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A comparative study of water wall model with a linear model and a neural network model

Un-Chul Moon*, Jaewoo Lim*, Geon Go*, Kwang. Y. Lee,**

* School of Electrical & Electronics Engineering, Chung-Ang University, Seoul, Korea, (e-mail: ucmoon@cau.ac.kr).
** Electrical and Computer Engineering, Baylor University, Waco, TX 76798-7356 USA (e-mail: Kwang_Y_Lee@baylor.edu)

Abstract: A water wall system is one of the most important systems used in boilers of thermal power plants. In this study, we assume that an exact nonlinear water wall model is given. Then, from the viewpoint of controller design, we compare the effectiveness of two models, a linear model and a neural network model. The linear model is developed by linearizing a nonlinear model at an operating point. The neural network model is developed using simulation data from a nonlinear model. To compare the qualities of these two models, a PRBNS (Pseudo Random Binary Signal) is applied to each model, and the errors of the models are compared. In comparison to the nonlinear model, two models performed adequately. The neural network model achieved a better performance than the linear model.

Keywords: Control system design, Process modeling and identification, Neural networks in process control,

1. INTRODUCTION

Thermal power plants are designed to handle fluctuating load demands, while nuclear power plants handle the base electrical load. Therefore, thermal power plants need to operate efficiently to keep up with the load change (Miao, 2011). One such method to achieve this is a good controller design based on a good quality model.

A water wall system is one of the most important heat exchanger systems in thermal power plants (Lu, 2008). Generally, a water wall system is modeled using a nonlinear system, which poses a challenge for controller design and analysis (Bentarzi, 2011).

However, most controllers were designed based on linear models. If the linear model is of a poor quality, the performance of the controller is also degraded (Moon, 2011). Thus, in order to overcome the nonlinearity of thermal power plants many control techniques are developed using neural network models (Draeger, 1995; Thibault, 1992; MacMurray, 1992).

In this study, we assume a nonlinear water wall model to represent the water wall system. Next, from the controller design perspectives, we compare the relative qualities of the two models, a linear model and a neural network model, with that of the nonlinear model. The linear model is developed by linearizing the nonlinear model at an operating point the neural network model is developed using simulation data from the nonlinear model. To compare the qualities of the models, a Pseudo Random Binary Signal (PRBNS) is applied to the nonlinear model, linear model, and neural network model.

2. WATER WALL MODELING

2.1 A Nonlinear Water Wall Model

In this paper, we consider a water wall model in a 600MW oil drum boiler-turbine systems as shown in Fig.1. The water wall is located between the circulating pump and the drum in the boiler. The circulating water in the water wall is heated in the furnace, and then poured into the drum.

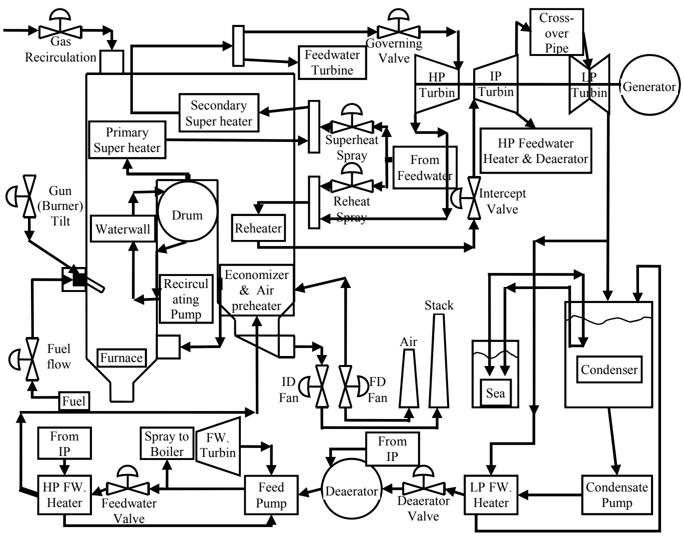

Fig. 1. Drum Boiler-Turbine Power Plant.

In this paper, we assume a water wall system as a nonlinear model that was used by Usoro (1977) and Kwang Y. Lee (2007). The model holds the following assumptions about the water wall system.

Assumption 1. Because mostly water is recirculated in the water wall system, the compression effect is ignored.

