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SHORT COMMUNICATION

Steady-state Modeling of Coal Boilers

Won Uk Lee and Yeong Koo Yeo†

Dept. of Chemical Engineering, Hanyang University, 17 Haengdang-dong, Sungdong-ku, Seoul 133-791, Korea
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Abstract−Coal boilers are widely used to generate process steam. Because of the highly nonlinear dynamics, coal boilers have not attracted the attention of many researchers. In the present study, two modeling approaches were investigated: parametric efficiency modeling and neural network modeling. Results of simulations compared with operation data demonstrate the effectiveness of the proposed modeling approaches.

Key words: Coal Boiler, Steady-state Modeling, Neural Network Model, Parametric Efficiency Model

INTRODUCTION

In chemical plants, boilers are the major utility systems and use a large portion of the total energy usage. Optimal operation of boilers to generate steam is imperative to improve the profitability of chemical plants. Selection of operating conditions based on modeling and simulations of boilers is the most effective way to achieve the optimal operation. Both oil and coal are used as basic fuels in the boiler operations. Although steady-state modeling of oil boilers has been widely studied, coal boilers have not attracted attention from researchers. One of the reasons might be the highly nonlinear behavior of coal boilers. The artificial neural network (ANN) can be a powerful candidate as the tool to analyze nonlinear processes such as the coal boiler. Since nonlinear relationships can be effectively handled, the ANN may present a cost-effective approach to modeling coal boiler processes. The ANNs have been applied in the analysis of chemical engineering processes [Hoskins and Himmelblau, 1988; Himmelblau, 2000] as well as in the control of chemical process systems [Bhat and McAvoy, 1989]. One of the authors investigated a neural PID controller for the pH neutralization process [Kwon and Yeo, 1999]. The ANN was also found to be effective in the modeling and optimization of chemical operations [Nascimento et al., 2000; Abilov and Zeybek, 2000]. The GADONN (genetic auto-design of neural net), which is a neural net coupled with the genetic algorithm, was suggested and applied to chemical processes [Boozarjomehry and Svrcek, 2001].

The purpose of the present study was to develop a systematic modeling procedure for the accurate computation and prediction of major performance variables. Two modeling methods were used: a parametric efficiency modeling and a neural net modeling.

1. General Consideration

The energy generated from the combustion of fuels fed into the boiler is mainly consumed in the production of steam with the remaining energy exhausted as the stack gas enthalpy and heat loss from the boiler body. Some results on boiler dynamics are reported [Yeo et al., 1996; Åström and Bell, 2000; Werner, 2001]. The general approach is to identify steam flow rates when the coal flow rates and the boiler feed water are adjusted. Fig. 1 shows streams of input/output of the coal boiler system. The global mass balance and energy balance are given by [Åström and Bell, 2000]

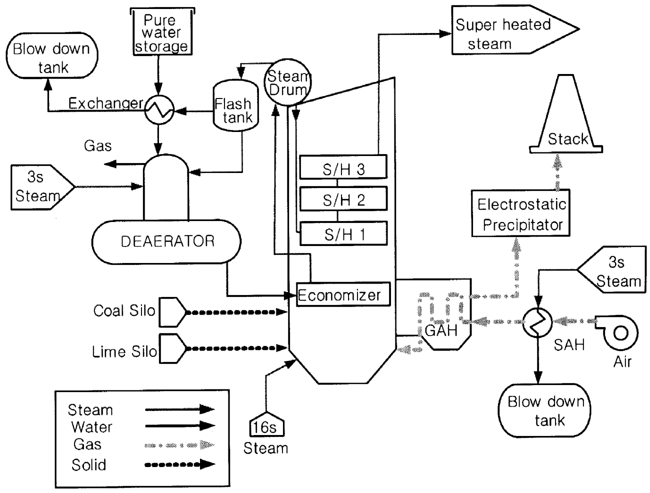

Fig. 1. The flow diagram of the coal boiler.

$$\frac{d}{dt}[\rho_s V_{st} + \rho_w V_{wt}] = q_f - q_s - q_b \tag{1}$$

$$\frac{d}{dt}[\rho_s u_s V_{st} + \rho_w u_w V_{wt} + m_t C_p t_m] = Q + q_f h_f - q_s h_s - q_b h_b \tag{2}$$

where Q represents the amount of heat supplied to the boiler. These equations represent an ideal case and use the boiler efficiency to encounter actual situations. The boiler efficiency and heat added are given by

$$\eta = \frac{q_s h_s - q_f h_f}{Q} \tag{3}$$

$$Q = q_c H_c + H_{SAH} \tag{4}$$

where q_c represents the coal flow rate, H_c is the heat of combustion of coal and H_{SAH} is the heat supplied by the steam air heater. At steady-state, Eqs. (1) and (2) become

$$(1-\eta)Q = q_g h_g - q_a h_a + q_b h_b + Q_{loss} \tag{5}$$

†To whom correspondence should be addressed.
E-mail: ykyeo@hanyang.ac.kr

Table 1. Technical data for the coal boiler being modeled

	Data		Data
Surface area	1,885 m^2	Thickness	1 m
Height	30 m	Diameter	10 m
Thermal conductivity of carbon steel	45 w/m·K	Inner temperature	220 °C
		Outer temperature	40 °C

