ESTIMATION OF DRUM BOILER PARAMETERS USING NONLINEAR CLOSED LOOP IDENTIFICATION TECHNIQUES

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Abstract

Boiler is one of the important units in power generation system. This paper describes the estimation of boiler model parameters through closed loop system identification techniques. The validated models can be used for simulations for studying the interrelation of different parameters such as drum level, steam flow, feed water flow , steam demand etc.

Keywords: Boiler, Model, simulation, Identification.

I. INTRODUCTION

Thermal power plants are the major source of electrical power generation contributing about 60 percent of globe's power generating capacity. The main principle of thermal power plants is to generate superheated steam from boilers and rotate high pressure turbines. The generator coupled to the turbines generates electricity. The schematic showing the material flow and the state of the matter is shown in figure 1. The combustion process utilizes the fossil fuels and generates required heat energy in the furnace. This liberated heat converts water in to vapor. The super heated vapor is used in high pressure turbine and after reheating steam is once again utilized in low pressure turbine.

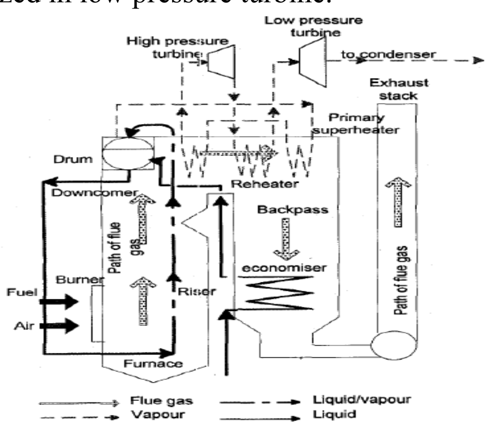


Figure1. Flow of material in boiler process

The overall efficiency of thermal power plant is the effect of three main components viz boiler, turbine and alternator. In general the efficiency of boiler is again combination of both furnace efficiency and boiler efficiency and is about only 60-75%. With the help of modern control schemes this can be improved further. Different test codes from American Society of Mechanical Engineers (ASME) also exist to evaluate the performance on a periodic basis [9]. One of the critical variables which will affect the efficiency is drum level control. The level transmitters used are of differential pressure (DP) type where increasing DP causes decrease in output signal. Three element drum level control is adapted to with a stand large and fast load changes. A typical level control scheme is shown in figure2.

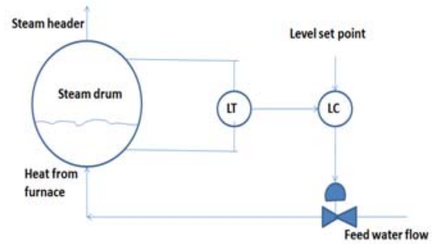


Figure 2. General drum level control

II. MODELING OF DRUM BOILER

A. Review of techniques

The boiler model is one of the most critical highly challenged industrial models due its multi variables, non linear, time delays[12], highly interactive and inverse dynamics.[7] The importance of modeling is profound in simulation and control system design. The two distinct approaches for modeling are first principle method and empirical method. These are derived based on energy and mass balance equations. Models derived from former method are proved to be accurate and producing promising results.[1][13] but are very complex and time consuming. More simplified low order models can be obtained by using approximations but are only suitable for low load and normal operating conditions. To derive strong models one has to relay on former approach which is tedious. To resolve this problem the complex boiler model is dealt in modular [14] fashion addressing different conditions [2] mainly

i) Cold startup
ii) Low load cycle
iii) High load cycle
iv) Fluctuating load

The efficiency of fossil thermal power plants is further improved by development of ultra supercritical (USC) models [3] by using neural networks (NN).

