Use of Methods of Statistical Dynamics Applied for Analysis of Steam Superheater

Abstract. This paper deals with verification of the Simulink model of dynamics of control circuit with real control circuit operating in superheater of Detmarovice power plant. This is carried out by means of exploring reaction of output superheater’s temperature to a disturbance signal, while the output regulated temperature is kept at constant value. The stochastic methods were used for evaluation of this nonlinear circuit. The last part of the paper is devoted to description of IME (Industrial Multivariate Explorer), which is graphical user interface for data visualization and basic analysis.

Streszczenie. Artykuł dotyczy weryfikacji Simulinkowego modelu dynamiki regulacyjnego obwodu z danymi zyskanymi z eksploatacji przegrzewacza w elektrowni Detmarovice. Odbywa się to poprzez analize reakcji temperatury na wyjściu z przegrzewacza na sygnał zakończenia, podczas gdy temperatura na wyjściu jest regulowana na stały poziom. Stochastyczne metody zostały wykorzystane do oceny tego nieliniowego obwodu. Ostatnia część artykułu jest podświetlenia opisów IME (Industrial Multivariate Explorer), która jest graficznym interfejsem użytkownika do wizualizacji i analizy podstawowych danych.

Keywords: identification, signal processing, superheater, statistic dynamics, Simulink

Introduction

The control circuit in Detmarovice power plant energetic block described in this paper consists of three cascading superheaters, each with its own main and fast control loop. Fast loop has to eliminate fast disturbances while a main loop serves for output temperature control. As the superheaters are divided into left and right parts, the experiments described here involve right section of the output superheater.

This control circuit includes concurrent superheaters together with the pipelines, referred to as unheated areas. These elements are described by partial differential equations (PDE) [5] and by finite difference method transformed into the set of ordinary differential equations and then coded into Simulink S-functions as derived in [14]. For evaluation of the system agitated by stochastic signals and further identification, the mathematical models of superheater and unheated areas were used, considering constant steam flow through the system.

Control Circuit of Steam Superheater

The control circuit described in this paper is designed to keep the constant temperature of steam \(T_1(L,t) = 540\)\(^°\)C at the outlet of superheater. \(L\) stands for the length of superheater [m], \(t\) for time [s]. The output superheater consists of a pipeline which brings the steam into concurrent heat exchanger. The pipeline is modeled supposing the ideal isolation of a pipeline which brings the steam into concurrent heat exchanger. The pipeline is modeled supposing the ideal isolation of a pipeline which brings the steam into concurrent heat exchanger.

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Mixer terms are described by algebraic equation (1):

\[
M_{mix} \cdot h_{mix} = M_{w} \cdot h_{w} + M_{v} \cdot h_{v},
\]

where \(h_{w}(p,T_w)\) a \(h_{v}(p,T_v)\) stands for enthalpy of the water and water vapor. Mathematical model supposes the same pressure \(p\) for both media coming into the mixer.

Calculation of the enthalpies of media is carried out through tables of thermodynamic properties of water and water vapor according industry-standard IAPWS IF-97 [7].

Fig. 2 shows the following signals measured under real operation and consequently used for running and verification of the simulation by use of the methods of statistical dynamics as follows: \(T_w\) steam temperature at mixer inlet, \(M_w\) steam quantity at the mixer inlet, \(T_{w8}\) water temperature at mixer inlet, \(M_{w8}\) water quantity at the mixer inlet, \(T_{mix}\) steam quantity at the mixer outlet, \(p\) steam pressure at the mixer outlet, \(T_{w88}\) desire temperature in main loop, constant, \(T_{fj} = T_f(0,t)\) flue gas temperature, \(T_o = T_1(L,t)\) superheater’s output temperature.

