RECURSIVE IDENTIFICATION OF THE BOILER DRUM BASED ON TIME-VARYING HAMMERSTEIN MODEL

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Abstract:

Modeling of the boiler drum is an important and difficult task. In this paper, a recursive identification method based on the time-varying Hammerstein model were proposed for the boiler drum in thermal power plant. By dividing it into the nonlinearity subsystem and the second linear subsystem, the Hammerstein model is used to represent the process dynamics. Recursive prediction error algorithm is used to identify the proposed Hammerstein model parameters. System identification experiment is carried out with boiler in the Pha-Lai Power Plant. Results are presented which compare the responses of the identified models with those of the plant, and show that the models provide an accurate representation of the real system.

Key words:

Drum-boiler, modeling of the boiler drum, time varying Hammerstein model, online identification, recursive prediction error method, singular value decomposition.

Tóm tắt:

Mô hình hóa cho bao hơi của lò hơi là một nhiệm vụ quan trọng và khó khăn. Trong bài báo này, phương pháp nhận dạng đệ qui dựa trên mô hình Hammerstein tham số biến thiên cho bộ bao hơi của lò hơi của nhà máy nhiệt điện được đề xuất. Bằng cách phân chia bộ bao hơi thành hai khối phi tuyến tĩnh và tuyến tính động, mô hình Hammerstein được sử dụng để mô tả động học của quá trình. Thuật toán sai số dự báo đệ qui được sử dụng để nhận dạng các tham số thay đổi theo thời gian của mô hình đã đề xuất. Thực nghiệm nhận dạng được tiến hành với lò hơi của nhà máy nhiệt điện Phả Lại. Các kết quả được thể hiện bằng cách so sánh tín hiệu ra của mô hình nhận dạng với tín hiệu ra thực cho thấy độ chính xác của mô hình đạt được.

Từ khóa:

Bao hơi-lò hơi, mô hình hóa lò hơi, mô hình Hammerstein tham số thay đổi, nhận dạng trực tuyến, phương pháp sai số dự báo đệ qui, phép phân tích giá trị suy biến.

1. INSTRODUCTION

Thermal power plants are the major source of electrical power generation contributing about 40 percent of national's power generating capacity. Boiler in thermal power plant plays important role in generation of power. 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. The modern control schemes require the availability of mathematical models that may adequately describe their dynamic behaviour. The importance of modeling is profound in simulation and control system design.

The boiler drum is the crucial part of the boiler system and there are many modelling efforts on it. The structure of drum-boiler is shown in Fig.1. The heat flow rate Q_{EV} from the furnace supplied to the drum causes boiling, changes with the fuel flow input. Feedwater, D_{fw}, is supplied to the drum and saturated steam, D_s, is taken from the drum to the superheaters and the turbine. Thus, the boiler drum unit can be simplified to a model with 3 inputs and 2 outputs, in which inputs consider as D_f, D_{fw} and Ds, while ouputs are drum pressure and drum level.

Because the fuel flow influences the drum level and drum pressure with the characterictics of nonlinearrity, parameter time-varying, therefore it is necessary to establish a nonliner model for the boiler drum. Although many modeling and identification for the boiler are available, only few papers deal with the nonlinear models for the boiler drum [1-5]. Lack of the nonlinear models is a restrictions for the application of modern control methods [1].

