GREY-BOX LPV MODEL IDENTIFICATION OF BOILER SUPERHEATED STEAM TEMPERATURE

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Abstract:

This paper focuses on the identification of grey-box LPV model for the boiler superheated steam temperature from local approach. Rather than building a model either from the law of physics or from experimental data independently, the combination of an analytic and an experimental approach is used to identify an LPV model of a boiler superheated steam temperature. The parameters of the LPV model are approximated as a rational function of the main steam flow. The global LPV model is estimated by applying a parameters interpolation technique of local linear model parameters. The proposed method is applied to the identification for Boiler superheated steam temperature process in the Pha-Lai Power Plant. The results show that the obtained model is of high accuracy and the proposed method is feasible.

Key words:

modeling of superheater steam temperature, grey-box model, LPV model identification, rational interpolation.

Tóm tắt:

Bài báo này tập trung nhận dạng mô hình tuyến tính tham số biến thiên - hộp xám cho nhiệt độ hơi quá nhiệt của lò hơi trên cơ sở lưu lượng hơi là thông số thay đổi theo thời gian theo phương pháp nhận dang cục bộ. Thay vì xây dựng một mô hình theo định luật vật lý hoặc từ dữ liệu thực nghiệm một cách độc lập, sự kết hợp giữa phương pháp phân tích và phương pháp thử nghiệm được sử dụng để xác định mô hình LPV của nhiệt độ hơi quá nhiệt của lò hơi. Các tham số mô hình nhiệt độ hơi quá nhiệt được xấp xỉ là hàm tỷ lệ của lưu lượng hơi quá nhiệt. Mô hình LPV toàn cục được ước lượng bằng cách áp dụng kỹ thuật nội suy tham số của các tham số mô hình tuyến tính cục bộ. Phương pháp đề xuất được áp dụng để nhận dạng nhiệt độ hơi quá nhiệt của Nhà máy điện Phả Lại. Kết quả cho thấy mô hình nhiệt độ hơi quá nhiệt thu được có độ chính xác cao và phương pháp đề xuất là khả thi.

Từ khóa:

mô hình hóa nhiệt độ hơi quá nhiệt, mô hình hộp xám, nhận dạng mô hình tuyến tính tham số thay đổi, nội suy tỷ lệ.

1. INTRODUCTION

Boiler superheated steam temperature is one of the most critical the behavior of the process variables to be controlled in a thermal power plant. Superheated steam temperature has characteristics including nonlinearity, time-varying and various disturbance factors. It is vital that an accurate and reliable nonlinear process model to describe the main steam temperature system's dynamic characteristic [1].

In fact, the steam flow influences the superheated steam temperature with the characteristics of nonlinearity, parameters time-varying [2]. However, in the previous studies, the influence of steam flow is always omitted when modeling the superheated steam temperature [3,4]. This study will consider the influences of the steam flow when identify the superheated steam temperature to improve the identification accuracy. The idea of approximating the time variation characteristics of the superheated steam temperature model with a linear parameter-varying (LPV) model. Because a linear time invariant (LTI) model can be insufficient when the system is used in wide operating range (because, e.g., the nonlinearities may vary with the operating conditions). LPV models are more and more introduced in modeling of boiler [5].

In this article, the main focus is placed on the identification of a grey-box LPV model for boiler superheated steam temperature A physical model is first developed for boiler and the unknown parameters are determined by local identification approach [1, 5]. By local approach, it is meant that a multi-step procedure is undertaken where (1) the local linear models corresponding to a series of fixed operating points are identified based on the locally gathered input-output data, (2) an LPV model is derived by parameter interpolating of these locally-estimated models.

In order to reach this goal, the local identification technique using parameter interpolation is applied. The use of rational parameter interpolation for state-space matrices directly is a key concept that we have investigated and applied to the grey-box LPV modeling of boiler superheated steam temperature in this paper.

2. MODELING OF SUPERHEATER SYSTEM

The Superheater system is mainly composed by three parts: primary superheater (SH 1), secondary superheater (SH2) and water-spray attemperator (DS) between the two superheaters, as shown in Fig. 1. The steam enters the superheater from the drum as wet steam (almost saturated) and leaves the superheater to the turbine in superheated condition [2,7].

