MODEL-BASED EVALUATION OF A POWER PLANT STEAM BOILER SYSTEM

Key words
Power plant, steam boiler, modelling, system identification, Matlab, Simulink.

Abstract
The method, involving the combination of first-principle and data-driven approaches towards assessing efficiency and diagnosing steam boilers, is presented in this paper. The objectives of this work are as follows: (i) to implement a moderately complex first-principle model of a steam boiler to reproduce operational measurements in real-time simulations, (ii) to develop a tuning method for this model, (iii) to propose key indicators of heater performance using a model-based approach, and finally (iv) to automate the calculation process of the indicators. The paper discusses a nonlinear least-square optimisation technique used to adjust the phenomenological parameters of the model. The model variables and estimated parameter values were used to formulate performance indicators intended for a model-based evaluation approach. The validation was successfully performed using operational data from a 225 MW coal-fired power unit.

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 minimise 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 the availability of advanced engineering knowledge essential for the power plant in case any malfunction or severe failure mode occurs. Process data are available on-line to the service centre for trending and analysis against fleet operating characteristics [4], and process parameters may be viewed and controlled by software systems, and analysed virtually from remote location systems featuring multiple diagnostic tools related to tracking critical machinery parameters and enabling early warning notification to be communicated, so preventive actions may be undertaken. The second trend concerns the tendency to concentrate the research staff, development laboratories and knowledge in engineering centres, and is becoming clearly recognisable 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, engineering and maintenance resources to be utilised with higher flexibility, and the risk of failure to be reduced. From a research and development perspective, “smart maintenance” stimulates the 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 centres 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 the case of a failure mode, as well as a decreased number of direct interventions in power plants.

The methodology proposed herein allows physical characteristics of a steam boiler to be reconstructed in order to analyse performance using key process indicators. The power of this approach lies in tracking key process indicators by means of instantaneously adjusting the parameters of the first-principle model based on process data [4]. The method is called the grey-box
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 system, and the “black-box” approach, which is purely based on data. Models developed using the grey-box method reconstruct the 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. steam boiler) to be created. These power balances can be integrated into a complete dynamic energy balance of a power unit and enable the visualisation of process imperfections (e.g. hysteresis). 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. Among the greatest challenges, though beyond the scope of this paper, is definition (e.g. by means of 2D/3D graphs) reflecting the 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.

This paper is divided into four sections. The second section provides a general overview of the intended model and its implementation. The third section presents an approach to updating the first-principle model of a steam generator with use of a parameter estimation technique. The fourth section discusses a proposal of performance indicators and provides an exemplary case study where these indicators were obtained based on operational data from a 225 MW unit. The last section is the summary.

1. The model implementation

In the field of boiler modelling, many models now exist, ranging from complex knowledge-based models to experimental models derived from customised plant tests. In the middle of this range are the so-called 'interpretation' models [4, 5, 6, 7, 8, and 9]. These models are complex enough to capture the essential physics required for the purpose of grey-box modelling [10, 11]. They provide physical insight into the modelled phenomena, including the influence of the frequently used multi-loop control strategies. On the other hand, such models allow the values of adjustable phenomenological parameters to be tracked based on the operational data. This paper discusses the implementation of the economizer-boiler model, the selection of adjustable physical meaning parameters, and the results of a case study where model parameters were tracked based on operational data.
The work discussed in this paper is intended to build the entire model of the boiler system including the drum, downcomer/riser components, economizer, and superheater. Nevertheless, the superheater system is still under development. The fourth-order drum model considered in this paper was developed by Åström and Bell [4]. The model consists of physical equations (differential and algebraic) which are completed with semi-physical formulas simplifying the physics and complex geometry of the drum and tubes. Therefore, the model equations are nonlinear and built up from global mass, energy balances and momentum equations describing the complicated dynamics of the economizer, drum, downcomer, and riser components (Figure 1).

