MODELING AND CONTROLLER DESIGN OF AN INDUSTRIAL OIL-FIRED BOILER PLANT

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ABSTRACT

In this study, a physical boiler system is modeled as a multivariable plant with two inputs (feed water rate and oil-fired flow rate) and two outputs (steam temperature and pressure). The plant parameters are modeled by identification based on experimental data collected directly from the plant. The routines of System Identification Toolbox™ with structure selection for Autoregressive Moving Average together with Recursive Least Square (ARX) were used to identify the model. The identified ARX model was validated using Akaike's Final Prediction Error (FPE) criterion. The identified model was further subjected to test, using the validation input data; simulated model outputs for both temperature and pressure agree closely with the actual plant outputs with error of 8% and 9% respectively. Furthermore, Proportional Integral Derivative (PID) Controller was developed to control the identified model. Simulation studies were carried out; the results obtained indicate the effectiveness of the technique. The controller was able to track the temperature and pressure set points steadily and rapidly.

KEYWORDS: *Boiler Modeling, Identification, ARX model, Akaike's Criterion, PID controller.*

I. INTRODUCTION

The function of a boiler is to deliver steam of a given quality (i.e. temperature and pressure) to a steam turbine and other process equipments [17; 20]. For instance, in Savannah Sugar Company Limited Numan, Nigeria, power generation is by thermal power plant whereby electric power is generated from combustion of black oil.

Investigation of the dynamics of power plant boiler requires detailed models with representation of plant components [8; 15; 16]. Large-scale models are generally based on first-principle equations (i.e. mass, momentum and energy balances), with phenomenological correlations (e.g. heat transfer correlations), and may be considered as knowledge models [19; 22]. However, to justify the basic structure of oil-fired boilers control systems, a different kind of model may be very helpful where only first-cut dynamics is captured in order to reveal the essential input-output interactions [6]. Such models may be called interpretation or identification models. Successful identification of nonlinear plant models is more problematic since, in addition to stimulating the dynamics, the plant must now be exercised across the operating range over which modeling is needed. One strategy which gave acceptable results in earlier work was to step the control inputs to drive the plant through its range of operating points while superimposing pseudo random binary signals at the same time [6]. This operation is difficult to effect while the boiler is in operation. On the other hand, to handle such a complex system with several inputs and outputs is complicated [11]. Therefore, the input and output data collected from the SSCLN power plant will be used for system modeling.

The oil-fired boiler system (OFBS) is very complex for which well organized control functions may result in real benefit both in terms of efficiency and plant availability [21]. Hence, sophisticated distributed control systems (DCS) have been applied to OFBS, incorporating traditional PID controllers, model-based feed forward compensators, parameter scheduling, Boolean functions and so on [7; 24].

The Industrial Oil Fired Boiler System (OFBS) continuously supplies 50tonns/hr of steam at a temperature of 420^{o}C and pressure of 3200KPa to a 3.2MWatts turbine for power generation and production process use. At the time of carrying out this study, the boiler plant at SSCLN was operated mostly on open-loop with human operators manually adjusting the plants variable so as to achieve some form of control. This result in frequent boiler failures with prolonged production stoppages, not to mention the health and environmental impact of excess heavy black smoke (containing CO_2 and CO which is a green house gas) released into the atmosphere due to incomplete combustion of black oil.

II. DATA COLLECTION AND PRE-PROCESSING

During operation a sampling period of 20 seconds was selected as a good compromise between the need of a low sampling rate according to the control design and wishes of the boiler engineers to have new control actions computed sufficiently rapidly after important perturbation. The input-output data for model construction and validation had been collected during different days. Therefore, the involved input sequence was detected by production constraints. The data was taken from where inputs suffered significant variations. However, it was checked a posteriori that the considered sequence was persistently excited.

The input raw data was converted to equivalent input flow rate data as follows: The raw data was taken using pressure and temperature gauges, but these quantities are controlled by flow control valves hence the need to convert the input variables into flow rates. The control valve characteristics are related to the pressure by [4];

$$P = 20\times10^3 Q_i^{\ 2} \tag{1}$$

Where P , is pressure of the fluid, Q_i is the flow rate of the fluid.

