An On-line Identification Method for the Slagging Factor in Coal-Fired Furnaces

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ABSTRACT

In order to evaluate the slagging characteristics of many coals in boiler furnaces, an identification method, which is the recursive least square algorithm with the forgetting factor applied on the linearized energy balance of the furnaces, and a parameterizing method for advancing of the slagging, which is characterized by maximizing the correlation with the velocity rate model, are introduced. Using both methods, results of the on-line identified slagging factor and parameters of the advancing at an actual power plant are also shown in this report.

1. INTRODUCTION

Recently, it becomes very important to evaluate the characteristics of slagging (adhesion of coal ash) on the heat transfer at boiler furnaces, since various coals which contain a lot of slag (adhesive ash) are required to be fired at the furnaces. Figure 1 shows a typical boiler furnace surrounded with water walls (assembly of evaporator tubes through which fluid from the feed water pump passes), and equipped with soot blowers (steam cleaner for the water walls of the slag at a certain interval) as well as burners firing pulverized coal. In the boiler, inputted heat from the burner is divided into the water wall heat absorption (radiational heat transfer at the furnace) and that of the super heater (convictional heat transfer from the furnace exit gas); thus, the

slagging factor (ratio of heat resistance increasing at the furnace caused by the slag on the water wall) dominate the basic performance of the heat distribution between the water wall and the super heater.

Fig.1 A typical coal-fired furnace

2. IDENTIFICATION OF SLAGGING FACTOR

2.1 Modeling for slagging

Since the heat transfer in boiler furnaces is mainly caused by radiation between gas around the burners and fluid through the water walls, the nominal heat flow a unit area q_w (in case of clean heating surface) is as

follows:

$$q_w = \beta_{w0} (T_{gw}^4 - T_{fw}^4) \quad (1)$$

where β_{w0} , T_{gw} and T_{fw} respectively denote nominal value of the radiational heat transfer co-efficient, averaged gas temperature and fluid temperature of the water wall.

Considering the slagging factor γ , the actual heat flow to the water wall Q_w can be described as follows:

$$Q_w = \frac{A_w}{\gamma} q_w \quad (2)$$

where A_w denotes the heating surface area.

The heat flow to the super heater Q_s is also obtained with assuming that fouling on the super heater surface is influencing rather low than the slagging of the furnace.

$$Q_s = A_s q_s \quad (3)$$

$$q_s \equiv \alpha_s (T_{gs} - T_{fs}) + \beta_s (T_{gs}^4 - T_{fs}^4) \quad (4)$$

where A_s , α_s , β_s , T_{gs} and T_{fs} denote, in order, heating surface area, convectional and radiational heat transfer co-efficient, averaged gas and steam temperature of the super heater.

Applying the linearization to the energy balance of the furnace, we have the following model:

$$\left(\frac{\partial T_{gs}}{\partial q_s} \right) \frac{\Delta Q_s}{A_s} = \left(\frac{\partial T_{gw}}{\partial q_w} \right) \frac{\Delta Q_w}{A_w} \gamma - \frac{\Delta Q_w}{c_p G_g} + r \quad (5)$$

where r , c_p and G_g denote, in order, measurement error, the specific heat and mass flow of the furnace exit gas.

2.2 Identification method

In this section, the following discrete time form of Eq.(5) shall be considered.

$$y_k = z_k \gamma + r_k \quad (6)$$

where subscript k denotes value at time $k\Delta\tau$ ($\Delta\tau$: identification time step). In this connection, γ and r_k are respectively assumed the slightly time-varying deterministic parameter and random measurement error; furthermore, the following random variables, which are sampled data obtainable from measurements at the boiler, are defined.

$$z_k = \left(\frac{\partial T_{gw}}{\partial q_w} \right)_k \frac{\Delta Q_{wk}}{A_w} \quad (7)$$

$$y_k = \left(\frac{\partial T_{gs}}{\partial q_s} \right)_k \frac{\Delta Q_{sk}}{A_s} + \frac{\Delta Q_{wk}}{c_p G_{gk}} \quad (8)$$

Thus γ , which is slowly changing, can be identified using the least square algorithm with the forgetting factor; namely, the following cost function J_k including the forgetting factor ρ ($0 < \rho \leq 1$) is to be minimized at each time step k .

$$J_k = \mathbf{r}_k^T \mathbf{W}_k \mathbf{r}_k = (\mathbf{y}_k - \mathbf{z}_k \hat{\gamma}_k)^T \mathbf{W}_k (\mathbf{y}_k - \mathbf{z}_k \hat{\gamma}_k) \quad (9)$$

where symbol $\hat{\gamma}$ means the estimate; in addition, the following matrix and vectors are defined.