Q_{loss} is given by

$$Q_{loss}=-kA\frac{T_a-T_m}{L} \tag{6}$$

where k is the thermal conductivity of the boiler, A is the surface area and L is the thickness of the boiler. The exact amount of heat loss cannot be known. We assume that the boiler body consists of carbon steel and is considered to be a cylinder. Based on the data given in Table 1, the steam flow rate can be obtained by

$$q_s=\frac{0.92q_cH_c+H_{SAH}+q_fh_f-q_gh_g+q_ah_a-q_bh_b}{h_s} \tag{7}$$

where the subscript g denotes the exhaust gas which consists of N_2, CO_2, H_2O, SiO_2, $CaSO_4$, CaO, C and ash (Al_2O_3, Fe_2O_3, Si_2O). The enthalpy of the exhaust gas is given by

$$h_g=\begin{pmatrix} 0.734C_P^{N_2}+0.147C_P^{CO_2}+0.0979C_P^{H_2O} \\ +0.003C_P^{CaSO_4}+0.0042C_P^{Al_2O_3}+0.0084C_P^{SiO_2} \\ +0.0014C_P^{Fe_2O_3}+0.002C_P^{CaO}+0.002C_P^{C} \end{pmatrix}(T_g-T_{ref}) \tag{8}$$

The coefficients of heat capacity in this equation depend upon the temperature and the amount of air and fuel. The heat capacities for each component are given in Table 2, and typical operation data are summarized in Table 3. In the present study, excess oxygen supply and complete combustion were assumed. Thus, the composition of the exhaust gas is dependent upon the coal flow rate and excess O_2 flow rate.

Table 2. Heat capacity of the exhaust gas and air: C_p [kJ/kg·K]=A+BT+DT^{-2}

Chemical species	Phase	T_{max}	A	B	10^7 D
N_2	Gas	2000	973.9	0.176	+0.118
CO_2	Gas	2000	1031.1	0.197	−2.18
N_2O	Gas	2000	1602.7	0.67	+0.56
SiO_2	Solid	848	760.9	0.609	−1.688
$CaSO_4$	Solid	1373	571.94	0.68	−0.48
CaO	Solid	1173	750	0.363	−2.307
C	Solid	1373	935.55	0.916	−4.091
Air	Gas	2000	955.25	0.164	−0.0455

CO_2: $\frac{4.4(53.33x_c+0.01x_a)}{x_c+x_a}\%$

H_2O: $\frac{1.8(20x_c+6.66x_c)}{x_c+x_a}\%$

N_2: $\frac{2.8(0.536x_c+26.96x_a)}{x_c+x_a}\%$

O_2: $\frac{3.2(7.26x_a-61.892x_c)}{x_c+x_a}\%$

Ar: $\frac{4.0(0.31\times x_a)}{x_c+x_a}\%$

Ash: $\frac{13.9x_c}{x_c+x_a}\%$

The enthalpy of the exhaust gas was changed by excess O_2 flow rate and coal flow rate. If the efficiency of the boiler in Eq. (3) is represented as a function of the amount of fuel consumption, steam generation can be predicted by the boiler efficiency. In the present study, we propose a parametric polynomial representation of the boiler efficiency in terms of the coal flow rate as

$$\eta=a+b\times q_c+c\times q_c^2+d\times q_c^3 \tag{9}$$

where $\boldsymbol{\eta}=[\eta_1,\eta_2,K,\eta_n]\in{}^n$.

$$\text{Let } p=[a\ b\ c\ d] \text{ and } \mathbf{q}=\begin{bmatrix}1\\ q_c\\ q_c^2\\ q_c^3\end{bmatrix} \tag{10}$$

Then $\boldsymbol{\eta}$=p×**q** and we have

$$p=\boldsymbol{\eta}\times(\mathbf{q}^T\mathbf{q})^{-1}\mathbf{q}^T \tag{11}$$

By taking into account the relevant data, we have

$$\eta=17.468-2.6303q_c+0.13691q_c^2-0.0023503q_c^3$$

2. Neural Network Modeling

In the neural network, the error is defined as the difference between the target output and the network output. The sum of these errors defined by the following equation is to be minimized:

$$MSE=\frac{1}{n}\sum_{i=1}^{n}e(i)^2=\frac{1}{n}\sum_{i=1}^{n}[t(i)-a(i)]^2 \tag{12}$$