For the ease of modeling boiler plant is divided in to five sub systems.[8]

i) Boiler furnace model
ii) Boiler drum model
iii) Primary super heater model
iv) Attemperator model
v) Secondary super heater model

Boiler drum model

$$\frac{d}{dt}[(v_d - v_{dw})\rho_d + v_{dw}\,\rho_{dw}] = F_{ew} - F_d \tag{1}$$

$$\frac{d}{dt}[(v_d - v_{dw})\rho_d h_d + v_{dw}\,\rho_{dw}\,h_{dw}] = \tag{2}$$

$$F_D h_w - (F_D - F_{ew})h_{dw} - F_D h_d$$

Where

V_d- is volume of drum
V_{dw}- is volume of water in drum
ρ_d- is density of drum steam
ρ_{dw}- is density of water in drum steam
F_{ew}- is flow of feed water
h_d- enthalpy of drum.

The boiler units are generally evaluated using the following performance metrics [9] one is Unit heat rate (UHR), which is ratio of heat input rate to turbine to product of generator electricity output and boiler efficiency. The boiler efficiency (BE) can be computed from heat loss as given in (3).

BE (%)=100%-Boiler Heat Loss(%) (3)

Another metric used in power industry is fuel electricity rate (FER) given from (4).

FER=fuel Btu rate/Electricity output (4)

The implementation of analytical models is very complex and time consuming. The data driven techniques are gaining much importance by power industry due to the ease of implementation of different optimization algorithms based on historical data. In some cases a seven - day historical data is considered to construct viable alternate models of different sub units of the real plant [10]. These data driven model simulations are promising that the plant efficiency can be improved by better models. Apart from using onetime plat data a cluster based control systems are also in practice for improving boiler efficiency [11].

B. System identification

system identification (SI) is a subject which mainly deals with the means and techniques for studying a process system through observed or measured data for the purpose of developing a suitable mathematical relation between input(s) and output(s)" as shown in figure3.

The complex boiler control can be modeled by combining sub models constructed from different experimental data sets. Non linear models are approximated using linear models of small period [12].

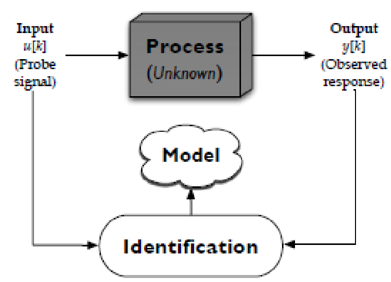


Figure3. scheme of system identification

In this paper the boiler three element drum level control loop (TDC) data is considered for modeling the dynamics under various load conditions. The SI techniques are used to identify the interrelation of different variables mainly stem demand signal, feed water flow rate, steam out flow rate and drum level. The TDC figure4 will consider the feed water flow in addition to water level and steam flow signals. Where steam flow serves the purpose of feed forward action in maintaining the water flow in response to steam demand.

C. Effect of Shrink and swell

The major threats in the level measurement are the shrink and swell effect which appears in increasing and decreasing load conditions.

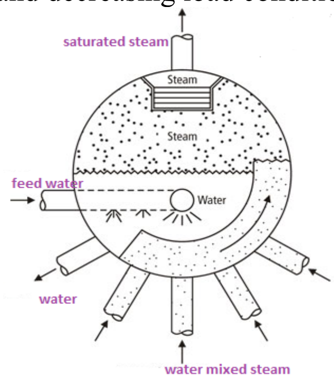


Figure4. water and steam in boiler

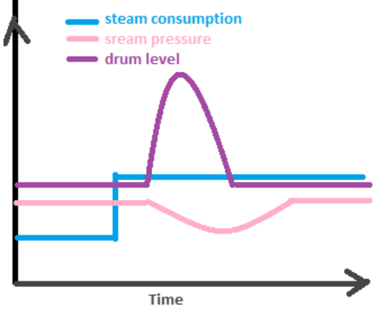


Figure5: typical shrink and swell effect in boiler drum

In order to meet increased steam demand additional feed water is supplied to boiler. The addition of low temperature water to saturated steam/water causes sudden collapsing of existing water bubbles causing a sudden decrease of level. This negative effect in level measurement is called "shrinking" phenomena. On the other hand though the decreased steam demand reduces the feed water flow and hence level due to the less pressure in the boiler tae rate of collapse of bubbles is also reduced causing increase in apparent level. This negative effect is called "swelling" phenomena as shown in figure4&5.