Its task is to regulate the saturated steam out of the drum to a rated temperature before delivering it to the turbine. Superheated steam temperature is adjusted by spray water and feedwater together. Spraying feed water decreases the enthalpy of the steam and thus decreases its temperature prior to entering the next stage of heating; this process is called attemperation. Spraying feed water in these locations avoids overheating of steam and overheating of the heat exchanger tube walls, protecting it from damage.

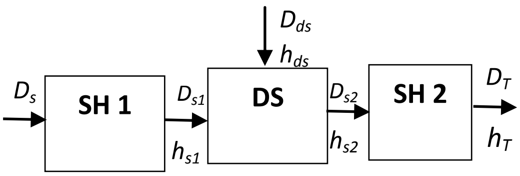

Fig 1. Diagram block of the superheaters

2.1. The mathematical model of boiler superheated steam temperature

The grey-box model of boiler superheated steam temperature is mainly derived from the prior works [6-8] and is briefly outlined in this section.

The mathematical model of superheater is derived using mass balance and energy balance equations. First, the steam temperature at the outlet of the primary superheater can be written as :

$$m_sC_s + m_mC_m \ \frac{dT_{s1}}{dt} = Q_{SH} + D_sC_p \ \ T_s - T_{s1} \tag{1}$$

$$\frac{dQ_{SH}}{dt} = \frac{1}{\tau_{SH}} \ \ -Q_{SH} + k_{SH}D_f \tag{2}$$

The mass and energy balances in the attemperator are given by

$$D_{s1} + D_{ds} = D_{s2} \tag{3}$$

$$D_{s1}h_{s1} + D_{ds}h_{ds} = D_{s2}h_{s2} \tag{4}$$

The steam temperature at the outlet of the second superheater can be simplified as:

$$m_sC_s + m_mC_m \ \frac{dT_{s2}}{dt} = Q_{SH} + D_{s2}h_{s2} - D_Th_T - \bar{h}_{s2} \ \ D_{sh2} - D_T \tag{5}$$

where D_s, D_T are steam mass flow rates from the steam drum and the secondary superheater (kg/s); D_{ds} is attemporator spray flow rate (kg/s); D_f is the fuel flow rate (kg/s); Q_{sh} is the heat supplied to the superheater from the furnace, V_{s1},V_{s2} are steam volumes in the primary and secondary superheater (m^3); h_s, h_{s1}, h_{s2} and h_{ds} are specific enthalpies of the steam in the drum, the steam in the primary and secondary superheater, and the spray water (kJ/kg), respectively; m is the mass of the metal tubes of the superheater, C_s is the specific heat of the metal tube of the superheater ; m_s, m_m are the mass of the steam and metal tubes of the superheater mass (kg).

By linearizing the equations (1, 2, 3, 4 and 5) around an operating point, we obtain the following equations:

$$\frac{d\Delta Q_{SH}}{dt} = \frac{1}{\tau_{SH}} \ \ -\Delta Q_{SH} + k_{SH}D_f \tag{6}$$

$$\begin{aligned}\frac{d\Delta T_{s1}}{dt} &= \frac{1}{M_{SH}}\Delta Q_{SH} - \frac{\bar{D}_sC_p}{M_{SH}}\Delta T_{s1} + \frac{k_T\bar{D}_sC_pk_P}{M_{SH}}\Delta P_D \\ &+ \frac{k_Tk_Pk_{SH}\bar{D}_sC_p\,\frac{2\bar{D}_{s2}}{\bar{\rho}_S} + \ \ \bar{h}_s - \bar{h}_{s1}}{M_{SH}}\Delta D_T - \frac{\bar{h}_s - \bar{h}_{s1}}{M_{SH}}\Delta D_{ds}\end{aligned} \tag{7}$$

$$\begin{aligned}M_{SH}\frac{d\Delta T_{SH}}{dt} &= \Delta Q_{SH} + C_p\bar{D}_{s1}\Delta T_{s1} - \bar{D}_TC_p\Delta T_{SH} + \ \ \bar{h}_{s1} - \bar{h}_{s2} \ \ \Delta D_{s1} \\ &- \ \ \bar{h}_{s2} - \bar{h}_{ds} \ \ \Delta D_{ds} - \ \ \bar{h}_T - \bar{h}_{s2} \ \ \Delta D_T\end{aligned} \tag{8}$$