The LMS (Least Mean Squares) algorithm adjusts the weights and biases of the linear network so as to minimize the mean square error. The LMS algorithm or Widrow-Hoff learning algorithm is based on the approximate steepest descent procedure. Standard back propagation is a gradient descent algorithm, as is the Widrow-Hoff learning rule in which the network weights are moved along the negative of the gradient of the performance function. In this study, the Levenberg-Marquardt algorithm was used in the back propaga-

Table 3. Typical operation data in the coal boiler process

Data	q_c [ton/hr]	H_{SAH} [kJ/kg]	q_f	h_f	q_g	h_g	q_a	h_a	q_b	h_b	h_s	Boiler load
1	24.55	0	202.0	511.97	278.2	196.15	250.49	24.97	2	1461.35	3386.86	100%
2	19.51	4313.3	161.6	511.97	223.16	184.35	201.06	24.97	1.6	1451.73	3386.86	80%
3	12.38	5485.8	101	511.97	142.9	166.73	128.92	24.97	1.0	1435.28	3386.86	50%
4	8.1	6372.7	66.66	511.97	137.8	173.76	128.92	24.97	0.66	1445.69	3386.86	33%

tion. The Hessian matrix is given by $\mathbf{H}=\mathbf{J}^T\mathbf{J}$ and the gradient is computed as $\mathbf{g}=\mathbf{J}^T\mathbf{e}$ where $\mathbf{J}$ is the Jacobian matrix that contains first derivatives of the network errors with respect to the weights and biases and $\mathbf{e}$ is a vector of network errors. The Levenberg-Marquardt algorithm the iterative procedure is given by

$$\mathbf{x}_{k+1}=\mathbf{x}_k-[\mathbf{J}^T\mathbf{J}+\mu\mathbf{I}]^{-1}\mathbf{J}^T\mathbf{e} \tag{13}$$

In the neural network modeling, the input values consist of the rate of the boiler feed water, the coal flow rate and the temperatures of boiler inlet water and outlet steam. The steam flow rate becomes the output. Since the number of the output is one, the number of the neuron of the output layer is one. The numbers of hidden layers were fixed to two. Nearly 300 operational data were used in the training of the nets. The training is completed when the mean square error between outputs of nets and object patterns is smaller than 0.0001 or training over 10000 epochs.

3. Results and Discussion

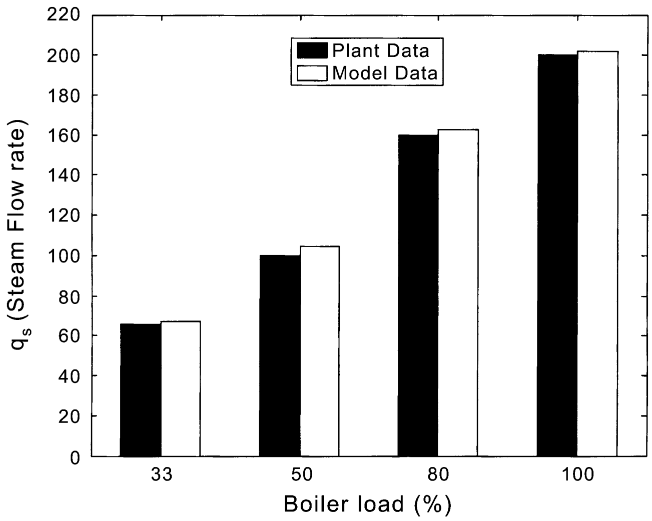

Fig. 2. Steam flow rate according to the boiler load (linear model, H_c=28,000 kJ/kg).

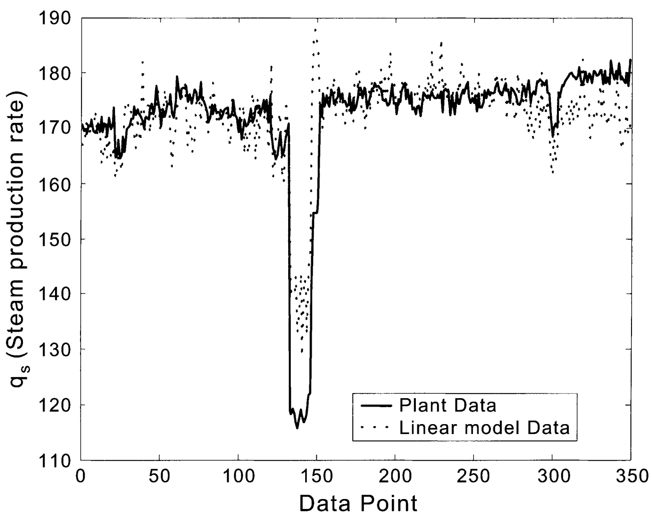

Fig. 3. Steam flow rate according to the boiler data point (linear model [operation data], H_c=28,000 kJ/kg).

