ASH FOULING MONITORING AND KEY VARIABLES ANALYSIS FOR COAL FIRED POWER PLANT BOILER

by

Yuanhao SHI and Jingcheng WANG*

Department of Automation, Shanghai Jiao Tong University and Key Laboratory of System Control and Information Processing, Ministry of Education, Shanghai, China

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Ash deposition on heat transfer surfaces is still a significant problem in coal-fired power plant utility boilers. The effective ways to deal with this problem are accurate on-line monitoring of ash fouling and soot-blowing. In this paper, an online ash fouling monitoring model based on dynamic mass and energy balance method is developed and key variables analysis technique is introduced to study the internal behavior of soot-blowing system. In this process, artificial neural networks are used to optimize the boiler soot-blowing model and mean impact values method is utilized to determine a set of key variables. The validity of the models has been illustrated in a real case-study boiler, a 300 MW Chinese power station. The results on same real plant data show that both models have good prediction accuracy, while the artificial neural networks model II has less input parameters. This work will be the basis of a future development in order to control and optimize the soot-blowing of the coal-fired power plant utility boilers.

Key words: *coal-fired power plant boiler, ash fouling monitoring, thermal efficiency, cleanliness factor, key variables analysis, artificial neural network*

Introduction

Ash fouling of heat transfer surfaces has always been one of the main operational concerns in coal-fired power plant utility boilers. It has been estimated to be an important source of losses of availability and energy efficiency in thermal power plants, that may amount to 1% under normal operating conditions [1]. The Electric Power Research Institute (EPRI) undertook a survey on ash fouling in 1987 [2]. The collected data showed 7% of units suffering from frequent fouling and 40% reporting occasional problems, out of a total of 91 pulverized-coal utility boilers in the USA. A large number of case studies can be found in recent decades [3-5], indicating a continuous worldwide interest in this problem.

The effect of ash fouling is a reduction of heat absorption, a boiler steam output reduction and a loss in thermal efficiency. In many parts of the world, high pressure and high temperature steam are always used to blow away the ash fouling, and a number of soot-blowers are continuously initiated according to pre-defined sequences and a fixed schedule. Though frequent operation of soot-blower can increase efficiency, it will cause waste of steam, increased maintenance cost, and tube erosion. On the contrary, too less blowing leads to soot accumulation and, consequently, decreases thermal efficiency. Therefore, traditional methods for coal boilers to reduce boiler fouling, in most cases, are not optimal without a proper boiler evalua-

* Corresponding author, e-mail: yhshi.sjtu@gmail.com

tion. Therefore, optimization for soot blowing system according to the actual cleaning need becomes more and more important. At first, an appropriate assessment for the ash fouling level of each heat transfer surface of the boiler is needed. Monitoring techniques become more and more important for the study of boiler behaviors and ash fouling influence in coal-fired power plant boilers and have attracted extensive research effort recently [6-8].

Ash fouling monitoring can be accomplished by means of on-line calculations and special power plant instrumentation or a combination of both techniques. On-line calculations always need to calculate the heat absorption of heat transfer surfaces. The conventional method of calculating the heat absorption rate is the log-mean-temperature-difference approach [6]. However, it is a static balance method which cannot show the dynamic behaviors of heat transfer surfaces. While special power plant instrumentation (*i. e.* heat fluxes meters [7]) can well reflect the status of heat absorption of heat transfer surfaces by providing a continuous signal, they induce significant increase of cost on sensors, installation, and maintenance. There are some commercial (ash fouling) boiler monitoring tools [8], but the internal behaviors of these applications are unclear.

Key variables analysis is a tool that is often used to study the behavior of a system, or a model, and to attain the dependency of outputs on each or some of input parameters [9]. Artificial neural network (ANN) has recently proved its availability to tackle with thermal engineering problems [10, 11]. ANN has also been used in system modeling, identification, control, forecasting, power systems and optimization [12-14]. ANN has also been proposed to deal with ash fouling [15], but it is not completely used for tackle the problem of variables influence. Some examples are important revisions of the ANN applications and references made in the field of energy [16].

In this paper, the cleanliness factors (*CF*) is defined to measure the ash fouling degrees of heat transfer surfaces. A dynamic mass and energy balance method is proposed to calculate the heat absorption. Results show that the dynamic method can well reflect the dynamic heat absorption process of the boiler. The on-line monitoring method can also well reflect the ash fouling level of conventional heat transfer surface. Moreover, key variables analysis based on artificial neural network is proposed to study the internal behaviors of ash fouling and thermal efficiency. Required input parameters were initially selected on the basis of expert knowledge and previous experience for the first ANN model (ANN model I). However, the set of parameters of ANN model with key variables (ANN model II) was decided through key variables analysis for an optimization between the number of input parameters and decided accuracy of prediction. Both models are found to be quite good in prediction of boiler efficiency and *CF* of economizer. However, ANN model II have less input parameters, it is more suitable for "on-line" applications. These studies explore the internal behaviors of soot-blowing system of such plants, and establish a road map for further studies of soot-blowing optimization.