Finally, the model for superheated steam temperature can be summarized in form of following state space equation as

$$\begin{cases}\dot{x} = Ax + Bu \\ \quad y = Cx\end{cases} \tag{9}$$

where:

input, output and state variables are:

$$u = \begin{bmatrix} \Delta D_f & \Delta D_{ds} & \Delta D_T \end{bmatrix}^T, \; y = \Delta T_{s2}$$

$$x = \begin{bmatrix} \Delta Q_{sh} & \Delta T_{s1} & \Delta T_{s2} \end{bmatrix}^T;$$

A is a state matrix, B input matrix, C output matrix.

$$A = \begin{bmatrix} a_{11} & 0 & 0 \\ a_{21} & a_{22} & 0 \\ a_{31} & a_{32} & a_{33} \end{bmatrix}; \; B = \begin{bmatrix} b_{11} & 0 & 0 \\ 0 & b_{22} & b_{23} \\ 0 & b_{32} & b_{33} \end{bmatrix}$$

$$C = 1 \quad 0 \quad 0$$

$$a_{11} = -\frac{1}{\tau_{SH}}; \; b_{11} = \frac{k_{SH}}{\tau_{SH}}$$

$$a_{21} = \frac{1}{M_{SH}}; \; a_{22} = -\frac{\bar{D}_s C_p}{M_{SH}};$$

$$b_{22} = -\frac{\bar{h}_s - \bar{h}_{s1}}{M_{SH}}$$

$$b_{23} = \frac{k_T k_P k_{SH} \bar{D}_s C_p \frac{2\bar{D}_{s2}}{\bar{\rho}_S} + \;\; \bar{h}_s - \bar{h}_{s1}}{M_{SH}}$$

$$a_{31} = \frac{1}{M_{SH}}; \; a_{32} = \frac{C_p \bar{D}_s}{M_{SH}}; \; a_{33} = -\frac{\bar{D}_T C_p}{M_{SH}}$$

$$b_{32} = -\frac{\bar{h}_{sh2} - \bar{h}_{ds}}{M_{SH}}; \; b_{33} \approx -\frac{\bar{h}_T - \bar{h}_{ds}}{M_{SH}}$$

$$M_{SH} = m_s C_s + m_m C_m$$

By grey-box modeling technique, several elements of the state matrices can be fixed (as 0 or 1) while the rest of them (the unknown parameters) need to be estimated.

2.2. Description of the model parameters

We have, see [8]:

$$M_{SH} = K_1 + K_2 p_{SH} + K_3 p_{SH}^2 \qquad (10)$$

In one hand, the pressure drop of drum pressure and superheated steam pressure has a square root relation to the steam flow:

$$D_T = K_s \sqrt{p_{SH}} \qquad (11)$$

From these function (eqs.10, 11), the elements of the state matrices (A, B) are determined as follow:

$$a_{21} = \frac{1}{1 + \lambda_1^{(21)} D_T^2 + \lambda_2^{(21)} D_T^4}$$

$$a_{22} = \frac{\lambda_1^{(22)} + \lambda_2^{(22)} D_T}{1 + \lambda_3^{(22)} D_T^2 + \lambda_4^{(22)} D_T^4};$$

$$b_{11} = \gamma_1^{(11)} + \gamma_2^{(1)} D_T^2 + \gamma_3^{(11)} D_T^4$$

$$b_{22} = \frac{\gamma_1^{(33)} + \gamma_2^{(33)} D_T^2}{1 + \gamma_3^{(33)} D_T^2}$$

$$b_{23} = \frac{\gamma_1^{(34)} + \gamma_2^{(34)} D_T + \gamma_3^{(34)} D_T^2}{1 + \gamma_4^{(34)} D_T^2 + \gamma_5^{(34)} D_T^4}$$

