DEMONSTRATION OF A GREY-BOX APPROACH TOWARDS THE DIAGNOSTICS OF A FEEDWATER HEATER (PART II) – MODEL TUNING BASED ON OPERATIONAL DATA

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Summary

Work related to the first-principle modeling of a boiler feedwater heater operating in a power unit is presented, along with theoretical discussion concerning its structural simplifications, parameter estimation, and dynamical validation. The objectives of this work are as follows: (i) formulate a moderately complex first-principle model of a feedwater heater to reproduce operational measurements in real-time simulations, (ii) develop a tuning method for this model, (iii) propose key indicators of heater performance using a model-based approach, and finally (iv) automate the calculation process of the indicators. The first objective has been addressed in the first paper while the remaining objectives are dealt with in this paper. The paper discusses a nonlinear least-square optimization technique used to adjust the phenomenological parameters of the feedwater heater model, i.e. heat transfer coefficients. The model variables (e.g. variability of the power rate of energy exchange) and estimated parameter values were used to formulate key performance indicators intended for a model-driven diagnostics approach. The computational process was organized in an iterative process of updating model parameters and indicators. The validation was successfully performed using operational data from a 225MW coal-fired power unit.

Key words: power plant, feedwater heater, modeling, system identification

Streszczenie

Artykuł przedstawia proces modelowania podgrzewacza regeneracyjnego pracującego w systemie bloku energetycznego z wykorzystaniem równań fizycznych. Artykuł zawiera dyskusje dotycząca uproszeń struktury modelu, estymacji jego parametrów oraz walidacji. Celami pracy jest: (i) sformułowanie umiarkowanie złożonego modelu wymiennika odtwarzającego dane pomiarowe w rzeczywistej skali czasu, (ii) przedstawienie metody strojenia modelu, (iii) zaproponowanie wskaźników użyteczności podgrzewacza na podstawie podejścia wspartego modelem, oraz (iv) automatyzacja procesu wyznaczania tych wskaźników. Pierwszy z celów zawiera się w pierwszej części pracy, a pozostałe w części drugiej. Artykuł zawiera dyskusję wyników zastosowania nieliniowej metod najmniejszych kwadratów w celu dostrojenia parametrów fenomenologicznych modelu podgrzewacza wody zasilającej, tj. współczynników wymiany ciepła. Zmienne modelu (np. chwilowy transfer energii) oraz wartości estymowanych parametrów zostały użyte w celu sformułowania wskaźników odpowiednich dla diagnostyki bloku energetycznego wspartej modelem. Proces obliczeniowy został zorganizowany w sposób iteracyjnego uaktualniania parametrów modelu oraz wskaźników, na podstawie danych operacyjnych pochodzących z 225 MW bloku opalanego węglem kamiennym.

Słowa kluczowe: elektrownia, podgrzewacz regeneracyjny, modelowanie, identyfikacja systemów.

