IDENTIFICATION OF A STEAM SUPERHEATER IN A DRUM-TYPE STEAM BOILER WITH FLUIDIZED BED COMBUSTION

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Steam boilers and steam generators represent essential equipment for energy conversion in industrial plants, primarily aimed at producing steam and subsequently generating electricity. Processes in thermal power systems are characterized by a high degree of complexity and nonlinearity, which necessitates the application of modern automatic control theories based on accurate mathematical models in state space. Given the dynamic behavior and interdependence of process variables, the implementation of control algorithms is not feasible without the use of computer technology and advanced measurement systems, which are essential for real-time process identification. Effective application of this approach requires knowledge of both the static and dynamic characteristics of the processes occurring within a thermal power plant. Mathematical modeling is based on the formulation of balance and supplementary equations, which together form a closed system for solving. A certain set of parameters is adopted in advance, while others require estimation due to the inability to determine them precisely, which may lead to some deviations in model accuracy. If such deviations are not significant, they can be corrected through the application of process identification methods, i.e., by estimating the insufficiently known parameters. This paper focuses on the identification of the dynamic behavior of the process, with the aim of developing more reliable mathematical models as a foundation for designing advanced control systems.

Key words*: steam boiler, mathematical model, combustion dynamics, automatic control, heat exchanger, identification*

1. Instruction

The global and national increase in electricity consumption has led to a greater reliance on thermal power plants for electricity production. Modern thermal power plants are characterized by improved working conditions, optimized steam block operating parameters, advanced signaling and safety systems, the implementation of more sophisticated technical solutions, and the increasing integration of computer-controlled production processes. The dynamic characteristics of individual units, as well as the overall plant, have become critical for ensuring the efficient and safe operation of thermal power facilities [1].

The management of steam boilers, as the central element of a thermal power plant, requires meeting strict criteria to ensure stable operation under varying working conditions. Plant economy and reliability become particularly prominent during commissioning, sudden unit shutdowns, load

fluctuations, and transitions to emergency operation modes. Traditional control systems were not designed to meet such stringent requirements [2], highlighting the need for the development of more advanced control strategies [3].

The steam boiler operates as an open-flow system in which multiple energy transformations take place, viewed through thermodynamic and control system perspectives [4]. The process dynamics inside the boiler are further complicated by the presence of both single-phase and two-phase flows across areas of different dimensions, resulting in multiple interdependencies between the physical quantities that must be simultaneously regulated. This complexity necessitates the application of advanced control strategies, including local regulation, interconnected loops, and feedback control systems.

To design reliable and efficient control systems, it is essential to possess accurate mathematical models of the objects and processes involved. Within control theory, models expressed through systems of differential equations are of critical importance. Two fundamental approaches exist for constructing such models: the analytical-physical approach, based on the fundamental laws of physics, and experimental identification, where process dynamics are inferred through observation and measurement of real systems.

A major breakthrough in system identification was achieved by Ljung, who introduced the concept of transfer function representation using variance error and bias [5]. Subsequent developments shifted the focus of control problems toward addressing design issues, studying the influence of varying experimental conditions, structure selection, and selection criteria [6,7]. Since the 1990s, system identification for control purposes has progressed significantly, with increasing emphasis on model quality constraints, while the standard input-output model had already been established in 1978 [8].

All systems that do not satisfy the conditions of linearity are considered nonlinear. The identification of nonlinear systems represents an extremely broad and complex research area. Every identification process relies on three main components: input-output data, a selected set of candidate models, and an estimation method, followed by validation to confirm model accuracy. No estimated model can be a completely faithful representation of the real system, as it is merely an approximation subject to variations from one experiment to another. Unmeasured random process noise can systematically affect the system output, indicating the need for careful investigation and compensation of noise effects in nonlinear systems [9].

It has been demonstrated that modifying the cost function to incorporate estimation error information can be beneficial [10]. More generalized frameworks for nonlinear modeling have been developed by combining or modifying existing model structures [11]. Specifically, the introduction of memory-based nonlinearities at the input and non-invertible nonlinearities at the output has enabled more accurate modeling of systems exhibiting hysteresis [12]. Optimization problems involving block-oriented nonlinear process models have been further explored and extended based on specific existing structures [13].