From equation (1), the flow rate is obtained as:

$$Q_i = \sqrt{\frac{P}{20\times10^3}} \tag{2}$$

III. BOILER SYSTEM IDENTIFICATION

System identification allows one to build a mathematical model of a dynamic system based on measured data [26]. This is achieved by adjusting parameters within a given model until its output coincides as close as possible with measured output.

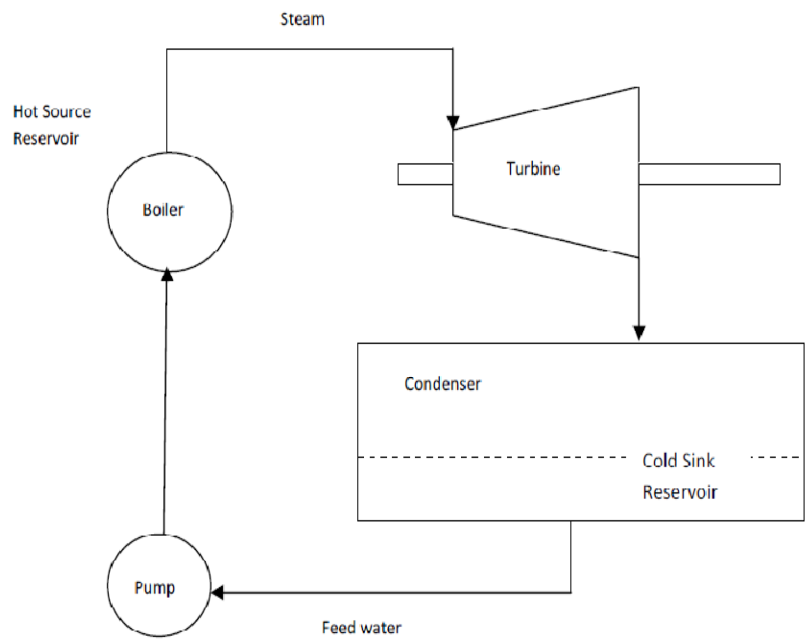

Figure 1. Components of a steam boiler plant

To obtain a model that is satisfactory under a given environmental condition, measured input output data from the system were used to provide the equivalent estimated input and output parameters which are used for building the parametric model. Parametric model are linear and the recursive nature of self-tuning algorithms suggests that discrete time modeling is appropriate [7; 12].
The model identification approach is based on the fundamental assumption that the plant dynamics can be well approximated by a finite order slowly varying linear system [25].

3.1 Model choice

Linear models are simple and easy to implement on wide range of controllers. A linear model is often sufficient to accurately describe system dynamics and, in most cases of system identification, fitting linear models are tried first [25; 27]. The initial trial of fitting linear models gave acceptable preliminary results. Hence, an ARX model structure (Autoregressive Moving Average together with Recursive Least Square) has been chosen as;

$$y(t) + a_1 y(t-1) + ... + a_{n_a} y(t-n_a) =$$
$$b_1 u(t-1) + ... + b_{n_b} u(t-n_k-n_b+1) + e(t) \quad (3)$$

The parameters n_a and n_b are the orders of the ARX model, and n_k is the delay.
A more compact way to write the difference equation is:

$$A(q)\begin{bmatrix} y_1 \\ y_2 \end{bmatrix} = B(q)\begin{bmatrix} u_1 \\ u_2 \end{bmatrix} + \begin{bmatrix} e_1 \\ e_2 \end{bmatrix} \quad (4)$$

where q is the delay operator.

$[y_1, y_2]$ is the output vector, with y_1 as the steam temperature and y_2 as steam pressure.

$[u_1, u_2]$ is input vector, with u_1 as feed water flow rate and u_2 as the oil flow rate.

$[e_1, e_2]$ is the model error vector which is white noise.

$$A(q) = 1 + a_1 q^{-1} + ... + a_{n_a} q^{-n_a} \quad (5)$$

$$B(q) = b_1 + b_2 q^{-1} + ... + b_{n_b} q^{-n_b+1} \quad (6)$$

A(q) and B(q) parameters was estimated using MATLAB® Identification Toolbox.
The ARX model structure is sufficient to represent random drift disturbances, which influence the system performance [25].