INTRODUCTION

Recently, two trends concerning the maintenance of power plants have been noticeable in the market. The first trend concerns the so-called “smart maintenance” strategy to outsource maintenance services in small- and mid-scale power plants. This is done in order to minimize the involvement of the in-house resources to only necessary and basic maintenance activities. In this respect, leading Original Equipment Manufacturers (OEMs) of power plant equipment (turbine, control system, generator) offer to such power plants services of remote monitoring and continuous plant follow-up in the form of maintenance packages involving third-parties’ equipment [1]. Typically, smart maintenance agreements oblige service providers to support power plants in achieving designed performance with more operational flexibility and better control of the risk of operational interruptions. Implementing a “smart maintenance” strategy ensures reliable daily operation of power units and provides, essential for the power plant, availability of advanced engineering knowledge in case any malfunction or severe failure mode occurs. Such a maintenance strategy requires vital components and configuration settings to be monitored remotely and data to be automatically logged. Process data are available on-line to the service center for trending and analysis against fleet operating characteristics [1]; process parameters may be viewed and controlled by software systems, and analyzed virtually from remote location systems featuring multiple diagnostic tools related to tracking critical machinery parameters and enabling early warning notification to be communicated, and therefore preventive actions to be undertaken. The second trend concerns the tendency to concentrate the research staff, development laboratories and knowledge in engineering centers, and is becoming clearly recognizable in the market. These integrated resources can provide daily monitoring services remotely to many power plants under a "smart maintenance" strategy and allow maintenance costs to be significantly reduced, flex engineering and maintenance resources to be utilized with higher flexibility, and risk of failure to be reduced. From a research and development perspective, "smart maintenance" stimulates development of model-based methodologies that create high-level physical insight into the monitoring process and defines new key indicators of process performance. For instance, a heat transfer coefficient is a high-level indicator, as opposed to low-level indicators measured directly by the plant instrumentation system, e.g. pressure or temperature. Nevertheless, models require measurements of numerous variables for which a well-developed instrumentation and software infrastructure has to be available in power plants. Therefore, engineering centers providing "smart maintenance" services tend to equip monitored power plants with a number of sensors greater than justified by usual power plants safety and availability requirements. Such investments in infrastructure are paid back by savings in time and costs related to shortening the reaction time in case of a failure mode, as well as a decreased number of direct interventions in power plants. Additionally, only the procedure for fixing a failure mode is communicated to the power plant without engaging highly skilled engineering resources in analyzing the situation directly in the power plant. Development of a model-based approach is nevertheless costly, and is profitable only when knowledge is concentrated and utilized simultaneously for the monitoring of many power plants. This requires not only advanced engineering knowledge but also well-organized business and information processes.

The method, involving the combination of first-principle and data-driven approaches towards assessing efficiency and diagnosing power units, is presented in this paper. The methodology proposed herein allows physical characteristics of a feedwater heater to be reconstructed in order to analyze performance using key process indicators. The power of this approach lies in tracking key process indicators by means of instantaneously adjusting, based on process data, parameters of the first-principle model developed in [2]. The method is called the greybox approach, to indicate the fact that it combines the "white box" approach, which is based on analytical physical models, but requires knowledge of several detailed parameters of the machine, and the "black box" approach, which is purely based on data, but does not yield any physically interpretable parameter values.

Models developed using the greybox method reconstruct estimates of the physical process, such as the amount of exchanged heat energy (i.e. transferring power) that, in turn, enable dynamic energy balances of components (e.g. feedwater heater) to be created. These power balances can be integrated into a complete dynamic energy balance of a power unit and enable process imperfections (e.g. hysteresis) to be visualized. These imperfections, corresponding to energy wastage in the power generation process, contribute to the overall efficiency of a power unit, A decrease in the performance of components may also indicate a technical issue resulting from a faulty mode or non-optimal settings.

The method proposed in this work is not intended to detect severe faults, which activate the safety systems of a power unit; but aims at detecting relatively slow, i.e. of hours or days, changes in processes, e.g. internal leakage through a cracked pipe. A key process indicator, namely the power rate of energy exchange in a component reflects such a fault, enabling first-level analysis and indicating deviation from the targeted efficiency. The second-level analysis, including utilization of the engineering expertise and technical indicators which are reconstructed parameters of a first-principle model, e.g. heat transfer coefficients, energy heat exchange rates, enthalpies, is performed. Investigations of this kind can be supported by process and control data, e.g. a tendency of the system to deviate from a required setpoint of a controller. Among the greatest challenges, though beyond the scope of this paper, is definition, e.g. by means of 2D/3D graphs reflecting relationships among critical variables of patterns of key process indicators corresponding to a healthy system. These graphs require statistical bounds defining confidentiality range and involving process uncertainty to be imposed.

The structure of this paper is the following. In the first section, tuning and validation of a first-principle model of a feedwater heater are presented. The second section discusses a proposal of performance indicators of a feedwater heater, while the third section provides an exemplary case study where these indicators were obtained based on operational data from a 225MW unit. The last section is the summary.

1. TUNING OF A FEEDWATER HEATER MODEL

The procedure of model tuning consists of two in-a-loop phases: (i) simulation of a model by solving differential equations numerically, and (ii) numerical minimization in the parameter space with respect to an error-related criterion function. The function describing the error has to be a positive and decreasing function of the differences between the measurement signals and model responses. The interested reader may find more information concerning the available methods and algorithms that support identification of first-principle models in [3-4].