Today, several precise and stable nonlinear modeling techniques are widely used, including fuzzy models [14,15], Volterra series [16], and neural networks (NNs) [17]. However, in practice, block-oriented models, which combine linear dynamic blocks with memoryless nonlinear blocks, are most prevalent due to their simple structure and good structural matching with real systems [18,19]. The most commonly applied block-oriented structures include the Hammerstein model [20], the Wiener model [21], the Hammerstein-Wiener model [22], and the Wiener-Hammerstein model [23].

By collecting input-output process data under normal operating conditions, it is possible to perform an identification procedure that verifies initially developed mathematical models and corrects inadequately determined parameters. Thus, analytical modeling is complemented and refined through experimental identification, leading to a more precise description of the steam boiler behavior. Therefore, the primary goal of this research is to carry out a process identification procedure in a steam boiler based on previously developed mathematical models.

2. Materials and methods

The term *identification* refers to the process of obtaining a mathematical model of a system based on measurements performed on it. More precisely, the identification of a process involves determining a model from a specific class of models using measurements of the system's input and output signals. Identification can be considered in a broad or narrow sense: in the broader sense, it involves the determination of the complete model of the process (structure, order, and parameters), whereas in the narrower sense, it refers only to the estimation of unknown parameters and/or system states. The latter case is considerably simpler and more commonly found in the literature.

The literature [24] presents various methods that can be successfully applied depending on the specific conditions (such as the amount of a priori information, type of model, collected input/output signals, required accuracy, duration of data collection, and time available for processing results). Special attention is given to the issues of real-time (on-line) identification and identification with post-processing of collected data (off-line), as well as the corresponding recursive (sequential) one-step estimation algorithms. Additionally, guidelines for selecting appropriate methods in concrete cases are provided, with all discussions focusing on the identification of processes characterized by lumped parameters.

3. Development of a mathematical model of the steam superheater

Based on the developed mathematical model, specifically the balance equations [25], it is possible to formulate the mathematical model of the steam superheater:

$$E_{pp} \cdot \dot{\boldsymbol{x}}_{pp}(t) = A^*_{pp} \cdot \dot{\boldsymbol{x}}_{pp}(t) + \boldsymbol{b}^*_{pp} \cdot u_{pp}(t) + \boldsymbol{f}^*_{pp} \cdot \boldsymbol{z}_{pp}(t) \tag{1}$$

$$x_{ipp}(t) = \boldsymbol{c}^T_{pp} \cdot \boldsymbol{x}_{pp}(t) \tag{2}$$

when the:

$$E_{pp} = \begin{vmatrix} e_{88} & 0 & 0 \\ e_{98} & e_{99} & 0 \\ 0 & 0 & e_{1010} \end{vmatrix};\ A^*_{pp} = \begin{vmatrix} a^*_{88} & 0 & 0 \\ a^*_{98} & a^*_{99} & 0 \\ 0 & 0 & a^*_{1010} \end{vmatrix};\ \boldsymbol{b}^*_{pp} = \begin{vmatrix} 0 \\ \vdots \\ a^*_{1012} \end{vmatrix};\ \boldsymbol{f}^*_{pp} = \begin{vmatrix} a^*_{81} \\ a^*_{91} \\ 0 \end{vmatrix};$$

$$\boldsymbol{c}^T_{pp} = |0 \quad 1 \quad 0| \tag{3}$$

$$\dot{\boldsymbol{x}}_{pp}(t) = \begin{vmatrix} x_8 \\ x_9 \\ x_{10} \end{vmatrix};\ u_{pp}(t) = x_{12}(t);\ \ \boldsymbol{z}_{pp}(t) = x_1(t);\ \ x_{ipp}(t) = x_9. \tag{4}$$