It is necessary to determine the course of flue gas temperature, which cannot be directly measured due to the technological reasons. It is measured by other technological blocks that already affect the temperature course. Special algorithm was made up for calculation of flue gas temperature. Based on knowledge of temperatures \(T_{mix}\) and \(T_0\) it computes the flue gas temperature backward. Particularly it uses the splitting intervals method when the steady state of temperature \(T_o\) from simulation (hereafter denoted as \(T_{os}^{sim}\)) is compared with a temperature \(T_o\) measured under real operation. The temperature \(T_{os}^{sim}\) is a function of known (measured) steam temperature at the inlet of the superheater \(T_{mix}\) and working temperature \(T_{fj}\), which is determined from a predefined interval. Based on given acceptable value of relative error between temperatures \(T_o\) and \(T_{os}^{sim}\) and its difference, the temperature \(T_{fj}\) is being refined until the relative error between \(T_o\) and \(T_{os}^{sim}\) is less than a given threshold. Resulting temperature \(T_{fj}\) and comparison of \(T_o\) and \(T_{os}^{sim}\) is given in Fig. 3. These two temperatures are almost identical because the comparison is carried out for

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Fig. 1. Connection of unheated areas and concurrent steam superheater.

Fig. 2. Control circuit scheme for output superheater.

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put temperatures from simulation and real operation. Fig. 4 compares output of superheater temperatures $T$.

Fig. 4. Comparison of output temperatures $T_o$ and $T_{osimCL}$. The difference

The following pictures show comparison of chosen signals from simulation and real operation. Fig. 4 compares output temperatures $T_o$ and simulated $T_{osimCL}$. The difference

Measuring the plant by stochastic signals

Measured signals from real operation make up ten-day record from July/August 2009. The records are separated from daily periods when the power plant’s wattage was 180MW, with sampling period of $T_a = 3$ seconds.

The control circuit (see Fig. 2) was fed with stochastic signals $T_v, T_{wr}, T_{fg}, M_{mix}$ and $a_{mix}$, measured in real operation. The following pictures show comparison of chosen signals from simulation and real operation. Fig. 4 compares output temperatures $T_o$ and simulated $T_{osimCL}$. The difference

Ergodic hypothesis

Stochastic signal, as a name of continuous variable depending on time, can be stored in two different ways. It is either possible to make one record of infinite length or infinite number of finite length records. Despite the finite length of record of stochastic signal, infinite time interval is necessary to describe time dependence and sequence of the values. Ergodic hypothesis allows transition between these ways.

Due to the fact that length of the data to be processed would exceed the size of inverse matrix several times when computing numerical deconvolution, the whole record was divided into approximately 200 same time intervals. Then 200 correlation functions of the same type were calculated and summed up, and the final result was divided by the number of intervals. Using this way, so called ergodic hypothesis has been implemented. As a result of this, the estimation of correlation functions was refined.

By means of the term (2) three correlation functions were calculated. First one is autocorrelation function of the signal that indicates detrended temperature of a steam at the inlet of mixer $M$. Other two correlation functions define time dependencies between detrended temperatures $T_v, T_o$ and $T_{fg}$, $T_{osimCL}$.

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Identification the dynamics of control circuit with steam
superheater

Method of identification the system by statistic dynamics
is designed for linear systems. This paper describes its use
for comparison of modeled control circuit in Simulink and real
control circuit. The result of this identification is response of
steam temperatures at the superheater outlet to Heaviside
step of superheater inlet temperature. In simple words, it is
response of the control circuit to step change of disturbance,
representing steam temperature at the mixer inlet \( T_u \).

When computing numerical deconvolution, Wiener -
Hopf equation

\[
R_{uy}(\tau) = \int_0^\infty h(t) R_u(\tau - t) \, dt
\]

represents stochastic formulation of dynamic system. Under
a special condition, in case of bringing white noise into input
of the system having the following autocorrelation function

\[
R_u(\tau) = \delta(\tau),
\]

we get

\[
R_{uy}(\tau) = \int_0^\infty h(t) \delta(\tau - t) \, dt = h(\tau)
\]

Numerical calculation of weighting function is based on re-
placing integration process by summation and numeric de-
convolution. Discretizing equation (8) leads to:

\[
R_{uy}(\tau) \approx \sum_{k=0}^{N} R_u(\tau - k \cdot T_s) h[k \cdot T_s] \cdot T_s
\]

If time shift \( \tau \) is expressed as multiple of time step \( T_s \), that is
\( \tau = 0, T_s, 2T_s, \ldots, N \), it is possible, using the last equation,
a set of \( N + 1 \) linear algebraic equations [9], from which it
is possible to compute unknown values of weighting function
\( h[0], h(T_s), \ldots, h(NT_s) \).