$$a_{31} = \frac{1}{1 + \lambda_1^{(42)} D_T^2 + \lambda_2^{(42)} D_T^4}$$

$$a_{32} = \frac{\lambda_1^{(43)} + \lambda_2^{(43)} D_T}{1 + \lambda_3^{(43)} D_T^2}; \; a_{33} = \frac{\lambda_1^{(44)} + \lambda_2^{(44)} D_T}{1 + \lambda_3^{(44)} D_T^2}$$

$$b_{32} = \frac{\gamma_1^{(43)} + \gamma_2^{(43)} D_T^2}{1 + \gamma_3^{(43)} D_T^2}; \; b_{33} = \frac{\gamma_1^{44} + \gamma_2^{(44)} D_T^2}{1 + \gamma_3^{(44)} D_T^2}$$

From the above equations, it can be shown that the unknown elements of the state matrices (A, B) are the rational function of the steam flow D_T.

2.3. The LPV model of boiler superheated steam temperature

According to the above analysis, the LPV model is perfectly suitable to describe the dynamic characteristics of this system. We consider that the system can be represented by the following discrete-time LPV model in state-space innovation noise form [5, 7]:

$$\begin{cases} x(k+1) = A(\mathrm{w}(k))x(k) + B(\mathrm{w}(k))u(k) + K(\mathrm{w}(k))e(k) \\ y(k) = Cx(k) + e(k) \end{cases} \tag{12}$$

where: the mail steam flow is chosen as scheduling variable *w(k)* (working-point variable), *e(k)* is white noise sequence, *K(w(k))* is the observer gain matrix. The model matrices (A, B, K) are the functions of the main steam flow variable.

Equation (12) can be equivalently written as:

$$\begin{aligned} \hat{x}(k,\theta) &= F(\mathrm{w}(k))\hat{x}(k,\theta) + G\ \mathrm{w}(k)\ \mathrm{z}(k) \\ \hat{y}(k,\theta) &= C\hat{x}(k,\theta) \end{aligned} \tag{13}$$

where

$$F\ \mathrm{w}(k)\ = A\ \mathrm{w}(k)\ - K\ \mathrm{w}(k)\ C$$

$$G\ \theta\ = \left[B\ \mathrm{w}(k)\ , K\ \mathrm{w}(k)\ \right]$$

$$z(k) = \begin{bmatrix} u(k) \\ y(k) \end{bmatrix}_{nu+ny}$$

The identified LPV model is then:

$$M: \begin{cases} \hat{x}(k+1) = \Phi\ k\ ^T \theta\ \mathrm{w(k)} \\ \hat{y}(k) = C\hat{x}(k) \end{cases} \tag{14}$$

where:

Φ(k) is a regression vector

$$\Phi^T(k) = \begin{bmatrix} \hat{x}^T(k) & 0 & \cdots & 0 & z^T(k) & 0 & \cdots & 0 \\ 0 & \ddots & \ddots & \vdots & 0 & \ddots & \ddots & \vdots \\ \vdots & \ddots & \ddots & 0 & \vdots & \ddots & \ddots & 0 \\ 0 & \cdots & 0 & \hat{x}^T(k) & 0 & \cdots & 0 & z^T(k) \end{bmatrix} \in \mathbb{R}^{nx \times d}$$

The unknown parameters to identify are gathered into the vector $\theta(\mathrm{w}(k))$:

$$\theta(\mathrm{w}(k)) := \left[vec(F(\mathrm{w}(k))^T \quad vec(G(\mathrm{w}(k))^T \right] \in \mathbb{R}^d$$

with

$$d = nx\ \ nx + nu + ny$$

We can parameterize *θ(w(k))* as follows:

$$\theta_r\ \ \mathrm{w(k)}\ = \frac{\vartheta_0^{(\mathrm{r})} + \vartheta_1^{(\mathrm{r})}\mathrm{w}^2(k) + \vartheta_2^{(\mathrm{r})}\mathrm{w}^4(k)}{\eta_0^{(\mathrm{r})} + \eta_1^{(\mathrm{r})}\mathrm{w}^2(k) + \mathrm{w}^4(k)} \tag{15}$$

with $r = 1,\ldots, d$.

