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The Disturbance Detection in the Outlet Temperature of a Coal Dust–Air Mixture on the Basis of the Statistical Model

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Abstract: The reliability of a coal mill's operation is strongly connected with optimizing the combustion process. Monitoring the temperature of a dust–air mixture significantly increases the coal mill's operational efficiency and safety. Reliable and accurate information about disturbances can help with optimization actions. The article describes the application of an additive regression model and data mining techniques for the identification of the temperature model of a dust–air mixture at the outlet of a coal mill. This is a new approach to the problem of power unit modeling, which extends the possibilities of multivariate and nonlinear estimation by using the backfitting algorithm with flexible nonparametric smoothing techniques. The designed model was used to construct a disturbance detection system in the position of hot and cold air dampers. In order to achieve the robust properties of the detection systems, statistical measures of the differences between the real and modeled temperature signal of dust–air mixtures were used. The research has been conducted on the basis of the real measuring data registered in the Polish power unit with a capacity of 200 MW. The obtained high-quality model identification confirms the correctness of the presented method. The model is characterized by high sensitivity to any disturbances in the cold and hot air damper position. The results show that the suggested method improves the usability of the statistical modeling, which creates good prospects for future applications of additive models in the issues of diagnosing faults and cyber-attacks in power systems.

Keywords: outlet temperature of a dust–air mixture; coal mills; additive regression model; anomaly detection; monitoring of a combustion process

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1. Introduction

The main task of coal mills is to grind, dry and transport the pulverized coal to the boiler. Due to the increased performance requirements of power stations, the reliability of coal mills is becoming increasingly important. A low level of coal in the bunker may lead to destabilizing the operation of the control system. On the other hand, increasing the level of the pulverizing chamber's filling increases the risk of the so-called backfilling of the mill, i.e., its immobilization due to the excess of the fuel to be pulverized. In turn, too much or too little primary air may potentially result in unnecessary heating or unburned fuel, respectively. In order to optimize the combustion process, it is necessary to optimize the mill's control system which must control the ratio of the primary air flow to coal dust flow, thus keeping the coal mill efficient [1,2].

A significant parameter characterizing the operation of the system supplying the boiler's burners with fuel is the temperature of the dust–air mixture at the outlet of a coal mill. The temperature of primary air transporting the dust to the boiler must be high enough to allow moisture to evaporate from the coal, but at the same time relatively low to prevent the ignition of the dust–air mixture. Keeping the temperature of the dust–air mixture within the set values is implemented by the opening degree of the cold and hot air dampers. It is intentional not to allow the excessive increase in the temperature of a dust–air mixture, as it may cause the ignition inside the coal mill. As a consequence, a blow-through of hot air towards the fuel bunker may ignite the fuel. Hence, monitoring the temperature of a dust–air mixture significantly affects the operational safety of a coal mill [3].

Preparing the dust–air mixture necessary for the boilers fired is a nonlinear process, not allowing for measuring all of the crucial parameters of a coal mill operation. An example of such a parameter may be the flow of coal dust to the combustion chamber. It is estimated using the feeder's rotational speed measurements or the speed of the primary air. While the estimates are reliable in a stationary state, transient processes that occur during the changes in the power unit load, are to blame for the low object control quality and for generating false alarms by diagnostic systems [4].

The strategy for controlling coal mills that is commonly used in power stations consists of controlling the several single loops of PID controllers [5]. Control loops differ greatly in terms of dynamics and delay time. What is more, between control loops of the key parameters such as quantitative flow of the coal and primary air to the mill, and temperature at the mill outlet, a strong coupling is observed. Moreover, the parameters such as moisture, sulfur and calorific content of the raw coal supplied to the mill, which are determined experimentally, significantly affect the control quality [6,7]. Due to these reasons, it is difficult to keep the control system in optimal operating conditions [8,9].

In order to improve the quality of the coal mill control, plenty of advanced techniques are used nowadays, such as decoupling control, predictive control, fuzzy control or adaptation of different types of control (e.g., fuzzy control combined with PID) [10–13]. A coal mill model is required for many of these strategies to work, as well as for designing diagnostic systems. For this purpose, analytical models are used based on the mass and heat balance dependencies. Due to the process complexity that occurs during the preparation of a dust–air mixture, designing such models is often very hard. Moreover, the analytical solution cannot be obtained easily with the standard local optimization methods (e.g., least-squares techniques), due to the need to identify many parameters in parallel. Thus, genetic algorithms are used, allowing for efficient estimation of these parameters that are non-measurable [6,14,15]. However, despite the adopted simplifications, the number of the estimated parameters is large enough to limit the applicability of such models.

