Combustion distribution control using the extremum seeking algorithm

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Abstract. Quality regulation of the combustion process inside the furnace is the basis of high demands for increasing robustness, safety and efficiency of thermal power plants. The paper considers the possibility of spatial temperature distribution control inside the boiler, based on the correction of distribution of coal over the mills. Such control system ensures the maintenance of the flame focus away from the walls of the boiler, and thus preserves the equipment and reduces the possibility of ash slugging. At the same time, uniform heat dissipation over mills enhances the energy efficiency of the boiler, while reducing the pollution of the system. A constrained multivariable extremum seeking algorithm is proposed as a tool for combustion process optimization with the main objective of centralizing the flame in the furnace. Simulations are conducted on a model corresponding to the 350MW boiler of the Nikola Tesla Power Plant, in Obrenovac, Serbia.

1. Introduction

Thermal power plants are in the group of large-scale systems with many complex processes taking place inside of them. There are a number of papers dedicated to the modeling, control and fault detection to these relevant processes [1], [2]. As such, the optimization of the combustion process is a very important task. Proper control algorithm could significantly increase the efficiency of the process, which is one of the main goals in this sort of systems. At the same time, the consequence of the poor control algorithm is a low safety and reliability of the system. Namely, prolonged exposure to high temperatures inside the furnace contributes to the short lifetime of the components and can result in different kind of failures. Over 30% of all the failures in the boilers are caused by high temperatures. Whether the change is instant or gradual over time, high temperature can lead to unwanted deformations and material cracks [3].

Inevitable by-products of the combustion process are the deposits of soot and slag on the walls of the boiler components. Soot and slag are the products of molted ash, which is located on the surfaces that absorb heat by emission. Large amount of soot and slag at the bottom section of the boiler contribute to higher temperatures and deposits at the top section of the boiler. These deposits decrease the heat transfer together with the coefficient of efficiency. Therefore, it is necessary to maintain the temperature inside the boiler below the melting temperature of the ash, so that it can be disposed using the ash transport system. Additional harmful products of combustion are oxides of nitrite, sulfur and

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carbon. Recent pollution standards are setting high objectives when it comes to these oxides. There are many ways of dealing with this problem. Some of them involve fuel additives, alternative fuels and low NOx burners and others involve optimal control algorithms. An important instrument for process simulation and therefore, an important tool for the analysis of influence of different fuels, geometry and firing, is the Computational Fluid Dynamics (CFD) [4], [5]. However, since CFD employs large amounts of data it is not convenient for online procedures.

That is one of the reasons for which we propose the use of non-model based extremum seeking control (ESC) approach. Although the basics of extremum seeking were set in the early 1920s, it was not until the end of 20th century that it secured an important role in both theory and practice [6], [7], [8], [9]. Widely known application of ESC is the combustion timing control for HCCI engines [10], antilock braking systems (ABS) design [11], increasing the efficiency in photovoltaic systems [12], etc. The aim of the ESC is to design a control algorithm which drives the parameters of the system towards their optimal value. For some systems the question of optimality is easily formulated, such as minimizing the net power output [13]. For others, objective function is a result of thorough analysis of system behavior and can be defined using the available measurements. In those cases, the model of the system is not needed in the optimization process, which is usually highlighted as an advantage of this approach. However, such control does not guarantee adequate transient performance. On the other hand, criterion function includes model and other dynamic related parameters of the system [14]. The main drawback of this approach is its sensitivity to model uncertainties.

The paper is organized as follows: Section 2 provides description of the thermal power plant boiler necessary for the combustion process understanding. Formulation of the combustion distribution optimization based on ESC is given in Section 3. Section 4 presents main results and comments on the performance of the proposed gradient extremum seeking based control algorithm implemented on the model of the boiler in thermal power plant Nikola Tesla, in Serbia.

2. Combustion process description

Thermal power plant Nikola Tesla A (TENT A) is located in Obrenovac, Serbia. It consists of six units with overall nominal power of 1650 MW. Lignite coal with low and variable calorific value (5000 kJ/kg to 9000 kJ/kg) is used as a regular fuel in all six blocks. Auxiliary oil fuel is used in the firing process and for supporting fire with low calorific value coal firing. The unwanted by-products of the firing process are large amounts of ash and slag, as well as the oxides of carbon and nitrite which contribute the increase in environmental pollution.

