Detection of Malfunctions and Abnormal Working Conditions of a Coal Mill

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Additional information is available at the end of the chapter

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Abstract

Coal mill malfunctions are some of the most common causes of failing to keep the power plant crucial operating parameters or even unplanned power plant shutdowns. Therefore, an algorithm has been developed that enable online detection of abnormal conditions and malfunctions of an operating mill. Based on calculated diagnostic signals and defined thresholds, this algorithm informs about abnormal operating conditions. Diagnostic signals represent the difference between the measured and the modeled values of two selected mill operating parameters. Models of mill motor current and outlet temperature of pulverized fuel were developed based on the linear regression theory. Various data analysis and feature selection procedures have been performed to obtain the best possible model. The model based on linear regression has been compared with two alternative models. The algorithm validation was carried out based on historical data containing values of operating parameters from 10 months of mill operation. Historical data were downloaded from distributed control system (DCS) of a 200-MW coal-fired power plant. Tests carried out on historical data show that this algorithm can be successfully used to detect certain abnormal conditions and malfunctions of the operating mill, such as feeder blockage, lack of coal and mill overload.

Keywords: predictive maintenance, coal mill, fault detection, digital twin, online diagnostic

1. Introduction

Safety, reliability and flexibility are some of the most important operation features of any power plant. The abnormal operation conditions and malfunctions of coal mills negatively affect the boiler operation and furthermore can be the cause of emergency boiler shutdown. Coal mills produce the air and pulverized fuel mixture, which is burned in the boiler; hence, abnormal operating conditions can decrease boiler efficiency and increase CO2 and NOx emissions. Undetected at the right time, mill faults are the causes of numerous issues like failing to keep steam parameters, reduction of generated power, and the flame instability in the furnace, which enforces fuel oil burner usage to maintain continuity of combustion; the flame instability can lead to flame loss and that is one of the most dangerous situations that may appear in power plant.

As a consequence of these problems, coal mill control and fault detection have been the main focus in many research activities. General overview of control and fault diagnostic methods are the topics in [1, 2]. The authors in [3] investigated models based on the mass and heat balance together with the energy model. This model has been used in [4, 5]. In [4], observer-based models are developed. The fault detection is based on energy balance analysis, producing fault residuals that are used in detection schemes. It has been shown that the fault (blocked coal inlet pipe) is detected as soon as the fault occurs. A dynamic coal mil model using conservation laws and empirical relations has been developed in [6]. Unknown model parameters are estimated using differential evolution algorithm, and data set contains parameters from 7 days of mill operation. From the validation results, it is concluded that the model fits the on-site measured data very well, but model has not been tested in control or diagnostic application. Non-linear coal mill modeling and its application to model predictive control are presented in [7]. Three system output parameters of vertical roller coal mill (the pressure drop over the mill, power consumed by the mill and outlet temperature) models have been developed and used in non-linear model predictive control with results in improving coal load response time and temperature control. The observer-based approach presented in [3, 4] is compared with the regression-based approach in [8, 9]. The methods have been tested on data with one given fault that is dramatic increasing of the moisture content. Results show that both methods detect faults as it emerges, but the observer-based model detects the tested fault earlier than regression-based model.

In this chapter, a novel coal mill fault detection approach is presented. This is done through applying the linear regression theory to model two mill operating parameters: motor current and outlet temperature of pulverized fuel. Even though the regression theory has been tested and compared in [8], this chapter presents complex approach with high volume of data analysis containing around 2 million of measurements, while model in [8] has been trained on 300 samples. Additionally, the parameter's time delay influence has been tested as it was not used before and the input variables have been selected with the usage of advanced techniques of feature selection. The regression-based models are also compared with two alternative models that are artificial neural network-based models and physical equation-based models. Finally, developed algorithm has been implemented in fault detection algorithm implemented in 200 MW power unit.

The outlier of this chapter is as follows. The coal mill is introduced in Section 2. Real data analysis downloaded from Rybnik power plant is presented in Section 3. Section 4 focuses on feature selection process. In Section 5, moisture content estimation is presented. Developed models are presented in Section 6, and the comparison between two other models' approaches is derived in Section 7. Section 8 presents the algorithm evaluation, and Section 9 shows algorithm fault detection performance.

2. The coal mill

The work presented in this chapter is based on a MKM-33 ball mill used at Rybnik Unit 4 (rated capacity 220 MW). The mill is one of six mills supplying the 650-k (steam production of 650 t/h) boiler. However, the proposed method in this chapter is so generic that it can be applied to other types of coal mills. The coal mill is illustrated in **Figure 1**.

The coal is fed to the coal mill through the central inlet pipe, where it is pulverized by a series of large balls separated by two types of rings. The pulverized material is carried out in the mill by the flow of air moving through it. The primary air is a mixture of cold air and air heated by the preheaters. The ratio of the hot and cold air flows is used to control the temperature and the flow of the primary air. The size of the pulverized particles released from the grinding section of the mill is determined by a classifier separator. Too large and heavy particles fall back on the gridding table and will be crushed by bowls again.