An alternative technique was applied, i.e., Additive Models [16] that were used to estimate and predict the temperature of a dust–air mixture at the mill outlet. This is a new approach to power engineering problems, which overcomes limitations related to nonlinear multidimensional modeling, as the regression function is modeled by the sum of the functions of particular input variables. Hence, the estimation of the parameters of the Additive Model performs much easier than when the model is a nonlinear combination of the parameters [17,18]. The simple structure and estimation algorithm of the Additive Model reduce computational costs, which is crucial in automation systems with large databases.

2. A Pulverized Coal-Fired Boiler

The research has been conducted on the basis of the real measuring data registered in the Polish power unit with a capacity of 200 MW. The power station is equipped with a pulverized coal-fired OP-650 shell-type boiler with a natural circulation of water. Coal dust combustion takes place in a vacuum combustion chamber. Coal dust from four ball-and-race mills gets into the boiler along with the air stream pressed by two fans and the resulting dust–air mixture burns. The exhaust gases after leaving the boiler give off heat in rotary air heaters and then, after passing through the electro-filter are pressed by the exhaust gas fans to the chimney. The scheme of a coal-fired boiler installation is presented in Figure 1 [19].

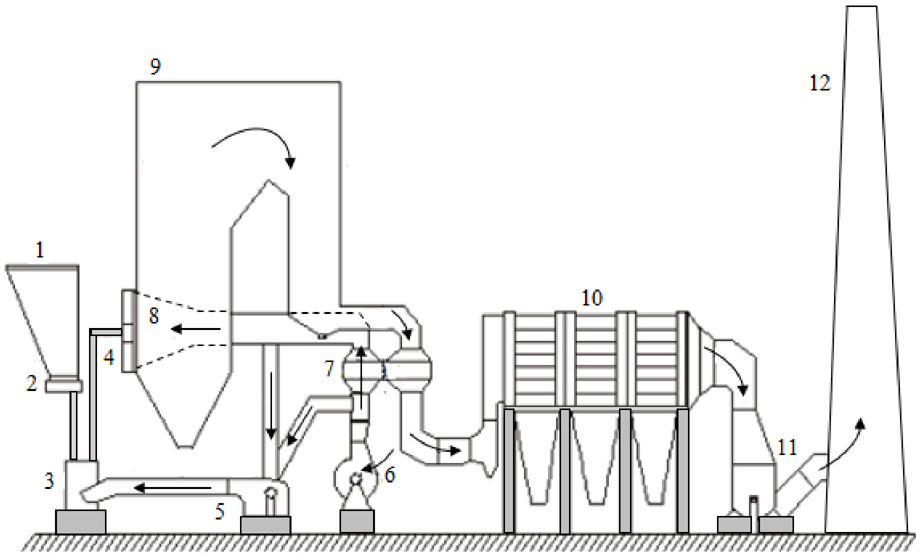

Figure 1. Power plant boiler installation scheme: 1—coal bunker; 2—feeding screw; 3—coal mill; 4—dust channels; 5—mill fan; 6—air fan; 7—rotary air heater; 8—combustion chamber; 9—boiler; 10—electro-filter; 11—exhaust gases fan; 12—chimney.

2.1. The Process of Preparing Dust–Air Mixture

Coal mills are responsible for setting the dust–air mixture up which is then burnt in the boiler. The research included the use of one of four medium-speed ball-and-race MKM-type coal mills. The raw coal comes down from the coal tank to the central chute pipe through the feeding screw and gets under the rolling balls being pulverized as a result. Then, it is dried and transported through hot air pressed by the fan. The hot air temperature must be high enough to allow moisture to evaporate from the coal, but at the same time relatively low not to ignite the dust. The resulting dust–air mixture is directed to the separators that do not let too large coal fractions in. Next, it is fed through the dust channels to the burners placed on the wall of the boiler's combustion chamber [2,19].

The processes that take place during the milling and drying of the coal are dynamic, and it is not possible to measure all crucial parameters of the coal mill operation, e.g., the quality of the coal. The decrease in moisture content in coal results in the increase in temperature of the dust–air mixture, and thus, the decrease in the quantitative hot air flow to the mill. On the basis of exploratory data analysis, including correlation analysis, among the available control signals and process variables, those have been selected that best describe the model of the temperature of a dust–air mixture at the outlet of a coal mill. The description, along with a measuring range of the accessible control signals and process variables that have been chosen to identify the model of the outlet temperature of a dust–air mixture is presented in Table 1.