By local identification approach, the parameters of the global LPV model is retrieved by interpolating the value of the parameters at each of the operating points considered. Therefore, the coefficients ($\vartheta_0^{(\mathrm{r})}, \vartheta_1^{(\mathrm{r})}, \vartheta_2^{(\mathrm{r})}$) and ($\eta_0^{(\mathrm{r})}, \eta_1^{(\mathrm{r})}$) will be determined to ensure that:

$$\theta_r^i = \theta_r\ \ \mathrm{w}_i\ = \frac{\vartheta_0^{(\mathrm{r})} + \vartheta_1^{(\mathrm{r})}\mathrm{w}_i^2 + \vartheta_2^{(\mathrm{r})}\mathrm{w}_i^4}{\eta_0^{(\mathrm{r})} + \eta_1^{(\mathrm{r})}\mathrm{w}_i^2 + \mathrm{w}_i^4} \tag{16}$$

with θ_r^i the identified parameter vector at each of the operating points w_i.

3. LPV MODEL IDENTIFICATION SCHEME USING PARAMETERS INTERPOLATION

In order to determine the parameters of the grey-box state space LPV model derived in the previous Subsections (see Eqs. ((14)-(15)), the following multi-step procedure is employed.

Step 1. To determine a sufficient number of representative operating points of the system;

Step 2. Collect input/output data and the corresponding time-varying parameter w(k) for the selected operating points;

Step 3. Estimate the model parameters $\hat{\theta}(\mathrm{w}_i)$ of local LTI model at the operating points w_i.

Step 4.

Obtain the superheated steam temperature system's LPV model $\hat{\theta}(\mathrm{w})$ from the local model parameters $\hat{\theta}(\mathrm{w}_i)$.

Then, the article presents the estimation algorithm for the coefficients ($\vartheta_0^{(r)}, \vartheta_1^{(r)}, \vartheta_2^{(r)}$) of *p(w(k))* and ($\eta_1^{(r)}, \eta_2^{(r)}$) of *q(w(k))* of the rational interpolant $\theta_r(\mathrm{w})$.

3.1. Local LTI model identification

Based on the collected data, the model parameters $\hat{\theta}(\mathrm{w}_i)$ of local LTI model are estimated at *m* different operating points w_i (*i*=0,., *m*) by using prediction error identification, see our previous work [7].

3.2. LPV model identification

After the m local identification experiments, the next step in determining the LPV model is to interpolate the value of the parameter vector $\hat{\theta}(\mathrm{w}_i)$ at different operating points w_i.

The coefficients $\vartheta_j^{(r)}$ (j=0, 1, 2) and the coefficients $\eta_k^{(r)}$ (k=0, 1) of the *r*th parameter θ_r w(k) satisfying (16) are determined by using the rational interpolation method which is described as follows [9].

Firstly, set: $z = \mathrm{w}^2$

therefore:

$$\theta_r(z) = \frac{\vartheta_0^{(r)} + \vartheta_1^{(r)}\mathrm{z} + \vartheta_2^{(r)}\mathrm{z}^2}{\eta_0^{(r)} + \eta_1^{(r)} z + \mathrm{z}^2} = \frac{p^{(r)}(z)}{q^{(r)}(z)} \quad (17)$$

Put:

$$f(z) = \;\; z - z_0 \;\;\; z - z_1 \; \ldots \; z - z_m \quad (18)$$

and

$$f_i = \prod_{\substack{j=0 \\ j \neq i}}^{m} \; z_i - z_j \quad (19)$$

By applying of the Lagrange interpolation formula, one has:

$$\left[g \;\; z \; \right]_{0 \ldots m} = \sum_{i=0}^{m} \frac{g_i}{f_i} \quad (20)$$

Where $g_i = g(z_i)$ (21)

From (17), one has:

$$\sum_{i=0}^{m} \frac{z_i^j}{f_i} \theta_r^i q(\mathrm{z}_i) = \sum_{i=0}^{m} \frac{z_i^j}{f_i} p(\mathrm{z}_i) \quad (22)$$

