

Automatika

Journal for Control, Measurement, Electronics, Computing and Communications



ISSN: 0005-1144 (Print) 1848-3380 (Online) Journal homepage: <https://www.tandfonline.com/loi/taut20>

One approach to temperature distribution control in thermal power plant boilers

Aleksandra Marjanović, Sanja Vujnović & Željko Đurović

To cite this article: Aleksandra Marjanović, Sanja Vujnović & Željko Đurović (2020) One approach to temperature distribution control in thermal power plant boilers, *Automatika*, 61:2, 273-283, DOI: [10.1080/00051144.2020.1733792](https://doi.org/10.1080/00051144.2020.1733792)

To link to this article: <https://doi.org/10.1080/00051144.2020.1733792>



© 2020 The Author(s). Published by Informa UK Limited, trading as Taylor & Francis Group



Published online: 02 Mar 2020.



Submit your article to this journal [↗](#)



Article views: 323



View related articles [↗](#)



View Crossmark data [↗](#)



One approach to temperature distribution control in thermal power plant boilers

Aleksandra Marjanović, Sanja Vujnović and Željko Đurović

School of Electrical Engineering, University of Belgrade, Belgrade, Serbia

ABSTRACT

Optimization of the combustion control process in a tangentially fired pulverized coal boiler, to achieve uniform temperature distribution, is discussed in the paper. This issue is even more critical in those thermal power plants which are not equipped with modern systems for combustion enhancement, such as low NO_x burners. Research has shown that the temperature distribution inside the boiler of such power plant can be controlled by adjusting firing, through coal redistribution among the mills. Furthermore, disturbed flame symmetry (i.e. non-uniform temperature distribution in the boiler) is reflected in a large difference between the output temperatures measured on the left and right sides of the boiler. Given the non-stationary conditions typical of thermal power plant boilers, an adaptive control approach is proposed, based on PI controllers which are very popular in industry and widely accepted. Self-tuning of the PI controllers is based on dynamic model parameters derived applying the weighted recursive least squares (WRLS) method to real data recorded at Nikola Tesla B thermal power plant in Serbia, whose nominal power is 650 MW. The same model was later used to test the proposed control approach.

KEYWORDS

Self-tuning controllers; adaptive PI control; system identification; weighted recursive least squares algorithm; thermal power plant; temperature distribution control

1. Introduction

Combustion is one of the key processes at thermal power plants (TPPs) [1]. The efficiency and availability of the entire TPP depend on its adequate control [2–5]. A good solution for the control task results in many benefits, such as robust maintenance of steam parameters, reduced environmental pollution, less ash and soot, improved efficiency and reliability through the avoidance of large pressure and temperature fluctuations, prolonged exposure of various components to high temperatures, and the like. In the regard, the design of a suitable control algorithm requires theoretical and practical knowledge that can be applied to formulate criteria which encompass all of the above aspects and their interactions. It has been shown that in the case of tangentially fired boilers, all of the above requirements can be addressed by appropriate flame control or, more precisely, by ensuring a central position of the flame [6,7]. The task is not simple because a boiler is a distributed system with many inputs and outputs, such that a satisfactory control design is conditional upon permanent monitoring and understanding of multiple processes.

Over the past decades, different approaches have been proposed and applied to ensure the conditions required for monitoring of various processes that take place in a TPP, aimed at fault detection, preventative maintenance and upgrading of control loops. From a theoretical perspective, expert knowledge is aggregated

in computational fluid dynamics (CFD) models based on Navier–Stokes equations. Experts in thermal power plants use CFD to analyse the impact of different geometries, fuels, firing methods, etc. on the combustion process [8–11]. Even though CFD is a very powerful simulation technique for various phenomena, it uses large amounts of data and consequently requires substantial computation time, and as such it is inadequate for online (real time) applications, which necessitate timely response to changes in the system. For this reason, considerable efforts are being made to improve combustion monitoring, in order to compensate for the lack of a fast model that would help arrive at suitable control actions. This is reflected in the development and implementation of different types of sensor systems that are expected to provide sufficient information on the status of all relevant subsystems [12]. In recent years, optical technologies such as pyrometers - intelligent thermal radiation-based sensors have been of special interest, given that they allow temperature in the TPP furnace to be measured in a non-invasive manner. By installing an adequate network of pyrometer units at different heights and at different points in the same horizontal plane, it is possible to obtain a 3D representation of the temperature field in the boiler [13].

However, a standard boiler design is most often such that the installed control system focuses more on monitoring steam parameters than flame behaviour indicators. In many cases, combustion performance can be

assessed through its reactants (coal consumption, air flow) and products (flue gasses, ash). Many TPPs rely on a limited number of measurements that either provide global information, like the total coal demand, or local information like excess oxygen measured at a single point. As such, investigations that establish a correlation between available measured data and the nature of processes inside the boiler are extremely important. For example, the flue gas temperatures on the left and right sides of the boiler directly indicate whether the respective walls of the boiler are exposed to high temperatures, and to what extent. If one of these two temperatures is significantly higher over a relatively long period of time, then the walls of some of the boiler components are constantly affected by high temperatures, which may lead to numerous undesirable effects, like degradation and cracking of the material and corrosion. Experience shows that this type of temperature profile is indicative of flame asymmetry. On the other hand, the aforementioned pyrometer system could give a more detailed insight into the spatial temperature distribution, due to the large number of measuring points. However, due to high demands concerning the maintenance of pyrometer system functionality (such as clear optical path), which are usually hard to satisfy in critical operating conditions inside TPP boilers, the practice has shown that these measurements can be quite sensitive and unreliable. This is why the operators in TPPs continue to measure flue gas temperature at the top of the furnace on the left and right sides of the boiler as an indicator of the non-uniform temperature field. One of the main contributions of this paper lies in the employment of these common temperature measurements for the improvement of flame symmetry in the boiler, namely in the applicability of the proposed control algorithm in conditions lacking numerous measurements from expensive, modern sensor systems, e.g. pyrometers.

Temperature field inside the boiler can be affected in different ways: air flow control, coal quality, deslagging, etc. Let us stress out that this issue is very important in those TPPs which are not equipped with modern systems such as low NO_x burners. One such TPP is Nikola Tesla B1 (TENT B1). Even though it is among the bigger ones in Serbia, it is yet to be modernized with low NO_x burners and OFA channels are nonexistent at the moment. This is why the combustion regulation requires more attention and higher quality which can be achieved due to better controllability of mill's parameters. The present research explores the possibility of furnace temperature distribution control based on the number of active mills and their loads. The effect of mill contribution in tangentially fired boilers is studied in detail in [14–16]; it appears that appropriate adjustment of the mill load can control the position of the centre of the flame. Namely, the raise in the speed of the feeder associated with particular mill increases the