D. Three element drum level control

Three element drum level control shown in figure6&7 is the most used control strategy compared to single element and two elements. In addition a feed forward plus feedback cascade mechanism is used to improve the performance. The important aspect in level control is the accuracy of level measurement. Differential pressure transmitter is the most common type and prone to err due to the interaction of drum pressure and densities of both steam and water. Hence the level measurement should be compensated for pressure correction as given from (3)-(11).

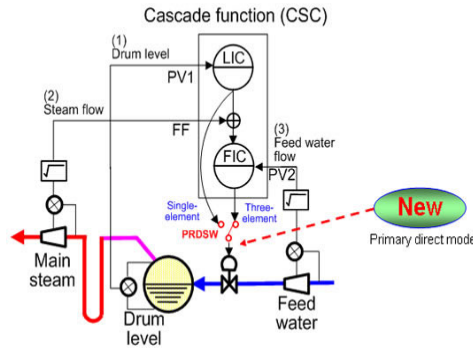


Figure6: Three elements drum level control

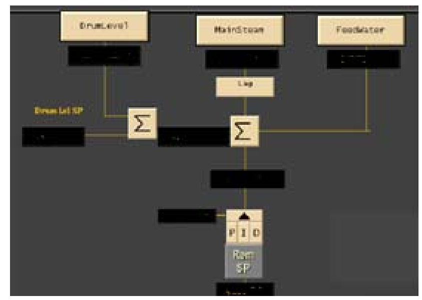


Figure5. Courtesy of three element drum level control

$$\Delta P = hd_c - ld_h - (h-l)d_s \quad (5)$$

$$= hd_c - l(d_h - d_s)hd_s \quad (6)$$

$$l = -[\,\Delta P + hd_s - hd_c] \,/\, d_h - d_s \quad (7)$$

$$l = \frac{hdc - hds - \Delta P}{dh - ds} \quad (8)$$

$$l = l_0 + h_b \quad (9)$$

$$l_0 = l - h_b \quad (10)$$

$$l_0 = \frac{hdc - hds - \Delta P}{dh - ds} - h_b \quad (11)$$

Where ΔP is differential pressure, l is the level, h is the total height of the drum, l_0 is the compensated level of water from zero mid line and d_h, d_s, d_c are the densities of hot water, steam and cold water respectively.

E. Experimental data from boiler unit

Historical data related to various boiler load conditions is collected from a thermal power generation unit. Different data sets are prepared for identification of level control loop dynamics. The boiler works at a base load of 200MW. The real industrial data is collected from unit4 boiler with a drum level set point of -140.00. The experimental data can be used to construct LTI uncertain models [15] and these are further used in robust control design. The power plants are in demand of coordinated control systems in order to with stand the demands of power grid frequency control section. This in turn demands for fast response of various sub sections of the boiler. Changes of some important parameters with small changes in load are given in table1.

S.No	Variables	Load MW 212.8	Load MW 214.9	Load MW 214.5
1.	MSTMP deg C	532.5	533.6	536.7
2.	RHTMP deg C	514.6	514.8	513.6
3.	MSPR kg/cm^2	145.2	146.6	147.5
4.	MSFL T/H	663.8	668.7	666.4
5.	FWFL T/H	669.9	660.0	654.6
6.	FURPR kg/cm^2	-17.2	-15.8	-15.3
7.	DRLV mmWcl	-137.5	-140.9	-128.9
8.	DRPR kg/cm^2	159.2	160.6	161.3
9.	RPM	2987.6	2992.0	2999.1

III. CLOSED LOOP IDENTIFICATION

This paper discusses about the closed loop identification of the boiler drum level control. Closed loop identification is preferred due to following reasons.