Brief description of the boiler

The system in consideration is a 300 MW coal fired utility boiler of the power plant in Guizhou province, China. The schematic diagram of the boiler with W shape flame is shown in fig. 1.

The boiler type is HG-1025/17.3-WM18, drum type with steam reheating. It has subcritical pressure of 17.3 MPa and natural circulation. It is fired with Qianxi anthracite coal and "W" type flame combustion. The boiler has four pulverizes two of which mainly operate with load changes while the other two always remain constant. Boiler produces 909.6 t/h of

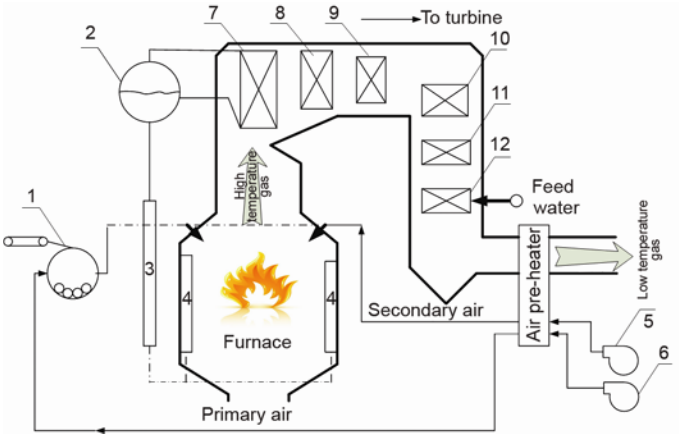

Figure 1. Schematic diagram of the boiler; 1 – pulverizers, 2 – steam drum, 3 – down comer, 4 – water wall, 5 – supply air fan, 6 – primary air fan, 7 – platen superheater, 8 – high temperature superheater, 9 – high temperature reheater, 10 – low temperature superheater, 11 – low temperature reheater, 12 – economizer

fresh steam with temperature of 540 °C and pressure of 17.25 Mpa. The boiler includes single furnace, double arch, and two superheaters, two reheaters, one economizer, and two air preheaters. The low heating value (*LHV*) of the coal varies from 16 to 21 MJ/kg. In the period used for analysis in this study, the *LHV* of the coal is approximately constant, *i. e.* 17.8 MJ/kg.

The design checked coal of the boiler is Qianxi anthracite coal. With the purpose of keeping the boiler clean, there are 66 steam sootblowers distributed in the boiler heating transfer channel, in which there are 20 IR-type sootblowers located in the furnace left, rear and right walls, 42 IK-type sootblowers located in the heat transfer surfaces in the flue gas channel and 4 IKAH-type sootblowers arranged in the two air preheaters.

Ash fouling monitoring

Ash fouling monitoring provides the opportunity to know the fouling effect in the boiler and the basis for the optimization of the soot-blowing.

Traditionally, boiler monitoring includes the on-line evaluation of heat transfer coefficient in heat transfer surfaces. 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.

Figure 2 shows the architecture of the ash fouling monitoring model of the boiler. Firstly, the flue gas composition is calculated by the combustion model. Once the flue gas properties in the boiler are known, available temperature, pressure and mass flow in the steam and gas sides allow the heat transferred in the boiler to be calculated by means of mass and energy balance in each heat transfer surface. Obviously, heat absorbed in the heat transfer surfaces not only depends on surface fouling, but also on operational strategies especially the load change. Therefore, to avoid the unwanted influences, the dynamic mass and energy balance are used. The heat storage variation both in the metal heat transfer surface and the working substance are considered. These values are corrected in order to eliminate the load change influence. And then the actual heat transfer coefficient (*AC*) is obtained. Moreover the theoretical heat transfer coefficient (*TC*) is obtained by theoretical thermal calculated methods. Finally a comparison between *AC* and *TC* supplies a significant index of the fouling level.