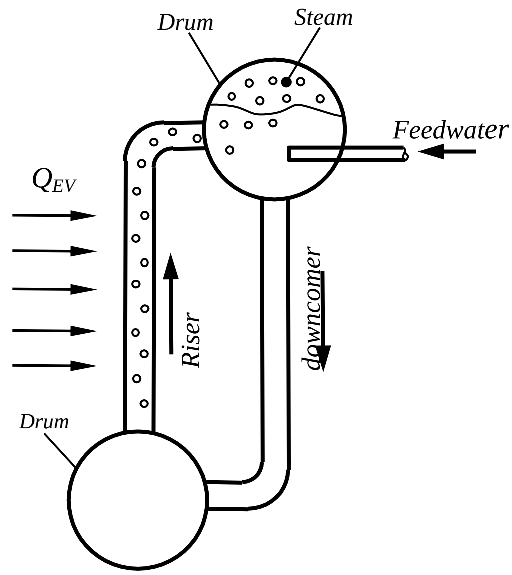

Fig. 1. Schematic diagram of boiler drum

In this paper, the Hammerstein nonlinear model is applied for modeling the behavior of the boiler drum. The Hammerstein models consisting of a static nonlinearity followed by a dynamic linearity, are the simplest representation of a nonlinear system and can be used to describe the the behavior of the system over wide operating range. Futhermore, model parameters are time varying, and some means of updating parameters on line, or from time to time, is desirable**.**

Up to now, several works on the Hammerstein model for boilers have been suggested, but the results are time-invariant (TIV) Hammerstein models [1, 2]. These models are too limited for process control applications and not suitable for online application. In this contribution, we study the identification of the time-varying (TV) Hammerstein model of the boiler drum directly from test data. The model will be used to determine plant responses, in the design of controllers, and to investigate the possible use of adaptive controllers.

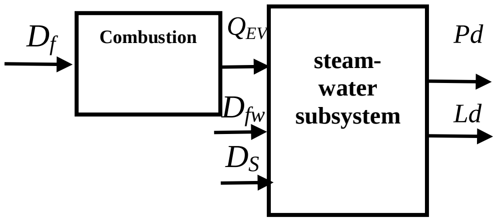

Fig. 2. Input-output structure of the drum

To achieve this, a specialized identification technique that involves the use of the singular-value decomposition (SVD) techique and recursive prediction error method (RPEM) approaches is proposed to estimate the TV Hammerstein model parameters [6]. Finally, the proposed method was applied to identification of the boiler drum of the Pha-Lai coal-fired Power Plant and the experiment was conducted during normal operation. Results confirm that accurate models have been obtained.

2. TIME-VARYING MODELING OF THE BOILER DRUM

2.1. Nonlinear characteristic of the object

From the modeling and control viewpoint the boiler drum can be represented as a combination of two subsystem: combustion and steam-water subsystem. The steam -water side involves converting water into high-temperature steam. The combustion-side involves burning fuel to generate the heat necessary for steam generation. Thus, the essential input-output relationship in the drum was described in the block diagram of Fig. 2.

In most control problems, the combustion subsystem may be considered as a non dynamic process part and the water-steam subsystem is dynamic process part. Thus in this paper, the combustion subsystem and the water-steam subsystem are assumed to be a static nonlinear block and a dynamic linear block. This is the structure of the Hammerstein model which is shown in Fig. 3.

In the process of combustion, the non-linearity of the heat transfer phenomena can be described by a polynomial function as:

$$Q_{EV} = f(D_f) = \beta_0 + \sum_{i=1}^{m} \beta_i (D_f)^i \qquad (1)$$

where Q_{EV} is the heat flow rate (kJ), D_f is the fuel flow to the furnace (kg/s), $f(.)$ is the static nonlinear function, and β_i, i=1, ···, m are coefficients in the polynomial function, m is the order of the polynomial.

The linear dynamic block for the drum is described by the linearized model as follows [7] :

$$\frac{d\Delta P_D}{dt} = c_1\Delta P_D + c_2\Delta Q_{EV} + c_3\Delta D_{fw} + c_4\Delta D_s$$

$$\frac{\Delta L_D}{dt} = c_5\Delta P_D + c_6\Delta Q_{EV} + c_7\Delta D_s + c_8\Delta D_{fw}$$

(2)

Where**:**

Pd- is drum pressure;

Ld- is drum level;

In which, c_i, i=1÷8, are the model parameters.

From the above discussion it should also be clear that the fuel flow influences the drum with the characterictics of nonlinearrity, parameter time-varying, so the TV Hammerstein model for boiler is desirable.