A substantial parameter that has an impact on the level of temperature of a dust–air mixture is a quantitative flow of coal to the mill which is affected by the efficiency of the coal feeder. For an MKM-33-type coal mill, the efficiency changes approximately in direct proportion to the change in the rotational speed of the screw roller and is within the range of $4 \div 40$ t/h (with the assumed coal bulk density within the range of $0.8 \div 0.9$ t/m^3). This corresponds to a range of 0–100% control. The mill outlet temperature of the dust–air mixture is also strongly affected by the quantitative flow F_{air} and temperature T_{hot} of hot air to the mill.

2.2. Automatic Control System of the Temperature of a Dust–Air Mixture

Control of the temperature of the dust–air mixture at the outlet of the mill is performed through the opening degree of the cold and hot air dampers. If the temperature increases above the set level, the cold and hot air damper opens and closes accordingly, at the same time. Signals of the cold and hot air dampers—D_{cold} and D_{hot}, along with the signal of a temperature of the dust–air mixture—T_{out} for exemplary data are presented in Figure 2.

Table 1. Variable description.

Notation	Variable Name	Range and Unit
T_{out}	Temperature of a dust–air mixture at the mill outlet	0–200 [°C]
T_{hot}	Temperature of hot air to the mill	0–370 [°C]
P_{air}	Air pressure to the mill	0–20 [kPa]
F_{air}	Quantitative air flow to the mill	0–55 [kNm^3/h]
D_{cold}	Cold air damper position	0–100 [%]
D_{hot}	Hot air damper position	0–100 [%]
F_{coal}	Quantitative flow of the coal to the mill	0–40 [t/h]
V_c	Control of the coal feeder	0–100 [%]
P_{set}	Set power unit (regular operation, no deep disturbances)	0–200 [MW]

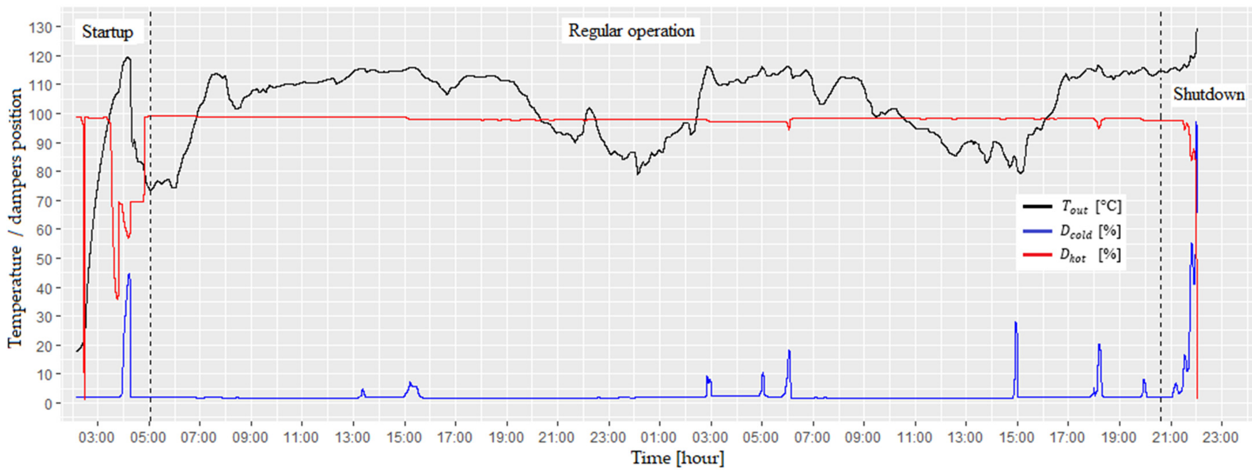

Figure 2. The plot of the temperature of a dust–air mixture with the position of cold and hot air dampers for data from 1 March 2016–2 March 2016 during mill start-up, regular operation and shutdown.

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During regular operation of the mill with no deep disturbances, cold air is only slightly supplied to the inside of the milling chamber. The spikes that can be observed in Figure 2 may even reach 28%. In the case of hot air dampers, these values are much lower. The conclusion to be made on the basis of measuring data analysis and expert knowledge is that under regular operating conditions, a maximum of 6–8% in the cold air damper opening level and 92–94% in the hot air damper opening level is allowed. Any deviation from these values will be considered disturbances.