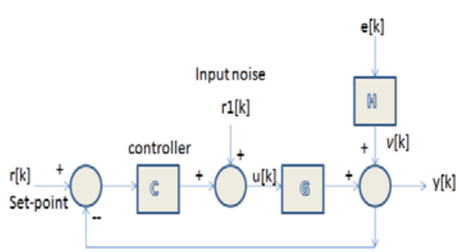


Figure8 : typical closed loop system used in identification

1. The open loop systems are inherently unstable.
2. The industrial system stabilized under open loop may disrupt the plant operation when working under feedback
3. All non linear systems will be mostly linearized under closed loop. Hence closed loop identification will lead to good models.
4. Various control schemes can be applied directly on closed loop model especially control based identification.

Various variables and elements for identification are shown in figure8.

Despite different advantages the closed loop identification faces some challenges that are common in industrial systems.

- Correlation between inputs and disturbances. This can be sorted out easily under open loop but in closed loop the estimates may suffer biasing.
- As the inputs are designed by the controllers the user can introduce only changes in set points. No change in input is allowed.
- The controller will keep the output excitation and other signals in the system within the boundaries posing a limited operating region.
- It is difficult to distinguish between the process model and the inverse dynamics of the active controller due to the fact that input is derived from the system output as given (12-13)

$$y[k]= Gp(q^{-1})u[k] \quad (12)$$

$$u[k]= - Gc(q^{-1})y[k] \quad (13)$$

The closed loop system can be perturbed in three different ways.

1. Set-point changes: In most of the industrial process the changes in set point is invited. Making changes in set point for the purpose of identification is common practice where there is no operational constraint.
2. Dither signal: these dither signals are introduces either at set point or at controller out put such as r1 shown in figure. Knowledge about the process is required to avoid off spec outputs.
3. Undefined input noise: in many cases the noise in the input signal is identified. This can be treated as an external excitation.

The closed loop identification methods are classified in to three types based on the knowledge of the following

1. Direct method: feedback is not considered and open loop techniques are imposed on

identification data.

2. Indirect method: It identifies the closed loop system based on set point and output data first and then identifies the open loop system in order to know the regulator.
3. Joint input – output method: system transfer function is constructed based on multi variable identification. This method treats set-point as source for driving both input and output.

IV. NON LINEAR IDENTIFICATION

Most of the industrial processes are non linear in nature including drum boiler system. Though approximate linear models exist they cannot fully describe the dynamics of nonlinear systems. Hence the scope of linear models is limited. General representation of the parameterized system is given in (14)

$$y[k]=g(\varphi[k],\theta)+v[k] \qquad (14)$$

Where $g(\varphi[k],\theta)$ is a non linear function and

$v[k]$ is stochastic term

The regression vector is composition of inputs and outputs as given in (15)

$$\varphi[k]=[y[k-1] \ldots y[k-n_y]\ u[k-1] \ldots u[k-n_u]]^T \qquad (15)$$

Substituting (15) in (14) and making $v[k]=e[k]$ will result in NRAX predictor without feedback as in (16)

$$\hat{y}[k]=g(y[k-1] \ldots y[k-n_y]\ u[k-1] \ldots u[k-n_u],\theta) \qquad (16)$$

on the other hand the predictor for the non linear output error model (NOE) is composition of past predicted outputs and inputs giving scope for feedback.

$$\hat{y}[k]=g(\hat{y}[k-1] \ldots \hat{y}[k-n_y]\ u[k-1] \ldots u[k-n_u],\theta) \qquad (17)$$

The properties of ARX and OE models used for linear systems are can also be applied to NARX and NOE. NARX models are easy to construct and accounts for one step ahead prediction error. Whereas the NOE model structure is complicated but provides good models for simulation purpose.

A. Simple nonlinear models

There are two different famous models under this.

i) Volterra model and

ii) Hammerstein and Wiener model

Volterra model: these are nonlinear FIR models with the scope of estimation terms of higher order. But in practice it is limited to only bilinear terms due to the problem of dimensionality and provides stable models.