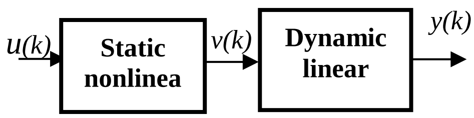

Fig. 3. Hammerstein model

2.2. Time varying Hammerstein model of the boiler drum

From eqs.(1) and (2), the drum boiler is modeled by the TV hammerstein model as follows:

$$\begin{aligned} &x(\mathrm{k}+1) = A_k x(\mathrm{k}) + B_k v(\mathrm{k}) + K_k e(\mathrm{k}) \\ &v(\mathrm{k}) = f\ \ u(\mathrm{k}) \\ &y(k) = Cx(k) + e(k) \end{aligned} \tag{3}$$

In Hammerstein model structure, *x(k)*, *u(k)* and *y(k)* are the state vector, input and output of the system, *v(k)* is the intermediate signal, *e(k)* is the white noise, *k* is the sample sequence number.

$$u = \ u_1\ u_2\ u_3\ ^T$$

$$y = \ y_1\ y_2\ ^T$$

$$x = \ x_1\ x_2\ ^T$$

$$v = \ v_1\ v_2\ v_3\ ^T$$

u_1: the fuel flow rate (kg/s);

u_2: the feedwater flow rate (kg/s);

u_3: the steam mass flow rate (kg/s);

x_1- is drum pressure (kg/cm^2);

x_2- is drum level (mm).

Thus:

$$C(k) = \begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix}$$

A_k, B_k and K_k are the time varying matrices of the system.

Suppose a second order polynomial was used to represent the static nonlinearity:

$$f(D_f) = \beta_0 + \sum_{i=1}^{2} \beta_i\ \ D_f\ ^i \tag{4}$$

Where βi are the parameters to be estimated. Thus:

$$\begin{aligned} &v_1(k) = Q_{EV} \\ &\qquad = \beta_0(k) + \beta_1(k) u_1(k) + \beta_2(k)\ u_1(k)\ ^2 \\ &v_2(k) = u_2(k) \\ &v_3(k) = u_3(k) \end{aligned} \tag{5}$$

We have:

$$v(k) = \begin{bmatrix} \beta_0 & \beta_1 & \beta_2 & 0 & 0 \\ 0 & 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & & 1 \end{bmatrix} \begin{bmatrix} 1 \\ u_1(k) \\ u_1(k)\ ^2 \\ u_2(k) \\ u_3(k) \end{bmatrix} \tag{6}$$

$$= \theta_{nl}^T \phi(k)$$

Where:

$$\theta_{nl}^T = \begin{bmatrix} \beta_0 & \beta_1 & \beta_2 & 0 & 0 \\ 0 & 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & & 1 \end{bmatrix}$$

$$\phi(k) = \begin{bmatrix} 1 & u_1(k) & u_1^2(k) & u_2(k) & u_3(k) \end{bmatrix}^T$$

From eq.(6) and eq. (3) can be written as:

$$\begin{aligned} &x(k+1) = A_k x(k) + B_k \theta_{nl}^T \phi(k) + K_k e(k) \\ &y(k) = Cx(k) + e(k) \end{aligned} \tag{7}$$

The system described by (3) can also be represented in the predictor form:

$$\begin{aligned} &\hat{x}(k+1) = F_k \hat{x}(k) + G_k\ \mathrm{z(k)} \\ &\hat{y}(k) = C\hat{x}(k) \end{aligned} \tag{8}$$

where

$\hat{y}(k)$ and $\hat{x}(k)$ are the estimate of *y(k)* and *x(k)* at time *k*.