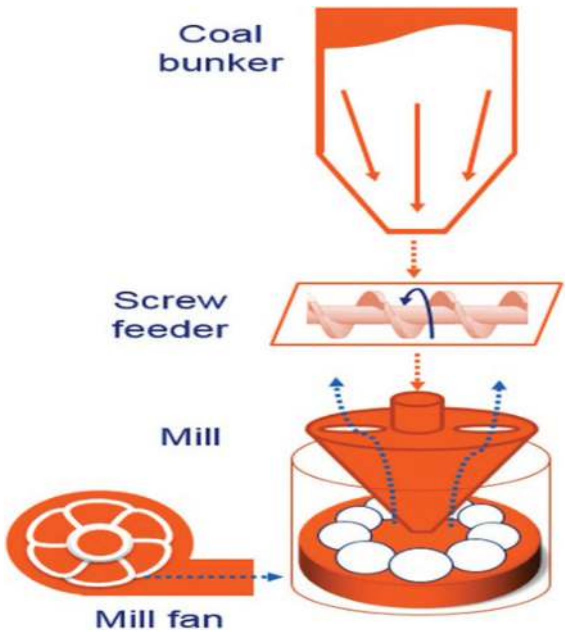

Figure 1. Coal mill scheme.

3. Real data analysis

3.1. Data set

The research has been performed on data set downloaded from Rybnik power plant DCS system. Data contain measurements values of 22 parameters from 10 months of mill operation (January 2014 to October 2014) with 10-s sampling period, except outside temperature and temperature in coal bunker which have 1-min sampling period. All parameters are presented in **Table 1**. In this chapter, variable names presented in **Table 1** have been used.

3.2. Data filtration and distribution analysis

Models presented in this chapter have been developed to describe mill normal working conditions based on historical data. Therefore, from the data set starts up, shuts down and work with feeder speed less than 10% has been removed. Additionally, seven new columns have been added to improve process description. Newly added columns are presented in **Table 2**.

No.	Variables	Description	Units
1	MW	Unit power	MW
2	MW_DMD	Unit power demand	MW
3	TURB_PRESS	Steam pressure at turbine inlet	MPa
4	PRESS_CORR	Corrected pressure demand for the boiler	MPa
5	STEAM_FLOW	Steam flow	t/h
6	FUEL_DMD	Fuel demand	%
7	FAN_DMPR	The fan blade setting	%
8	MILL_IN_PRESS	Primary air inlet pressure	kPa
9	MILL_OUT_TEMP	Temperature of pulverized fuel	°C
10	P_AIR_FLOW_DMD	Primary air flow demand	Nm^3/h
11	P_AIR_FLOW_BIAS	Primary air flow demand correction (manual)	Nm^3/h
12	P_AIR_FLOW	Measured primary air flow	Nm^3/h
13	HOT_AIR_DMPR	The opening of the hot air dumper	%
14	MILL_OUT_TEMP_DMD	Mill outlet temperature demand	°C
15	COLD_AIR_DMPR	The opening of the cold air dumper	%
16	FEEDER_LOAD	Feeder speed	%
17	AMPS	Mill motor current	A
18	TEMP_MILL_IN	Primary air inlet temperature	°C
19	PRESS_FAN_IN_L	Pressure in primary air collector (left side)	Pa
20	PRESS_FAN_IN_R	Pressure in primary air collector (right side)	Pa
21	TEMP_ON_LOAD	Temperature in coal bunker	°C
22	TEMP_OUTSIDE	Ambient temperature	°C

Table 1. Data set variable description.

New variable	Description	Formula
P_PP_IN_AVG_kPa	Pressure difference in primary air [kPa]	$\frac{P\_PP\_IN\_L+P\_PP\_IN\_P}{2}$
P_AIR_FLOW_kgs	Unit change from Nm^3/h to kg/s	$g_{air} = \frac{MILL\_IN\_PRESS}{r*\left(T_{PP_{IN}}+273\right)}$ $\text{P\_AIR\_FLOW\_kgs} = \frac{P_{AIR_{FLOW}}*g_{air}}{3600}$
DELTA_PA_mbar	Pressure difference between mill inlet and primary air collector	$10*(MP\_PP\_IN\_AVG_{kPa} \quad - P\_PP\_IN\_AVG\_kPa)$
FUEL2POWER	Proportion FUEL_DMD/MW, possible estimation of fuel quality	$\frac{FUEL\_DMD}{MW}$
FUEL_DMD_REG	Mean value FUEL_DMD for a given power obtained from linear regression for all historical data	$0.0749435882327*MW + 26.9627419581$
FQUALITY	Difference between FUEL_DMD and FUEL_DMD_REG - second, more accurate fuel estimation quality	$FUEL\_DMD - FUEL\_DMD\_REG$
SUPPLIED_HEAT	Product of STEAM_FLOW and TEMP_ON_LOAD (proportional to the heat supplied)	$STEAM\_FLOW*TEMP\_ON\_LOAD$

Table 2. Added variable.