3.2 Design of PID Controller

A PID controller is a simple three-term controller. The transfer function of the most basic form of PID controller was used [14; 23].
The schematic diagram of the PID control of the boiler plant system is shown in Figure 2. The two non-interactive loops presented in Figure 2 are each controlled by independent PID. The PID controllers are chosen because of their good performance and robustness features in many industrial applications [14; 18; 23].

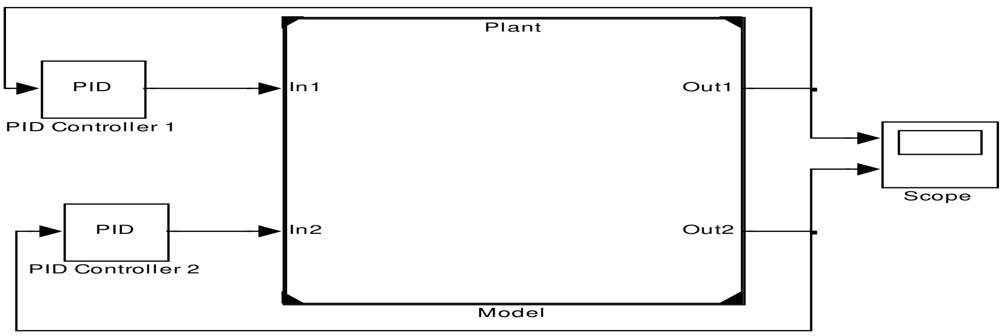

Figure 2. Schematic diagram of the PID control boiler plant

IV. IDENTIFICATION AND VALIDATION RESULTS

The dynamic model of the boiler process is obtained in which the main variables of the boiler process are identified using ARX model structure around operating points. The routines of identification toolbox with structure selection for ARX model were used [19; 27].