Fig. 1. A schematic representation of the steam drum system including riser/downcomer components

The considering steam boiler consists of a natural circulation drum. The model requires one to establish the following assumptions for a drum model: (i) the specific enthalpy of steam leaving the boiler is equal to the vapour enthalpy, (ii) the pressure of feedwater is equal the pressure of steam, (iii) heat transfer is dominated by convection, (iv) ideal heat transfer between the feedwater inside the drum and the surrounding metal is assumed, (v) the metal temperature is equal to the saturation temperature of water for the pressure inside the drum. The feedwater in the drum absorbs heat and changes into steam at 370°C and 13 MPa. It is separated from the water inside a drum at the top of the furnace. The saturated steam is introduced into superheat pendant tubes that are installed in the hottest part of the combustion gases as they exit the furnace, where it is superheated to 540°C.

The fourth-order model formulated based on the mass and energy balance detailed described in [4] was used in drum modelling.
Equations of the feedwater model were implemented in a convention required by Simulink [14]. Equations have the form of algebraic expressions grouped into blocks rather than a network of connections among elementary blocks, which allows the avoidance of a “spaghetti code” caused by a large number of elementary blocks (e.g. gains, adders) and mutual links. The underlying idea is to facilitate conversion of the Simulink code to other modelling languages, e.g. Modelica. The model requires conditional operators that were also coded in m-files for the transparency of the model topography. Look-up tables with derivatives of steam properties were smoothed by means of interpolation to remove discontinuities or thresholds. Blocks were masked so that only selected parameters are transferred to these blocks as Matlab data structures. Exemplary topography of the feedwater model is depicted in Figure 2.

The control of the drum-boiler system involves the manipulation of the feedwater and heat input rates to compensate for the mass of steam exiting the system. The three-element controller is the industry standard, utilising the drum level, the steam flow rate and the feedwater flow rate as its feedback elements. A three-element control system is essentially a form of cascade control in which the inner loop is a fast acting loop to follow load changes, and the outer loop a slower trim loop for water level. This approach allows rapid load changes to be handled, due
to the shrink and swell effect in the riser. In this work, the load (fuel) controller was omitted and the energy rate to the model is reconstructed based on the electric power of the turbogenerator using a correlation factor. The equivalent load of the boiler was formulated as a transfer function, which covers the simplified dynamics of the superheater and the steam turbine. The simulation model considered in this section consists of sub-models of an economizer (simplified static model), a drum, an equivalent load model (simplified dynamics of a steam turbine), and a model of a PID control system (drum level control).

2. Adjustment of model parameters based on operational data

The procedure for adjusting a model consists of two in-a-loop phases: (i) the simulation of a model by solving differential equations numerically, and (ii) the numerical minimisation 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 reference and modelled outputs. The number of stages in this multistage iterative process leads to very high computational cost in comparison to estimations of a parameter of a linear model by the linear least-square algorithm [12]. The interested reader may find more information concerning available toolboxes that support the identification of first-principle models in [5]. The objective of the estimation is to minimise the squared error function between the measurement signals and model responses by means of an iterative numerical technique.

The model was adjusted using three signals, namely (i) the steam pressure in the drum, (ii) the flow rate, and (iii) the temperature of the feedwater to the economizer-drum system. The adjustment process allowed improving the model fit to operational data of almost 50%, where the starting point was a trial-and-error approach. The adjustment process based on the optimisation method allows one to achieve repeatable results within short time (a few minutes) instead of the time-consuming trial-and-error process.

Geometrical and physical parameters of the drum model were extracted from the operational documentation and are assumed to be known. Three parameters in the entire model were selected to be adjusted, based on the operational data of the drum-boiler system. These adjustable parameters have phenomenological interpretations that allow the modelling to take advantage of a grey-box approach. The first considered parameter is the non-dimensional friction coefficient $k$, which describes the overall fluid friction effect causing a pressure drop in the downcomer-riser loop. Next, the residence time $T_d$ defines the time that is required to release the steam contained in the drum when the steam flow through the drum is retained. The final one is the $\beta$ experimental parameter, which quantifies the difference between the inlet and outlet of the downcomer-riser system. The three parameters are present in equations (5-20) given in [4].
The range of operating conditions corresponds to the range of the power ratio of the turboset, i.e. between 140 and 225 MW. Execution of the procedure for numerically adjusting these parameters allowed values of these parameters to be found that assure the heater model best fits the data. The model has been tested on a PC with an Intel Pentium 2.8 GHz CPU and 4 GB RAM under Microsoft Windows XP Professional x64 Edition; Matlab version 7.2 (R2006a) has been used [14]. The parameters of the economizer-drum model were updated according to the flowchart presented in Figure 3, using a data set of 350 hours of power unit operation.