$$\mathbf{W}_k = \begin{bmatrix} 1 & 0 & \dots & 0 \\ 0 & \rho & & 0 \\ \vdots & & \ddots & \vdots \\ 0 & 0 & \dots & \rho^{k-1} \end{bmatrix} \quad (10)$$

$$\mathbf{r}_k = (r_{k-1} \ r_{k-2} \ \dots \ r_0)^T \quad (11)$$

$$\mathbf{y}_k = (y_{k-1} \ y_{k-2} \ \dots \ y_0)^T \quad (12)$$

$$\mathbf{z}_k = (z_{k-1} \ z_{k-2} \ \dots \ z_0)^T \quad (13)$$

The seeking estimate is known the following batch form, considering Eq.(6).

$$\begin{aligned} \hat{\gamma}(k\Delta\tau) &= (\mathbf{z}_k^T \mathbf{W}_k \mathbf{z}_k)^{-1} \mathbf{z}_k^T \mathbf{W}_k \mathbf{y}_k \\ &= (\mathbf{z}_k^T \mathbf{W}_k \mathbf{z}_k)^{-1} \mathbf{z}_k^T \mathbf{W}_k (\mathbf{z}_k \gamma + \mathbf{r}_k) \\ &= \gamma + \left(\sum_{m=0}^{k-1} \rho^{k-m} \mathbf{z}_m^2 \right)^{-1} \sum_{m=0}^{k-1} \rho^{k-m} \mathbf{z}_m r_m \end{aligned} \quad (14)$$

In this connection, though r_k might be non-Gaussian or colored noise, it can be supposed zero-mean and independent of the phenomena concerning z_k ; thus, as long as γ can be regarded as a constant parameter, $\hat{\gamma}_k$ is unbiased estimate of it.

By the way referring Graupe[1], the following recursive algorithm called Sequential Least Square method for $\hat{\gamma}_k$, which should be known as being derived from Eq.(14), is applied to this problem.

$$\hat{\gamma}(k\Delta\tau) = \hat{\gamma}(k\Delta(\tau-1)) + \frac{p_{k-1} z_k \hat{\varepsilon}_k}{\rho + p_{k-1} z_k^2} \quad (15)$$

$$\hat{\varepsilon}_k = y_k - z_k \hat{\gamma}(k\Delta(\tau-1)) \quad (16)$$

$$p_k = \frac{1}{\rho} \left(p_{k-1} - \frac{p_{k-1}^2 z_k^2}{\rho + p_{k-1} z_k^2} \right) \quad (17)$$

2.3 Examples at a actual plant

At actual power plant, a construction of the on-line identifier shown in Fig.2 is applied. In this system, firstly ΔQ_s and ΔQ_w are calculated from the enthalpy pick up, which are function of pressure as well as temperature (steam tables), at the inlet/outlet of super heater steam and the water wall fluid respectively; then, γ shall be obtained with the S.L.S. algorithm in Eqs.(15)~(17).

Fig.2 An on-line identifier for γ

Figure 3 is an example of input data and identified slagging factor at the construction of Fig.2. Through this example, advancing processes of slagging factor after soot blowing are clearly grasped.

3. PARAMETERIZE OF SLAGGING ADVANCING

3.1 Modeling for advancing

In order to characterize coals on slagging, the velocity rate model in Fig.4 is applied to the advancing sections after soot blowing in time-trends of the identified γ .

$$\gamma(t) = \gamma_0 + b(1 - \exp\{-at\}) + \varepsilon \quad (18)$$

where a , b , γ_0 and ε denote velocity rate, advance (saturated width of the advancing), base (remaining after soot blowing) and modeling error, in order.

Then the values at $t_n = n\Delta t$ (Δt : parameterizing time step) on Eq.(18) becomes the form for consideration at next section as follows:

$$\varepsilon_n = \eta_n - b(1 - \exp\{-at_n\}) \quad (19)$$

Fig.3 A result of the on- line slugging factor identification in a coal- fired furnace

where the following variable is defined from the identified slugging factor

$$\eta_n = \hat{\gamma}(t_n) - \gamma_0 \quad (20)$$

Fig.4 Velocity rate model of slugging advance

3.2 Parameterizing Algorithm

In this section, parameters a and b shall be determined due to minimizing the following cost function.

$$J(a, b) = \sum_{n=1}^N \varepsilon_n^2 = \sum_{n=1}^N \eta_n^2 - 2b \sum_{n=1}^N \eta_n (1 - \exp\{-at_n\}) + b^2 \sum_{n=1}^N (1 - \exp\{-at_n\})^2 \quad (21)$$

where N denotes the number of samples for the parameterizing.