In the startup and shutdown conditions, closing and opening of the hot and cold air dampers are clearly observed. These are two of the very important stages of the coal mill operation. In the initial startup phase, the mill is fed hot air with a maximum temperature of 370 °C. Next, the mill is filled up with coal or biomass in a blend with coal, which reduces the temperature inside the mill. In normal conditions, the temperature inside the mill is approximately 110 °C. Until the mill's operation is stabilized, the inside provides perfect conditions for ignition and fire. When shutting down the mill, the first phase is cutting off the fuel supply. The hot air is still fed to the mill, which results in an increase in the temperature in the mill, which in turn increases the risk of fire or explosion.

The most often occurring disturbances in boiler operation are a lack of coal, a blockage in the feeder and coal overhanging in the coal bunker. By carefully monitoring the temperature of the dust–air mixture it is possible to detect if the mill has a lack of coal and thus prevent disturbances in the smoothness of coal feeding. This can happen when a large chunk of coal gets stuck in the bunker and clogs the flow from the coal bunker or does not flow properly inside the conveyor thus stopping the feeder screw. A common phenomenon that occurs is coal overhanging in the coal bunker, which may also lead to deviations in values of the control signals and process variables [18]. Usually, the lower coal temperature than added air leads to cooling down the temperature of the dust–air mixture. Thus, when the amount of coal reaching the mill decreases, the dust–air mixture heats up and the risk of fire increases.

3. The Model of the Temperature of a Dust–Air Mixture

Due to the dynamic nature of the preparation process and supply of the dust–air mixture to the boiler, the choice of the adequate structure of the model significantly affects the quality of identification. Adopting an oversimplified or too complicated model can have a negative impact on the reliability of the control or monitoring systems. On the basis of expert knowledge and correlation analysis, input variables of the model were selected significantly affecting the signal of the dust–air mixture. To compare two or more models, Akaike Information Criteria were applied which by acknowledging the number of the parameters of the model, assesses the adjustment of the model to measured data.

Additive Models (ADM) [16] were used to overcome the limitations that nonlinear multidimensional modeling has. This technique allows us to construct a model on the basis of expert knowledge and measuring data available in contemporary automatic control systems. ADM structure is as follows:

$$Y = \alpha + \sum_{j=1}^{p} f_j\left(X_j\right) + \varepsilon \tag{1}$$

where Y is an output variable, α is a constant and error ε is independent of the input variables $X_1, X_2, \ldots, X_p$, with $E(\varepsilon) = 0$ and $Var(\varepsilon) = \sigma^2$. Functions f_j of a variable X_j are one-dimensional with no monotonicity or analytical forms assumed. Prediction models can be nonlinear towards X_j, but are still linear towards $f_j\left(X_j\right)$. Thus, the estimation of the parameters is much easier. Independence of the variables X_j [17] allows us to use signal X_j delay lines, thus ensuring the dynamic properties of the model (1).

Formally, determining an ADM on the basis of measuring data $\left\{\left(x_{t1}, \ldots, x_{tp}, y_t\right)\right\}_{t=1}^{n}$ registered during the exploitation of a coal mill, can be expressed by the task of minimizing the sum of squares of errors:

$$argmin_{\alpha, f_j} \sum_{t=1}^{n} \left(y_t - \alpha - f_j\left(x_{tj}\right)\right)^2 \tag{2}$$

This means finding a constant α, equal to $\hat{\alpha}$ and p function of one variable $\hat{f}_j(\cdot)$ specified on a straight line and not in the original p-dimensional space. This way we avoid the necessity to solve the estimation task in multidimensional space. In order to automatically identify the parameters of an ADM, a Backfitting Algorithm was used which, when meeting certain assumptions, converges to an unambiguous solution starting from any initial values [16].

On the basis of the performed analysis, a set of input variables was used for the identification of the model of T_{out} signal:

$$F_{coal}, T_{hot}, D_{cold}, D_{hot} \tag{3}$$

To improve modeling quality, a signal of a dust–air mixture temperature was also used as an input variable thus creating a recurrent dependency. Such models provide a higher estimation accuracy but are also able to increase the risk of overtraining. To properly model the dynamics of an output signal, the first order structure was used—all variables from set (3) were included in the model with a 5 s delay, which corresponds to a displacement of one sample. The increase in the order of the model did not cause a significant change in results improvement in relation to the increase in the model's complexity.