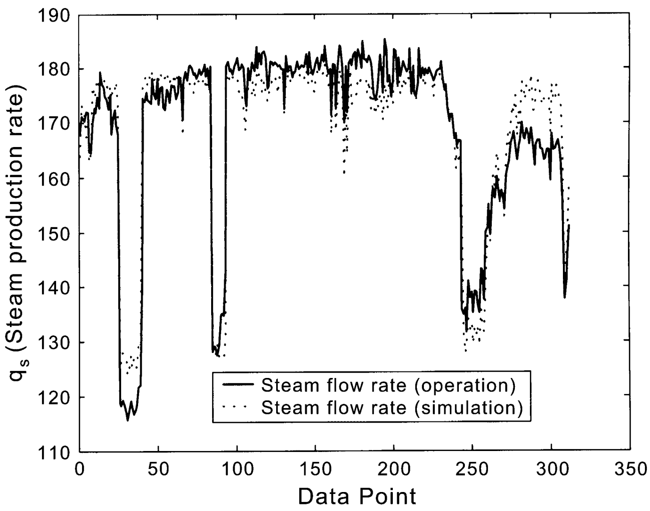

Fig. 4. The comparison of steam production rates (parametric efficiency model).

Fig. 2 shows results of simulations based on the linear relation (11) compared to operational data. We can say that these results are very restrictive because of few operation data of the boiler. Fig. 3 shows the result of simulations based on the linear model of Eq. (7) considered excess O_2. Fig. 4 shows the results of the prediction of the steam production rate based on the parametric efficiency model proposed. As can be seen, the efficiency η given by (9) gives acceptable prediction of changing tendency of steam rate. The magnitude of the errors in neural nets was examined for two types of activation function of the output layer: linear and tangent sigmoid. The tangent sigmoid function was used as the activation functions of hidden layers. The neural network model with the linear function shows more rapid convergence. However, the neural network with tangent sigmoid functions showed better performance than that with linear function as the number of neurons increases. The present neural network model, whose mean square error and maximum error were 4.1514 and 8.6607, respectively, used the linear

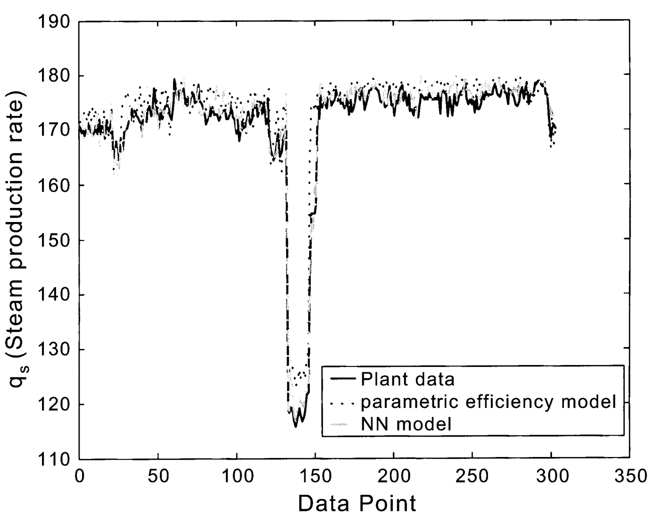

Fig. 5. The prediction of steam production rate (MSE_{PEM}=17.5757, MSE_{NN}=4.1514).

transfer function which was more stable. Fig. 5 shows the results of simulations based on the parametric efficiency model and the neural net model proposed in the present study. Compared with operation data, the neural net model as well as the parametric efficiency model exhibits acceptable prediction of operational trends.

CONCLUSIONS

In the present study, two modeling approaches were proposed and analyzed: parametric efficiency modeling and neural net modeling. From the results of simulations compared with operation data, we found that both modeling methods could generate dependable predictions of the key variables. Considering the convenience, the simple parametric efficiency model might be the choice of plant engineers.

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NOMENCLATURE

V : volume [m^3]
u : internal energy [kJ/kg]
T : temperature [^oC]
q : mass flow rate [ton/hr]
h : specific enthalpy [kJ/kg]
p : vector of parameter
q : vector of coal flow rate
e(·) : absolute error
t(·) : true output
a(·) : output of neural networks

Greek Letters

ρ : density [kg/m^3]
η : efficiency of boiler

Subscripts

s : steam
w : water
st : steam of total system
wt : water of total system
f : the boiler feed water
t : total boiler
b : the flow to flash tank
m : metal
c : coal for fuel
a : air
PEM : parametric efficiency model
NN : neural network model

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