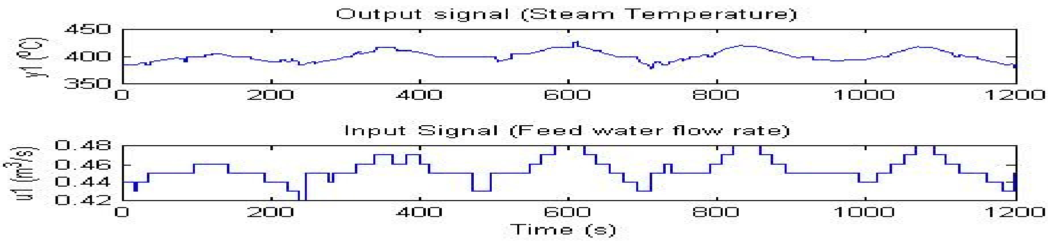

Figure 3. Output y_1 due to input u_1

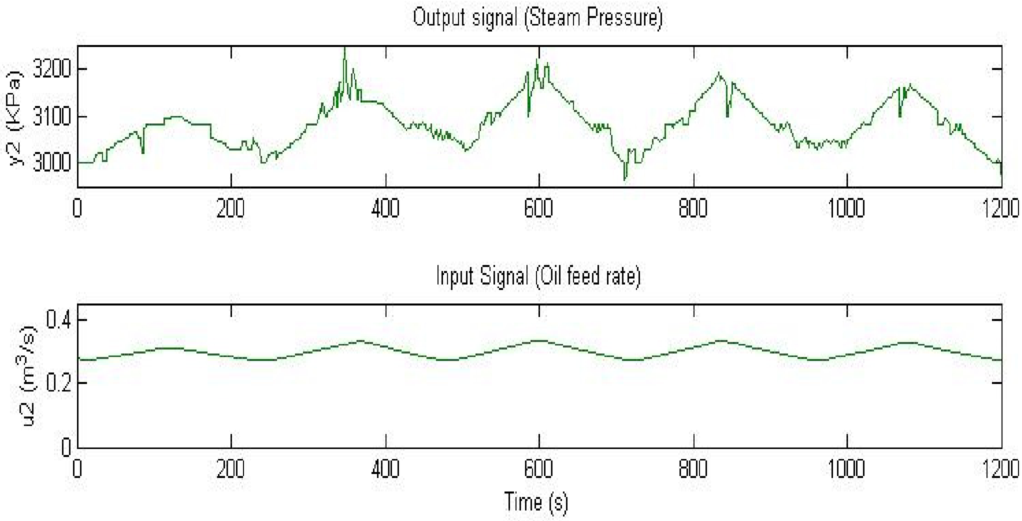

Figure 4. Output y_2 due to input u_2

The data of Figure 3 and Figure 4 are divided into two equal half with the first part as working data and the other half as validation data. Sampling time is twenty seconds and the excitation signal is a discrete white noise. Figure 5 represents the estimated data obtained for validation set using ARX model for the output temperature. A good prediction behavior is observed as indicated in Figure 6, which shows the error plot of measured and simulated model output temperature.