amount of coal supplied to the boiler by that mill. In order to fulfil technological requirements, the amount of secondary air changes accordingly. This increases the speed of the air mixture coming out of that burner's nozzle, thus shifting the centre of the flame away from that nozzle. The same effect is noted at different heights of the boiler. Furthermore, the control problem can be simplified in terms of reducing the number of control variables by monitoring pairs of opposite mills instead of individual mills. This is achievable due to the fact that adjustment of feeder outputs within a mill pair results in a shift of the flame along the axis formed by the burners' nozzles of the respective mills. Taking these control variables and temperature measurements on the left and right sides of the boiler, the paper proposes a flame centring solution for boilers not equipped with advanced sensor systems. However, significant changes in mills' load can greatly influence the composition of flue gases and consequently the quality of combustion process, irrespective to the flame centring. That is why this control task must be approached with much caution. Proportional-integral (PI) control is considered, given that it is the most widely applied control approach at industrial facilities [17,18]. Given the great importance of such controllers, numerous modifications and upgrades of the basic configuration have been developed over time to address its shortfalls. Analytical tuning of PI controller parameters for different types of processes is discussed in [19,20], but artificial intelligence methods can be used for that purpose as well [21–24]. In view of the fact that PI controllers are basically designed to function around a specific operating point, a large number of PI controller upgrades are related to self-tuning of controller parameters, depending on different operating modes. For this reason, the present research considers PI control with occasional controller parameter updates. Therefore, the additional contribution of the paper is the implementation of a conventional PI control instead of a complex algorithm such as neural networks, genetic algorithms, extremum seeking control and others, which have been used for combustion control.

Following Introduction, Section 2 describes various concepts associated with the combustion process and highlights firing, whose adjustment for control purposes is addressed in the paper. The same section also provides an overview of the consequences of improper combustion control and emphasizes the importance of improving this regulation loop. A description of the proposed control approach and a brief theoretical background of the process identification method on which the proposed control approach is based are provided in Section 3. Section 4 presents the main results of testing of the proposed control approach on a model identified using real measurement data from TENT B1 in Serbia.

2. Description of the coal firing process

Coal firing is one of the main processes in a thermal power plant and it consists of several stages. The coal is transported from a bunker through dosers and feeders to recirculation channels and ultimately to mills. Partially dried coal that reaches the mills is additionally dried and then ground. Coal-drying flue gas is supplied from the top of the boiler furnace to the mill inlets via the recirculation channels. The air mixture is then routed to the pulverized coal burner. Two fresh air fans supply fresh air to the boiler. The air is heated in a regenerative heater using the heat of the flue gases. The heated air is divided into three flows: primary, secondary and tertiary. The so-called primary air is used for controlling the temperature of the air mixture. The secondary air is led to the burners to ensure stoichiometric combustion. It is blown into the furnace by means of special nozzles. A part of the tertiary air is routed under a bar for additional combustion and the remainder is used to cool burners for secondary (liquid) fuel. The heat, as a combustion product, is delivered via flue gases to the operating fluid (water or steam), which circulates through a system of pipes (economizer, evaporator, reheaters and superheaters), causing unavoidable losses. The heat loss is the difference between the supplied and produced useful amounts of heat, whereas boiler efficiency is defined as the ratio of heat evaporated in the steam to heat provided by the fuel. Boiler efficiency is commonly expressed as a percentage and depends on overall losses of heat, which can arise in several different ways.

The greatest loss is associated with exiting flue gases. The elevated temperature at the outlet largely depends on the position of the flame, level of cleanliness of the piping, boiler load and the like. Even though these types of heat losses cannot be fully suppressed, they can usually be reduced by proper combustion control. Apart from increased heat losses as a result of high temperatures, which to a large extent depend on combustion process parameters, different types of faults can occur in the furnace. The temperature may increase gradually over the years, but also instantaneously, due to a sudden decrease in water or steam flow. Large temperature variations can lead to damage, deformation or cracking of material. Some parts of the system have a considerably reduced life cycle due to permanent exposure to high temperatures, an aggressive environment, corrosion, etc. Investigations have shown that more than 40% of all faults at TPPs are caused by high temperatures [25]. Apart from damage to material due to high temperatures, which can degrade performance but also have serious consequences for the system, precipitation and slagging on the walls of the boiler and its subsystems is a major problem [26]. Proper flame (i.e. furnace temperature) control ensures cooling and removal of ashes by a special ash transport system. Failing this,

deposits on pipe walls impair heat transfer and thus reduce boiler efficiency. On the other hand, they can also limit the flow of flue gases. A robust combustion control design should regulate this and reduce corrosion of the furnace and its various components, such as the reheaters and superheaters.

It clearly follows from the above that maintenance of a uniform temperature distribution is essential. However, the need for combustion optimization is often constrained by the level of capability to monitor and control the process. In general, combustion can be monitored in various ways, depending on the purpose of the information provided – whether the operator needs it for manual control or fault diagnostics or automated control. Instrumentation provides some information on flame behaviour (temperature, radiation, pressure, etc.) in the form of raw data, from which characteristic parameters that describe the flame at a given time need to be derived. Certain quantities obviously need to be measured in absolute terms, with a certain level of accuracy, whereas others are measured relative to nominal values, maximum permissible values and the like. If a measured quantity is used in its original form, without subsequent processing for monitoring and control purposes, then we have direct monitoring of the flame. This approach is ideal but often difficult to implement in practice, in an industrial environment. Contrarily, indirect monitoring involves system state assessment based on processing of measured data in situations where absolute quantities do not provide significant information and when the combustion process parameters do not have a direct relationship with those measurements. For example, sometimes it is necessary to make certain correlations with previous situations in order to explain the system behaviour and obtain meaningful estimation of combustion conditions [27]. In both cases, the control algorithm needs to be consistent with the amount and type of available and relevant measured data and its relation to the desirable optimal behaviour of the system.

Once set up, the controller configuration and parameters may remain constant if they ensure satisfactory performance of the various stages of the system. However, due to variable conditions to which TPP subsystems are exposed, adaptive control approaches are often used, which adapt their parameters to the working conditions. Despite the fact that a large number of manipulated variables at TPPs are correlated and that their behaviour cannot be fully decoupled, most controllers are of the single-input–single-output (SISO) type, primarily owing to their simplicity and intuitive tuning of parameters. As a result, a multivariable control problem is often reduced to several SISO control loops. The shortfalls of this approach can be noted when the nominal operating mode is disturbed or changed because interfacing of the various control channels becomes

prominent. Additionally, at TPPs the control structures are mostly linear, such as PI controllers which cover more than 90% of practical control requirements. Given the variable conditions in TPP boilers, the PI structures have been improved over time and this paper proposes an innovative adaptive approach to temperature distribution regulation.

3. Adaptive control algorithm design

The temperature field in TPP boilers is under the influence of many technological and control parameters, as well as different disturbances. However, bearing in mind the significant impact of mill loads on the flame asymmetry and its controllability with respect to these inputs, the paper focuses on the simplified model which describes the influence of relative feeder speed differences on the temperature difference $T_L - T_R$. The layout of the proposed control approach is shown in Figure 1. The main controller of the TPP unit specifies the total amount of coal needed to achieve the reference pressure of fresh steam, which is directly correlated with the required nominal power output. The coal demand is commensurate with the total speed of all feeders. This paper deals with firing reallocation among the mills or, in other words, the way in which the speed of each mill feeder is determined (d_1, \dots, d_N). Assuming that N mills are active, the load reallocation to each individual mill is an optimization problem with $N-1$ degrees of freedom because the only limitation that needs to be observed is the total load of all the mills. If a tangentially fired boiler has N mills, then the number of pairs of opposite mills is equal to $N/2$. To simplify the problem and ensure balanced loading of the mill pairs, this paper assumes that the same amount of coal is assigned to each mill pair. Also, the previous conclusions hold: (1) asymmetry information comes from the difference in temperatures measured on the left and right sides of the boiler ($T_L - T_R$) and (2) flame asymmetry can be

manipulated by varying mill loads or, more precisely, by adjusting the load of mills within each mill pair by changing the speed of respective feeders ($n_1, \dots, n_{N/2}$, where $n_i, i = 1, \dots, N/2$ stands for the relative difference in feeder speeds within the i th pair).