Assumption 2. Effective masses of water, steam, and metal are lumped into the single quantities.

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Mass balance equation, energy equilibrium equation, and thermal equilibrium equation can be defined based on boiler structure and physical principles. The description of the water wall system is as follows,

Mass balance equation is given by:

$$W_{wwo}=W_{rw}+K_{wrps} \quad (1)$$

where, W_{wwo} : Massflow of water wall output,

W_{rw} : Massflow of recirculating water,

K_{wrps} : Massflow of recirculating pump.

According to (Usoro, 1977), K_{wrps} accounts for recirculating pump leakages and seal injection. It is small and may be neglected.

Energy equilibrium equation is given by:

$$M_{wwme} \times K_{swwm} \times \frac{d}{dt}(T_{wwm})=Q_{wwgm} - Q_{wwmw} \quad (2)$$

where, M_{wwme} : Effective mass of water wall metal,

K_{swwm} : Specific heat of water wall metal,

T_{wwm} : Temperature of water wall metal,

Q_{wwgm} : Heat transfer rate of gas to metal,

Q_{wwmw} : Heat transfer rate of metal to water.

$$M_{wwme}=K_{mwwm}+\frac{K_{vww} \times R_{drw} \times H_{drw}}{K_{swwm} \times T_{wwm}} \quad (3)$$

where, K_{mwwm} : Mass of water wall metal,

K_{vww} : Volume of water wall,

R_{drw} : Density of drum water,

H_{drw} : Enthalpy of drum water,

$$Q_{wwmw}=K_{uwwmw} \times (T_{wwm} - T_{drs})^3 \quad (4)$$

where, K_{uwwmw} : Constant with dimension of [W/K^3].

T_{drs} : Temperature of drum steam,

Thermal equilibrium equation of circulating water is given by:

$$W_{wwo} \times (H_{wwo} - H_{rpo})=Q_{wwmw} \quad (5)$$

where, H_{rpo} :Enthalpy of recirculating pump output,

H_{wwo} : Enthalpy of water wall output,

The following constant values are used:

K_{mwwm}=1063000, K_{vww}=2318.61, K_{swwm}=0.11, K_{uwwmw}=173.5205

For equations (1)-(5), we define the inputs, the outputs, and the states as follows,

Input :

$$U=[u_1,u_2,u_3,u_4,u_5,u_6]^T=[W_{rw},H_{rpo},R_{drw}, H_{drw},T_{drs},Q_{wwgm}]^T \quad (6)$$

Output :

$$Y=[y_1, y_2, y_3]^T=[W_{wwo}, H_{wwo}, T_{wwm}]^T \quad (7)$$

State :

$$X=[x]=[T_{wwm}] \quad (8)$$

Then, the nonlinear model of water wall system is represented in the following equation,

$$\dot{x} = \frac{u_6 - K_{uwwmw} \times (x - u_5)^3}{(K_{mwwm} + \dfrac{K_{vww} \times u_3 \times u_4}{K_{swwm} \times x}) \times K_{swwm}} \quad (9)$$

$$y_1 = u_1 \quad (10)$$

$$y_2 = u_2 + \frac{K_{uwwmw} \times (x - u_5)^3}{u_1} \quad (11)$$

$$y_3 = x \quad (12)$$

From the above equations, we notice that the water wall system has severe nonlinearity.

2.2 A Linear model of Water Wall System

The nonlinear model, given by equations (9)-(12), is linearized using the first order Taylor approximation at an operating point. The operating point was selected so as to keep the power output steady at 500MW. Table 1 shows the operating point of 6 inputs, 3 outputs, and a state.

Table 1. The operating point

Variables	Operating value
u_1 (W_{rw})	4596.1272
u_2 (H_{rpo})	725.5982
u_3 (R_{drw})	33.5881
u_4 (H_{drw})	744.7551
u_5 (T_{drs})	1138.1153
u_6 (Q_{wwgm})	356915.0337
y_1 (W_{wwo})	4600.4286
y_2 (H_{wwo})	803.1653
y_3 (=x, T_{wwm})	1150.832