Fig. 3. Procedure of updating model parameters

Fig. 4. Real time vs. time available for computations
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 routinely implemented in the Optimization Toolbox of Matlab and used to update model parameters is efficient enough, as proved in Figure 4, to follow the operational data in the real-time mode.

Values of updated parameters are used as initial guess conditions in the algorithm adjusting model parameters for the next data sequence. As a result, the minimisation algorithm has a better starting point resulting in a smaller number of iterations required in each sequence. The value of the objective function error and the number of iterations are used as stopping criteria for the parameter updating process. Upon completion of an updating round, the results are recorded and the next sequence of the updating process is started for a new set of operational data (Figure 3). Performance of the procedure of adjusting model parameters is evaluated by analysing the value of the Pearson’s product-moment correlation coefficient between the measured and simulated values of the N-samples long output signals. For each output signal, the correlation coefficient is computed separately. The fit indicator of the model response to data varies over sequences from very low values that indicate a lack of correlation to values that indicate “acceptable” to “very good” correlation. This implies that the procedure of updating model parameters should reject sequences corresponding to low values of the data-fit measures, which is an important conclusion, because it enables the quality of the method to be controlled.

3. Model-based indicators

Performance indicators have been defined in order to assess 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. the amount of transferring 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 the normal operation of a power unit define the tolerance range beyond which the performance is unacceptable. The methodology proposed herein does not eliminate the need for specialists and experts to contribute to the fault recognition process, since their role is to interpret trends in indicators. The method is an extension of available symptom indicators obtained directly from measurements to provide early warning model-based indicators of physical meaning, which gives a straightforward interpretation of the state of the monitored process. The indicators use the energy balance of the drum, which provides total incoming, outgoing, and internal energy transfer rates as formulated in [4]. The mass and energy balance equation given in [4] includes dy-
Dynamic effects, such as energy accumulation, and is given in the general form with the following formula:

$$\begin{align*}
\text{rate energy} & \text{transfer to steam} + \text{rate energy} \text{transfer to feedwater} + \text{rate energy} \text{transfer to metal} = \\
\text{..} & = \text{heat energy rate} + \text{feedwater energy rate} + \text{steam energy rate}
\end{align*}$$

The overall energy transfer rate for the drum is split into the incoming energy rate (feedwater + fuel heat energy) and outgoing energy rate (produced steam). The residual energy rate captured by the left side of the equation (1) is the difference between the incoming and outgoing energy rate to and from the drum. The residual energy rate includes energy transfer from/to steam, water, the metal of the drum, and the downcomer-riser loop.

Figure 5 presents an efficiency indicator based on the energy transfer rate, i.e. the relation of the electrical power rate to the corresponding incoming and outgoing energy rates. The results were obtained for the Jaworzno III TG2 power unit equipped with a coal fired wet bottom steam generator OP-650 driving the three-casing turbine and generator (225 MW). A seven-stage boiler feedwater regeneration system with two condensers and a deaerator is used in this installation. Figure 6 presents an efficiency indicator based on the energy transfer rate, i.e. the relation of the electrical power rate to the corresponding residual energy rates (to/from water, steam, and metal).

![Graphs showing efficiency indicators](image)

Fig. 5. An example of a reconstructed incoming-outgoing rate of energy transfer as a function of the measured electrical power rate
Fig. 6. An example of the reconstructed residual rate of energy transfer as a function of the measured electrical power rate

As shown in Figures 5-6, data points approximately lie along a line (blue solid line) and are bounded by 95% confidence intervals (dashed red lines).