The aforementioned conclusions have been studied in detail and reported in the literature, but also corroborated by a large number of experiments conducted at TPPs in Serbia by the authors of this paper. Some of these results are provided in the next section. The regulation goal can be defined by maintaining the left and right boiler temperatures nearly the same (their difference around zero). Hence, the control algorithm receives one input - temperature difference and has $N/2$ outputs for coal redistribution among each pair (if the controller output is zero, both mills of the pair have an equal share in firing). In some scenarios, the number of control variables can be less than $N/2$. The exact design of the control algorithm is implemented in the *Controller Structure Selection module* and it will be additionally explained.

The basis of the presented control approach consists of $N/2$ PI controllers. As previously mentioned, these controllers have been well accepted in industry and most TPP control loops have been implemented using PI controllers. TPP operating conditions vary, such that PI controller settings need to be updated from time to time. Consequently, one of the PI controller self-tuning methods is recommended, either some iterative approach [28,29] or periodic parameter tuning using one of the common procedures (e.g. the Ziegler Nichols method). The results presented below are based on the step response tuning (SRT) method, as proposed in [30]. Moreover, the step response needs to be known in order to implement this method. To ensure non-invasive tuning (avoid disturbing the ongoing process), the recommended approach relies on the WRLS procedure for model parameter estimation (*Online Model Identification module*).

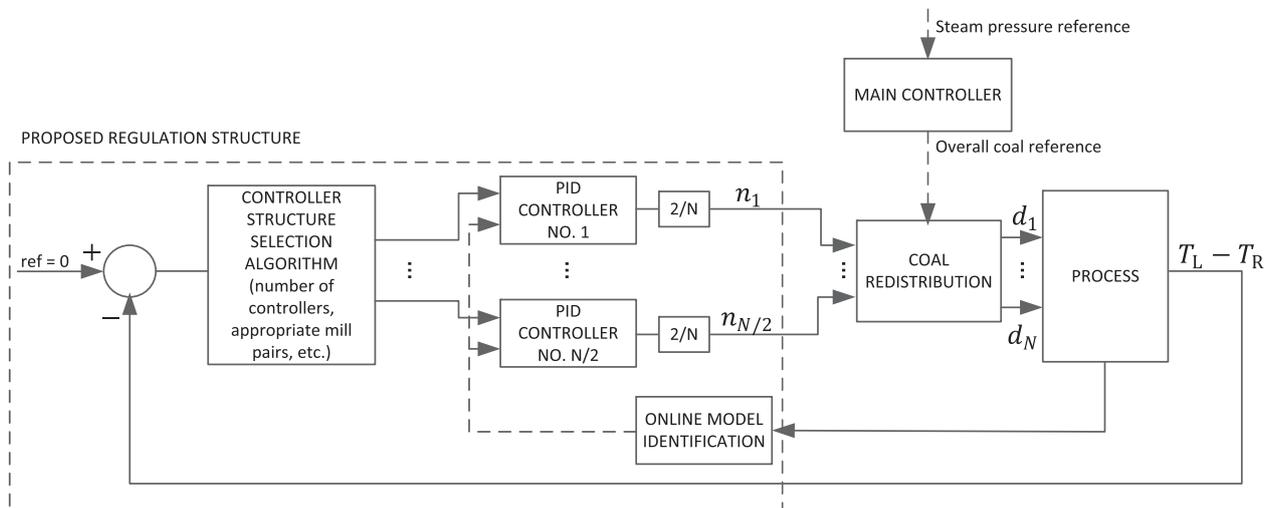


Figure 1. Block diagram of the proposed control approach.

Note that Figure 1 includes the *Coal redistribution module*, which has great importance in the real system. The role of this module is to divide the total coal demand over all active mills considering the parameters n_i . The absolute value of T_L and T_R temperatures will be dictated by this total coal demand, and therefore by d_1, \dots, d_N . However, the difference $T_L - T_R$ does not depend on the absolute, but the relative feeder speed differences, i.e. parameters n_i . Since this temperature difference is the desired controlled variable, the paper suggests the model from the inputs n_i to the output $T_L - T_R$, without taking into consideration the overall coal demand. The proposed algorithm consists of following steps:

- *Step 1: (Online model identification module)* Perform model identification on process input ($n_1, \dots, n_{N/2}$) and output ($T_L - T_R$) measurements as described in detail in Section 3.1. This is done bearing in mind that the system behaves differently depending on the disposition of active mills, namely the shutdown of each mill has different effect on the flame symmetry. Thus the model structure varies with the change of active mill number and position. On the other hand, the process itself is highly non-stationary due to changing condition of mill impellers, variable calorific value of coal and exposure to different sorts of disturbances. Therefore, it is necessary to perform online identification procedure such as WRLS method. Additional explanations concerning this module are provided in Section 3.1.
- *Step 2: (Controller structure selection algorithm module)* Taking into account the number and the position of active mills, select the control structure. In general case, there will be $N/2$ mill pairs, i.e. $N/2$ control variables. However, as is often the case, if one of the mills is inactive, the number of mill pairs is reduced to $N/2 - 1$. The active mill which is opposite to the inactive one is kept at a constant load of $1/(N - 1)$ of the total amount of coal, and the remaining coal demand is distributed evenly over $N/2 - 1$ pairs. In other words, the control algorithm must take into account the number of active mills and identify mill pairs that require firing reallocation. For example, let us observe the boiler configuration from Figure 2. If all the mills are active, the appropriate controller configuration would include four PI controllers for each mill pair M1–M5, M2–M6, M3–M7 and M4–M8. The total amount of coal would be divided in four equal shares over each mill pair, and then additionally distributed among each pair in accordance with calculated control signals n_1, \dots, n_4 . However, if one of the mills is inactive, e.g. M3, then there would be three control variables, one for each active pair M1–M5, M2–M6 and M4–M8. The share of the mill M7 in overall coal demand would be kept constant at $1/7$, while

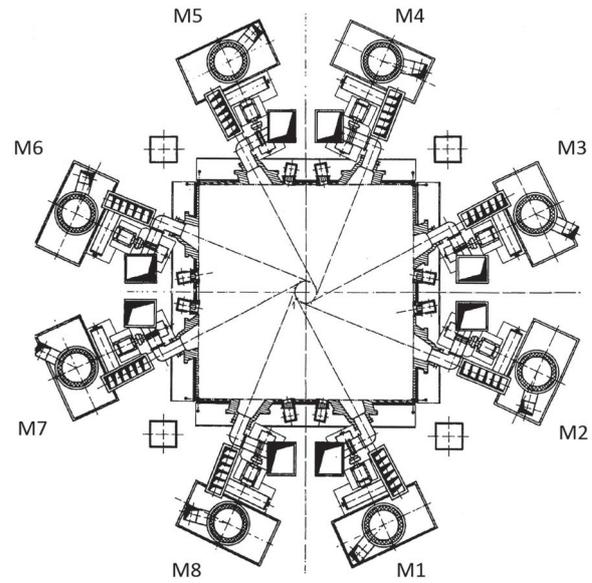


Figure 2. Tangential mill configuration at TENT B1.

the remaining $6/7$ of total coal demand would be distributed evenly over active mill pairs.