Then, the first order approximation of equations (9)-(12) at the operating point is given by,

$$\begin{aligned} \dot{x} = & -3.9975 \times 10^{-6} \times (u_3 - 33.5881) - 1.8028 \times 10^{-7} \\ & \times (u_4 - 744.7551) + 0.5031 \times (u_5 - 1138.1153) \\ & + (5.9763 \times 10^{-6}) \times (u_6 - 356915.0337) \\ & + (-0.5031) \times (x - 1150.832) \end{aligned} \quad (13)$$

$$y_1 = u_1 \quad (14)$$

$$
\begin{aligned}
y_2 = 803.1653 - 1.0126\times10^{-4}\times(u_1 - 4596.1272)\\
+(u_2 - 725.5982) - 18.2988\times(u_5 - 1138.1153)\\
+18.2988\times(x - 1150.832)
\end{aligned} \tag{15}
$$

$$y_3 = x \tag{16}$$

When all the variables are defined as deviations from the operation values in Table 1, the linear model is given by,

$$
\begin{aligned}
\Delta\dot{x} = -3.9975\times10^{-6}\times\Delta u_3 - 1.8028\times10^{-7}\times\Delta u_4\\
+0.5031\times\Delta u_5 + 5.9763\times10^{-6}\times\Delta u_6 - 0.5031\times\Delta x
\end{aligned} \tag{17}
$$

$$\Delta y_1 = \Delta u_1 \tag{18}$$

$$
\begin{aligned}
\Delta y_2 = -1.0126\times10^{-4}\times\Delta u_1 + \Delta u_2 - 18.2988\times\Delta u_5\\
+18.2988\times\Delta x
\end{aligned} \tag{19}
$$

$$\Delta y_3 = \Delta x \tag{20}$$

We notice that equation (17) is a simple first order system with a pole at s = -0.5031 and the overall system is stable without any oscillation mode. The transfer function matrix, $\overline{G}(s)$, of equations (17)~(20) for the 6-input 3-output system is given by,

$$
\overline{G}(s) = \begin{pmatrix}
1 & 0 & 0 & 0 & 0 & 0\\
\dfrac{-0.0001403s}{s+0.5031} & 1 & \dfrac{-7.315\times10^{-5}}{s+0.5031} & \dfrac{-3.299\times10^{-6}}{s+0.5031} & \dfrac{-18.3s}{s+0.5031} & \dfrac{0.0001094}{s+0.5031}\\
0 & 0 & \dfrac{-3.998\times10^{-6}}{s+0.5031} & \dfrac{-1.803\times10^{-7}}{s+0.5031} & \dfrac{0.5031}{s+0.5031} & \dfrac{5.976\times10^{-6}}{s+0.5031}
\end{pmatrix} \tag{21}
$$

2.3 Neural Network Model of Water Wall System

Neural network has been widely applied in various fields because of its ability to learn arbitrary functions (Fausett, 1994). In this study, water wall system is modeled using a perceptron network.

Fig. 2 shows the training data from the nonlinear model represented by equations (9)-(12). In the figure, 6 inputs were generated by random signal. The training data is rearranged to reflect the water wall system dynamics as follows,

$$Y(k+1) = f\{Y(k), Y(k-1), U(k)\} \tag{22}$$

where k is the discrete time step.

Fig. 3 shows the structure of neural network used to train the water wall system. The input of perceptron is U(k), Y(k), Y(k-1), and the number of input nodes is 12. The output of the neural network is Y(k+1), the number of output node is 3. The number of hidden layer nodes is determined to be 13. Fig. 4 shows the reduction of mean square error while the neural network is being trained using the Matlab toolbox. Finally, the trained perceptron is used as a water wall model.