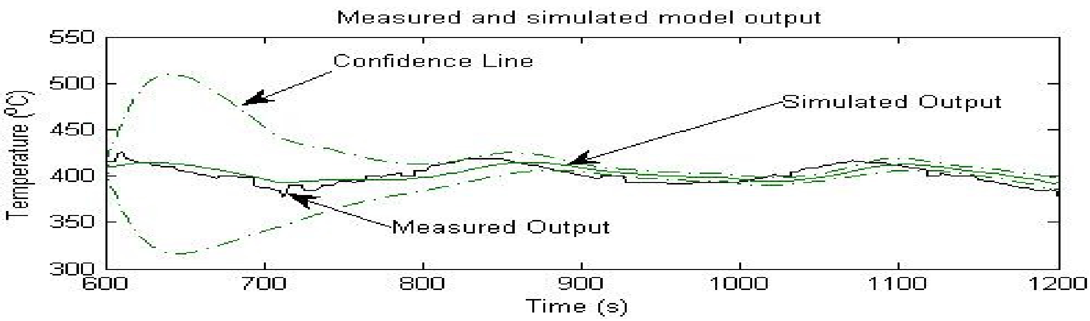

Figure 5. Measured and simulated model output temperature

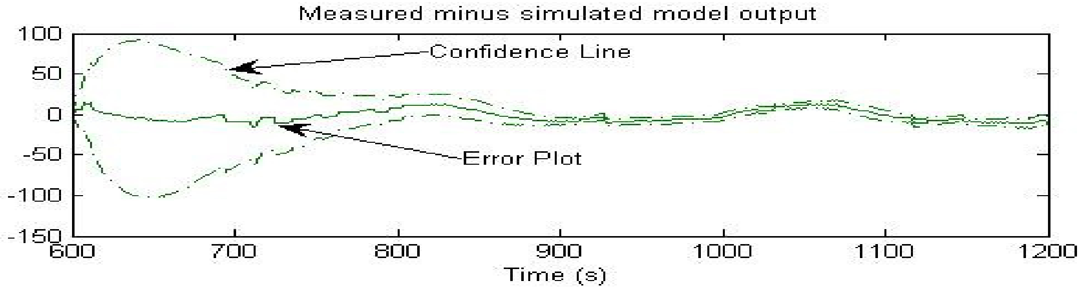

Figure 6. Error plot of measured and simulated model output temperature

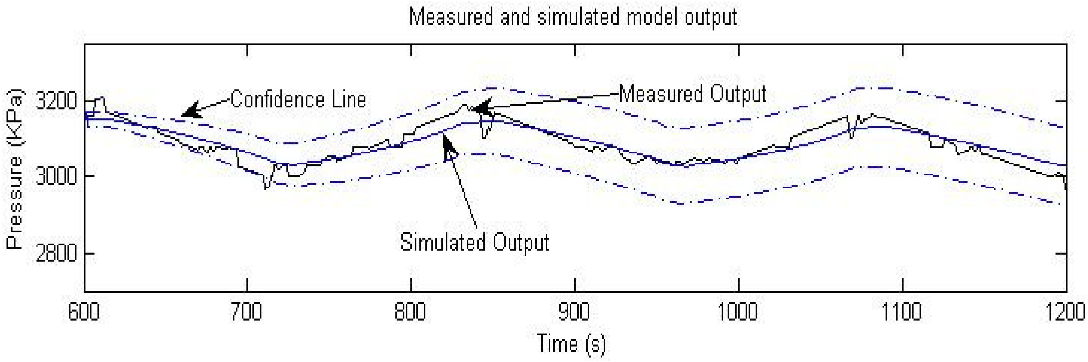

Figure 7. Measured and simulated model output pressure

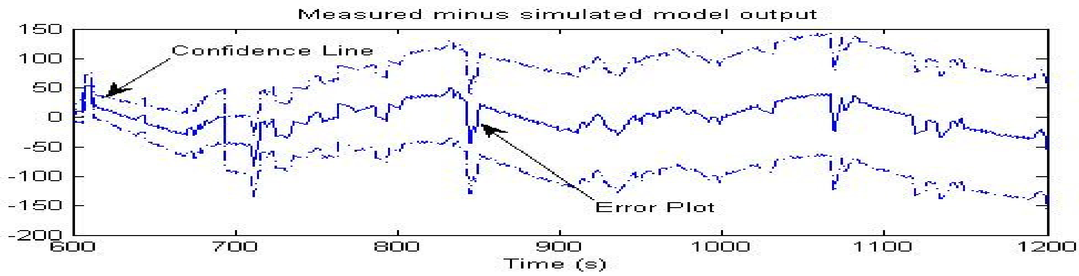

Figure 8. Error plot of measured and simulated model output pressure

Similarly, Figure 7 represents the estimated data obtained for validation set using ARX model for the output pressure. A good prediction behavior is observed as indicated in Figure 8, which shows the error plot of measured and simulated model output pressure.

Discrete-time ARX model:

$$A(q)y(t) = B(q)u(t) + e(t) \quad (7)$$

$$A(q) = 1 - 1.016q^{-1} + 0.03743q^{-2} \quad (8)$$

$$B(q) = 13.33q^{-1} + 5.668q^{-2} \quad (9)$$

Equation (8) and (9) are the estimated $A(q)$ and $B(q)$ parameters for temperature sub-model using MATLAB® System Identification Toolbox™.

$$A(q) = 1 - 1.046q^{-1} + 0.04763q^{-2} \quad (10)$$

$$B(q) = 1717q^{-1} - 1697q^{-2} \quad (11)$$

Equation (10) and (11) are the estimated $A(q)$ and $B(q)$ parameters for pressure sub-model using MATLAB® System Identification Toolbox™.

The ARX model was validated using Akaike's Final Prediction Error (FPE) criterion. According to Akaike's theory, the most accurate model has the smallest FPE [9; 25].

Akaike's Final Prediction Error (FPE) is defined by [9; 25]:

$$FPE = V\left(\frac{1+\frac{d}{N}}{1-\frac{d}{N}}\right) \tag{12}$$

Where V is the loss function, d is the number of estimated parameters, and N is the number of values in the estimation data set.

The toolbox assumes that the final prediction error is asymptotic for $d<<N$ and uses the following approximation to compute FPE:

$$FPE = V\left(1+\frac{2d}{N}\right) \tag{13}$$

The loss function V —which is the normalized sum of squared prediction errors—is defined by [25]:

$$V = \det.\left(\frac{1}{N}\sum_{1}^{N}\varepsilon(t,\theta_N)(\varepsilon(t,\theta_N))^T\right) \tag{14}$$

Where, Θ_N represents the estimated parameters.

$V = 1.21$ and $FPE = 1.22$ for the temperature sub-model.

$V = 6.578$ and $FPE = 6.622$ for the pressure sub-model.

4.1 PID Simulation Result and Discussion

A simulation study was made to determine the degree of improvement that could be gained in SSCLN boiler plant by the application of model proportional integral derivative control. Figure 9 and Figure 10 show the tracking response for the steam temperature and pressure using PID controller.