- *Step 3: (Controller parameters tuning)* Update the parameters of PI controller using the SRT method [30]:

$$K_p = \frac{\mu T}{K\tau}, \quad K_i = \frac{\mu}{K\tau}, \quad (1)$$

where parameters τ , T and K are determined experimentally as the time needed for the step response to achieve 10% of the steady-state value, the time interval in which step response goes from 10% to 63% of the steady-state value and the ratio between steady-state values of output and input, respectively. Parameter μ is adjusted with respect to desired phase margin, within the range

$$0.32 \leq \mu \leq 0.54. \quad (2)$$

It is important to emphasize that the step response needed for the estimation of the PI controllers' parameters is obtained using the input–output models obtained in *Step 1*. In other words, tuning of PI controller parameters is based on a model whose parameters are updated to reflect changes in the real system. The PI controllers are retuned when the difference between the boiler's left- and right-side temperatures exceeds a predefined threshold value. If the temperature difference is not the result of a change in the process itself, but a consequence of some disturbance, the estimated model parameters will remain the same and the PI controller gains will not change. Otherwise, the parameters need to be adjusted to the new behaviour of the process.

- *Step 4: (Coal redistribution module)* Given that the control loop contains only one output and there are $N/2$ PI controllers in the general case, the contribution of each controller is scaled by $2/N$. The obtained

values $n_1, \dots, n_{N/2}$ are forwarded to the *Coal Redistribution module*, where the amount of coal to be supplied to the boiler by each mill is determined based on the recommended relative differences within each mill pair and the total coal demand (set by the main controller), as explained in *Step 2*.

3.1. WRLS parameter estimation

The idea behind estimating linear model parameters is comprised of estimating the model coefficient and estimating the desired output, based on a properly selected criterion function which determines the correlation between estimation robustness and the difference between the measured and estimated outputs. In dynamic (non-stationary) systems, the recursive approach to parameter estimation is significant because it enables constant updating of model parameters based on different operating modes [31–34]. Let us assume that the structure of the process model is

$$y(k) = - \sum_{n=1}^{M_y} a_n(k) y(k-n) + \sum_{m=1}^{M_u} b_m(k) u_m(k-1) + \zeta(k), \quad (3)$$

where u and y are corresponding input and output signals, M_y is the model order, M_u is the number of model inputs and $\zeta(k)$ is the measurement noise. The coefficients $a_n(k)$ and $b_m(k)$ are unknown model parameters, which are varied in the recursive procedure based on the behaviour of the system. The above equation can also be written in the form of linear regression:

$$y(k) = W^T(k) X_i(k) + \zeta(k), \quad (4)$$

where W^T is the regression vector comprised of corresponding measured inputs and outputs, and $X_i(k)$ is the vector of unknown parameters. The model parameter identification problem is then reduced to proper selection of a criterion function. The present research considers the application of an exponentially weighted recursive least squares (EWRLS) method. The main difference between this and the original RLS procedure is limited memory, i.e. limited effect of previous measurements on parameter estimation. In other words, by introducing a forgetting factor, the weight of old measurements is reduced so that the algorithm can be more sensitive and can better reflect the changes in parameters. This is achieved by a criterion function of the form:

$$J_\rho(k) = \sum_{i=0}^k \rho^{k-i} e^2(i), \quad (5)$$

where $\rho \in (0, 1]$ is the forgetting factor and $e(k) = y(k) - W^T(k-1)X(k)$ is the prediction error. Selecting $\rho = 1$, the algorithm is reduced to the conventional RLS approach. However, if the parameters

vary over time, the selection of $\rho < 1$ will have a different effect - a different level of forgetfulness of previous measurements. A low forgetting factor will result in quicker adaptation of parameters, because old measurements become less important (i.e. the memory of the algorithm is shorter). Consequently, the parameter estimation variance increases because the algorithm is more sensitive to new, noisy measurements. Minimization of criterion (5) is reduced to the recursive form:

$$\hat{W}(k) = \hat{W}(k-1) + K(k)e(k), \quad (6)$$

where

$$K(k) = P(k-1)X(k)[\rho + X(k)P(k-1)X(k)]^{-1}, \quad (7)$$

and the gain matrix is

$$P(k) = \frac{1}{\rho} [P(k-1) - K(k)X^T(k)P(k-1)]. \quad (8)$$

The above procedure will be used to identify the model, from relative load difference within each mill pair to the temperature difference between the left and right sides of the boiler, i.e. we consider $y = T_L - T_R$ to be the output and relative loads $n_1, \dots, n_{N/2}$ to be the inputs of the model ($M_u = N/2$). In case of inactive mills, the model structure is slightly changed. Namely, the modelling is done using $M_u = N/2 - 1$ model inputs corresponding to each active mill pair, while the inactive mill is referred to as a disturbance. For example, consider the mill configuration shown in Figure 2, in scenario when mill M3 is inactive. Then the variables n_1, n_2 and n_3 represent relative feeder speed differences within pairs M1–M5, M2–M6, M4–M8. This results in three transfer functions, one from each mill pair to the output temperature difference. For TPP employee safety, the proposed control approach was initially tested using such a model.

4. Case study: tangentially fired 650 MW TPP boiler

Nikola Tesla B TPP (TENT B) is located on the right bank of the Sava River, 50 km upstream from Belgrade. It comprises two of the largest power supply facilities in Serbia, whose nominal power is 650 MW. During reconstruction of TENT B1, a Distributed Control System (DCS) was installed. This enabled upgrading of control structures. The steam boiler at TENT B1 was designed by the Polish company Rafako under license from Sulzer [35]. The cross section of the boiler is 20 m × 20 m. The primary fuel is lignite coal with highly varying calorific value, and the secondary fuel, used for startup and fire stabilization, is fuel oil. Unit B1 has eight mills of equal capacity, located at the ground level of the boiler room, and there are three levels of

burners. Combustion uniformity at the different levels of the furnace is achieved by controlling each of the three burner apertures. In unit B1, the configuration of the burners is tangential (Figure 2), to induce whirling of combustion products and thus improve combustion and heat exchange. This configuration additionally results in combustion stability and lower maximum flame temperatures.