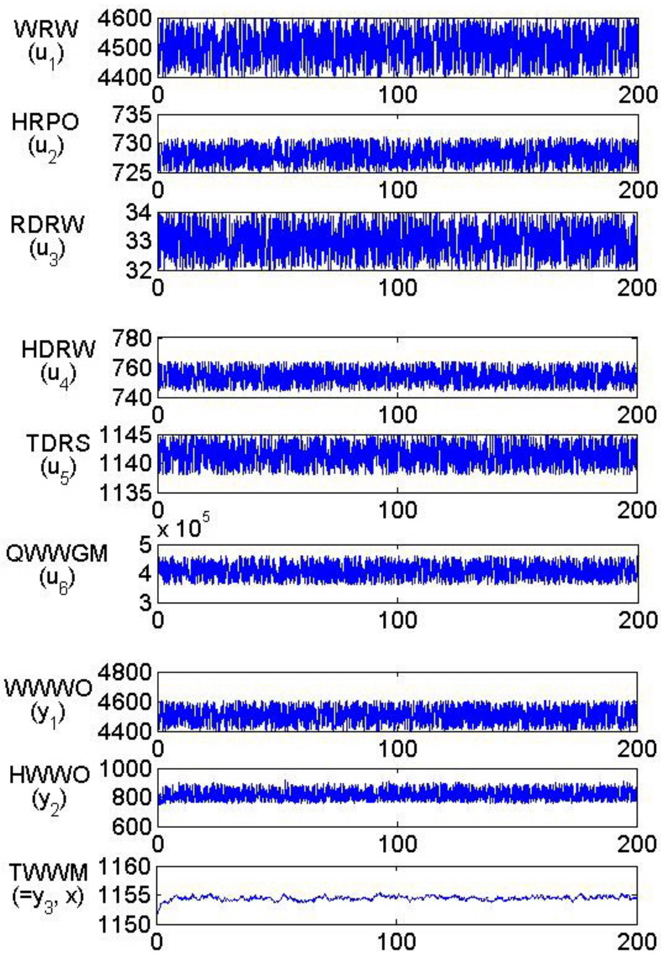

Fig. 2. Training Data For Neural Network

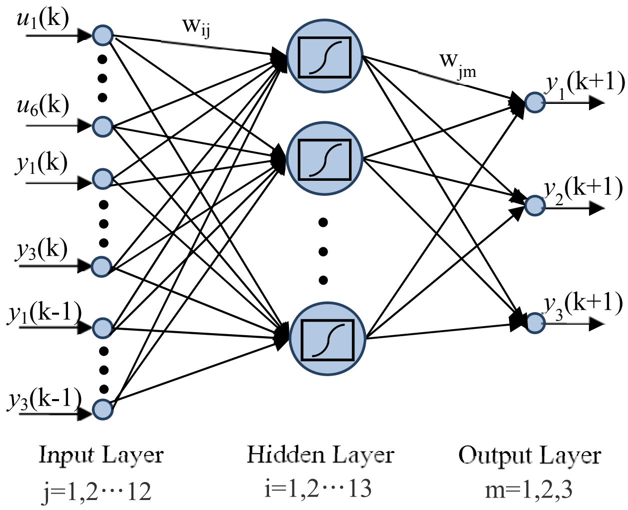

Fig. 3. Simulated Neural Network Configuration

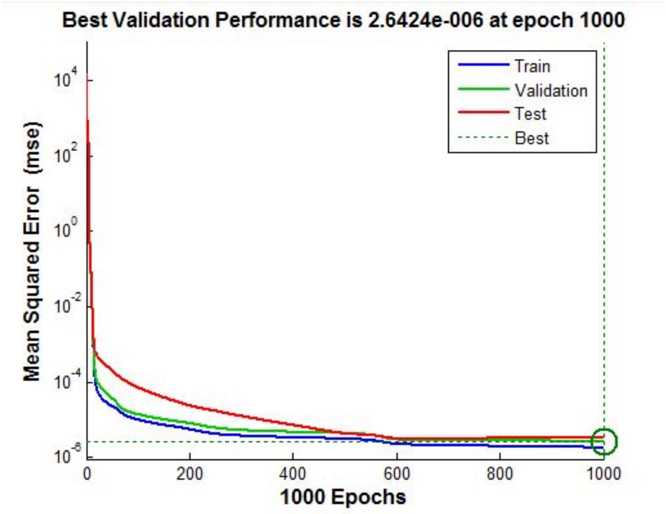

Fig. 4. Mean Square Error reduction in training process

3. SIMULATIONS

The qualities of two models are tested by simulation. First, a set of PRBNS inputs are designed to perturb the system. Then, the PRBNS inputs are applied to each of the three models, nonlinear model, linear model and neural network model independently. Fig. 5 shows the six PRBNS inputs used in the simulation.