This paper focuses on the identification of the combustion process in the unit A6 with 350 MW of nominal power. The main control task is to maintain the reference block power, while controlling the fresh steam pressure in front of the turbine. One way to achieve this is to control the amount of coal and fresh air inserted into the boiler. Block A6 has six mills, as shown in Figure 1. Therefore, the required amount of coal is divided onto six parts and the operators have certain degree of freedom during this partitioning. The mills are positioned as to form a tangential configuration of the furnace. Figure 1. also shows the displacement of the six oil fuel burners used to support fire during ignition and some unexpected events.

Lignite coal is transported from the bunker, using doser and mill feeders. The amount of transported coal is proportional to the doser speed. After being partially dried in the recirculation channel, it is fed to the mill. Final coal drying is performed inside the mill, together with pulverization. The so-called air mixture is further sent to the mill separator. There, under the influence of inertia, insufficiently pulverized particles are extracted and returned back to the mill for re-pulverizing. From the mill separator, aero-mixture is transported throughout the channels to the burners. The combustion air is introduced using the fresh air fan. Heated air is divided into three streams: primary, secondary and tertiary. Primary air is fed to the recirculation channel and it is used for regulation of the aero-mixture exit temperature. Secondary air is transported to the burners and blown into the furnace,

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separately from aero-mixture. One part of the tertiary air is used for the additional combustion bar and the other is used for cooling during burner ignition.

During the reconstruction phase, a distributed control system was introduced to the block A6, which enabled additional possibilities in terms of control process quality. Data monitoring and storing is performed using SCADA system as well as the novel sensor system consisting of 42 pyrometers and several thermographic cameras. The pyrometers are distributed over five different levels (heights). Depending on the physical conditions of the furnace and the experience of the engineers working with it, the number of pyrometers varies with height. The levels at 17 m and 51 m are equipped with 4 pyrometer units per level, while there are 12 pyrometers per level at 25 m, 38 m and 43 m of height (Figure 2). The pyrometers are two-color processing units, meaning that the measurements are obtained at two close wavelength ranges (0,96μm and 1,05μm). This provides two significant information about the one-color and two-color temperature. The one-color temperature is the effective temperature and the two-color temperature is approximately the maximum temperature on the optical path. The nature of the two-color temperature estimation eliminates the influence of unburned coal particles, smoke, steam, etc. On the other hand, these particles affect the one-color temperature. Therefore, the difference between these two temperature estimations is a measure of combustion process efficiency.

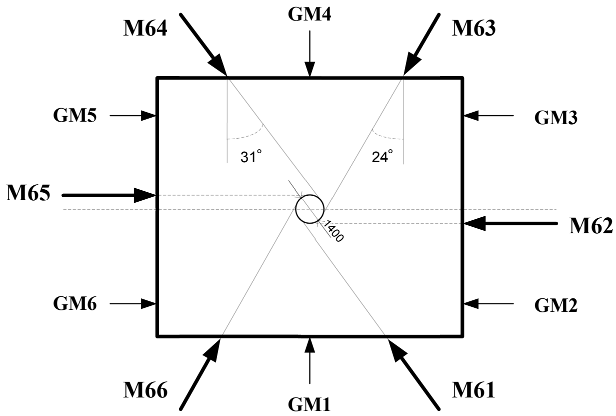

Figure 1. Displacement of the mills (M61 to M66) and oil fuel burners (GM1 to GM6) in block A6 of thermal power plant Nikola Tesla, Obrenovac, Serbia.