3.2.1. Estimate the coefficients of the polynomial q(z)

Eqs. (22) can be written as:

$$\left[z^j \theta_r^i q(\mathrm{z}) \right]_{0,\ldots m} = \left[z^j p(\mathrm{z}) \right]_{0,\ldots m}$$

Hence

$$\left[z^j p(\mathrm{z}) \right]_{0,\ldots m} = 0 \quad \text{for j=0, 1 (j+2<m)}$$

and therefore:

$$\left[z^j \theta_r^i q(\mathrm{z}) \right]_{0,\ldots m} = 0 \quad (23)$$

One has:

$$q(\mathrm{z}) = \sum_{h=0}^{2} \eta_h z^h \quad (\eta_2 = 1) \tag{24}$$

So:

$$\sum_{i=0}^{m} \frac{z_i^j}{f_i} \theta_r^i \sum_{h=0}^{2} \eta_h z^h = 0 \tag{25}$$

Eqs. (25) can be writen as follows:

$$\sum_{h=0}^{2} h_{j+h} \eta_h = 0 \tag{26}$$

where

$$h_s = \sum_{i=0}^{m} \frac{z_i^s}{f_i} \theta_r^i ; \quad 0 \le s = h + j \le 3 \tag{27}$$

Finally, we have:

$$\begin{bmatrix} h_1 & h_2 \\ h_2 & h_3 \end{bmatrix} \begin{bmatrix} \eta_0^r \\ \eta_1^r \end{bmatrix} = - \begin{bmatrix} h_0 \\ h_1 \end{bmatrix} \tag{28}$$

To determine the coefficients (η_0^r, η_1^r), it is possible to use least squares algorithm, the singular value decomposition (SVD) technique or the iterative method to increase the accuracy of the parameters. In this paper the parameters are estimated by the LS algorithm, see [7].

3.2.2. Estimate the coefficients of the polynomial p(z)

From (17), one has:

$$\theta_r(z)\ 1 + \eta_1^{(\mathrm{r})} \mathrm{z} + \eta_2^{(\mathrm{r})} \mathrm{z}^2 \ = \vartheta_0^{(\mathrm{r})} + \vartheta_1^{(\mathrm{r})} \mathrm{z} + \vartheta_2^{(\mathrm{r})} \mathrm{z}^2 \tag{29}$$

After obtaining the coefficients of the polynomial *q(z),* the coefficients $\left[\vartheta_0^{(\mathrm{r})}, \vartheta_1^{(\mathrm{r})}, \vartheta_2^{(\mathrm{r})}\right]$ of the polynomial *p(z)* will be determined based on the data set $z_i, \theta_r(z_i) q^{(r)}(z_i)$.

Put:

$$S_r(\mathrm{z}) = \vartheta_0^{(\mathrm{r})} + \vartheta_1^{(\mathrm{r})} \mathrm{z} + \vartheta_2^{(\mathrm{r})} \mathrm{z}^2 \tag{30}$$

Eqs. (29) can be rewritten:

$$S_r(z) = \theta_r(z)\ 1 + \eta_1^{(\mathrm{r})} z + \eta_2^{(\mathrm{r})} \mathrm{z}^2 \tag{31}$$

Then applies the Newton interpolation algorithm to find *p(z).*

$$S_r(w) = \vartheta_0^{(\mathrm{r})} + \vartheta_1^{(\mathrm{r})}\ \mathrm{z} - \mathrm{z}_0\ + \vartheta_2^{(\mathrm{r})}\ \mathrm{z} - \mathrm{z}_0\ \ \mathrm{z} - \mathrm{z}_1 \tag{32}$$

The coefficients $\left[\vartheta_0^{(\mathrm{r})}, \vartheta_1^{(\mathrm{r})}, \vartheta_2^{(\mathrm{r})}\right]$ of the polynomial *p(z)* can be determined as follows

$$\vartheta_0^{(\mathrm{r})} = S(\mathrm{z}_0) = S_0 \tag{33}$$

$$\vartheta_1^{(\mathrm{r})} = S\ \ \mathrm{z}_0, \mathrm{z}_1 \tag{34}$$

$$\vartheta_2^{(\mathrm{r})} = S\ \ \mathrm{z}_0, \mathrm{z}_1, \mathrm{z}_2 \tag{35}$$