Summary

This paper focuses on the tuning and validation process of the first-principle steam boiler model intended for model-driven evaluation and diagnostics. Moreover, the paper proposes performance indicators that reflect operational changes in the process of generating steam versus assumed statistical bounds. The scope of the proposed methodology is limited to power plant systems with modern data acquisition systems. Such systems should be capable of gathering required input-output data with a sampling frequency adequate for capturing relevant heat transfer and fluid flow dynamics. This paper presents a representative case study where data are gathered with a sampling frequency of 60 seconds. This resolution is sufficient when compared to the normal operation of a power plant. On the other hand, the application scope is limited by assumptions of the model listed in [4].

The first objective of this work was to implement a moderately complex first-principle model of a steam boiler to reproduce operational measurements in real-time simulations. The model was deployed as shown in Fig. 2. The Virtual Power Plant environment [2, 3] was used for this purpose.

The second objective was to develop a tuning method for the model. Such a method 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 since only their rough pre-calculated initial values are available. Measurement data from a 225 MW coal-fired unit were used to validate the
accuracy of the model. 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 70-90%. This proves that the model can be used in further studies and in the development of techniques related to model-driven diagnostics.

To complete the third objective of this paper, the 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 large amount of operational data. Pattern analysis allows a few scenarios to be created, represented by different patterns that correspond to the sequential operation of power units. 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 < 200), transient (200 < rpm < 2950), and synchronised (2990 < rpm < 3010). Sequential operation of a power unit enables two groups of patterns, belonging to transient and steady operation, to be obtained. The indicators (measures) introduced in this paper reflect almost linear relationships and are therefore represented by first order trend curves.

The fourth objective was to automate the calculation process of the indicators. In this respect, a parametric representation of the performance indicators was proposed to allow boundary conditions to be easily imposed. These boundaries can be automatically detected and, as such, are able to be utilised in an early warning malfunction notification. Moreover, such parametric representation facilitates the quantification of the uncertainty of the diagnosis. There are numerous statistical methods supporting the decision-making process that are based on sets of uncertain and inconsistent data. 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 are important from a diagnostic point of view since these indicators directly yield confidence intervals for adjusted parameters and confirm, statistically, the correctness of the proposed approach. The boiler model will also be extended to the superheater sub-model to cover the complete process of steam production. New indicators will be added after consultations within the plant engineering. A new agreement was signed with another power plant in Poland to have more reference validation data sets.

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Bibliography


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Ocena efektywności pracy kotła parowego w elektrowni węglowej

Słowa kluczowe
Elektrownia cieplna, kocioł parowy, modelowanie, identyfikacja układów, Matlab, Simulink.

Streszczenie

W artykule przedstawiono metodę oceny efektywności pracy kotła parowego. Proponowana metoda umożliwia również diagnostykę kotłów parowych w elektrowniach węglowych. Metodologia zaproponowana w artykule umożliwia wyznaczenie fizycznych parametrów kotła parowego w celu analizy jego wydajności za pomocą kluczowych wskaźników procesu. Cele tej pracy są następujące: (i) zbudowanie modelu kotła parowego do odtworzenia pomiarów eksploatacyjnych w symulacji w czasie rzeczywistym, (ii) opracowanie metody strojenia dla tego modelu, (iii) zaproponowanie kluczowych wskaźników wydajności podgrzewacza za pomocą podejścia opartego na modelu, a na końcu (iv) zautomatyzowanie procesu obliczania wskaźników. W artykule omówiono technikę optymalizacji z wykorzystaniem nieliniowej metody najmniejszych kwadratów, która została wykorzystana do dostrojenia parametrów modelu. Zmienne modelu oraz szacunkowe wartości jego parametrów zostały wykorzystane do opracowania wskaźników oceny wydajności kotła opartych na zbudowanym modelu. Walidację modelu przeprowadzono dla danych eksploatacyjnych zarejestrowanych w 225 MW bloku elektrowni węglowej.