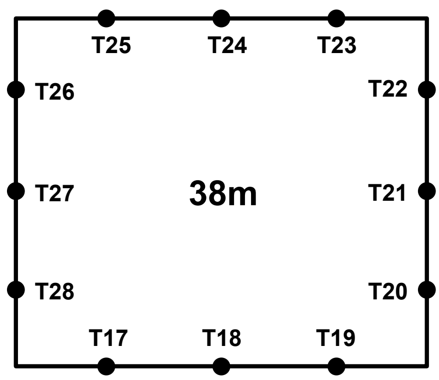

Figure 2. Configuration of the pyrometer sensor system at 38 m of height: three per each side of the boiler.

Previous detailed analysis of the system showed certain correlation between the mills loads and the temperature distribution inside the furnace. Furthermore, important conclusions have been drawn with respect to the relation of coal distribution over mills and the position of the flame using the visualization of the spatial temperature distribution. These results are an important step in obtaining optimal control law for the system. The combustion process is one very important and critical process. Therefore, in order to obtain and test the desired control algorithm, we first conducted a system identification procedure [15]. The system itself is exposed to different kinds of disturbances (variable calorific fuel value, non-consistent coal granulation and others). Used parameter estimation method is adaptive and provides the time-varying parameter estimation. At the same time it is robust to different kinds of disturbances present in the system. The constructed model is simplified as much as possible, but at the same time it describes all the important phenomena in the behavior of the system. As described in [15], this simplification implies the model with $M = 6$ inputs d_m (mill loads) and $N = 12$ output temperatures T_n (temperatures at 38m of height):

$$T_i(k) = -\sum_{n=1}^{N} a_{in} T_n(k-1) + \sum_{m=1}^{M} b_{im} d_m(k-1) + \zeta(k), \tag{1}$$

where a_{in} and b_{im} are the model parameters obtained from the system identification procedure, $i = \overline{1, N}$ denotes the index of the output temperature and $\zeta(k)$ is the process noise. Equation (1) can be shown as a linear regression form

$$T_i(k) = W^T(k)X_i(k) + \zeta(k), \tag{2}$$

where $W^T(k) = [-T_1(k-1)\ \dots -T_n(k-1)\ d_1(k-1) \dots\ d_2(k-1)]$ is the regression vector of the model and $X_i(k) = [a_{i1} \dots a_{in}\, b_{i1} \dots b_{im}]$ is the parameter vector. Note that in general case the parameters are not constant and that the time index has been omitted due to notation simplicity.

Additionally, cross-correlation analysis shows antagonistic activity of the opposite mills. Figure 3. illustrates the influence of two mills M61 and M64 onto the difference of temperatures on the right side of the boiler [16]. Namely, this difference increases with increasing the load of mill M61, meaning that the flame slowly shifts towards the rear side of the furnace. On the other hand, the increase of mill M64 load shifts the flame towards the front side of the furnace. This is a very significant result because it can contribute to further control algorithm structure simplification.

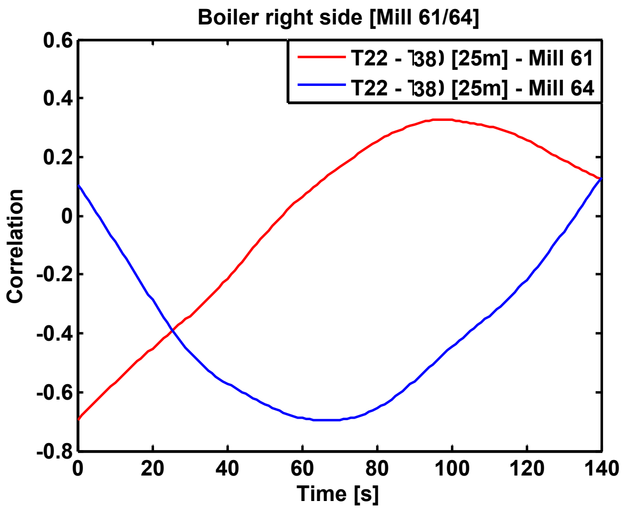

Figure 3. Influence of mills M61 and M64 onto the temperature difference on the right side of the furnace

3. Controller design

3.1. Optimization problem formulation

Previous section provides detailed description of the combustion process modelling. As explained, the process behaviour is essentially dictated by the pair of opposite mills rather than each mill separately. Therefore, there are three instead of six system inputs from control point of view. Furthermore, the overall coal requirement is the result of an external control algorithm and is not discussed in this paper. Let us assume that each mill pair should contribute to the combustion process equally, meaning that the total amount of coal is divided evenly onto these three pairs. Optimization problem is then reduced to finding the coal distribution within each pair. In other words, the control task is to determine the coal division ratio between each two mills, which would help optimize the combustion process. Let us denote by $n_1, n_2,$ and n_3 the ratio between d_1 and d_4, d_2 and d_5, d_3 and d_6, respectively (corresponding to the M61 to M66 in Figure 1).