Following the multiplication applied to the left-hand side of the equation (1) with the matrix E_{pp}^{-1} is obtained:

$$\dot{\boldsymbol{x}}_{pp}(t) = A_{pp} \cdot \boldsymbol{x}(t) + \boldsymbol{b}_{pp}(t) \cdot u_{pp}(t) + \boldsymbol{f}_{pp} \cdot z_{pp}(t) \tag{5}$$

as well as equation (2) in its unchanged form, where:

$$A_{pp} = \begin{vmatrix} -0.50 & 0 & 0 \\ 0 & -2.2 & 0 \\ 0 & 0 & -0.12 \end{vmatrix};\ \boldsymbol{f}_{pp} = \begin{vmatrix} 5.02 \\ 82.40 \\ 0.00 \end{vmatrix};\ \boldsymbol{b}_{pp} = \begin{vmatrix} 0 \\ 0 \\ 5.92 \cdot 10^{-3} \end{vmatrix};\ \boldsymbol{c}_{pp}^{T} = |0 \quad 1 \quad 0|. \tag{6}$$

Furthermore, the corresponding transfer function can also be determined:

$$W(s) = \frac{X_{ipp}(t)}{Z_{pp}(t)} = \frac{\boldsymbol{c}_{pp}^{T} \cdot \boldsymbol{f}_{pp}}{sI - A_{pp}} = \frac{82.4}{s+22}. \tag{7}$$

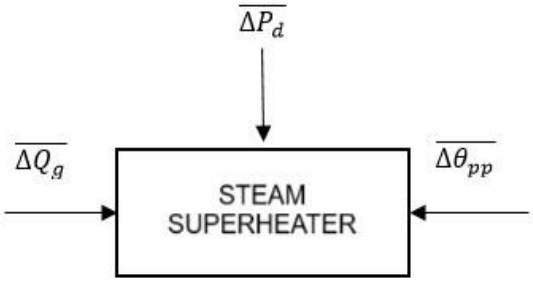

Figure 1. Process diagram of the steam superheater

From the previous equation (7), the transfer function can also be expressed in the following form:

$$W(s) = \frac{\sum_{k=0}^{n} b_k s^k}{\sum_{k=0}^{n} b_k s^k} = \frac{82.4}{s+22} \ \text{za}\ \ b_0 = 82.4\ \text{i}\ \ a_0 = 22, a_1 = 1. \tag{8}$$

The coefficients of the polynomials in the numerator and denominator, which are otherwise derived based on the characteristics (design and operating features) of the steam superheater for a given nominal operating mode, can be more easily identified by alternative means. Since a large number of parameters that define these coefficients are either insufficiently accurately determined or assumed, a correction is performed based on the behavior of the input and output variables of the steam superheater under actual operating conditions. The correction of the insufficiently accurate polynomial coefficients a_i and b_i of the transfer function, as well as the application of the selected identification method, will be demonstrated based on the simulation results of a drum-type steam boiler with fluidized bed combustion, as presented in [26].

The mathematical model of the steam superheater was developed under the assumption that the process within the superheater can be treated as a lumped-parameter system, for which an appropriate identification method was selected, as described in [24].

4. Method for process identification in the steam superheater

As previously indicated, in lieu of experimentally acquired data on the behavior of the steam superheater, the study will employ simulation-derived results.

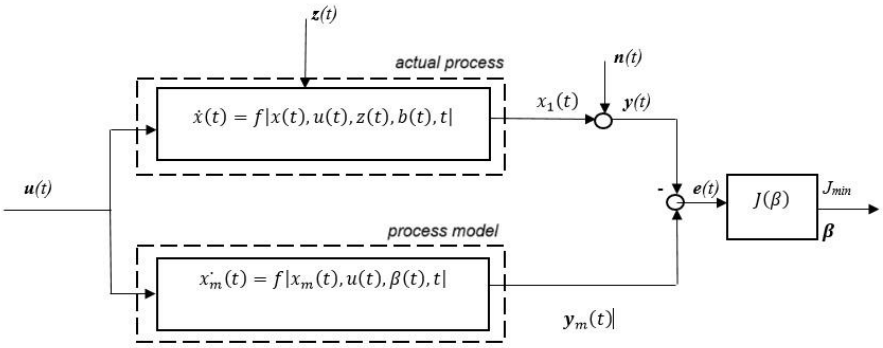

Figure 2. Diagram of the identification procedure

In Figure 2, the following variables can be identified:

$\dot{\boldsymbol{x}}(t) = \boldsymbol{f}|\boldsymbol{x}(t), \boldsymbol{u}(t), z(t), \boldsymbol{b}(t), t|$ – vector differential state equation of a system or process,

$\boldsymbol{x}_i(t) = g|\boldsymbol{x}(t), \boldsymbol{u}(t), \boldsymbol{z}(t), \boldsymbol{b}(t), t|$ – output equation of the system or process,

x(t) – state vector,

$\boldsymbol{x}_i(t)$ – output vector,

u(t) – vector of control (known or useful) signals,

z(t) – the vector of disturbance signals acting on the system, which is generally assumed to be defined for all time instances *t z(t)≡0*,

b(t) – the vector of unknown parameters of the real process, which may, in the general case, represent a random variable,

$\boldsymbol{\beta}(t)$ – the vector of unknown parameters of the process model and the estimation of this parameter ***b***,

$\widehat{\boldsymbol{\beta}}(t)$ – the vector of estimated values of the unknown process parameter vector *b*, which minimizes the adopted equivalence criterion,

n(t) – the vector of noise signals affecting the measurement of the process output variable,

$\boldsymbol{y}(t) = \boldsymbol{x}_i(t) + \boldsymbol{n}(t) = \boldsymbol{y}(\boldsymbol{x}(t), \boldsymbol{u}(t), \boldsymbol{z}(t), \boldsymbol{b}(t), \boldsymbol{n}(t), t)$ – the measurement output vector of the process, which is 'contaminated' or additively influenced by measurement noise. This equation represents the observation model and defines the manner in which the measured data are acquired.

$\boldsymbol{e}(t) = \boldsymbol{y}(\boldsymbol{t}) - \boldsymbol{y}_{\boldsymbol{m}}(t)$ – error vector,

$J(\boldsymbol{\beta})$ – equivalence criterion,

$(\cdot)_m$ – all quantities indexed with the letter 'm' refer to the model and are analogous in meaning to the quantities defined for the real process.

We consider the following issues prior to the identification itself in order to ensure the correctness of the identification procedure:

- determining the degree and nature of the relationship between input and output variables (signals),

- examining the stationarity properties of the excitation and other present random signals,
- assessing the degree of similarity between the adopted model and the original system,
- evaluating the level of nonlinearity of the system and the nonstationarity of its parameters, etc.,
- methods of data acquisition and processing of the measurement results of the system or process.

The transfer function given by

$$W(s) = \frac{X_i(s)}{U(s)} = \frac{b_{n-1}^* s^{n-1} + \cdots + b_1^* s + b_0^*}{s^n + a_{n-1} s^{n-1} + \cdots + a_1 s + a_0}, \qquad a_0 \neq 0 \tag{9}$$

is represented in the following canonical form:

$$\dot{\boldsymbol{x}}(t) = \begin{vmatrix} -a_{n-1} & -a_{n-2} & \cdots & -a_1 & -a_0 \\ 1 & 0 & \cdots & 0 & 0 \\ 0 & 1 & \cdots & 0 & 0 \\ \vdots & \vdots & \ddots & \vdots & \vdots \\ 0 & 0 & \cdots & 1 & 0 \end{vmatrix} \cdot \boldsymbol{x}(t) + \begin{vmatrix} b_1 \\ b_2 \\ \vdots \\ b_n \end{vmatrix} \cdot \boldsymbol{u}(t), \tag{10}$$

$$\boldsymbol{x_i}(t) = |-a_{n-1} \quad -a_{n-2} \quad \cdots \quad -a_1 \quad -a_0| \cdot \boldsymbol{x}(t) \tag{11}$$