In order to verify the quality of the estimated ADM (1), a local identification error was determined:

$$r_t = T_{out,t} - \hat{T}_{out,t} \tag{4}$$

Which is a difference between the value of the output variable $T_{out,t}$ and its estimated value $\hat{T}_{out,t}$ in t time. The global identification error was determined with the use of Mean Absolute Error (MAE), Normalized Mean Absolute Error (NMAE) and Standard Deviation (STD):

$$\begin{gathered} \mathrm{MAE} = \frac{1}{n}\sum_{t=1}^{n}|r_t| \\ \mathrm{NMAE} = \frac{1}{n}\sum_{t=1}^{n}\frac{|r_t|}{(max(T_{out})-min(T_{out}))}\cdot 100\% \\ \mathrm{STD} = \sqrt{\frac{1}{n-1}\sum_{t=1}^{n}(r_t-\bar{r})^2} \end{gathered} \tag{5}$$

where r_t and $\bar{r}$ is the local identification error in t time and its mean for n data points.

The implementation of the system aimed at monitoring the object requires a correct model, which on the one hand should be accurate and allow to properly estimate the output signal, but on the other hand—allow for robust prediction in the presence of unknown but bounded disturbances and measurement noises. For this purpose, the relation f_j between output signal T_{out} and set of input signals (3) is estimated with the use of Natural Cubic Spline functions. These are nonparametric estimation methods with a single smoothing parameter controlling the amount of smoothing the regression function [20]. The right choice of the value of the smoothing parameter allows for reducing the poor model performance, caused by overfitting or underfitting the data.

The Results of the Model Identification

The available database includes a coal mill's operation period from February 2016 to May 2016 in the condition of mill start-up, regular operation and shutdown. The sampling interval for all data was the same (5 s). A training set included selected data registered during regular operation between 1 March 2016 and 2 March 2016, approximately 25 thousand samples in total. The set did not include data from the processes occurring during start-up and shutdown, or deep disturbances. Exploratory data analysis showed the existence of outliers that were neglected during identifying the model parameters.

The estimated values $\hat{T}_{out,t}$ are compared with the measured values $T_{out,t}$ in Figure 3.

The values of local identification error r_t which were normalized to the range [–1, 1] are presented in Figure 4. It should be noted that the presented signals do not chronologically reflect the temperature distribution due to the omitted data from disturbances in the cold air damper position (Figure 2).

Local error fluctuated between −0.023 and 0.032. The juxtaposition of the values of accuracy coefficients is included in Table 2.

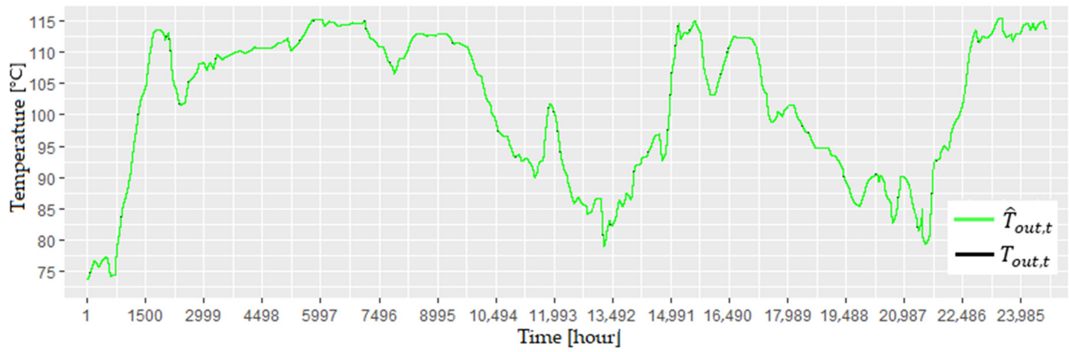

Figure 3. The plot of the estimated and measured temperature of dust–air mixture for training data.

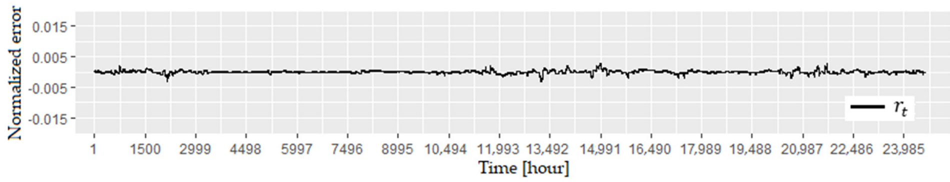

Figure 4. The plot of the local identification error for training data.