Next important step is formulation of an adequate optimization criterion. As suggested, the idea is to centralize the flame inside the furnace. One solution to this problem is to ensure the approximately same temperatures on the opposite sides of the furnace. Keeping in mind the notation in Figure 2, we propose the following criteria

$$J_n = \sum_{i=17}^{22} (T_i - T_{i+k})^2, \tag{3}$$

where parameter $k = 6$ provides the summation of diametrically opposite temperature differences. Minimization of this criteria leads to an elliptical flame configuration. In the perfect scenario, all three ratios equal to one, meaning the uniform coal distribution onto six mills, would result in a minimum value of optimization function (around zero). In practice this is rarely the case, since there are many parameters influencing the combustion: coal burning process, current state of the mills, etc. For practical reasons, the ratio within each pair of mills is limited to $n_i \in [0.8, 1.2]$, $i = 1,2,3$. This imposes a correction of the criteria (3) in order to include the constrains:

$$J = J_n + J_c, \;\; J_c = \sum_{i=1}^{3} C \cdot \left[max\left(\frac{n_i - n_{max}}{n_{max}}, 0, \frac{n_{min} - n_i}{n_{min}} \right) \right]^2, \tag{4}$$

where $n_{min} = 0.8$, $n_{max} = 1.2$ and parameter $C = 5 \cdot 10^5$ is selected as to insure the significance of the constraints in the overall criteria. The correction factor is equal to zero for distribution ratio within bounds and increases with distance from this range. Finally, the optimization problem reduces to minimization of the criteria (4) with respect to n_1, n_2 and n_3.

3.2. Extremum seeking control

As a tool for optimization, we propose the use of the extremum seeking approach which is widely used in optimization theory in many available forms. Paper employs the use of perturbation signals in optimization process. The basic structure for the multivariable nonlinear maps in presence of dynamics is shown in Figure 4. It is important to emphasize that the perturbation frequencies should ensure a sufficient time scale separation between the ES loop and the plant. Additionally, the perturbation signal $S(t)$ and demodulation signal $M(t)$ are chosen in such a way to ensure convergence of the algorithm. For an input vector consisting of three variables $n = [n_1 \quad n_2 \quad n_3]^T$

$$S(t) = [a_1\, sin(\omega_1 t) \quad a_2\, sin(\omega_2 t) \quad a_3\, sin(\omega_3 t)], \tag{5}$$

$$M(t) = \left[\frac{2}{a_1} sin(\omega_1 t) \quad \frac{2}{a_2} sin(\omega_2 t) \quad \frac{2}{a_3} sin(\omega_3 t) \right], \tag{6}$$

where perturbation frequencies should satisfy several conditions: 1. each two should be different $(\omega_i \neq \omega_j)$, 2. the ratio of each two should be rational $(\omega_i / \omega_j \in Q)$, 3. the sum of each two should not be equal to the third one $(\omega_i + \omega_j \neq \omega_k)$, $i, j, k = 1,2,3, i \neq j \neq k$.