Modeling

The ash fouling level of heat transfer surfaces can be described by *CF*. The *CF* of each heat transfer surface is defined as:

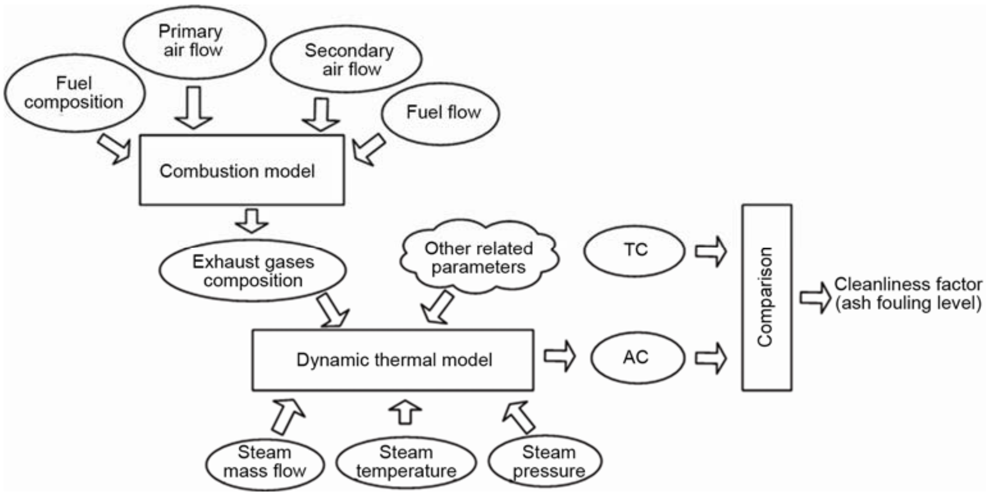

Figure 2. Ash fouling monitoring model of the boiler

$$CF = \frac{K_r}{K_0} \tag{1}$$

where K_r and K_0 are the actual heat transfer coefficient (*AC*) of the heat transfer surface and the theoretical heat transfer coefficient (*TC*), respectively. Obviously, the value of *CF* should range from zero to one, with one corresponding to the clean status of the heat transfer surface.

Theoretical heat transfer coefficient (*TC*) K_0 corresponds to the heat transfer efficiency of the heat transfer surface in the clean status, which is usually expressed as the sum of theoretical radiation heat transfer coefficient α_f and theoretical convection heat transfer coefficient α_d:

$$K_0 = \alpha_f + \alpha_d \tag{2}$$

They are always calculated by the equations:

$$\alpha_f = 5.7 \cdot 10^{-8} \frac{a_{gb} + 1}{2} a_h T^3 \left[\frac{1 - \left(\dfrac{T_{gb}}{T} \right)^4}{1 - \dfrac{T_{gb}}{T}} \right] \tag{3}$$

$$\alpha_d = 0.65 C_s C_z \frac{\lambda}{d} \left(\frac{wd}{\upsilon} \right)^{0.64} \mathrm{P}_\mathrm{L}^{0.33} \tag{4}$$

where a_{gb} and a_h are the blackness of the heat transfer surface and the flue gas, respectively, T and T_{gb} – the temperature of the heat transfer surface and the flue gas, respectively, C_s and C_z – the horizontal and vertical structure parameters of the heat transfer surface, respectively, λ is the heat conductivity coefficient of the flue gas, d – the pipe diameter of the exchanger, w – the gas flow rate, υ – the dynamic viscosity coefficient of the flue gas, and P_L – the Planck constant.

The gas flow rate can be calculated as:

$$w = \frac{V_b}{A} \tag{5}$$

where A is the cross-sectional area of the heat transfer surface, V_b – the standard flue gas flow through the heat transfer surface, which can be calculated by Avogadro's law:

$$V_b = \frac{\dfrac{p_r V_r}{p_b}}{1+\dfrac{t_r}{273.15}} \tag{6}$$

where V_r is the measured flue gas flow, t_r – the flue gas temperature, p_r – the flue gas pressure, and p_b – the standard atmospheric pressure.

In the conventional log-mean-temperature-difference (LMTD) approach, the actual heat transfer coefficients can be calculated as:

$$K_r = \frac{Q_y}{F \Delta t_m} \tag{7}$$

where Q_y is the energy released in the gas side, F – the area of the heat transfer surface, and Δt_m – the log-mean-temperature difference, which can be described as:

$$\Delta t_m = \frac{\Delta t_{\max} - \Delta t_{\min}}{\ln \dfrac{\Delta t_{\max}}{\Delta t_{\min}}} \tag{8}$$

where $\Delta t_{\max}$ and $\Delta t_{\min}$ are the maximum temperature difference and the minimum temperature difference between the gas side and the work substance side, respectively.