1.1. Estimation of model parameters

A physical model can conveniently be represented as a set of nonlinear state-space equations formulated in the continuous-time domain as:

$$\begin{aligned} &\frac{d}{dt}x(t) = f\left(t, x(t), u(t), w(t); \theta\right) \\ &y(t) = h\left(t, x(t), u(t), v(t); \theta\right) \\ &x(0) = x_0 \end{aligned} \qquad (1)$$

,

where the vector f(.) is a nonlinear, time-varying function of the state vector x(t) and the input vector u(t), while the vector h(.) is a nonlinear measurement function; w(t) and v(t) are sequences of independent random variables and θ denotes a vector of unknown parameters. In nonlinear systems, the state vectors and the measurement vectors may have non Gaussian distribution. The sum of squared errors is used as an error criterion. This problem is known in numerical analysis as "the nonlinear least-square problem" [3]. The objective of the estimation is to minimize the error function between the measurement signals and model responses by means of an iterative numerical technique.

1.2. Parameters of the modeled heater

A high-pressure heater denoted as XW1 was used as a reference system characterized by the operational and constructional data presented in Table 1. The heater is a part of a feedwater regeneration circuit in which feed pumps pass the condensed steam (feedwater) from a condenser through heater banks, heated by the steam extracted from the high, intermediate and low-pressure sections of a steam turbine. The condensate is pumped to the deaerator, through the bank of low-pressure heaters XN12, XN3, XN4 and XN5, and further, from the deaerator to the steam generator (boiler) through the bank of high-pressure heaters XW1, XW2 and XW3.

1.3. Settings of the Optimization and Simulation Algorithms

The simulation and optimization settings used in the parameter adjustment process are presented in Table 2. The Newton-Gauss method, lsqnonlin(.) routine implemented in the Optimization Toolbox of Matlab, was used to minimize the function describing the error in the measurement signals and model responses.

1.4. Adjustment of Model Parameters Based on Operational Data

The simulation model considered in this section consists of a heater model and a model equivalent to a control system installed in a power plant. The control system could not be directly reconstructed in the simulation, due to its complexity and limited relevance to the functionality required in the model (e.g. trip logic). Hence, the module maintaining a constant level of the condensate inside the heater was simplified using a PID controller model. Geometrical and physical parameters of the heater model (Table 1) were extracted from the operational documentation and were assumed to be known. Four phenomenological heat transfer parameters were identified and the two selected model responses are presented graphically in Fig. 1.

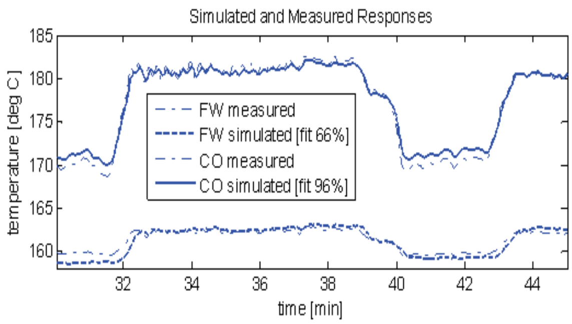

Fig. 1. Graphical representation of the results (FW – feedwater, CO – condensate)

The model reproduced the trend in the condensate and the feedwater temperatures with acceptable accuracy. The model was run and tested on a PC with an Intel Pentium 2.8GHz CPU and 4 GB RAM under Microsoft Windows XP Professional x64 Edition. Matlab version 7.2 (R2006a) was used. Convergence trajectory plots (not presented here) show a stable trend towards constant values of the parameters, which correspond to a convergence towards the minimum of the criterion function, within less than 6 iterations.

Table 1. Parameters of the high-pressure heater XW1 used in simulation.