Table 2. Model accuracy coefficients for training set.

MAE	NMAE	STD
0.0138	0.033%	0.0369

The obtained quality of model identification of T_{out} did not exceed 0.05% of the variability range of the modeled temperature.

4. Disturbance Detection in the Outlet Temperature of a Dust–Air Mixture

The algorithm intended to analyze the temperature of the dust–air mixture in terms of disturbances should take the problem of the model's uncertainty into consideration. This leads to the need to design an algorithm that is robust to the model inaccuracy, the influence of unmeasurable disturbances and measurement noises. In research, robustness was achieved through the use of nonparametric estimation methods and statistical measures of the uncertainty of local identification error (4). The applied decision algorithm consists of comparing r_t values with threshold values. The disturbance symptom is detected when the diagnostic signal $s(r_t)$ takes the value of 1, i.e., when the threshold value U or L is exceeded by a local error in t time:

$$s(r_t) = \begin{cases} 0\ gdy\ L \leq r_t \leq U \\ 1\ gdy\ r_t < L \ \vee \ r_t > U \end{cases} \tag{6}$$

The possibility to generate false symptoms greatly depends on the values of the adapted limitations as permissible values and time slots being the basis for making a decision. The acceptable range (U, L) was calculated with the use of data characterizing the r_t value during regular exploitation of the coal mill in the following way:

$$\begin{cases} U = max\{r_t\} + 3 \cdot std(r_t) \\ L = min\{r_t\} - 3 \cdot std(r_t) \end{cases} \tag{7}$$

where r_t is the normalized error, $std(r_t)$ is an unbiased estimator of a standard deviation of the normalized error. In order to verify the properties of the decision algorithm, disturbance detection time was measured:

$$T_{dt} = t_{ds} - t_d \tag{8}$$

Which is the time measured from the moment of the disturbance t_d started to the time the symptom occurred t_{ds}.

5. Results and Discussion

Verification tests have been conducted on the basis of the following characteristic states of operation of a coal mill:

- Start-up (SU): starting according to the power station's procedures;
- Regular operation (R): full capacity operation;
- Disturbances (D): operation during disturbances in cold and hot air damper position;
- Shutdown (SD): shutdown according to the power station's procedures.

Test sets included data registered during several days of operation of the object in February and March. Under steady-state conditions, the control of the coal feeder was about 70%, the quantitative air flow to the mill was about 50 kNm^3/h, the temperature of hot air to the mill was about 280 °C and the temperature of the dust–air mixture was about 105 °C. The disturbances (D) were part of daily operations and the causes of their occurrence were not specified.

Figures 5–10 present selected local prediction error r_t obtained for the proposed additive model along with the threshold values U and L determined according to (6) at level $\pm$ 0.01. The values of local prediction error for test data during disturbances (D) registered on 5.02, 11.02, 16.03 and 23.03 have occurred for the temperature of the dust–air mixture within the range of 113–123 °C. Higher temperature values, between 115.5 °C and 125 °C were observed during the shutdown (SD) of the mill. In the case of start-up (SU), registered on 1.02, the values of local prediction error have occurred for the temperature of the dust–air mixture of the smaller values from range 17–74 °C and from the range 116–119 °C.

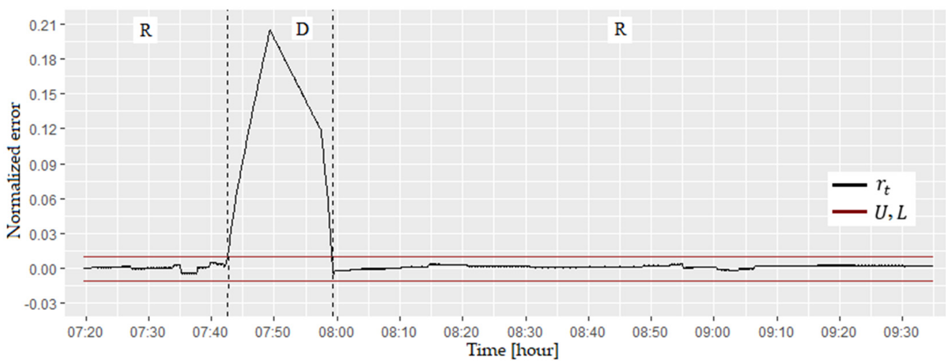

Figure 5. The plot of the local prediction error with threshold values for test data during regular operation of the mill (R) and disturbances (D); date: 5 February 2016.