The LMTD is basically a steady-state method that is not preferred by plant engineers. In the traditional mass and energy balance method, the energy released by the flue gas Q_y equals to the energy absorbed by the steam Q_q:

$$Q_y = Q_q \tag{9}$$

However, the temperature of each heat transfer surface is changing with the load change of the boiler. Moreover, the specific heat capacity of the heat transfer surface and the steam is always changing. Therefore, in this study, the dynamic mass and energy balance equation is modified as follows to accommodate these uncertainties:

$$Q_y = Q_q + \Delta Q_j + \Delta Q_q \tag{10}$$

where ΔQ_j is the energy storage change of the metal, and ΔQ_q – the energy storage change of the steam.

The energy absorbed by steam Q_q, the energy storage change of the metal ΔQ_j and the energy storage change of the steam ΔQ_q are:

$$\Delta Q_j = C_j m_j \frac{\partial \theta_j}{\partial \tau} \tag{11}$$

$$\Delta Q_q = C_q m_q \frac{\partial \theta_q}{\partial \tau} \tag{12}$$

$$Q_q = D(H_{\text{out}} - H_{\text{in}}) \tag{13}$$

where C_j and C_q are the average specific heat capacity of the metal and the steam, respectively, m_j and m_q – the metal mass of the heat transfer surface and the steam mass in the exchanger, respectively, θ_q and θ_j – the metal temperature and the steam temperature, respectively, H_{out} and H_{in} are the steam enthalpy of the exchanger inlet and outlet, respectively, D is the steam flow rate of the heat exchanger, and τ – the time.

The enthalpy H, as a function of steam temperature and pressure, can be determined from the formulae IAPWS-IF97 [17]. In this project, the formulae are programmed as algorithms that run in real-time in the system.

Monitoring results and analysis

The monitoring results of the coal-fired power plant boiler using this model are as follow. Figure 4 shows the *CF* of the economizer of the boiler, where the calculation procedure is carried out in 24 hours. The data are obtained from the DCS and the sample frequency of measured variables was 1 sample per 30 seconds. It is observed that the variation of *CF* of the economizer is approximately between 0.4 and 0.6.

There are three obvious increase points in fig. 3. Figure 4 shows the plot of soot-blowing signals of 24 hours. It is clear that the point 'I' and the point 'II' are the real soot-blowing points. The *CF* of the economizer increased obviously after the soot-blowing. However, the point 'III' which was also an obvious increase point was not a real soot-blowing point. What causes this situation?

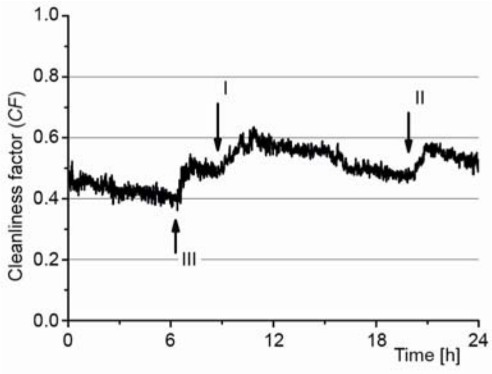

Figure 3. The *CF* curve of the economizer

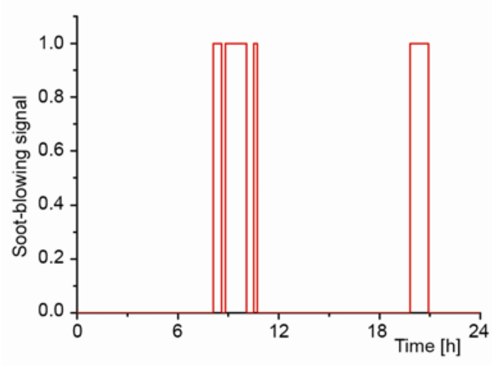

Figure 4. Soot-blowing signal

Figure 6 shows the boiler unit load of the day and fig. 7 shows the heat exchange efficiency against the flow gas rate. There are many ash particles in the flue gas. When the flue gas flow through the convection heating transfer surface, some of the particles will be deposited in the heating transfer surface, at the same time, some deposited ash in the heating transfer surface will be blow away by the flue gas. There is a balance between fouling deposition and fouling erosion. Assuming that the concentration of the ash particles contained in the flue gas maintains constant, the relationship of ash deposition and ash erosion can be described as:

$$\begin{cases} m > m' & \text{Low flue gas velocity stage} \\ m = m' & \text{Balance point} \\ m < m' & \text{High flue gas velocity stage} \end{cases} \tag{14}$$

where m is the mass of ash fouling deposition, and m' – the mass of ash fouling erosion.

