coefficient.

The method described above provides a real time (and historic) approach to computing the actual heat transfer coefficients. Traditionally, the cleanliness factor associated with a heat transfer surface is computed by dividing the actual heat transfer coefficient by a "design" heat transfer coefficient. The design heat transfer coefficient is determined based upon a set of first principle calculations which uses tube geometry, material specifications, etc. The design heat transfer coefficient may be supplied by the OEM or may be computed based upon the heat transfer surface design specifications.

One significant problem in the calculation of the design heat transfer coefficient is that it often has to be computed using incomplete information as either the information is not available or the heat transfer surface has been significantly modified and the exact design specifications are no longer available. In such cases, the design heat transfer coefficient can be in error and subsequently results in large errors in the calculation of a "design" based cleanliness factor. Furthermore, if this cleanliness factor is used in an intelligent sootblowing system, the errors in the calculation can lead to improper sootblowing activations.

To overcome this problem, we have developed a "neural network" based cleanliness factor for each of the heat transfer surfaces. Instead of computing the cleanliness factor by dividing the actual heat transfer coefficient by the design heat transfer coefficient, we divide the actual coefficient by a neural network prediction of the heat transfer coefficient. The neural network is trained (curve fitted) to a set of historic data – in this case, the steam flows and ambient temperatures are used as input to the neural model and the output is the heat transfer coefficient. Using this approach, we get a much more robust estimate of the cleanliness factor which is based more on recent history rather than on design data.

To understand the effects of blower activation on various cleanliness factors, a neural network based modeling is once again employed. In this case, several months of recent data that includes the blower activations and cleanliness factors are used to create models that can be used to predict the cleanliness factors given a set of recent blower activations.

In addition to understanding the effect of blower activation on cleanliness factors, we are also interested in understanding the effects of such activations on heat duty for each of the heat transfer surfaces. Given the model of the cleanliness factor and the heat duty of a heat transfer surface, the change in heat duty can be approximately calculated by multiplying the current heat duty by the change in cleanliness factor due to a blower activation.

3.0: Optimizing Blower Activation

Given the models of cleanliness factors and heat duties, an optimization scheme is used to select the best sootblower to activate in real-time. The goal of the optimization scheme is to improve boiler performance while guaranteeing that constraints on blower activation are not violated (typically minimum and maximum idle times).

At the demonstration site, the sootblowing optimizer executes at a one minute interval. Based upon the performance goals, constraints and recent blowing, the optimizer determines every optimization cycle (once a minute) whether a blower needs to be activated. (If it is determined that multiple blowers need to activated, a prioritization scheme is used to decide which blower is activated.) Once the optimizer has determined which blower to activate, a command is sent to the DCS (or PLC) to activate the selected blower. The optimizer monitors the performance of the activated sootblower to guarantee that it has properly operated.

As shown in Figure 1, the blowers are located in and around the heat transfer surfaces. Blowers located in similar areas can be organized into zones. For instance, in Figure 1, the blowers located between the Superheat Platen and the Reheat Front Pendant (blowers 5, 7, 9 and 11) can be organized into a zone. At our demonstration site, we organized the blowers into nine zones based upon location.

The sootblowing optimizer uses a two step process for determining which blower to activate. First, using an expert system, it determines if any of the nine zones need to be cleaned and if so which gets the highest priority. Second, it uses the neural network models of cleanliness (and possibly heat duty) to determine which available sootblower in a zone will have the greatest effect on cleanliness (or heat duty).

Determining which available sootblower has the greatest effect in a zone is done in the following manner. The application engineer that configures the implementation specifies a mathematical formulation that represents the desired effect. For example, the application engineer may specify that the greatest effect is defined as the maximum change in cleanliness caused by a blower activation in a zone. Alternatively, if the zone affects two heating surfaces, the application engineer may specify that the greatest effect is the average change in cleanliness factors over the two heating surfaces. At execution time, once a zone is selected, the effects of blowing each eligible sootblower in a zone is analyzed using the neural models and mathematical formulation specified by the application engineer. The blower that maximizes the mathematical function for the zone is selected by the optimizer.

4.0: Results

The optimizer described in the previous section was compared to a more traditional intelligent sootblowing scheme where a rules based system was used to select the zone and then a simple time since last activation rule was used to select the blower within the zone. Thus, we are comparing the new approach where the blower to be activated is chosen based upon greatest impact to a more traditional technique where the blower to be activated is selected based upon the greatest time since previously being activated. We would expect that the former based upon greatest impact will unevenly distribute the activations over time in a zone while the later will evenly distribute activations over time in a zone. For convenience, we will refer to the new approach as the neural selector (greatest impact) approach and the more traditional technique as the baseline (maximum time since) technique.

To provide a comparison between the neural selector and the baseline approaches, we executed the two schemes over two separate but similar two week periods. (The load profiles over the two separate two week periods were similar.) During both time periods, the optimizer was in closed loop 100% of the time, thus, all activations of the sootblowers were controlled by the optimizers. Both schemes were used to control the sootblowers shown in Figure 1 above (in this case, the zones between the division panel and air heater).

In Table 1, we show a comparison of the number of sootblowing operations using both schemes. In total, over the two periods, the baseline approach (maximum time since) resulted in 1,391 sootblowing operations whereas the neural selector approach resulted in 1,109 operations. Thus, we saw a 20 percent reduction in sootblowing operations.

Zone	**Baseline**	**Neural Selector**	**Percent Change**
Superheat Platen	93	96	3.2
Reheat 1	257	163	-36.6
Reheat 2	423	251	-40.7
Low Temp SH	225	151	-32.9
Economizer	393	448	14.0
Total	**1,391**	**1,109**	**-20.3**

Table 1: Comparison of sootblowing operations between the baseline scheme and the neural selector scheme over two separate two week periods. There was a 20% reduction in the number of sootblowing operations between the two approaches.

Average Temp	**Baseline**	**Neural Selector**	**Change**
Superheat East	992	997	5
Superheat West	999	998	-1
Reheat East	965	980	15
Reheat West	968	976	8
Average			**7**

Table 2: Comparison of steam temperatures between baseline scheme and the neural selector scheme over two separate two week periods. There is a 7 degree increase in average temperature mostly due to improvement in the reheat temperature.

In Table 2, we show a comparison of the average steam temperatures using both schemes. At this unit, due to boiler geometry and the switch to low sulfur PRB coal, operations has difficulty maintaining reheat temperatures near the design temperature of 1000 degrees. For this reason, any improvements in operating temperatures is critical to operation of this unit. As shown in Table 2, we were able to achieve a significantly increase in the reheat temperature using the neural scheme. In addition, we also saw some improvement in the superheat temperatures. Increasing the average superheat and reheat temperature results in an improved heat rate of the unit.

5.0: Conclusion

A novel approach to sootblowing optimization was implemented on a large, T-fired unit. The technique combined performance calculations (including heat duty and cleanliness factors), neural network modeling, expert systems and optimization approaches. The technique was compared to a more traditional intelligent sootblowing system which relied primarily on a rule based zone selection system and did not select blowers within the zone based on greatest impact but rather choose them based upon greatest time since last activation.

The novel technique which used neural models for blower selection within the zone was found to significantly reduce blowing (by 20 percent) and improve steam temperatures (by an average of 7 degrees) which resulted in improved overall unit heat rate. Based upon the results presented in this paper, the novel approach to sootblowing optimization has been adopted as standard operating procedure for activation of sootblowers at the demonstration site.