To illustrate the non-uniformity of the temperature field and the control capability, the graphics below show temperature variations on the left and right sides of the boiler in 1 day. Figure 3 depicts temperature in the coordinated operating mode (firing controlled by fresh steam pressure ahead of the turbine and turbine valves controlled by the active power of the block). It is apparent that the temperature difference between the left and right sides of the boiler during long time intervals was even greater than 100°C . This can be a

consequence of boiler's load, especially since the bigger load puts more emphasis on the difference in mills' properties and therefore contributes to the temperature imbalance. However, it is interesting to note that the difference decreased in the interval from 1000 to 1200 min. Then the active power dropped to the technical minimum and the mill that led to the loss of symmetry was shut down. Another example of temperature non-uniformity across the horizontal section of the boiler is shown in Figure 4, when the block was in the uncoordinated mode for most of the time, meaning that the feeder speeds were manually set by the operators bearing in mind the condition of each mill. The differences are still in part large, but what is interesting is that the left-side temperature is usually higher than that on the right side. This diagram demonstrates that the temperature difference is an extremely dynamic parameter; apart from asymmetric mill load changes,

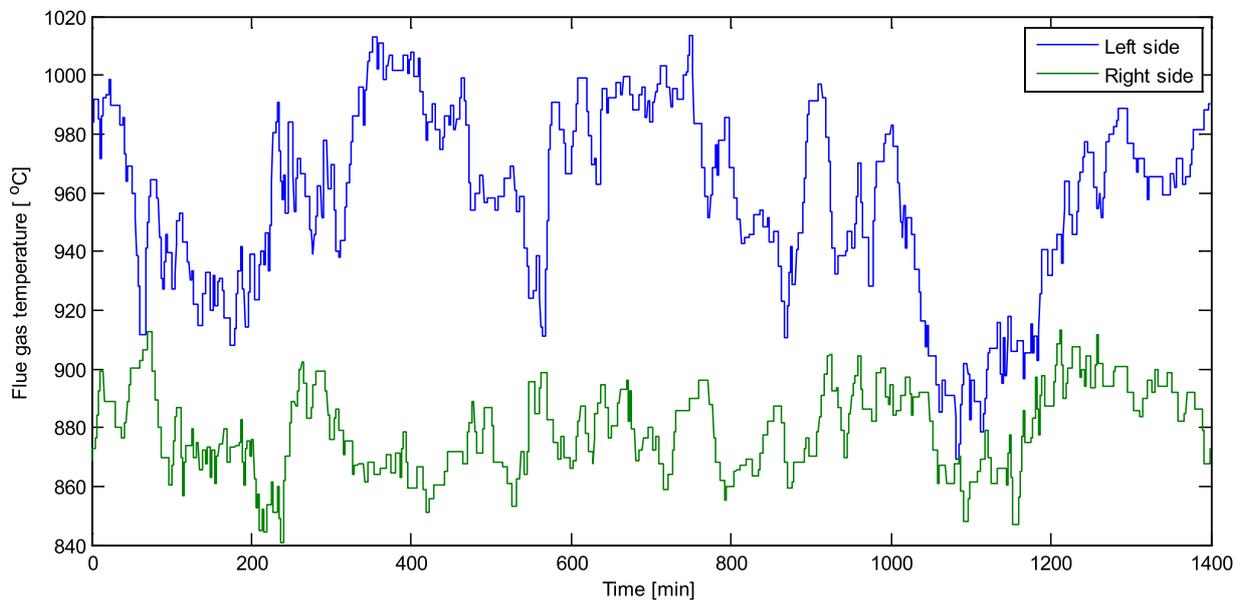


Figure 3. Flue gas temperatures in the coordinated operating mode during a single day.

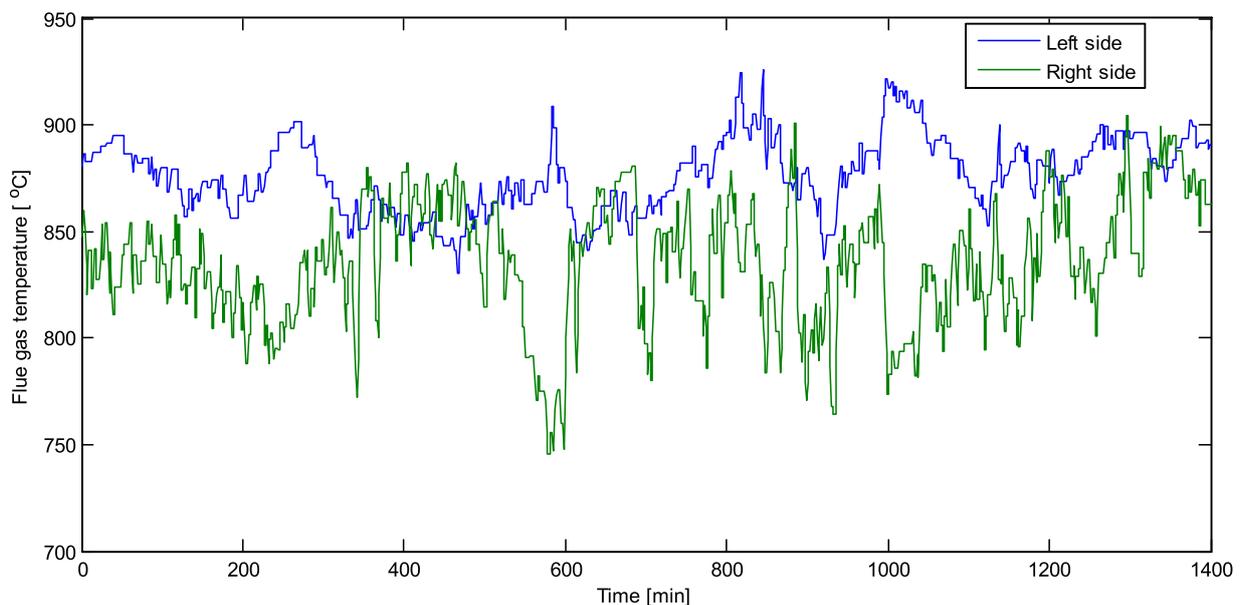


Figure 4. Flue gas temperatures in the uncoordinated operating mode during a single day.

it is influenced to a large extent by the capacity and current state of the impellers, ventilation capacity of the active mills, but also by non-uniform physical and chemical properties of the coal currently delivered to the mills. Analyses of this type further emphasize the importance of the attempt to ensure uniform temperature distribution inside the boiler. Thanks to the visual display afforded by the pyrometer sensor array installed at TENT B1, it has been confirmed that the temperature difference between the flue gases on the left and right sides of the boiler reflects the extent of displacement of the centre of the flame (in this case towards the left side).

As previously pointed out, past analyses of the feeder speed impact have shown that the behaviour of the feeders can be viewed in pairs. In other words, by adjusting the speeds of opposite feeders within each pair, the centre of the flame can be moved along the axis determined by the position of the respective burners' nozzles. As a result, the number of control inputs is reduced upfront to four. However, before proceeding to closed-loop testing, let us look at the results of model parameter estimation by the WRLS method described in Section 3.1, which will be used to tune the PI controllers. A second-order ($M_y = 2$) model is proposed, which assumes that the temperature difference $T_L - T_R$, as the output from the model at any time, depends on the temperature difference of the previous two samples and the relative speed differences within each feeder pair, which represent inputs ($M_u = 4$) into the model. The structure of the model depends on the number and disposition of active mills. To ensure continuous operation of the entire system, only one mill is overhauled at a time. In other words, the state of the mills differs, as does the impact of mill pairs on temperature. The difference in impact is modelled through parameters b_m of the model (3).