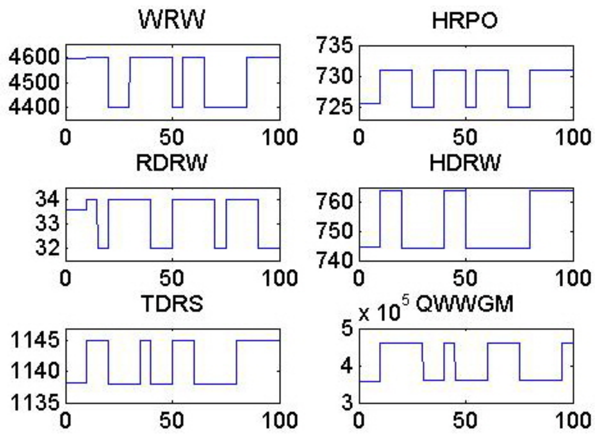

Fig. 5. Six PRBNS Inputs.

Fig. 6 shows the output y_1 of the three models, nonlinear, linear, and neural network. In Fig. 6, three outputs show almost similar response. This is because y_1 is a linear system from (10), which is not a function of the state x. Therefore, the responses of the linear model and the nonlinear model are mathematically equivalent for y_1. The y_1 of the neural network also matches with that of the nonlinear model. This means that the neural network effectively describes the dynamics of y_1.

Fig. 7 shows the output y_2 of the three models. In this case, y_2 of the neural network and the nonlinear model are almost similar. Although y_2 of the linearized model shows a similar response to that of the nonlinear model, the undershoot responses shows some differences. Fig. 8 is a zoomed in version of Fig. 7. Fig. 8 shows a clear difference between the linear model and the neural network model. In this figure, the response of the neural network is almost the same with that of the nonlinear model. Fig. 9 shows the output y_3 of the three models, and Fig. 10 is a zoomed in version of Fig. 9. For y_3, the output of the neural network is almost similar to that of the nonlinear model, while the linear model exhibits some difference.

Table 2 shows the absolute error for the linear and the neural network model. In the table, linear model exhibits better performance for y_1, while neural network model exhibits better performance for y_2 and y_3. The better performance of the linear model for y_1 can be attributed to y_1 being a linear output.

The outlet of the water wall is a mixture of water and steam, i.e. saturated condition. At that phase, assuming constant pressure, the temperature of the fluid is constant while the enthalpy may change as a function of water/steam ratio. This can be a major reason the temperature is modeled exactly while the enthalpy shows some undershoot.

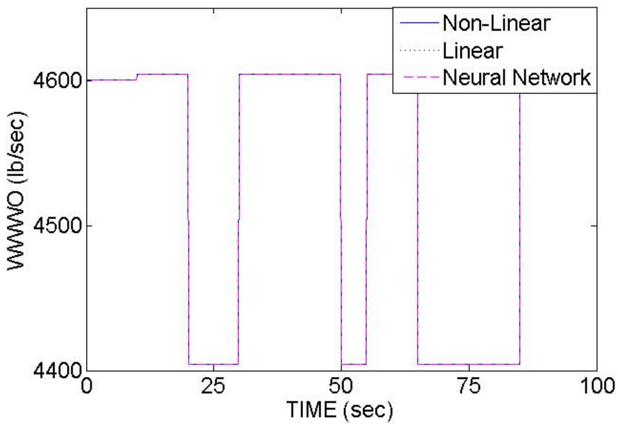

Fig. 6. y_1 (W_{WWO}, Mass flow of Water wall Output)

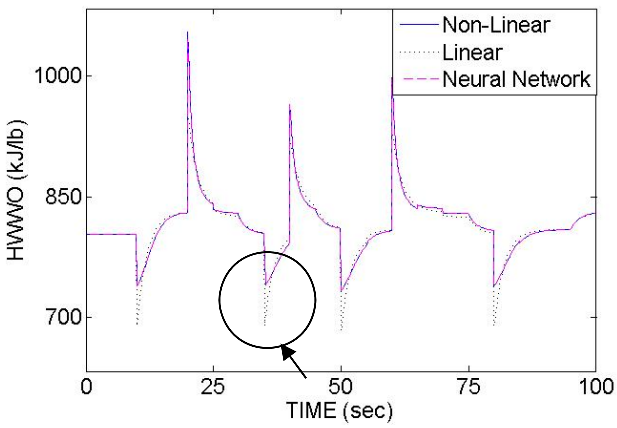

Fig. 7. y_2 (H_{WWO}, Enthalpy of Water Wall Output)