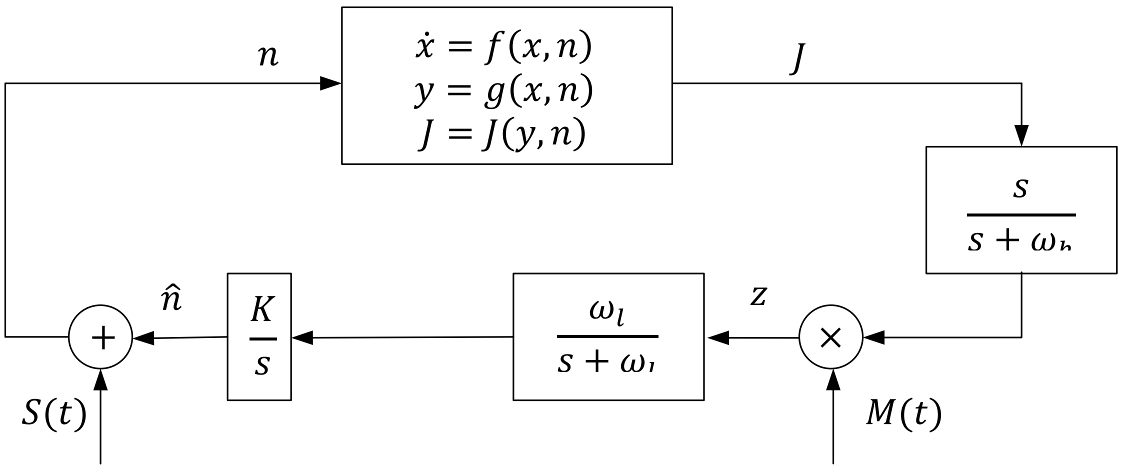

Figure 4. Gradient based ES algorithm for a dynamic multivariable nonlinear map.

Perturbation amplitude a and diagonal matrix K are small parameters responsible for the stability and the convergence speed of the algorithm. There are several papers dealing with the analysis of stability of ES control for nonlinear dynamic systems [8], [17], which was not the focus of this paper. The two filters decrease the effect of the perturbation signals. Their role is to eliminate the DC component of the optimized signal J (high-pass filter) and to isolate a DC component of the product signal z necessary for gradient estimation (low-pass filter). Thus, the filters should have slower time scale than the periodic perturbations and therefore the plant itself. If all the conditions are met, the algorithm converges minimizing the criteria (4) obtained by the optimal value of input vector n^*.

4. Experimental results

In order to verify the proposed control approach, we employ the obtained model of the system, as described in Section 2. We introduce the reference speed to the algorithm, which represents the overall needed doser speed for all six mills. As indicated before, the speed of the doser is proportional to the coal amount requirement. Normally, this information is provided by the external control loop in charge of the desired fresh steam pressure. Dictated overall doser speed is given in Figure 5.

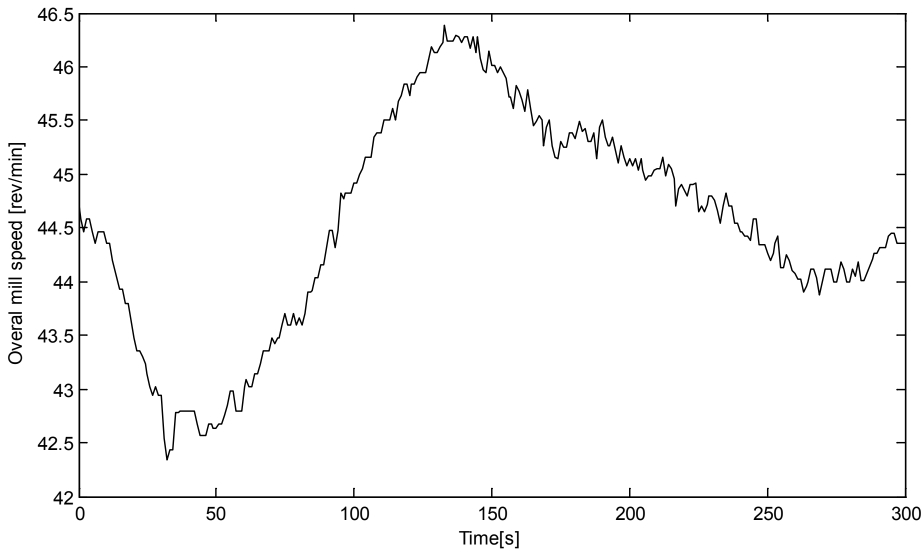

Figure 5.Overall doser speed proportional to the overall coal load requirements.