$$F_k = A_k - K_k C_k ; G_k = \left[\tilde{B}_k \quad K_k\right];\ \tilde{B}_k = B_k \theta_{nl}^T$$

$$z(k) = \begin{bmatrix} \phi(k) \\ y(k) \end{bmatrix}$$

Define the parameter vector as

$$\Theta(k)^T := \left[vec(F_k)^T \quad vec(\mathrm{G}_k)^T\right]^T \tag{9}$$

and the information matrix

$$\hat{\varphi}^T(k) = \begin{bmatrix} \hat{x}^T(k) & 0 & \cdots & 0 & z^T(k) & 0 & \cdots & 0 \\ 0 & \ddots & \ddots & \vdots & 0 & \ddots & \ddots & \vdots \\ \vdots & \ddots & \ddots & 0 & \vdots & \ddots & \ddots & 0 \\ 0 & \cdots & 0 & \hat{x}^T(k) & 0 & \cdots & 0 & z^T(k) \end{bmatrix} \tag{10}$$

where *vec(·)* denotes the operation to form a long vector from a matrix by stacking its column vectors.

Finally, we have the time varying model of the boiler-drum as follows:

$$\begin{aligned} \hat{x}(k+1) &= \hat{\varphi}^T(k)\hat{\Theta}(k) \\ \hat{y}(k) &= C\hat{x}(k) \end{aligned} \tag{11}$$

With $\hat{\Theta}(k)$ denote the estimate of $\Theta(k)$ at time *k*.

The purpose of identification is to estimate recursively the time-varying parameters based on the observed input and output data {*u(k), y(k)*}.

3. IDENTIFICATION OF TIME VARYING HAMMERSTEIN MODEL

The TV parameters of the model are estimated by an optimal identification algorithm which based on RPEM and SVD. The RPEM can be used to estimate the time varying parameter $\Theta(k)$. Then by recurring to the SVD, optimal estimates of the parameter matrices characterizing the linear and nonlinear parts can be obtained.

3.1. Recursive prediction error algorithm

RPEM algorithm is used for optimization of model parameters. The RPEM are based on minimisation of a function of prediction error, and the algorithms use input/output measurements [6, 7].

Difine the prediction error:

$$\varepsilon_k(\theta) = y(k) - \hat{y}(k) \tag{12}$$

The cost function is given by:

$$V(\theta) = \frac{1}{2} E\left[\varepsilon_k{}^T \Lambda^{-1} \varepsilon_k\right] \tag{13}$$

where *E*[.] denotes the expectation operator, *Λ* denotes the (unknown) covariance matrix of the measurement disturbance.

Applying the RPEM algorithm to the model described by eq. (10), the parameter vector $\Theta(k)$ will be estimated as [6]:

$$\hat{\Theta}_k = \hat{\Theta}_{k-1} + \gamma_k R_k^{-1} \Phi_k \Lambda^{-1} \varepsilon_k \tag{14}$$

Where Φ_k is the gradient of the output predictor with respect to $\Theta(k)$, and γ_k is the gain sequence of the algorithm.

$$\Phi_k^T = C \frac{\partial \hat{x}_k}{\partial \theta_k} = H_k^T C^T$$

$$H_{k+1} = F_k H_k + \hat{\varphi}_k$$

where H_k is the derivative of the state with respect to the parameter vector.

$$H_k = \frac{\partial \hat{x}_k}{\partial \theta_k} \tag{15}$$

Compute the Hessian matrix of the cost function:

$$R_k = R_{k-1} + \gamma_k \ \Phi_k \hat{\Lambda}_k^{-1} \Phi_k^T - R_{k-1} \tag{16}$$

The covariance:

$$\hat{\Lambda}_k = \hat{\Lambda}_{k-1} + \gamma_k \left[\varepsilon_k \varepsilon_k^T - \hat{\Lambda}_{k-1} \right] \tag{17}$$

where $\hat{\Lambda}_0 = E[\varepsilon\ \theta_0\ \varepsilon^T\ \theta_0\ ]$.