One has:

$$S\ \ \mathrm{z}_0, \mathrm{z}_1, \mathrm{z}_2 \ = \frac{S\ \ \mathrm{z}_1, \mathrm{z}_2\ - S\ \ \mathrm{z}_0, \mathrm{z}_1}{\mathrm{z}_2 - \mathrm{z}_0} \tag{36}$$

To summarize, rational interpolation for LPV model of Boiler superheater steam temperature can be carried out in the following manner:

Algorithms: Rational interpolation for LPV model

1) Identify the local linear models for each working-point.

And then the corresponding state-space matrices are interpolated as follows:

2) Set z $=\mathrm{w}^2$ and compute f_i using (19) for $0 \le i \le m$.

3) Compute the coefficients (η_0^r, η_1^r) of $q^{(r)}(z)$.

- Compute h_s using 27.
- Solve (28) to find the coefficients (η_0^r, η_1^r).

4) Interpolate the data set $z_i, \theta_r(z_i) q^{(r)}(z_i)$

To compute the coefficients $\left[\vartheta_0^{(r)}, \vartheta_1^{(r)}, \vartheta_2^{(r)}\right]$ of $p^{(r)}(z)$ using Newton interpolation algorithm according to the Eqs. 33 throught 36.

4. IDENTIFICATION RESULT

In this section, the proposed methodology is applied to the identification of the boiler superheated steam temperature. The boiler is a pulverized coal-fired 300 MW unit used for electric power generation at Pha-Lai thermal power plant [7].

The data are collected from the experiment during normal operation with the sampling rate is 1 sec, when the steam flow can change from 120 kg/s to 240 kg/s; see Fig. 2.

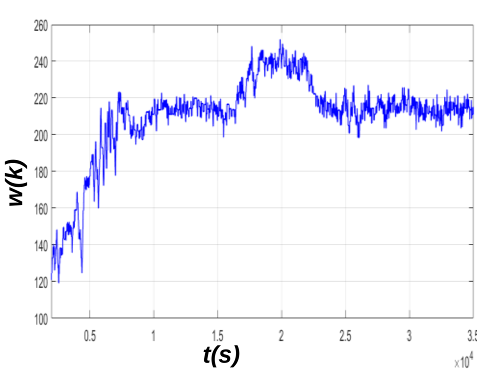

Fig 2. The steam flow

First, the local LTI model obtained at five working points: w_1 = 160 kg/s, w_2 = 180 kg/s, w_3 = 200 kg/s, w_4 = 210 kg/s, w_5 = 220 kg/s.

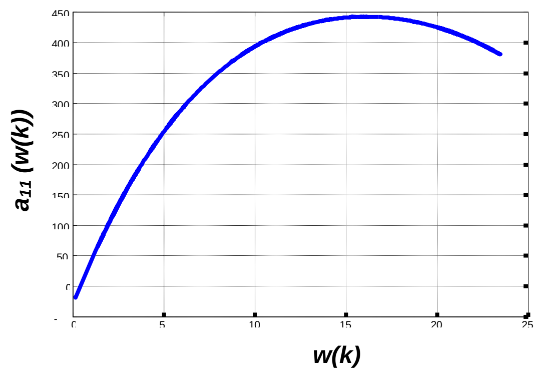

Fig 3. The parameter a_{11}

Then, the grey-box LPV model is obtained by applying the interpolation algorithms in section 3. The LPV model parameters are found to be:

$$a_{11} = 1.5\times10^8\text{-}9.1964\times10^3 D_T^2 \text{ -}127.6835 D_T^4$$

$$a_{21} = \frac{1}{1+\ 4.3908\text{x}10^4 \text{D}_T^2 - D_T^4}$$

$$a_{22} = \frac{6.6234\text{x}10^3 + 91.0615 D_T}{1+4.3238\text{x}10^4 D_T^2 - D_T^4}$$