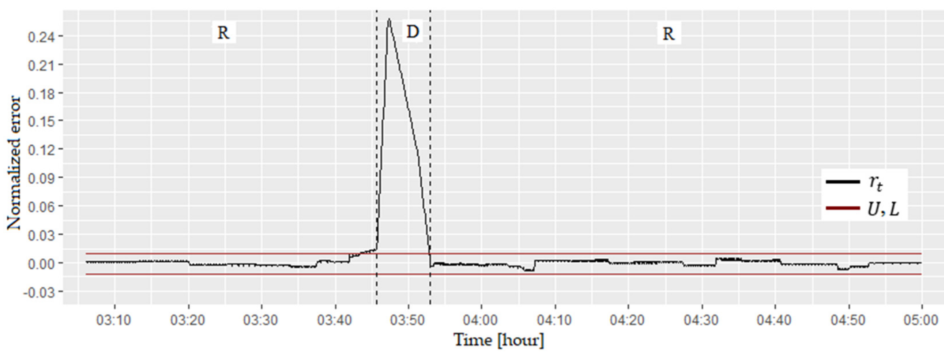

Figure 6. The plot of the local prediction error with threshold values for test data during regular operation of the mill (R) and disturbances (D); date: 11 February 2016.

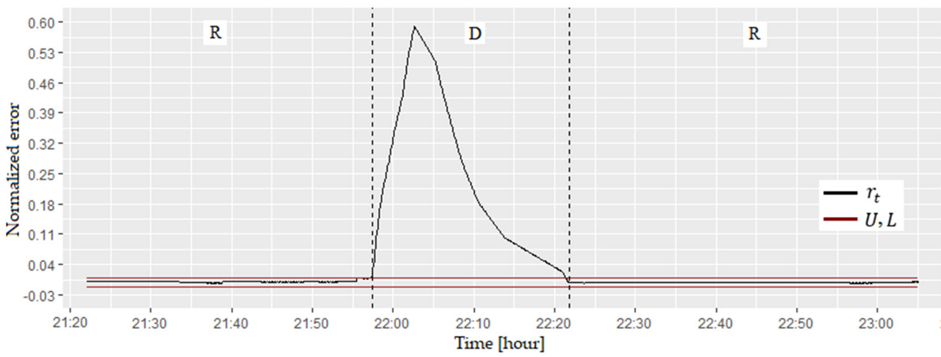

Figure 7. The plot of the local prediction error with threshold values for test data during regular operation of the mill (R) and disturbances (D); date: 16 March 2016.

The plots in Figure 5 to Figure 8 clearly reveal the sensitivity of a diagnostic test (6) to the occurrence of particular disturbances while not being sensitive to data registered during a regular operation of the mill. This is confirmed by the values of the detection time T_{dt} of particular disturbances presented in Table 3, e.g., $T_{dt} = 15$ means that the delay in detecting disturbances in the position of cold and hot air dampers was three sample intervals.

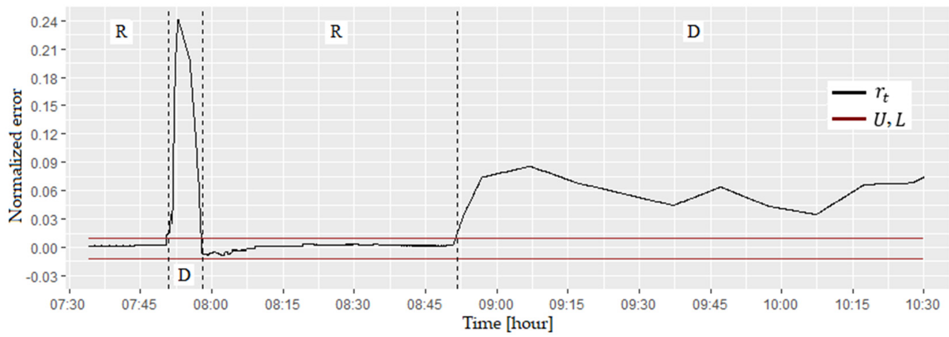

Figure 8. The plot of the local prediction error with threshold values for test data during regular operation of the mill (R) and disturbances (D); date: 23 March 2016.

Table 3. Decision algorithm accuracy coefficient T_{dt}[s] for test sets.