The *RPEM algorithm* of identifying the TV Hammerstein model summarized as follows:

Algorithms 1

1. Collect the input–output data $u(k)$ and $y(k)$.

2. Initialize the nonlinear coefficients, $\Theta(k)$ in (9).

3. Build the information matrix, $\varphi(k)$ in (10).

4. Compute $\hat{\Lambda}_k$ by (17) and compute R_k by (16).

5. Update the parameter vector $\hat{\Theta}(k)$ by (14).

6. Compute the state estimate $\hat{x}_{k+1}$ and $\hat{y}_{k+1}$ by (11).

7. Increase k by 1 and go back to step 2.

The matrices A_k, $\tilde{B}_k$ and K_k can easily be reconstructed from $\hat{\Theta}(k)$ (F_k and G_k). The main difficulty is need to define the nonlinear parameters β and the system matrix B_k in $\tilde{B}_k$. To overcome this problem, SVD will be used.

3.2. Estimation of the nonlinear parameters

In this next step, the parameter β can be extracted from $\tilde{B}(k)$ by using the singular value decomposition (SVD) [8]. We compute the SVD of $\tilde{B}_k$:

$$\tilde{B}_k = U \Sigma V^T \tag{18}$$

$$\beta = V \Sigma \tag{19}$$

$$B = U \tag{20}$$

The optimization process could be said to be a two step process. In the first step, the parameter vector $\Theta(k)$ are initialized and subsequently updated at time k using RPEM algorithm. In the second step, $\boldsymbol{\beta}$ and B are computed using (19) and (20). The detailed algorithm is given below.

Algorithms 2:

1. Compute $\Theta(k)$ using Algorithms 1.

2. Reconstructed A_k, $\tilde{B}_k$ and K_k from $\Theta(k)$.

3. Using SVD technique, update $\Theta(k)$ by:

(a) Compute the SVD of $\tilde{B}_k$ using (18);

(b) Compute β using (19);

(c) Update B_k using (20).

4. APPLICATION TO THE NOILER DRUM IN PHALAI POWER

In this section, the recursive algorithm developed above are applied to online or recursive identification of the boiler drum. The boiler is a pulverized coal-fired 300 MW unit used for electric power generation at Pha-Lai thermal power plant.

The data are collected from experiment during normal operation with the sampling rate is 1 sec. The test which lasted for 4 days was conducted. The first 2000 test data were used to identify the TV Hammerstein model of the boiler drum, while the remaining 2000 data were used for validation purposes.

For the identification based on first 2000 data, we have used the identified results based on 100 data as the initial estimate. By so doing, we can improve the convergence and shorten the computational time. Fig. 4 and Fig. 5 show the sampled data of the boiler drum. The estimated parameters are given in Figs. 6, 7 and 8. Where, the timevarying parameters of linear sybsystem in Hammerstein model are shown in Figs. 6, 7, and the timevarying parameters of static nonlinearity are shown in Fig. 8.