$$a_{36} = \frac{6.9465\text{x}10^{-10}}{1+\ \ 4.3051\text{x}10^4 D_T^2 - D_T^4}$$

$$a_{31} = \frac{1}{1+4.4342\text{x}10^4 D_T^2 - D_T^4}$$

$$a_{32} = \frac{8.1203\text{x}10^3 +\ 111.6410 D_T}{1\ +4.3474\text{x}10^4 D_T^2}$$

$$a_{33} = \frac{4.3037\text{x}10^4 + 133.5127 D_T}{1+\ 4.3037\text{x}10^4 D_T^2}$$

$$b_{11} = \ 6.57\text{x}10^{11}\text{-}594.65.10^7 D_T^2\text{-}594.6 D_T^4$$

$$b_{22} = \frac{1.7008\text{x}10^3\text{-}127.6086 D_T^2}{1\text{-}1.9728\text{x}10^{-5} D_T^2}$$

$$b_{23} = \frac{-5.79x10^{7} - 5.57.10^{4} D_T \ -128.5 D_T^2}{1 + 2.8.10^{4} D_T^2 - D_T^4}$$

$$b_{32} = \frac{10^{-13}}{1 \times 10^{5} \ -2.3223 D_T^2}$$

$$b_{33} = \frac{1.3936x10^{-16} D_T^2}{10^{5} - 2.2762 D_T^2}$$

The parameter a_{11} and b_{11} are represented in Figures 3 and 4, respectively.

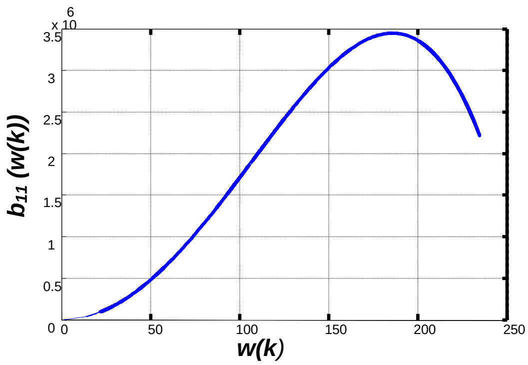

Fig 4. The parameter b_{11}

The improvement of the accuracy of the identified LPV model can also be evidenced by comparing the output of the real system with the output of the identified LPV model. Fig. 5 compares the estimated output with the measured outputs, where the measured output is represented by blue solid lines and the estimated output is represented by red dashed lines. According to the presented results, it can be concluded that the estimated LPV model captures well the non-linear dynamics of the original system over a wide operating range.

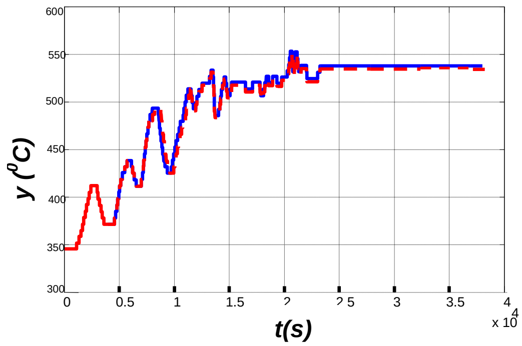

Fig 5. Measured output versus the estimated output of LPV model

5. CONCLUSION

In this article, the LPV model identification methodology has been used in order to derive a reliable grey-box state space LPV model from local experiments gathered on the real system. In the proposed identification method, the LTI and the LPV models have a particular structure that is derived from the laws of Physics. This approach lets the user take advantage of both analytical and experimental modelings of the system. The core idea behind the proposed approach is to formulate a global parameterization of the matrix functions and these parameter are determined by using rational parameter interpolation of the locally identified LTI models at each considered operating point.

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Biography:

Ly Trinh Thi Khanh received the M.Sc degree in Instrument and control and the Ph.D. degree in Control Engineering and Automation from Hanoi University of Science and Technology, in 2004 and 2017, respectively. Currently, she is a lecturer at the Faculty of Automation Technology, Electric Power University in Hanoi, Vietnam.

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