For illustration purposes, let us examine a scenario in which mill M3 is inactive. Figure 5 shows real signals measured at TENT B1, which were used as modelling inputs. As can be seen from the same figure the concentration of oxygen experiences significant changes during time. Such changes can also have a negative impact on the quality of combustion process and should not be neglected. They were sampled at a rate of $T = 1$ s. The signals represent the difference in the participation of opposite mills, scaled by that of the decoupled mill. Figure 6 shows the results of the proposed estimation method (output estimation is based on previous predictions, not the measurements), along with the measured temperature difference between the left and right sides. It is apparent that the estimated and real temperature differences are close and that the model appropriately reflects the dynamics of the system, and that it is therefore adequate for PI controller tuning and testing of the proposed control approach itself. In order to additionally examine the obtained model, we

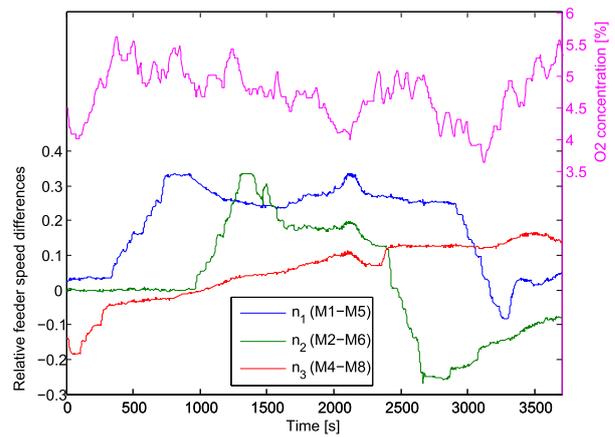


Figure 5. Relative differences of feeder speeds within each pair (left-side axis) and O_2 concentration (right-side axis).

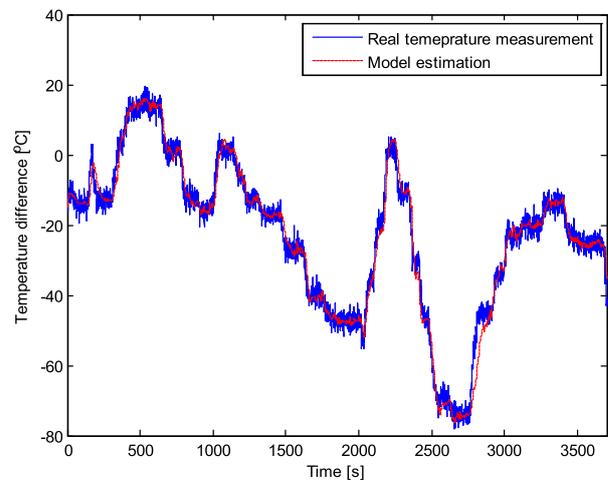


Figure 6. Real temperature versus estimated model output.

conducted the validation procedure described in [36]. Figure 7 shows autocorrelation function of measurement residuals as well as the correlation between one of the inputs and measurement residuals. The first is similar to Dirac function, and the latter also has extremely low values, which is a good indicator of successful modelling.

The sampling rate of the main controller is $T = 200$ ms. It issues a coal demand command commensurate with the total feeder speed. However, given that temperatures are much slower physical quantities, the sampling rate of the control structures shown in Figures 1 and 8 is $T = 1$ s. As previously mentioned, one of the mills is usually inactive at TENT B1, so a modification of the firing reallocation structure from Figure 1 was proposed. The main change is shown in Figure 8. Instead of dividing the total reference amount of coal into four equal parts and forwarding the information to the algorithm to determine the optimal distribution within each pair, first $1/7$ of the total quantity was allocated to the mill coupled with the inactive mill (e.g. if mill M3 is inactive, mill M7 gets $1/7$ of the total load), while the remainder of the total demand was divided among the three pairs of active mills, where

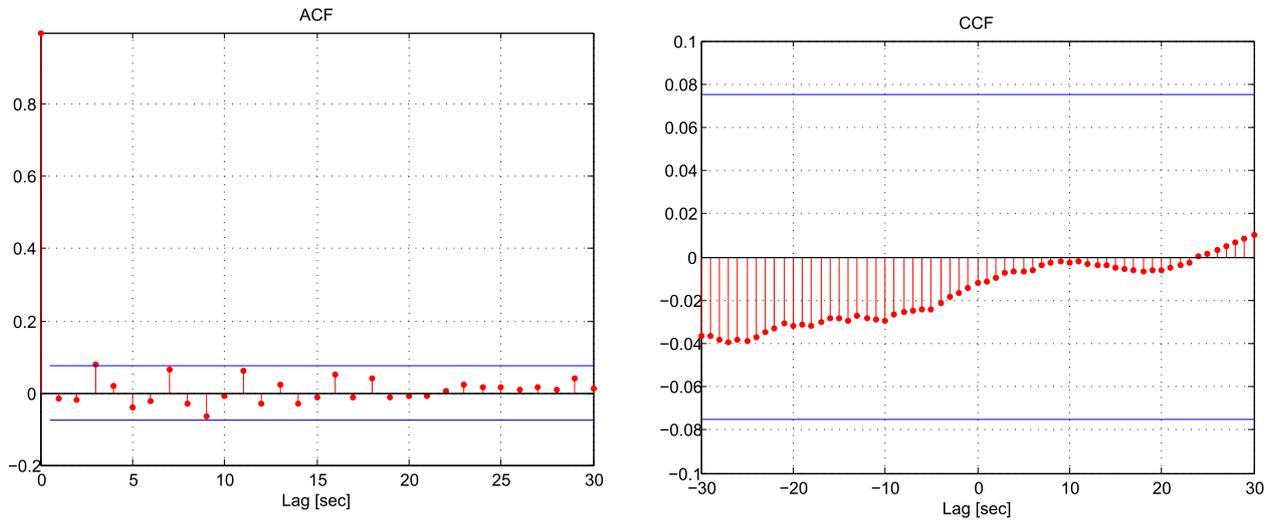


Figure 7. Model validation: autocorrelation of measurement residuals (left) and cross-correlation between input n_2 and measurement residuals (right).