Alternatively, in condensed form:

$$\dot{\boldsymbol{x}}(t) = \begin{vmatrix} -\boldsymbol{a^T} & | \\ - - - \; & -+- \quad --- \\ E_{n-1} & | \quad 0 \end{vmatrix} \cdot \boldsymbol{x}(t) + \boldsymbol{b} \cdot u(t), \tag{12}$$

$$\boldsymbol{x_i}(t) = \boldsymbol{c}^T \cdot x(t), \tag{13}$$

where:

$$\boldsymbol{a}^T = |a_{n-1} \quad a_{n-2} \quad \cdots \quad a_1 \quad a_0|, \tag{14}$$

$$\boldsymbol{c}^T = -\boldsymbol{a^T} = |-a_{n-1} \quad -a_{n-2} \quad \cdots \quad -a_1 \quad -a_0|, \tag{15}$$

(15)

$$\boldsymbol{b^T} = |b_1 \quad b_2 \quad \cdots \quad b_j \quad \cdots \quad b_n|. \tag{16}$$

The elements of the vector *b* are obtained according to the following relation:

$$b_j = -W_j(s)\big|_{s=0}; j = 1,2,\cdots,n, \tag{17}$$

where:

$$W_1(s) = W(s),\ Q_{j+1}(s) = \frac{1}{s}\big(W(s) + b_j\big). \tag{18}$$

From the preceding equations, we obtain the following equality:

$$b_{k+1} = -\frac{b_j^* + \sum_{k=1}^{j} b_k \cdot a_{j+1-k}}{a_0},\ j = 0,1,2,\cdots,n-1. \tag{19}$$

During the identification procedure, the vector of unknown process parameters must be determined:

$$\boldsymbol{\beta} = \left|\frac{\boldsymbol{a}}{\boldsymbol{b}}\right|,\ \boldsymbol{a} = \begin{vmatrix} a_3 \\ a_2 \\ a_1 \\ a_0 \end{vmatrix},\ \boldsymbol{b} = \begin{vmatrix} b_4 \\ b_3 \\ b_2 \\ b_1 \end{vmatrix}. \tag{20}$$

If β is determined, the coefficients a_i are immediately known, and using vector $\boldsymbol{b}$ and equation (19), the coefficients b_i in the transfer function (9) can also be determined.

Based on the condensed matrix notation, the following unification can be performed:

$$\dot{\boldsymbol{x}}(t) = \Omega \cdot \boldsymbol{x}(t) + \boldsymbol{b} \cdot u(t) + \boldsymbol{d} \cdot y(t), \tag{21}$$

where:

$$\Omega = \left| \begin{matrix} \mathbf{0^T} \\ - - - - - \\ E_{n-1} \quad 0_{n-1} \end{matrix} \right|, \ \boldsymbol{d^T} = |1 \quad 0 \quad 0 \quad \cdots \quad 0 \quad 0|, \tag{22}$$

$$y(t) = x_i(t) = \boldsymbol{c}^T \cdot \boldsymbol{x}(t) = -\boldsymbol{x_i}(t) = -\boldsymbol{a}^T \cdot \boldsymbol{x}(t). \tag{23}$$

The input is chosen so that, after a sufficiently long period of time, it reaches a constant value different from zero. Since the system is assumed to be stable, equation (21) then takes the following form.:

$$\Omega \cdot \boldsymbol{x_N} + \boldsymbol{b} \cdot u_N + \boldsymbol{d} \cdot y_N = 0. \tag{24}$$

Furthermore, from the preceding equation, we obtain:

$$b_1 = -\frac{Y_N}{u_N}, \quad b_j = -\frac{X_{(j-1)N}}{u_N}, \ j = 2,3,\cdots,n. \tag{25}$$

Assuming zero initial conditions, equation (21) yields the following equalities:

$$\dot{x}_1(t) = b_1 \cdot u(t) + y(t) \quad \Rightarrow \quad x_1(t) = \int_0^t \big(y(t) + b_1 \cdot u(t)\big) dt, \tag{26}$$

$$\dot{x}_j(t) = x_{j-1}(t) + b_j \cdot u(t) \quad \Rightarrow \quad x_j(t) = \int_0^t \Big(x_{j-1}(t) + b_j \cdot u(t)\Big)\, dt. \tag{27}$$

The unknown parameter *b* is determined using a recursive procedure based on equation (24), with the application of equations (26) and (27).