The heat transfer efficiency of each heat transfer surface is maximal when it is in cleanest status. Heat transfer efficiency decreases rapidly with the ash deposited when the flue gas velocity remains low. The point 'A' in fig. 6 is the balance point. With the increasing of the flue gas velocity after the balance point, the ash erosion rate is greater than ash deposition rate. The heat transfer efficiency of the heat transfer surface will increase slowly.

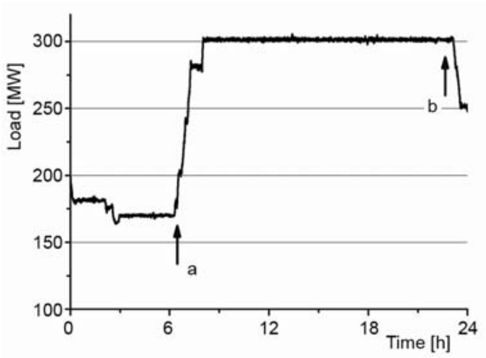

Figure 5. Unit load

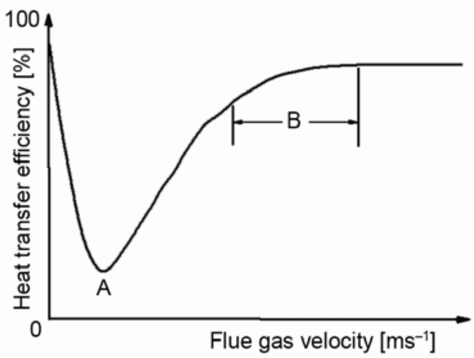

Figure 6. Heat transfer efficiency trends *vs.* flue gas velocity

In this study, the flue gas velocity of the coal-fired power plant boiler was designed as 6 m/s to 12 m/s. It is in the 'B' range in fig. 6. We can see clearly from figs. 3 and 5 that the point 'III' corresponds to the load increase point 'a'. The flue gas velocity will increase significantly when the units load increases. So the heat transfer efficiency and *CF* have a significant increase, see point 'III' in fig. 4.

Key variables analysis based on ANN

The purpose of ash fouling monitoring is to understand the behaviors of the boiler. One of the main influences of ash fouling is the reduction of boiler efficiency. Intensive research is needed to understand the cause-effect relationship in boiler input and output variables. The problem discussed in this section is to study the internal behaviors of boiler's efficiency and *CF*.

Problem statement

In coal-fired power plant, the boiler operator can manipulate a set of controllable variables to achieve the load demand as well as other goals.

Controllable variables are directly manipulated by the operator from the control panel interface, *i. e.* coal mass flow primary air, *etc*. Uncontrollable variables are those that are not affected by or not sensitive to the changes of controllable variables, *i. e.* coal quality, outside air temperature, *etc*.

Our task of identifying the key variables can now be re-formulated as the following equations and statement:

$$Y = f(X) \tag{15}$$

where $Y = \{Efficiency, CF\}$ is the vector of outputs variable, X – the vector of controllable and no controllable variables. $X = \{X_c, X_n\}$, X_c, X_n are the controllable and uncontrollable variables, respectively.

One purpose of this study is to find a subset $X'_C \subset X_C \subset X$, and derive a variation model $Y = f(X'_C)$. In this work, the elements of subset X'_C are termed as key variables, which represent the underlying causes of variation in the plant operation.

The objective of this section is to investigate the possibility of using artificial neural networks (ANN) to measure the sensitivity of the variables.

Basics of ANN

ANN is a tool that mimics the neural structure of the human brain [18]. It is efficient and reliable algorithms capable of performing functional input/output mappings. In contrary to traditional mathematical models, which are programmed, ANN learns the relationship between selected inputs and outputs by training.

Neural network has a strong modeling capability that lets a user to test and explore simulated models faster and easier. Training of the model is done with available data. The input and output data are introduced to the neural network and the network is trained by using a neural network program of Matlab. When the training is finished the model is validated with data that were not used during the training procedure. If satisfactory accuracy of the model is achieved it is ready to be employed in practice.

ANN Training and validation

Data processing

Before training the ANN model using data from the power plant, some preprocessing is required. This is necessary as there will always be some erroneous data in a large data set. This may be caused by faulty sensors, human errors, errors in data capturing system, *etc*. Thus, a critical scrutiny of obtained real data is required to identify and remove these erroneous data, called “outliers”. Moreover any data for the off-nominal operation of the plant must be removed from the training data set as it may confuse the ANN. This process of “data-filtering,” *i. e*., removing unwanted data from the available “raw data” is needed.