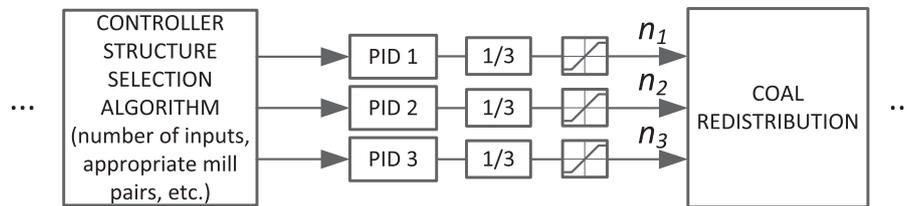


Figure 8. Segment of the structural block diagram modified for the one inactive mill scenario.

it was redistributed. The way in which the redistribution takes place is determined by the outputs from the corresponding PI controllers. Additionally, restrictions of control signals $(n_{\min}, n_{\max}) = (-0.4, 0.4)$ were introduced, as required in practice. The restrictions prevent underloading and overloading of the individual mills. The previously developed second-order model with time-variable parameters was used to test the proposed control structure. In other words, a dynamic model corresponding to the real process observed in the analysed time interval was employed for further testing. The simulations were performed in *Simulink* environment with fixed sample time of $T = 1$ s. First, we analyse the closed-loop behaviour of the system, in the case of the fixed PI controller parameters, specified at the beginning of simulation sequence using the model parameters provided by the identification procedure. The simulation starting point is carefully chosen so that the model is stationary during that time period, i.e. the parameters are more or less constant. These initial parameters result in three transfer functions, from relative difference in feeder contributions $n_i, i = 1, 2, 3$ to the temperature difference $y = T_L - T_R$ (according to Figure 1):

$$G_1(z) = \frac{Y(z)}{N_1(z)} = \frac{1.281z^{-1}}{1 - 0.595z^{-1} - 0.3447z^{-2}},$$

$$G_2(z) = \frac{Y(z)}{N_2(z)} = \frac{-26.749z^{-1}}{1 - 0.595z^{-1} - 0.3447z^{-2}},$$

$$G_3(z) = \frac{Y(z)}{N_3(z)} = \frac{19.525z^{-1}}{1 - 0.595z^{-1} - 0.3447z^{-2}}.$$

In this case, the PI controller parameters were $K_{p1} = 0.1, K_{p2} = -0.005, K_{p3} = 0.006$ and $T_{i1} = T_{i2} = T_{i3} = 19$. Figure 9 shows the simulated model output with such parameters. It is evident that the PI controllers tuned in this manner controlled the system very well, maintaining the desirable temperature difference around 0°C , in the given time interval. The graphic shows proper response in the case of minor disturbances, effectively following the reference. However, after a certain time, when the operating mode changed, control was no longer appropriate; the error, or the output temperature difference, increased.

It is for this very reason that controller parameters need to be periodically tuned. Tuning was considered when the temperature difference exceeded 30°C . The outcome of such adaptive control is shown in Figure 10. Testing was conducted using the same sequence of model parameters as in the previous case (with fixed PI controller parameters). It is apparent that regulation was much more effective. When the temperature difference increased and reached the specified 30°C , the PI controller parameters were retuned, based on the model parameters that described the behaviour of the system at that time. Then a certain dead/blanking time was left for the process itself to begin to respond to the change in the controller parameters. This parameter is also pre-defined at can be set by the operator. This parameter

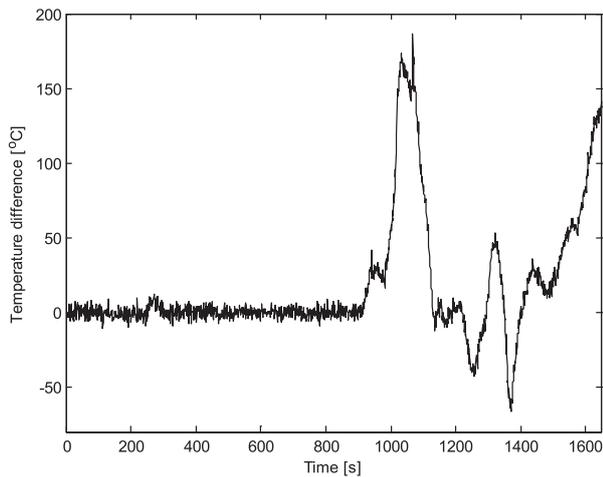


Figure 9. Output temperature difference regulation with fixed PI parameters.

was set to 10 s in the simulations. If the temperature did not drop at the end of that time, the controllers were retuned, and so on. The results shown in 10 are promising and suggest that this type of modification of conventional PI control can be used to maintain a uniform temperature distribution in the boiler furnace. Figure 11 shows the corresponding PI controller outputs, which indicate how the coal is redistributed among each mill pair (i.e. provide the share of each mill in the firing process). The actual amount of coal to be supplied by each mill to the boiler also depends on the total coal demand determined by the main controller. The redistribution of coal among the mills is responsible for the temperature difference between the left and right sides of the boiler, while the absolute values of these temperatures were determined by the total firing requirement. As stated before, quick changes in mills' load can have a bad influence on the composition of flue gases. Therefore, the proposed procedure for controller parameters' tuning should be done bearing in mind the permissible changes in gases' concentrations by limiting

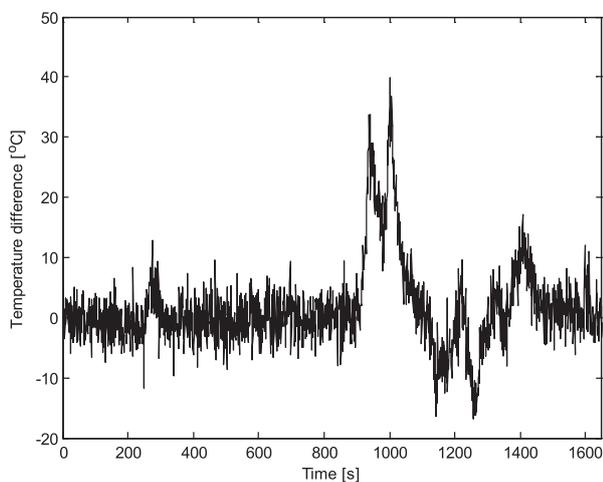


Figure 10. Output temperature difference with adaptive PI parameters.

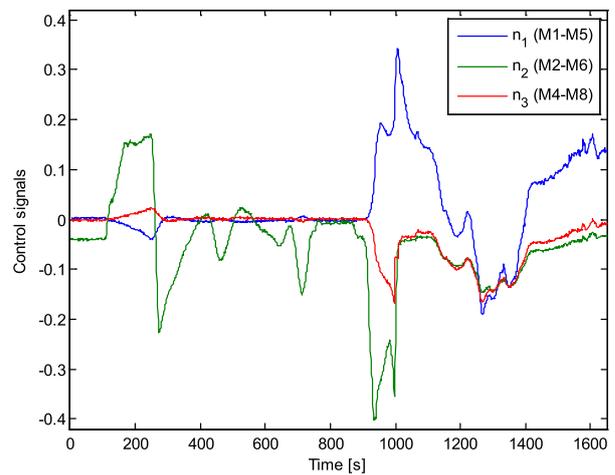


Figure 11. Control signals during regulation with adaptive PI parameters.

the speed of the regulated system. However, this kind of analysis was not carried out in the paper, because the testing was conducted on a simpler model which does not include outputs corresponding to the concentration of flue gases.