Type of parameter	Parameter	Symbol	Unit	Value
Geometrical	Heat Exchange area – steam	A_{12}	[m^2]	$f_A(V_{12})$
	Heat Exchange area – condensate	A_{23}	[m^2]	$A_{tot} - f_A(V_{12})$
	Overall heat exchange area	A_{tot}	[m^2]	600
	Steam and condensate volume ($V_{12} + V_{23}$)	V_{total}	[m^3]	2.9
	Feedwater volume	$V_{45} + V_{56}$	[m^3]	4
	Heater height	x	[m]	10
Physical	Mass of the metal of a heater	m_m	[kg]	35500
	Specific heat of a metal	c_{pm}	[J/kg·K]	$500 \cdot 10^{-3}$
Phenomenological	Heat transfer coefficient steam to metal	k_{12-m}	[kW·m^{-2}·K^{-1}]	1.5
	Heat transfer coefficient condensate to	k_{23-m}	[kW·m^{-2}·K^{-1}]	0.6
PID-settings	Proportional	P	[-]	0.8
	Integration	I	[s]	53
	Derivative	D	[s^{-1}]	0

Table 2. Simulation and optimization settings

Simulation		Optimization (minimization)	
Option	Value	Option	Value
Solver	ode23tb (stiff/TR-BDF2)	Gradient type	basic
Max step size	auto	Algorithm	lsqnonlin
Min step size	auto	Cost type	SSE
Zero crossing control	disable all	DiffMaxChange	0.1
Relative tolerance	auto	DiffMinChange	1E-08
Absolute tolerance	auto	Large scale	true
		MaxIter	28
		RobustCost	False
		TolCon	1E-6
		TolFun	1E-6

2. PERFORMANCE INDICATORS FOR A FEEDWATER HEATER

The range of operating conditions corresponds to the range of the power ratio of the turboset, i.e. between 140 and 225MW. Execution of the procedure for numerical adjustment of these parameters allowed values of these parameters that assure the heater model that best fits to the data to be found. The model was tested on the same PC configurations as presented in the previous section. Parameters of the feedwater heater model were updated according to the flowchart presented in Fig. 2 for low and high-pressure heaters, designated as XN4 and XW1 respectively. The results for models of both heaters are qualitatively the same, so only results for the XW1 will be presented in this section.

Parameters of the first-principle model are sequentially updated based on operational data. Every sequence of data has a length of 60 samples and corresponds to 60 minutes of operation time. The Newton-Gauss method, lsqnonlin(.) routine implemented in the Optimization Toolbox of Matlab, used to update model parameters is sufficiently efficient, as proved in Fig. 3, to follow the operational data in the real-time mode.

Values of updated parameters are used as initial guess conditions in an algorithm adjusting model parameters for the next data sequence. As a result, the minimization algorithm has a better starting point and so a smaller number of iterations is required in each sequence. The value of an objective function error and the number of iterations are used as stopping criteria for the parameter updating process.