It is very difficult to remove all outliers in a large data set. Several errors may be combined in a single measured data. At the beginning, the outliers are usually identified by plotting measured data and observing the data points which are quite different from the neighboring data points following a reasonably regular trend. Moreover, relations between trends of data for highly correlated parameters have to be checked. For example, increasing mass flow rate of coal must correspond to the effect on that of the load on the boiler, with a regular correspondence. Obviously, experience of the model developer helps to identify possible outliers at this stage.

Sampling frequency of measured parameters was 1 sample per 30 seconds. There were available 20160 rows of data corresponding to approximately 7 days. It was concluded that measured data points as show in square boxes were outliers. However, those included in elliptical boxes had a definite trend with respect to their neighboring points though they were not included in the *band* of majority of rest data. These were not considered as outliers.

Selection of input and output parameters

Training is a fundamental stage in the ANN development. This stage stores in ANN the implicit knowledge about the process. The recommended training method for feedforward ANN is called back propagation.

For a physical model, input and output parameters are automatic choices dictated by the equations representing the processes. Therefore, physical modeling requires an exact number of parameter values for calculation. Unlike a physical model, input and output parameters of an ANN model are not selected only on the basis of physics of the processes. In fact,

Table 1. Ranges of variation for the input parameters and the output parameters in the training set

Input parameters		Nominal rating	Variation range
t	Environmental temperature	20 °C	0-40 °C
Γ_p	Primary air flow rate	240 km^3/h	120-300·10^{3}m^3/h
T_p	Primary air temperature	120 °C	90-130 °C
Γ_S	Secondary air flow rate	1100 km^3/h	700-1200·10^{3}m^3/h
T_S	Secondary air temperature	350 °C	300-370 °C
m_{coal}	Mass flow rate of coal	40 kg/s	20-50 kg/s
Γ_{fw}	Feed water flow rate	1000 t/h	400-1100 t/h
T_{fw}	Feed water temperature	270 °C	220-280 °C
MW	Load demand	300 MW	170-320 MW
Output parameters			
η	Boiler efficiency		85%-92%
CF	*CF* of economizer		0-1

the input and output parameters in ANN modeling are mostly selected on the basis of the objective of the modeling and operators' experience. The input parameters are usually *optimized* on the basis of a compromise prediction by the ANN. This is finalized by the key variables analysis as discussed in the subsection on page 261. As a result, the number of input parameters for ANN model is usually smaller than that required for a physical model of the same system. This also has the advantage of avoiding sensor errors with a greater probability as lesser number of measured input parameters is required for ANN modeling. However, the experience and expert knowledge of relations between respective parameters help to initially decide input parameters of a set of output parameters. The input and output parameters and their ranges of variation are listed in table 1. The initial input and output parameters for the ANN modeling of the plant were shown in fig. 7.

ANN structure and training

A feed forward ANN structure with back propagation learning algorithm was used for this work. It was a fully connected multi-layer perceptron with one hidden layer. Data were divided into different groups, training data set, cross-validation data set and test data set. The data of first five days were used for training, following one day data were for cross validation and the rest day data were test data. Based on the previous experience and subsequent trials, hyperbolic tangent transfer function was found to be the most suitable one and was used for this ANN. The training of the ANN was performed with a variation of 1-20 neurons and 1500 epochs. The range of neurons and number of epochs were proved to be sufficient for the optimal solution. The training was repeated three times with the same data set. The accepted solution ANN converged at 10 neurons and 1000 epochs.

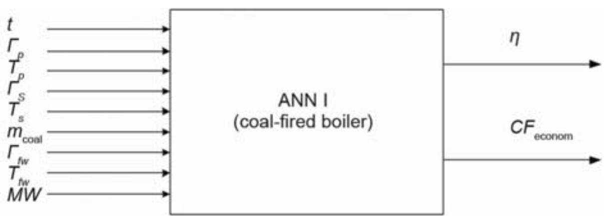

Figure 7. ANN I structure

Validation of the model

ANN model was built to predict the values of output parameters accurately using the real-life values of chosen input parameters. Only then the ANN model will be ac-