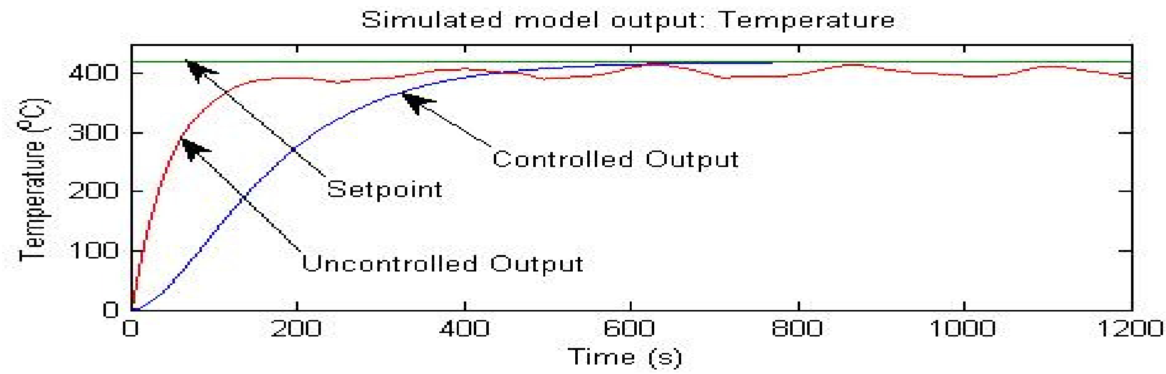

Figure 9. PID output of boiler plant (Temperature)

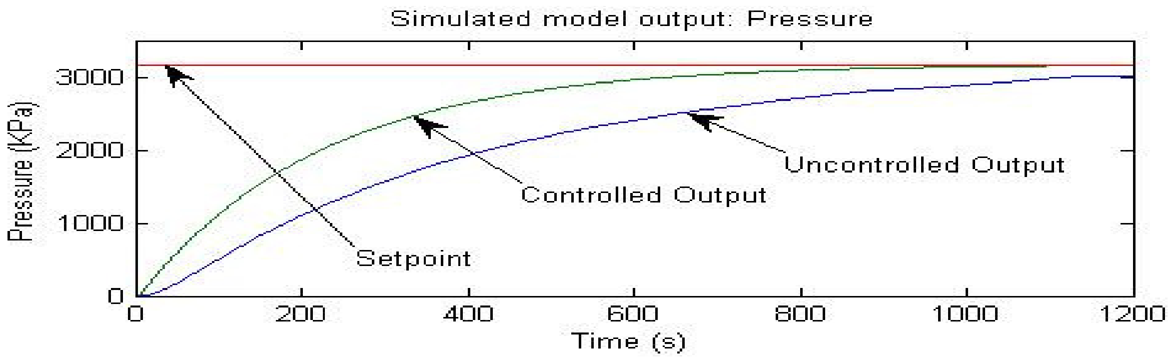

Figure 10. PID output of boiler plant (Pressure)

PID was able to overcome the startup instability experienced by some industrial controllers [5]. The temperature and pressure track the set point steadily. Any fluctuations and disturbance was handled without affecting the output from the controller. It is evident that the performance of the PID controller is satisfactory.

Table 1. PID controller parameters

PID Tuning Parameters	ARX Model	
	Temperature	Pressure
Proportional Gain, K_P	350	1390
Integral Gain, K_I	220	1230
Derivative Gain, K_D	10	5
Output Limit Upper	0.475	0.31
Output Limit Lower	0	0
Output Initial Value	0.1	0.1

The PID controller was tuned using Ziegler-Nichols tuning method [14; 23].

V. CONCLUSION

The estimated data obtained for the validation set using ARX model for the output temperature and pressure shows a good prediction behavior. The simulated model output lies mostly within the confidence line indicating that the validated model is good enough for measuring the fitness of the plant control system. It can be seen that the relationship between the measured and the simulated validation model is excellent. The error plot shows the error between the two as 9%.
The study also presented the application of proportional integral derivative control PID techniques for an industrial oil-fired boiler system. Simulation results obtained with the PID are very attractive in terms of rapidity, tracking error, stability and smoothness of control signals. The proposed structure is very simple and easy to implement.

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