5. Conclusion

The paper presented a boiler combustion control approach based on monitoring of flue gas temperatures on the left and right sides of the boiler, which are indicative of the spatial temperature distribution in the furnace. The proposed approach is comprised of several integral parts. One of them is the algorithm which determines the central part of the proposed strategy, in terms of the number of PI controllers, the mill pair controlled by a certain PI controller, and the like, based on the number of active mills, their configuration and other requirements that might arise during operation (such as the need to keep the contribution of one of the mills constant). PI controller tuning is event based and conducted applying the SRT method, when the controlled temperature difference exceeds a predefined value. A variable-parameter model, based on the WRLS identification method, was used to implement SRT and later test the control structure. The model itself was constructed using real data from Nikola Tesla B TPP, unit B1 (TENT B1), in Serbia. The adequacy of the model for control purposes was first checked by comparing estimated and measured data, demonstrating that the model was largely able to keep track of the dynamics of the real process. Despite the fact that the model was tested using real data from TENT B1, it is easy to generalize and apply the results to other, similar systems. The results are indicative of the potential of the proposed control approach and, to begin with, of the possibility of using it in parallel with the existing DCS system, to suggest adjustments. In conjunction, they are deemed to improve overall boiler performance.

Acknowledgments

The authors gratefully acknowledge the support from the Ministry of Education and Science of the Republic of Serbia, research projects TR32038 and III42007.

Disclosure statement

No potential conflict of interest was reported by the author(s).

References

- [1] Flynn D. Thermal power plant simulation and control. London, UK: IET; 2003.
- [2] Yin C, Caillat S, Harion JL, et al. Investigation of the flow, combustion, heat-transfer and emissions from a 609mw utility tangentially fired pulverized-coal boiler. *Fuel*. 2002;81(8):997–1006.
- [3] Krishnan PH, Vinoth R. Monitoring and controlling the combustion quality in thermal power plant boiler using image processing and robotic arm. 2014 international conference on green computing communication and electrical engineering (ICGCCEE); 2014. p. 1–4.
- [4] Yuvaraj D, Kareem AA, Ranjith SM, et al. Design and simulation of thermal power plant using PLC and SCADA. *Programmable Device Circuits Syst*. 2016;8(8):228–232.
- [5] Martín-Sánchez JM, Lemos JM, Rodellar J. Survey of industrial optimized adaptive control. *Int J Adapt Control Signal Process*. 2012;26(10):881–918.
- [6] Wang Xf, Zhou HC. Simulation on an optimal combustion control strategy for 3-d temperature distributions in tangentially pc-fired utility boiler furnaces. *J Environ Sci*. 2005;17(2):305–308.
- [7] Marjanović A, Krstić M, Kovačević B. Control of thermal power plant combustion distribution using extremum seeking. *IEEE Trans Control Syst Technol*. 2017;25(5):1670–1682.
- [8] Coimbra C, Azevedo J, Carvalho M. 3-d numerical model for predicting nox emissions from an industrial pulverized coal combustor. *Fuel*. 1994;73(7):1128–1134.
- [9] Saripalli R, Wang T, Day B. Simulation of combustion and thermal flow in an industrial boiler. Proceedings of 27th industrial energy technology conference, New Orleans, LA; 2005.
- [10] Asotani T, Yamashita T, Tominaga H, et al. Prediction of ignition behavior in a tangentially fired pulverized coal boiler using cfd. *Fuel*. 2008;87(4):482–490.
- [11] Korytyni E, Saveliev R, Perelman M, et al. Computational fluid dynamic simulations of coal-fired utility boilers: an engineering tool. *Fuel*. 2009;88(1):9–18.
- [12] Lockwood T. Advanced sensors and smart controls for coal-fired power plant. London, UK: IEA Clean Coal Centre; 2015.
- [13] Zhou HC, Lou C, Cheng Q, et al. Experimental investigations on visualization of three-dimensional temperature distributions in a large-scale pulverized-coal-fired boiler furnace. *Proc Combust Inst*. 2005;30(1):1699–1706.
- [14] Kvaščev G, Jakovljević M, Stevanović V, et al. One approach to combustion control in thermal power plants. POWER-GEN Europe conference, Vienna; 2013.
- [15] Marjanović A, Jakovljević M, Kvaščev G, et al. Combustion process control based on flame visualization. Power turbines Europe, Lisbon; 2013.
- [16] Marjanović A, Krstić M, Đurović Ž. Combustion distribution control using the extremum seeking algorithm. *J Phys Conf Ser*. 2014;570(5):052001.1–9.
- [17] Bobál V. Technical note self-tuning Ziegler–Nichols PID controller. *Int J Adapt Control Signal Process*. 1995;9(2):213–226.
- [18] Bobál V, Böhm J, Prokop R. Practical aspects of self-tuning controllers. *Int J Adapt Control Signal Process*. 1999;13(8):671–690.
- [19] Mishra A. A study on PID controller design for systems with time delay 2011 [PhD Thesis]. Rourkela: National Institute of Technology.
- [20] Sampath R, Dharmi SS, Srivastava S. A review of structure and performance of thermal power plant controllers. *Int J Emerg Technol*. 2016;7(1):25–31.
- [21] Zhu W, Sun J. P. Based on the BP Neural Network-PID Series Control Boiler Main-Steam Temperature System Research. *Advanced Materials Research*. 2011;354–355:968–73. <https://doi.org/10.4028/www.scientific.net/amr.354-355.968>.
- [22] Zhang J, Hou G, Zhang J. Adaptive neuro-control system for superheated steam temperature of power plant over wide range operation. Sixth international conference on intelligent systems design and applications, ISDA'06; 2006. p. 138–141.
- [23] Ma L, Lee KY. Neural network based superheater steam temperature control for a large-scale supercritical boiler unit. Power and energy society general meeting; 2011. p. 1–8.
- [24] Mahmoud MS, Hussain SA. Adaptive pi secondary control for smart autonomous microgrid systems. *Int J Adapt Control Signal Process*. 2015;29(11):1442–1458.
- [25] French D. Metallurgical failures in fossil fired boilers. Newyork, USA: John Wiley & Sons; 1993.
- [26] Furtado H, May I. High temperature degradation in power plants and refineries. *Mater Res*. 2004;7(1):103–110.
- [27] Ballester J, García-Armingol T. Diagnostic techniques for the monitoring and control of practical flames. *Prog Energy Combust Sci*. 2010;36(4):375–411.
- [28] Macháček J, Bobál V. Adaptive PID controller with on-line identification. *J Electr Eng*. 2002;53(9/10):233–240.
- [29] Hjalmarsson H. Iterative feedback tuning – an overview. *Int J Adapt Control Signal Process*. 2002;16(5):373–395.
- [30] Mataušek M, Kvaščev G. A unified step response procedure for autotuning of pi controller and smith predictor for stable processes. *J Process Control*. 2003;13(8):787–800.
- [31] Candy J. Model-based signal processing. New Jersey, USA: John Wiley & Sons; 2005.
- [32] Verhaegen M, Verdult V. Filtering and system identification: a least squares approach. Newyork, USA: Cambridge University Press; 2007.
- [33] Haykin S. Adaptive filter theory. New Jersey (Prentice HallUSA: Pearson Education India; 2008.
- [34] Xu Y, Jin W, Zhu X. Parameter identification of photovoltaic cell based on improved recursive least square method. 2017 20th international conference on electrical machines and systems (ICEMS); 2017. p. 1–5.
- [35] Rafako C. Documentation for unit B1. Raciborz, Poland: Rafako; 2012.
- [36] Ljung L. System identification: theory for the user. New Jersey, USA: Prentice-Hall; 1987.