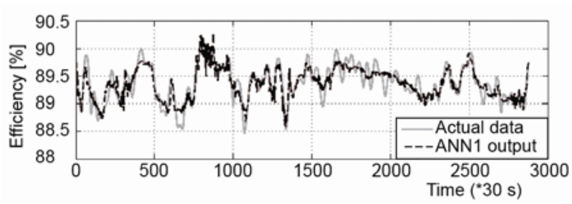

Figure 8. Boiler efficiency validation results of the ANN model

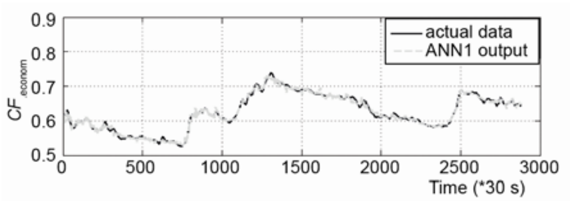

Figure 9. Economizer *CF* validation results of the ANN1 model

ceptable for real-life applications, either off-line or on-line. To check this aspect, it was provided with real measured values of input parameters from the data set which was not used during the training of the ANN. To imitate the real life, this set of data was not filtered for outliers. By comparing the prediction of the ANN model with the actual measured values of output parameters, the expected performance of this trained ANN in real life was assessed. The results of this process are shown in figs. 8 and 9 with simultaneous plots of values of boiler efficiency and *CF* of the economizer. As one can see, the ANN prediction follows with good accuracy trend of the actual data and the new steady state is simulated within an error of 5%.

Key variables analysis

As mentioned above, sensitivity analysis is important to investigate the key variables of a system under dynamic conditions. In this section, we wish to exploit the capabilities of neural networks algorithms for performing sensitivity analyses, in particular with respect to differential sensitivity analysis.

In order to see how much influence each assumed input parameter has on the output parameters and thereby to remove unnecessary inputs, if any, a key variables analysis was performed. Each input parameter was omitted one after another in order to examine how much it changed the accuracy of the ANN.

As the network is presented with the patterns of the transients of interests, we can build the corresponding matrix of sensitivity coefficients. The entries of the matrix provide us with an average measure of the effects on the output quantities, caused by variations in the input quantities. In this work the mean impact value (MIV) method is used to build the sensitivity coefficients [19].

In order to compare ANN models fairly, the following criteria were performed:

– the same settings with respect to neurons epochs and runs were applied for all the conducted trainings;
– the same pre-randomized data set was used in each ANN model; by using the same randomized data set it was assured that the same data were used in training, cross validation and testing data set for all ANN; this provided the common platform for comparison of results for different cases;
– the same proportion of data for training testing and cross validation was used for each ANN (5 days training, 1 day cross validation and 1 day testing).

In our case study of the boiler the seven input parameters are the controllable values in the boiler behavior and we need to identify those who have the biggest impact. Obviously, the impact of the various parameters depends on the transient considered.

To account for the dynamic feature of the transient analysis we compute the first-order sensitivity coefficients at every time step at which the ANN prediction is performed, and then average the results over all patterns thereby presented. The result is a 2×9 matrix containing the average first-order sensitivity coefficients which give an indication of the effects of input parameters on the dynamic evolution of the system. Figure 10 shows the transients which were generated by an initial –10% variation of all nine parameters. From the figure we note that independently of the kind of transient, the system response is most sensitive to variations in the parameters of coal mass flow rate, primary air flow rate, load demand whereas parameters of environmental temperature, secondary air temperature produce small effects.

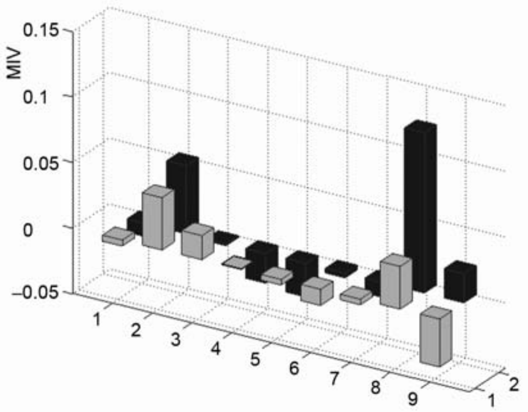

Figure 10. Average values of sensitivity coefficients: transient of –10% variations of all inputs 1 – t, 2 – Γ_p, 3 – T_p, 4 – Γ_s, 5 -T_s, 6 – m_{coal}, 7 – T_{fw}, 8 – T_{fw}, 9 – MW

From the operator's viewpoint, the variation tendency of coal mass flow rate m_{coal} contains the information of the changing of load demand MW. The primary air temperature T_p is an important factor affecting the combustion in furnace. Thus, boiler efficiency η is obviously directly influenced by T_p, and it is also mostly influenced by the feed water temperature T_{fw}, primary air flow rate Γ_p. The cleanliness factor of economizer is significantly influenced by Γ_p, T_p, $\Gamma_{s,}$ T_{fw}, and m_{coal}. The feed water flow rate Γ_{fw}, environmental temperature t and secondary air temperature T_s are somewhat less influential on the behavior of the two outputs.