The goal of the control algorithm is to regulate the flame inside the furnace, by minimizing the preset criteria (4). The reference speed is divided onto three pairs of dosers and the objective of the ES structure is to estimate the optimal ratios within these pairs. The adopted perturbation frequencies are 0.8 rad/s, 0.6 rad/s and 0.5 rad/s. Parameters $a = 0.002$ and a diagonal matrix K are carefully chosen. These parameters were determined empirically. Imposing the constraints on the control signal would normally limit the selection of the appropriate parameter and there for the speed of the algorithm in order to stay within the desired bounds. Introduction of these constraints throughout the penalty function gives us more freedom in that sense. Also, the filter cut-off frequencies $\omega_l = [0.8, 0.5, 0.3]$ rad/s and $\omega_h = 0.6$ are chosen as to satisfy the requirements from Section 3. Figure 7 illustrates the result of the optimizing procedure. Note that in the beginning all three ratios are in steady state close to one, meaning that they all contribute roughly the same in the control process. After the disturbance, introduced in the model parameters, criterion function experiences a peak (Figure 6), which is timely eliminated. At the same time, control signals experience a translation to a new steady state. In the first pair load is no longer equally distributed over mills. Namely, mill M61 is in charge of providing around 55% and mill M64 around 45% of the coal required from that pair.

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Mills M63 and M65 encounter similar scenario, where as the ratio of mills M62 and M66 is still close to one. Penalty constraints function provides the control signals within the desired bounds, although the algorithm itself is reasonably fast (around 70 sec needed to achieve new steady state). The influence of these ratios on the coal distribution over mills, meaning the doser speeds are depicted in Figure 8. ES algorithm manages to adapt and slide the control parameters towards new values which result with the minimum objective function. Obviously, the ES approach is successful in these simulations and represents a good basis for further research in terms of additional combustion distribution optimization.

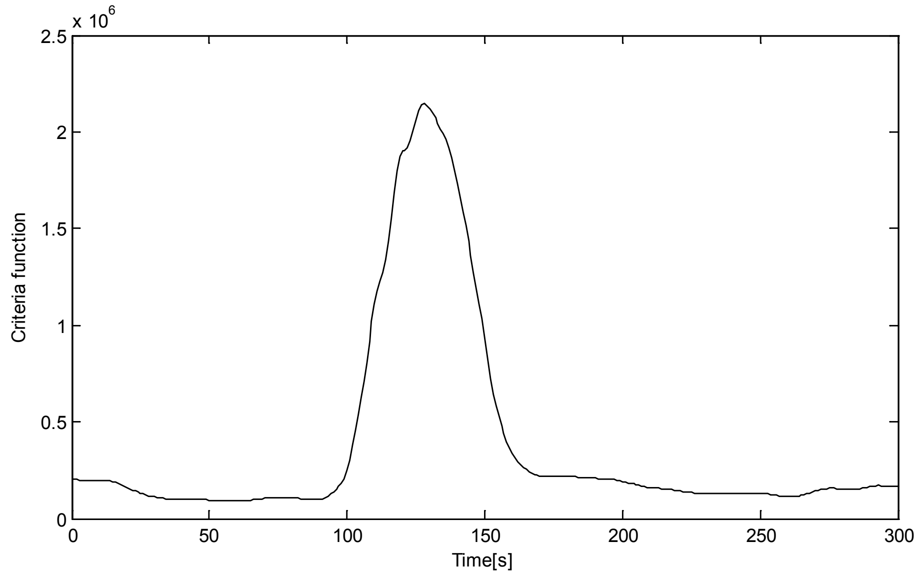

Figure 6. Algorithm criteria function.