Supposing a , which minimize the cost, would be known, b is obtainable as follows:

$$\frac{\partial J}{\partial b} = 0 = -2 \sum_{n=1}^N \eta_n (1 - \exp\{-at_n\}) + 2b \sum_{n=1}^N (1 - \exp\{-at_n\})^2 \quad (22)$$

namely b has to be the following.

$$b = \frac{\sum_{n=1}^N \eta_n (1 - \exp\{-at_n\})}{\sum_{n=1}^N (1 - \exp\{-at_n\})^2} \quad (23)$$

While, supposing b which satisfies Eq.(23) is known, the cost becomes as follows:

$$\begin{aligned} J(a, b) &= \sum_{n=1}^N (1 - \exp\{-at_n\})^2 \left\{ b - \frac{\sum_{n=1}^N \eta_n (1 - \exp\{-at_n\})}{\sum_{n=1}^N (1 - \exp\{-at_n\})^2} \right\}^2 \\ &+ \sum_{n=1}^N \eta_n^2 - \frac{\left[\sum_{n=1}^N \eta_n (1 - \exp\{-at_n\}) \right]^2}{\sum_{n=1}^N (1 - \exp\{-at_n\})^2} \\ &= \sum_{n=1}^N \eta_n^2 (1 - \kappa^2) \end{aligned} \quad (24)$$

where the following cross-correlation, which is independent of b , is considered.

$$\kappa = \frac{\sum_{n=1}^N \eta_n (1 - \exp\{-at_n\})}{\sqrt{\sum_{n=1}^N \eta_n^2} \sqrt{\sum_{n=1}^N (1 - \exp\{-at_n\})^2}} \quad (25)$$

Thus a , b can be obtained with the following procedures:

- 1) Search a which maximize Eq.(25)
- 2) Obtain b with Eq.(23)

Fig.5 Parameterized model

Figure 5 shows two different coal examples of the identified η in section 2 and their velocity rate model with parameterized a , b with the procedures.

3.3 Time step optimization

Since parameterized value of a , b depend upon the time step Δt on the procedures in section 3.2 (however, in section 2, γ has been unbiasedly identified with around $\Delta\tau=1$ second time step), the residual variance and whiteness of the velocity rate modeling are to be discussed in this section.

Firstly, the residual variance $\text{Var}\{\varepsilon\}$, which smaller value is preferred, can be estimated as follows:

$$\text{Var}\{\varepsilon\} = \frac{1}{N-1} \sum_{n=1}^N \left[\eta_n - b(1 - \exp\{-at_n\}) \right]^2 \quad (26)$$

Then, as an indicator for that the model has considered the total information of the dynamics, the following Durbine-Watson ratio $d\{\varepsilon\}$, which value shall be around 2 in case the residual can be regarded as white noise, is evaluated.

$$d\{\varepsilon\} = \frac{\sum_{n=2}^N (\varepsilon_n - \varepsilon_{n-1})^2}{\sum_{n=2}^N \varepsilon_n^2} \quad (27)$$

Fig.6 Time step for parameterizing

Combining $\text{Var}\{\varepsilon\}$ and $d\{\varepsilon\}$, Fig.6 shows that the optimal time step is around 150 sec.

3.4 Example of actual coals

Figure 7 shows distributions of the a and b in 48 after soot blowing cases, in which the slagging characteristics of coals from 3 mines shall appear.

Fig.7 Parameters of slagging advance model

4. CONCLUSION

In order to evaluate the slagging characteristics of many coals, an on-line identification method and a velocity rate model parameterizing which have the following features are introduced

- 1) For on-line identification of slagging factor, a Sequential Least Square algorithm with forgetting factor is applied
- 2) The SLS algorithm is expected unbiased estimate under non-Gaussian or colored noise circumstance.
- 3) For parameterizing the velocity rate etc., a Non-linear Least Square algorithm referring cross-correlation is applied.
- 4) The NLS algorithm is expected to include proper information of the dynamics with the proper time-step choosing based on the Durbin-Watson ratio

References

- [1] D.Graupe: Time series analysis, identification and adaptive filtering; Krieger, Malabar FL(1989)
- [2] T.Okuno et al.: Multivariate analysis; Nikkagiren, Tokyo JP(1971)
- [3] S.Sagara et al.: System identification; SICE, Tokyo JP(1970)
- [4] T.Nakamizo: Signal analysis and system identification; Corona, Tokyo JP(1988)
- [5] Y.Fukayama et al.: An advanced boiler start-up controller using the plant inverse model: *Trans. ISCIE*, 8, 11, 626/640, Kyoto JP(1995)

Fig.8 Parameterized model