Furthermore, expressions for the unknown parameter *a* are determined by using equality (23) under the adopted operating conditions

$y_N = -a^T \cdot \boldsymbol{x_N}$, follows:

$$y(t) = -y_N = -a^T \cdot (\boldsymbol{x}(t) - \boldsymbol{x_N}). \tag{28}$$

If the previous equation is multiplied on the right by $(\boldsymbol{x_N} - \boldsymbol{x}(t))^T$, and the resulting expression is integrated during the data collection process, we obtain:

$$\boldsymbol{a}^T = \int_0^T (y(t) - y_N) \cdot (\boldsymbol{x_N} - \boldsymbol{x}(t))^T dt \cdot \left(\int_0^T \big(\boldsymbol{x}_N - \boldsymbol{x}(t)\big) \cdot \big(\boldsymbol{x_N} - \boldsymbol{x}(t)\big)^T dt \right)^{-1} \tag{29}$$

where it is assumed that the initial conditions are equal to zero.

Thus, based on equality (29), the coefficients a_i are determined, and using equation (19), the coefficients b_i^* are subsequently derived:

$$b_0^* = b_1 \cdot a_0, \ \ b_j^* = b_{j+1} \cdot a_0 - \textstyle\sum_{k=1}^{j} b_k \cdot a_{j+1-k}, \ j = 1,2,\cdots,n-1 \tag{30}$$

Thereby, the vector of unknown parameters $\boldsymbol{\beta}$, as defined in equation (20), is also determined

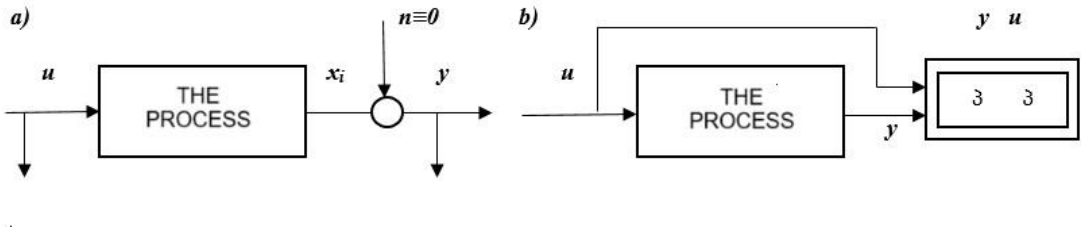

Figure 3. Data collection for the system (steam superheater):
a) data acquisition, b) permanent data recording

The key advantages of applying this method include:

- the influence of noise *n(t)*be neglected;
- even if noise is present, its impact is minimal due to continuous integration of the output signal during the procedure;
- in addition to collecting input-output data under normal operating conditions, typical excitation signals such as step functions can also be used, which significantly simplifies the identification process;
- it is not necessary to assume the order (dimension) of the process in advance, if it is not already known.

5. Results of the Steam Superheater Identification

The identification of the steam superheater is based on the results of a simulation of the dynamic behavior of the steam boiler over a time interval of 120 seconds [26].

As a result of this identification, the following transfer function is obtained:

$$W(s) = \frac{0{,}283 \cdot 10^{-3}}{s + 0{,}134} \tag{31}$$

which indicates a deviation from the initial results. This can be explained by the fact that, under real conditions, the input to the superheater is not a step signal, and that the identification time adopted was not sufficiently long.

Since the coefficients b_i and a_i are defined through partial derivatives, it can be stated that these values-originally determined during modeling without precise calculations - should be verified first.

6. Conclusion

This study addresses the issue of identifying a drum-type steam boiler with fluidized bed combustion as an object of automatic control, emphasizing that only the system itself is considered-without analyzing its input variables in detail.

As noted in [25], the mathematical model of the drum-type steam boiler includes parameters that were not accurately defined, which prompted the need for their identification-specifically for the steam superheater.

Based on the results of a simulation of the drum-type steam boiler with fluidized bed combustion [26], the changes in the output and input variables of the steam superheater were adopted, and by applying

the proposed identification procedure, the previously obtained coefficients of the superheater's transfer function were refined.

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