Hammerstein and Wiener model: This is also called as block oriented model (9-11) as the nonlinearity of the system is captured in static block and the system dynamics in linear block. In Hammerstein model the process is described as the linear models which receive input through a nonlinear filter. In case of Wiener model the above assumption is inversed and results in to nonlinear model, which receives input through a linear dynamic model. Hence the above two models are inverse models to each other. The combined model is known as Hammerstein and Wiener model, which is widely used for modeling different nonlinear systems.

The equation (15) can be expressed using only input terms resulting in to *Volterra model.* Pre filtering can be incorporated in (14) as in *prediction error* method (PEM). The nonlinearities present in the noise $v[k]$ can be addressed as white noise by nonlinear auto regressive exogenous (NARX) model.

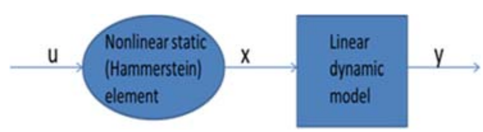


Figure9: Hammerstein model

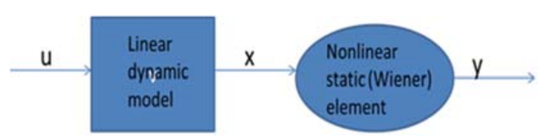


Figure10: Wiener model

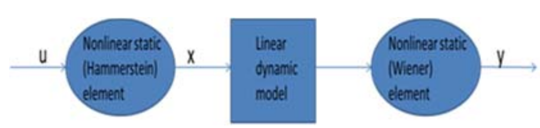


Figure11: Wiener-Hammerstein model

V. DRUM BOILER MODELING

The drum boiler unit is modeled using the data driven nonlinear estimation techniques. Plant data is collected during different operating conditions, feeding sudden surge and different hydra step conditions as shown in figure 12. The model estimated from low efficiency region can be an asset for designing optimal control system which useful even in startup conditions. Different signals are considered for estimation viz. actual drum level, steam flow, feed water flow, controller output, scoop master output and load signal etc.

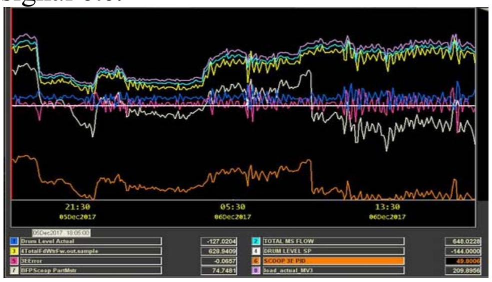
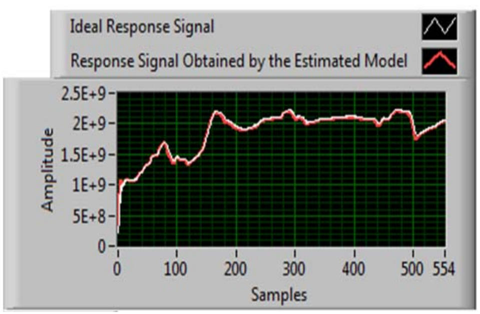
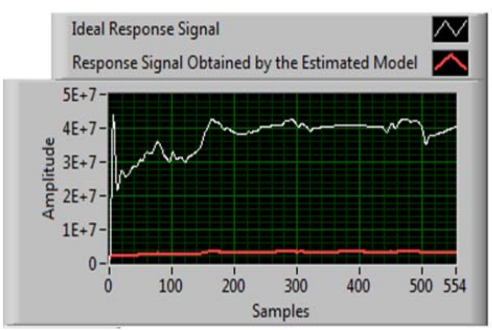


Figure 12: drum level control parameters

VI. RESULTS AND CONCLUSIONS

The drum boiler data is used for estimating the non linear models and results are compared as follows. Steam flow, feed water flow and steam load (demand) data is used for estimating non linear models as given from fig13 through 15. It is observed that Hammerstein model estimate responses are closure to the actual compared to other.