Using following feature of autocorrelation function

\[
R_u(\tau) = R_u(-\tau)
\]

and after introduction of shortened no-
tations of weighting function \( h_k = h[kT_s] \) and \( R_x[k] =
R_{xx}[kT_s] \), the set of equation can be rewritten into matrix
form (10).

\[
\begin{bmatrix}
    R_{uy}[0] \\
    R_{uy}[1] \\
    \vdots \\
    R_{uy}[N]
\end{bmatrix} =
\begin{bmatrix}
    R_u[0] & R_u[1] & \cdots & R_u[N] \\
    R_u[1] & R_u[0] & \cdots & R_u[N-1] \\
    \vdots & \vdots & \ddots & \vdots \\
    R_u[N] & R_u[N-1] & \cdots & R_u[0]
\end{bmatrix} \times
\begin{bmatrix}
    h_0 \\
    h_1 \\
    \vdots \\
    h_N
\end{bmatrix}
\]

Or in the matrix form.

\[
r = R \cdot h.
\]

Solution of weighting function can be reached by use of in-
verse matrix \( R^{-1} \) as follows:

\[
h = R^{-1} \cdot r.
\]

This numerical solution of deconvolution in Matlab is limited
by matrix until approximately elements.

Concerning that the length of measured data exceeds
the size of the matrix that would be created during nu-
merical solution of deconvolution, it is suitable to split the
record into several same sections and compute particular impulse
characteristics. The second reason for splitting is the
fact that time constant of superheater is smaller than time
of calculated impulse response that would be computed in
case of maximal possible solution of numeric deconvolution
\( (3000 \times T_s = 9000 \text{ seconds}) \). Due to this reason, the
ergodic hypothesis was used for estimation of impulse charac-
teristic. Applying numerical deconvolution of Wiener - Hopf

![Fig. 6. Comparison of estimations of impulse characteristics of disturbance transfer function.](image1)

![Fig. 7. Comparison of estimations of step characteristics of disturbance transfer function.](image2)
response of the circuit. In case of the comparison the result of this identification with the response to the Heaviside step, it would be necessary to change the flue gas temperature proportionally to the value of the step at the mixer inlet, with adequate advanced time interval corresponding to the soaking all of the superheaters so that inlet mixer temperature rises by 1°C.

A computing solution to monitor in short and long term

Explorer of Process Industrials (EPI) was developed in Matlab for Felton Power Plant [16, 17]. Their steam generators for two blocks, each one of 250 MW, were made by SES TLMACE (Slovenske Energeticke Strojarne) company. EPI is developed by a set of user graphical interfaces. Each one handles a set of variable corresponding to historical variables that were exported from a supervisory computer. Using two cursors on the main graphical EPI interface, the user chooses a short window of the signal corresponding to a steady state. Choosing each graphical interface makes it possible that a different computing task can be performed on each group of variables and results to be saved into Excel file. Among them, it can be listed the following ones: thermal energy transferred to water/steam through several heat transfer exchanging surface into steam generator, fuel overconsumption indexes calculation, etc.

Also, the second version has been developed, but the user’s interface is not associated to any specific power. It is called as Industrial Multivariate Explorer. It makes it possible to perform data analysis on long time windows. IME saves its computed data into a Secondary Data Base (SDB). Data comes into IME by a Primary Data Base (PDB). It consists of a time series set exported from an existing supervisory computer in the power plant. These features promoted its application on EDE power plant from Czech Republic.