Development of the ANN

As discussed above, the accuracy of the ANN model was good. It also proved its capability for producing good results with data not presented to it during training. The ANN model was thus accepted with input and output parameters as show in fig. 11.

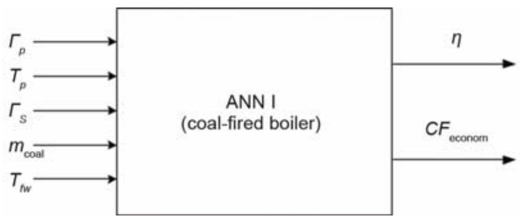

Figure 11. Input-output parameters of the development ANN structure

Identical set of data as it was used for the previous model was used for training of this alternate ANN mode I. This confirmed the identical training of ANN models and possible comparison between them.

Table 2. Summary of results of validation of the two ANN

		η	CF
Average error [%]	ANN I	2.36	0.04
	ANN II	3.73	0.07
Maximum error [%]	ANN I	4.77	0.74
	ANN II	5.22	1.05

The results of this validation are summarized in tab. 2 for all two output parameters. The average accuracy of second model is slightly lower than that of the previous one but the difference is insignificant. Because of the input variables of the second model are key variables. From discussed above, the ANN model trained by the key variables are quite similar with the first model. And it has less input variables and simpler structure. It can be used for off-line or on-line application for the boiler operation optimization.

Conclusions

On-line assessments of ash fouling tendencies in conventional coal-fired utility boilers are the basis of the optimization of soot-blowing of the boiler. Unlike the previous static models, an on-line dynamic model for ash fouling monitoring based on dynamic mass and energy balance method is developed in the paper. From the analysis of the monitoring results, it is clear that the on-line ash fouling monitoring model can correctly show dynamic tendencies of ash fouling deposit on heat transfer surfaces.

To study the internal behavior of the soot-blowing systems, artificial neural networks to perform key variables analysis in the boiler ash fouling problem is proposed. The artificial neutral networks are trained to become a predictive simulator of the system, thus creating a mapping between its inputs and outputs. This mapping is generated for different input conditions, all within the specified ranges of variability. Moreover the network can provide us directly with an indication of the importance of the various inputs, in terms of the effects of variation in their values on the output. In this term the mean impact values analysis method is used. This can be of particular significance in control settings where the ANN is trained to predict the time-evolution of a system and readily respond to any modification in its behaviors. At the end of the paper, a developed ANN model II based on the key variables analysis results is proposed. This model has less input variables and similar accuracy with the ANN model I. In such case, the final five input variables are the key variables of ash deposited and boiler efficiency, the final model can be used to measure the ash fouling and optimize the boiler's operation.

Nomenclature

A – cross-sectional area, [m^2]
a_{gh}, a_h – blackness factor of heat transfer surface and flue gas, respectively
CF – cleanliness factor
C_s, C_z – horizontal and vertical structure parameter, respectively
C_j, C_q – average specific heat capacity of metal and steam, respectively, [Jkg^{-1}°C^{-1}]
D – steam flow rate, [kgs^{-1}]
d – pipe diameter, [m]
F – area of heat transfer surface, [m^2]
$H_{\rm in}$, $H_{\rm out}$ – steam enthalpy of exchanger inlet and outlet, respectively, [J]
K_r, K_0 – actual and theoretical heat transfer coefficient, respectively
m_j, m_q – mental mass of heat transfer surface and steam mass in exchanger, respectively, [kg]
$\mathrm{P_L}$ – Planck constant
P_b, P_r – standard and measured gas pressure, respectively, [Pa]
Q_v, Q_a – energy released in gas side and energy absorbed by steam, respectively, [J]
ΔQ_j, ΔQ_q – energy storage changes of metal and steam, respectively, [J]
T_{gh}, T – temperature of heat transfer surface and flue gas, respectively, [K]
V_b, V_r – standard and measured gas flow rate, respectively, [m^{3}s^{-1}]
v – dynamic viscosity coefficient, [m^{2}s^{-1}]
w – gas flow rate, [m^{3}s^{-1}]

Greek symbols

α_d – theoretical convection heat transfer coefficient
α_f – theoretical radiation heat transfer coefficient
θ_j, θ_q –temperature of metal and steam, respectively, [°C]
λ – heat conductivity coefficient, [Wm^{-2}K^{-1}]
τ – time

Subscripts

in – inlet
out – outlet

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