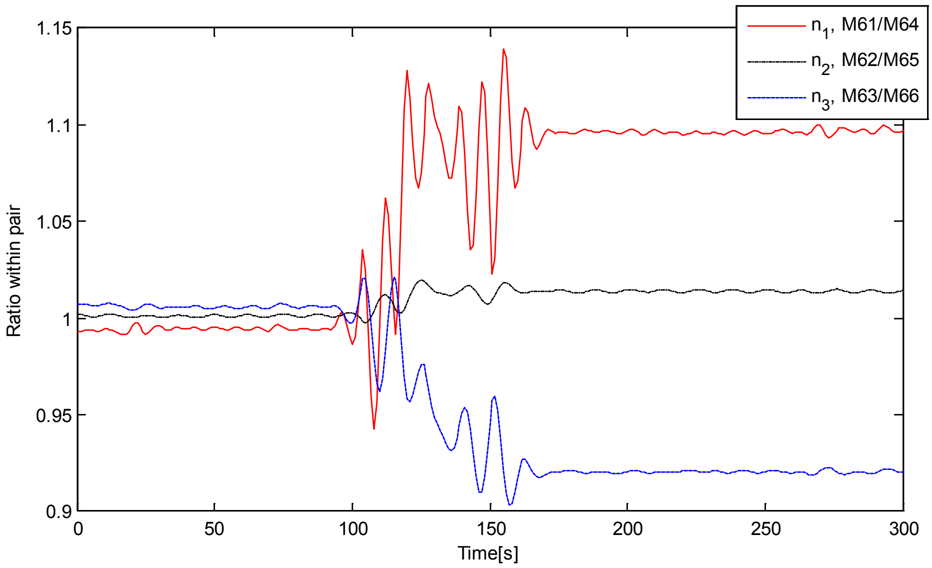

Figure 7. Control signals: ratios within each mill pair.

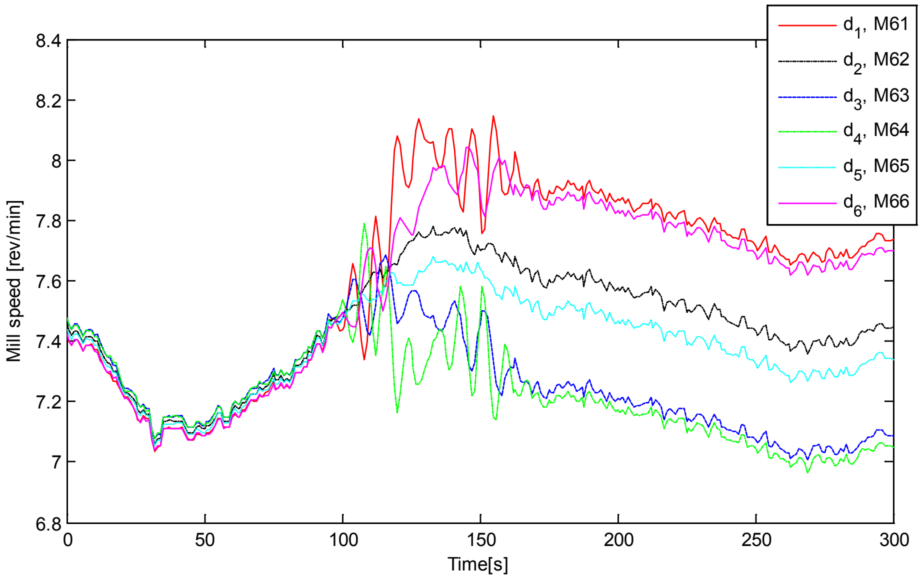

Figure 8. Model input signals: doser speeds.

5. Conclusion

The paper considers an application of extremum seeking in optimization of combustion distribution in thermal power plant furnaces. First we describe how the temperature spatial distribution depends on the firing and the coal partitioning over the mill circles. Next we provide a possible solution for flame geometry regulation in the form of an optimal control problem with an objective function which includes the set of constraints regarding the control signals. Finally, we introduce the proposed control algorithm to the model of the combustion process. There are many disturbances taking place inside the furnace and as a result of such disturbances the flame was shifted towards the front of the furnace. The results show good algorithm performance in terms of the temperature distribution control which provides ellipsoid flame configuration. Additionally, introduction of constraints into our objective function enables aggressive extremum seeking parameters and hence better convergence properties. Future work involves further algorithm tuning in terms of increasing the flame symmetry and more freedom when it comes to coal dissipation over mill pairs.

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