When a system submitted to thermodynamic transformations is not steady, thermodynamic system parameters are highly unstable. Some of the first investigations of system steady-state identification came from process control field studies [11, 2, 8, 10, 13].

Bad functioning of these control structures affects the power plant operation, [12]. The data available from plant sensors supplied to the control systems may also be analyzed to verify proper operation and to predict future behavior, [3]. Specific methods, for plant power monitoring and diagnosis, are currently being researched. For instance, for monitoring of practical flames [1], monitoring applications in nuclear power plants [6], thermo-economic diagnosis of the operation [15].

There are three following IME’ features, (see Fig. 8). To visualize up to 8 time series linearly normalized in amplitude and distributed on the plot, to choose a sub-set of vector’s components enclosed between two cursors (see Fig. 10) and to save into a Secondary Data Base (SDB) with the value of some statistics computed to set of elements chosen between cursors of each variable from a Primary Data Base (PDB), (see Fig. 11).

Application of IME to EDE Power Plant

IME aids to a simulated experiment for fouling detection into EDE Superheater experimental setup. Essays were performed by the closed loop temperature control scheme, shown in Fig. 2, running on a simplified model of experiment setup. The fouling effect was introduced on $\alpha_{S2}$ parameter changes into S-function of the Superheater, see Fig. 9. As it should be expected, the control system (set up by 2 PID controllers) is able to keep, in steady state the steam outlet temperature on like value, both without/and with fouling effect. Nevertheless, “$M_{wr}$” signal, i.e., water quantity at the mixer inlet have to changes when $\alpha_{S2}$ changes. Indeed, $\alpha_{S2}$ changes modify transferring energy course from flue gas to superheated steam. In Fig. 10 by a single look at the records on both $M_{wr}$ responses it is not possible to detect changes. Its waveforms are very like. Also, in a current industrial operation it only is recorded one response. Nevertheless, $M_{wr}$ mean values on lengthen time windows are different.

In Fig. 10, first record (yellow) corresponds to a time sequence on $\alpha_{S2}$ changes like to shown in Fig. 9. User is in charge to detect the time window where a quasi steady state exists. In this example, it is easy to choose $\alpha_{S2}$ without/with changes. IME’s SDB permits to save on Excel file the new $M_{wr}$ mean results, see Fig. 11. With this Long Time Window data base is now possible to assess fouling effects on the superheater’s surface.

In particular three $M_{wr}$ mean values are plotted in Fig. 12. Supported of scheme in Fig. 2 are performed two experiments: without fouling through $\alpha_{S2} = 71.8 \text{ Jm}^{-2} \text{K}^{-1} \text{s}^{-1}$ and by fouling modulation by a time sequence on $\alpha_{S2}$ changes shown in Fig. 10. To assess the $\alpha_{S2}$ changes effect on $M_{wr}$, by the two cursors, three time window are chosen as follow: [663 2348], [2685 6326] and [9629 11315]. On the first one, both simulated operation run without fouling, in the second chosen window, it has been introduced two $\alpha_{S2}$ step changes and lastly in the third window it has been introduced $\alpha_{S2}$ change with a value higher than previous one.
once a soot blowing operation has been carried out. Indeed the efficiency transferring energy course from flue gas to superheated steam has improved by fouling reduction.

**Conclusion**

Both superheater and unheated area are modeled as distributed-parameter systems which makes it possible to estimate the course of temperatures not only at the output but at any point of superheater. Due to this fact, the designers are able to tune the parameters of superheaters and control circuit so that the strain of the superheater and its other parameters are kept within the safe technological ranges. This basic tool called Industrial Multivariate Explorer was created to provide easy data visualization and analysis, using the strong computational capabilities of Matlab&Simulink environment. Identification by the method of statistic dynamics in this case clarified approximated compliance between models for optimal control of heat exchanger, in this case clarified approximated compliance between models for optimal control of heat exchanger.

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