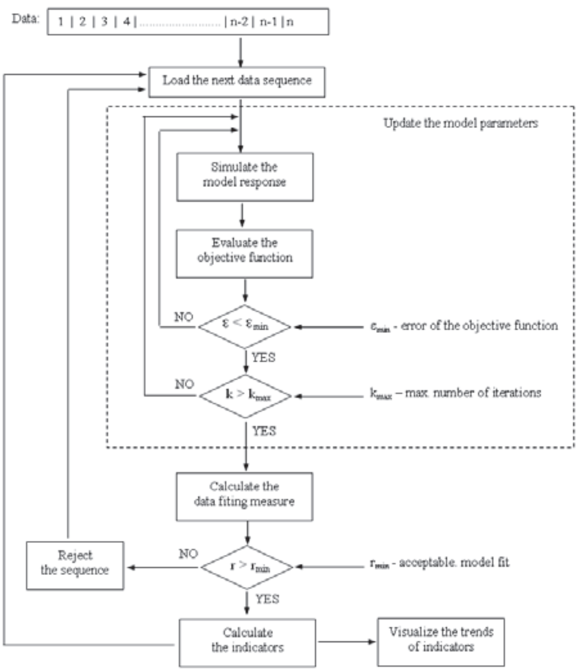

Fig. 2. Procedure of updating model parameters

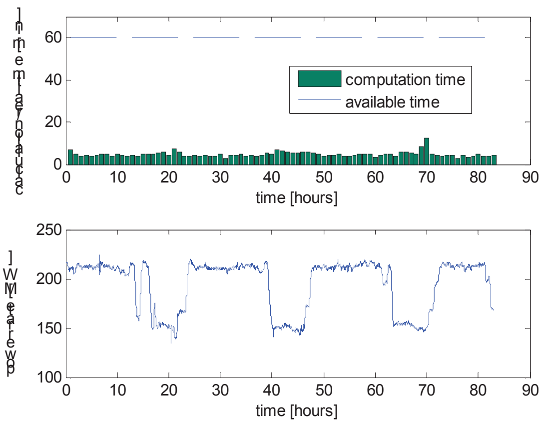

Fig. 3. Actual time vs. available real time for computations of a single heater

3. PERFORMANCE INDICATORS IN DETECTION OF ABNORMAL OPERATION OF A FEEDWATER HEATER

Two types of indicators, efficiency and technical ones, have been defined in order to asses the technical state of an object. Typically, such indicators take the form of a scalar value (e.g. amount of transferred energy) or a characteristic (e.g. power rate vs. amount of transferred energy) and allow a pattern of values corresponding to different regimes of operation (e.g. low vs. high power rate) to be defined. Bounds imposed on the pattern of normal operation of a power unit define the tolerance range beyond which the performance is unacceptable.

The diagnostic process proposed in this paper consists of two stages (i) the fault detection, and (ii) the fault recognition. Firstly, symptoms of a malfunction are detected based on variation of an efficiency indicator, i.e. by detecting the efficiency indicator crossing tolerance bounds. Secondly, a technical indicator enables a problem to be addressed more precisely. The methodology proposed herein does not eliminate the need for specialists and experts to contribute to the fault recognition process, as their role is to interpret trends in indicators. The method is an extension of available symptom indicators to provide new early warning indicators of physical meaning.

Fig. 4 presents an example of an efficiency indicator based on an operational curve, i.e. a relation of the electrical power rate to corresponding overall energy transfer rate from the steam to the feedwater (cf. left-most plot in Fig. 4).

The overall energy transfer rate can be split into the steam-to-feedwater and the condensate-to-feedwater transfer, for the upper and lower volume of a heater respectively (cf. middle and right-most plot in Fig. 4). These two energy transfer rates are governed by respective heat transfer coefficients present in the heater model. As shown in Fig. 4, data points approximately lay along a line (solid line) and are bounded by 95% confidence intervals (dashed lines). An example of technical indicators can be a hysteresis loop of the energy transfer in the steam-to-feedwater and the energy transfer in the condensate-to-feedwater, corresponding to two heat transfer coefficients used in the heater model. The size of a hysteresis loop, among others, is an indication of heat accumulation in the metal.