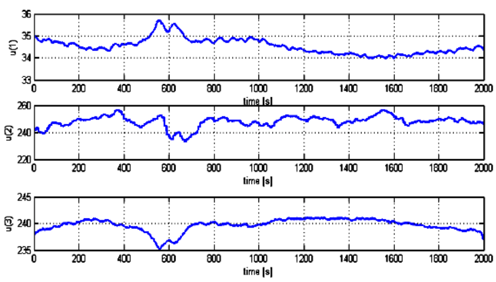

Fig. 4. The inputs of system

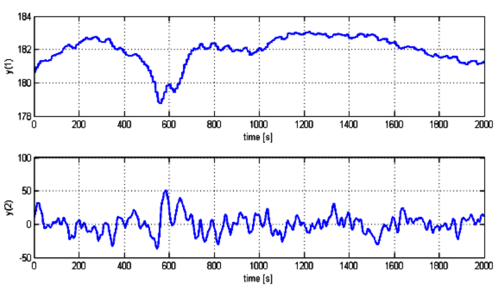

Fig. 5. The ouput of sysem

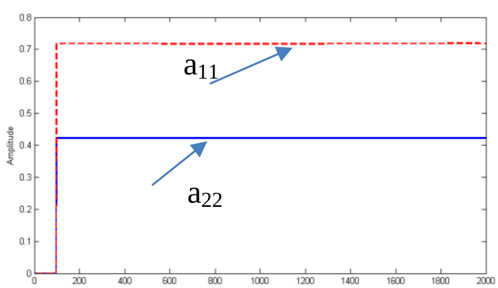

Fig. 6. Time varying coefficients of A matrix

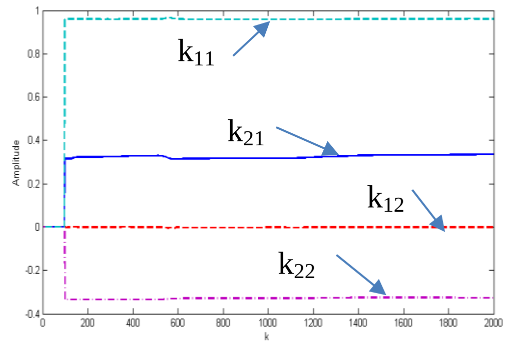

Fig. 7. Time varying coefficients of B matrix

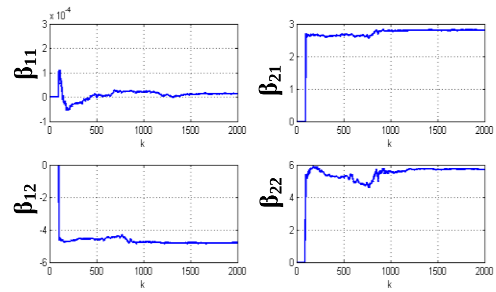

Fig. 8. Nonlinear coefficients of static nonlinearity

The accuracy of the estimated output is measured using the percent variance accounted for (%VAF) [6, 7] which gave 97% for the estimate shown in Fig. 9 and Fig. 10.

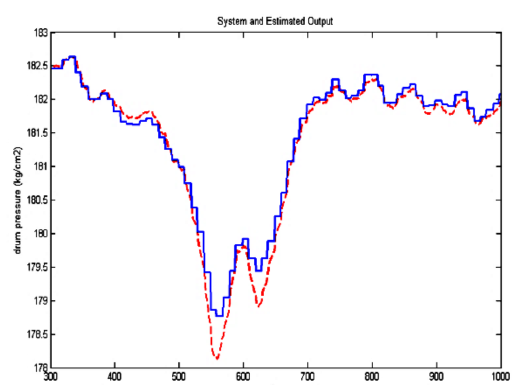

Fig. 9. A segment of predicted output (Drum pressure) from identified model (Dashed) and Measured output (Solid)

Fig. 9 and 10 compare the predicted

outputs with the measured outputs. From the results, the obtained model gives reasonably good approximation of the nonlinear process.

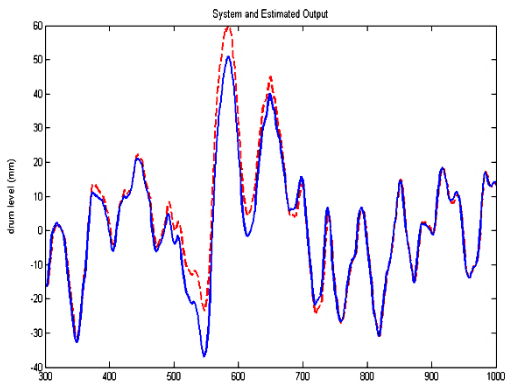

Fig. 10. A segment of predicted output (Drum level) from identified model (Dashed) and Measured output (Solid)

5. CONLUSION

A TV Hammerstein model is proposed for the boiler drum. An identification algorithm that combines the benefits of SVD and recursive prediction error minimization has been successfully developed and applied to the boiler drum.

The performance on the validation data set showed that the obtained model is quite capable of accurately capturing the main dynamic behavior of drum pressure and drum level. The results indicate that the proposed algorithm can provide good estimate for systems described by time-varying parameters. The TV Hammerstein model can be used for design of controller which can operate the plant at varying operating conditions.

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Biography:

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