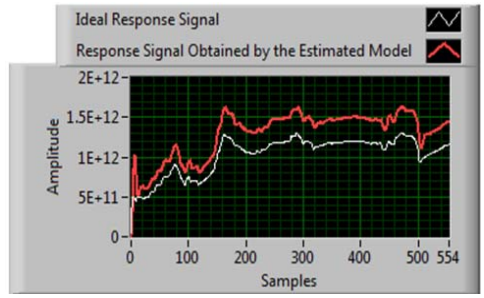
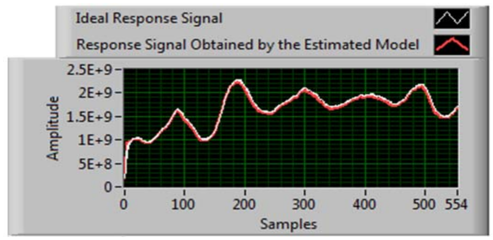
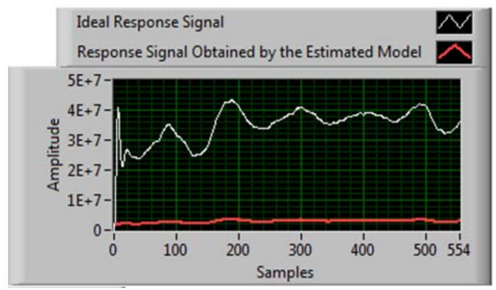


Figure 13: Response of estimated Hammerstein, wiener and wiener-Hammerstein models for steam flow signal





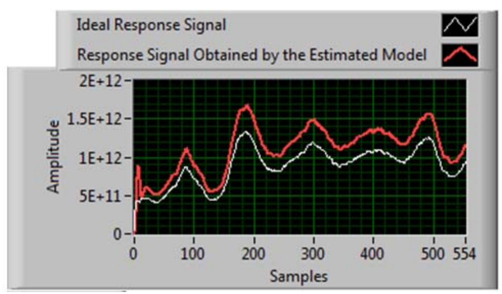
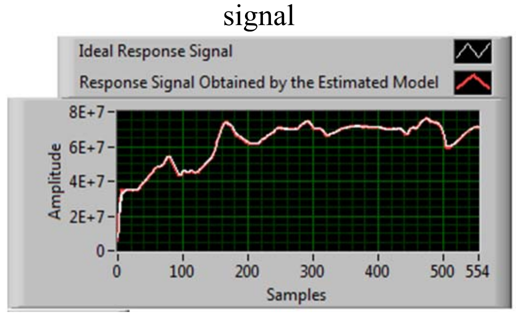


Figure 14: Response of estimated Hammerstein, wiener and wiener-Hammerstein models for feed water flow signal



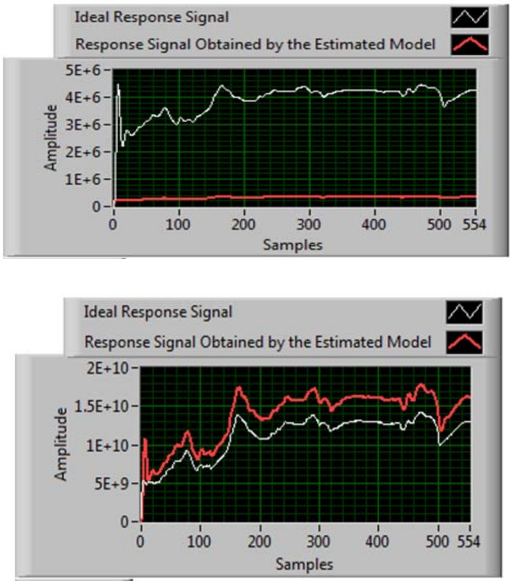


Figure 15: Response of estimated Hammerstein, wiener and wiener-Hammerstein models for steam load signal

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