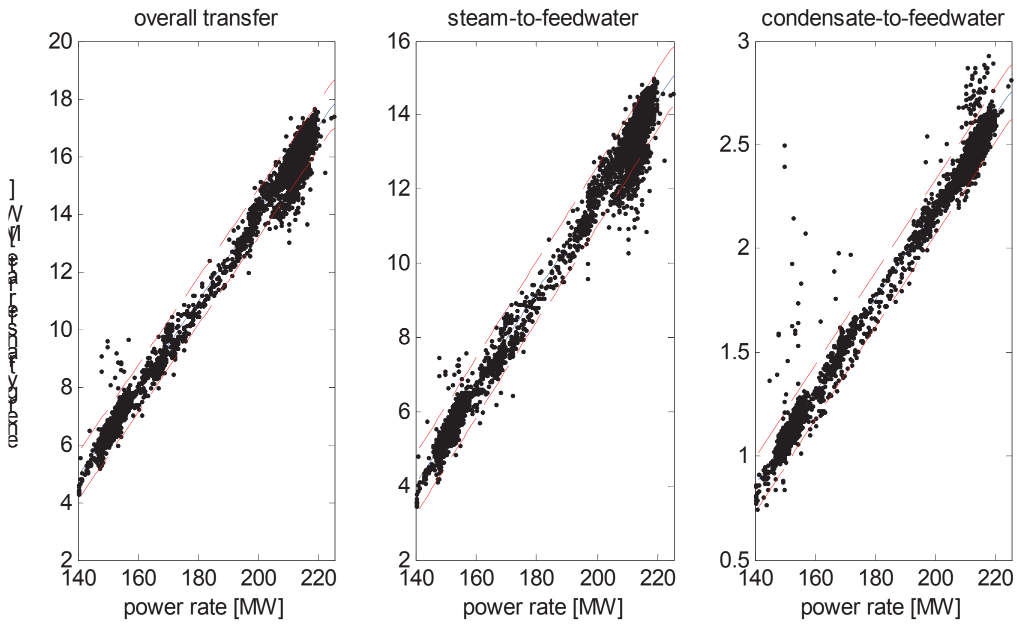

Fig. 4. Procedure of updating model parameters

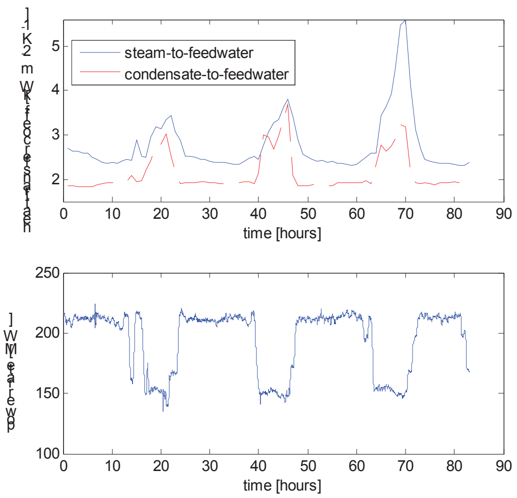

Fig. 5. Values of heat transfer coefficients over operational time

Another option for constructing a diagnostic tool is to investigate trends in heat transfer parameters versus the operational time (Fig. 5). Values of these parameters vary depending on the operating point of the power unit, however, and thus yet another possibility of constructing a technical indicator should be considered, namely the relationship between the value of the heat transfer coefficient and the temperature of the feedwater leaving the heater.

4. DISCUSSION OF RESULTS AND CONCLUSIONS

This paper focuses on the tuning and validation process of the first-principle feedwater heater model intended for model-based diagnostics as a part of the entire model of a power unit. Moreover, the paper proposes key performance indicators which reflect operational changes in the process of heating the feedwater versus assumed statistical bounds.

The proposed model tuning approach is advocated for industrial conditions when the values of physical and geometrical parameters are known, while the values of phenomenological ones have to be adjusted as only their rough initial guess values are available. The development process of a feedwater heater model is presented in [2]. Measurement data from a 225MW coal fired unit were used to validate the model's accuracy. The validation process presented in the paper indicates that the performance in steady and transient conditions is good, achieving a correlation between the simulations and measurements at a level of 60-90%. This proves that the model can be used in further studies and the development of techniques related to model-based diagnostics.

Efficiency and technical performance indicators were formulated using a statistical approach to facilitate the recognition of specific patterns in data. Pattern-based analysis was proposed as the most suitable form of analysis because of the availability of a high amount of operational data. Pattern analysis allows a few scenarios, represented by different patterns which correspond to sequential operation of power units, to be created. A power unit can be in a few operational states corresponding to its rotational speed expressed in rpm; these states usually are: idle (rpm = 0), turning gear (0 < rpm < 30), transient (500 < rpm < 2950) and synchronized (2990 < rpm < 3010). Sequential operation of a power unit enables two groups of patterns, belonging to transient and steady operation, to be obtained. Typically, the indicators (measures) introduced in this paper reflect nonlinear relationships and are therefore represented by first- or second-order trend curves. Parametric representation of the performance indicators allows boundary conditions to be easily imposed. These boundaries can be automatically detected and, as such, are able to be utilized in an early warning malfunction notification function. Moreover, such parametric representation facilitates the quantification of the uncertainty of the diagnosis. There are numerous statistical methods supporting the decision-making process which are based on sets of uncertain and inconsistent data [5]. Such methods should be considered to reject false alarms.

Future investigations are planned to focus on the repeatability and reproducibility of the system identification results separately, based on a number of data sets measured in similar operational conditions. Repeatability and reproducibility indicators are important from the diagnostic point of view since these indicators directly yield confidence intervals for adjusted parameters and confirm, statistically, the correctness of the proposed approach.

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