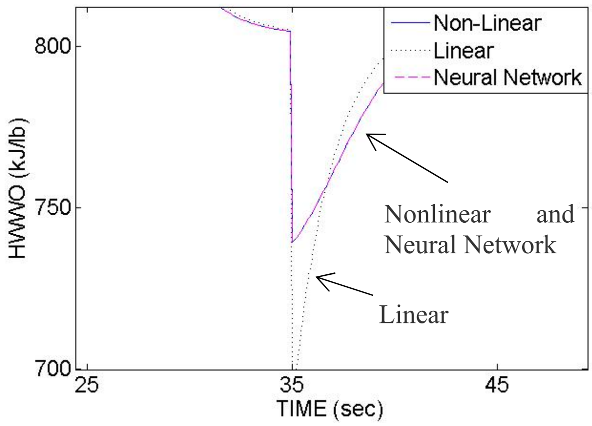

Fig. 8. An Enlargement of Fig. 7.

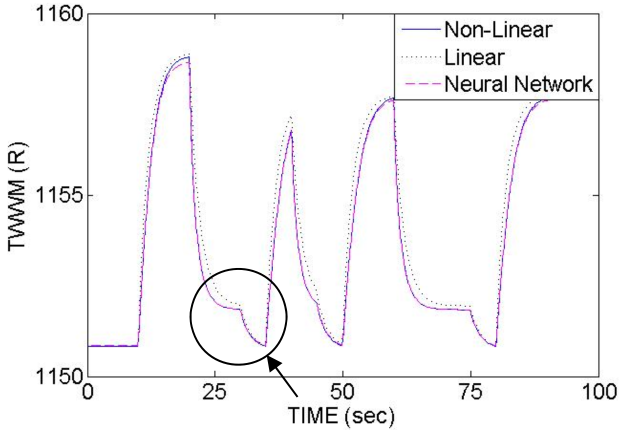

Fig. 9. y_3 (T_{WWM}, Temperature of Water wall Metal)

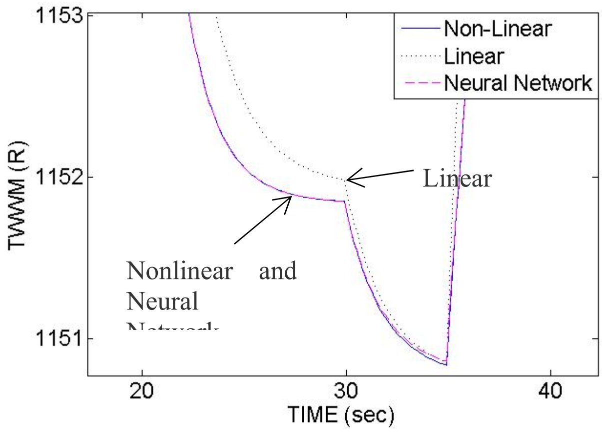

Fig. 10. An Enlargement of Fig.9

4. CONCLUSIONS

In this paper, we presented a comparison between linear model and the neural network model for the water wall system in drum boiler-turbine power plant. A simple perceptron neural network model shows almost similar responses to those of the nonlinear model. Though there are some differences, linear model also shows similar performance in comparison to that of the nonlinear model. Since the linear model is valid near nominal operating point, the performance of the linear model will be worse at low power generation while the neural network preserves the nonlinearity of the plant.

Because it is not easy to predict the control performance in design process, it is not clear that the quality of linear model is suitable for a controller design. If this model is used for part of the model of the boiler system describing the dynamics of energy flows, the mismatch in enthalpy needs to be considered. However, the presented model can be used for the temperature control problem. Similar analysis can be performed to heat exchangers placed in the superheater system since both the input and output are steam. In such case, both temperature and enthalpy may be equally sensitive to input variation. The control aspect of such heat exchanger is even greater.

Table 2. Comparison between Linear and Neural Network model error

	Linear model (% to neural network model)	Neural Network model
y_1	0 (0%)	0.0019
y_2	4.9218 (29296%)	0.0168
y_3	0.325 (900%)	0.0361

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