05.02	11.02	16.03	23.03 I	23.03 II
5	15	5	20	10

Starting and shutdown according to the power station's procedures are significant points in the coal mill operation. Figure 2 clearly shows the closing and opening of the hot and cold air dampers. The operator should precisely monitor the condition of the temperature of the dust–air mixture because during the start-up (Figure 9) and shutdown (Figure 10) perfect conditions for ignition and fire, or even explosion, can be observed.

Under normal operating conditions of the coal mill, the temperature of the dust–air mixture at the outlet of the coal mill is within the range of 80–115 °C. The received results show that the signaling low—about 80 °C and high—about 115 °C value of the temperature of dust–air mixture, predicted by the use of the Additive Model can help prevent dangerous situations that may appear in the power unit.

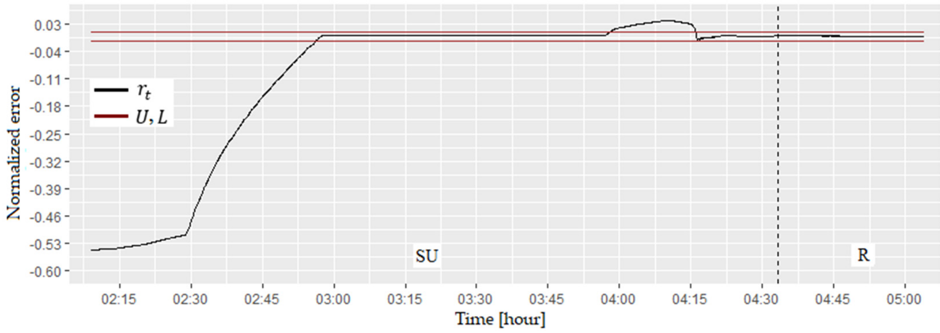

Figure 9. The plot of the local prediction error with threshold values for test data during start-up (SU) and regular operation of the mill (R); date: 1 March 2016.

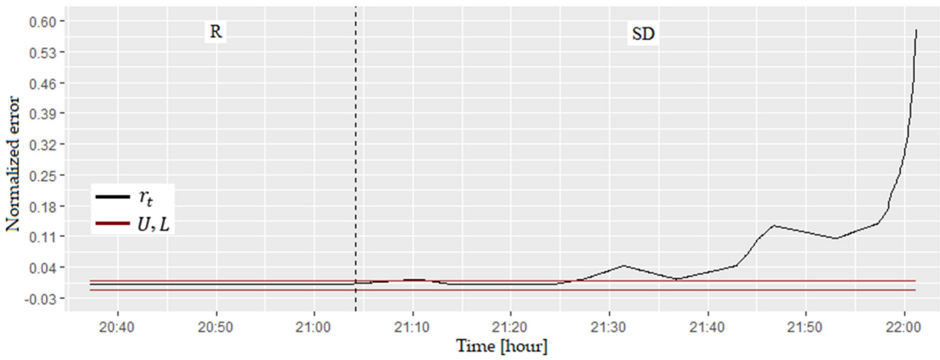

Figure 10. The plot of the local prediction error with threshold values for test data during regular operation of the mill (R) and shutdown (SD); date: 2 March 2016.

6. Conclusions

A significant parameter characterizing the combustion is the temperature of the dust–air mixture at the outlet of a coal mill. By monitoring the temperature distribution, it is possible to detect the disturbances in the smoothness of coal feeding and thus prevent situations where the coal mill downtime is necessary.

The paper presents a methodology for estimation and prediction of the temperature of a dust–air mixture at the outlet of a coal mill. The proposed Additive Model is a nonparametric estimation model that allows us to identify the dynamic processes with the use of real data from distributed control systems (DCS). This is a new approach to the power engineering problems, extending the possibilities of implementing the tasks of control and diagnostics of the processes occurring during the preparation of a dust–air mixture.

The accuracy of the Additive Model obtained in the identification phase was high and enough to use in disturbance detection algorithms. It should be noted that the choice of the model's structure (input signals, delay order) describing the temperature of a dust–air mixture, the quality of the data (training data comprising a full range of the mill operation signals variability), as well as the choice of threshold values in the decision algorithm were significant factors affecting the quality of identification, thus the quality of disturbance detection.

The model is characterized by high sensitivity to any disturbances in the cold and hot air damper position. The designed decision algorithm detected disturbances with a delay of no more than four sampling intervals and at the same time—it did not indicate abnormalities in the state of regular operation of the mill. The obtained results are satisfactory and may form the basis for further analysis of the possibilities to use the Additive Model of the temperature of a dust–air mixture at the outlet of a coal mill in the faults and cyber-attacks diagnosis tasks.

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