Finally, an additional column has been added for each input variable (all variables except AMPS and MILL_OUT_TEMP), and newly added columns contained the rolling mean of each column calculated according to the formula 1

$$x_{mean\_3}(t) = \frac{x(t-20s) + x(t-10s) + x(t)}{3} \tag{1}$$

where x is measured value at time t. The final data set contained 56 columns: 27 columns each for one depended variable, 27 columns for theirs means and two columns each for one independent variable. Histogram plots show that we can split data parameters into two groups:

1. Variables with normal distribution
2. Variables with bimodal distribution: MW,

MW_DMD, MILL_OUT_TEMP_DMD, MILL_OUT_TEMP, PRESS_CORR, STEAM_FLOW, FUEL_DMD_REG. Bimodal distribution of power is a result of unit working conditions (high power demand during morning hours, and low power demand during evening hours). Bimodal distribution of outlet temperature is caused by milled fuel type. During periods of coal and biomass co-milling, the mill outlet temperature demand has been set at 115°C. If the mill was gridding, only coal mill outlet temperature demand has been set at 105°C. Histograms are presented in **Figures 2** and **3**.

3.3. Co-correlations between model output and inputs

As presented in Section 2, the process of coal pulverizing in the mill consists of some sub-processes, for example hot and cold air mixtures before entering the mill. Some variable measurements (data set columns) can influence the main process with different time delay. To

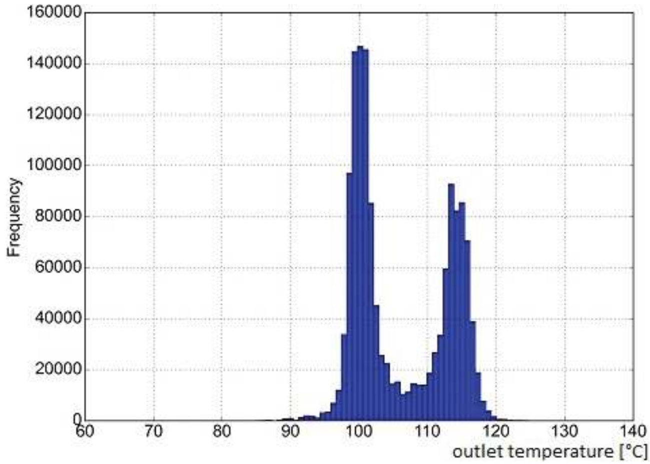

Figure 2. MILL outlet temperature (MILL_OUT_TEMP) histogram.

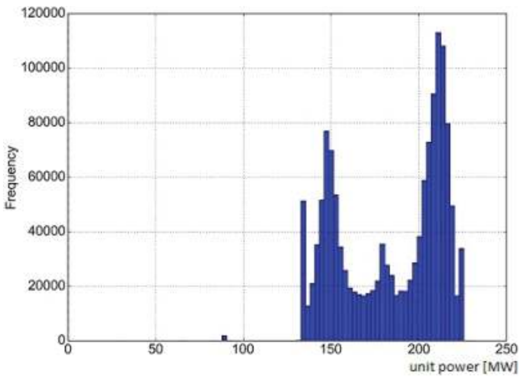

Figure 3. Unit power (MW) histogram.

explore the delay values, the Pearson correlation analysis has been made. Pearson correlation coefficient is a measure of the linear correlation between two variables.

For each depended variable, new columns have been added containing delayed variable values for 10, 20, 30,…,300 s. Afterwards, for each column presented in **Tables 1** and **2** and their mean values, the Pearson correlation coefficient has been calculated and the delay with the highest Pearson coefficient has been chosen. The results are presented in **Tables 3** and **4**.

For MILL_OUT_TEMP, most of the parameters are the best correlated with 6-min delay. This time shows the automatic process control reaction time for mill outlet temperature demand changes. Only the parameters which do not influence directly into demanded outlet temperature are correlated with very slow delay (10, 20 s) For the AMPS variable, the system is reacting for AIR_FLOW_DMD changes with around 6-min delay. However, parameters with strong influence into process are correlated with small delay. The best correlated with AMPS is variable

FEEDER_LOAD_mean3 (correlation value is equal to 0.395). The correlation coefficient higher than 0.3 has also variables: FEEDER_LOAD, FAN_DMPR, MILL_IN_PRESS, P_AIR_FLOW_kgs, DELTA_PA_mbar and theirs means. The best correlated with MILL_OUT_TEMP is variable: MILL_OUT_TEMP_DMD_mean3. With correlation coefficient 0.926 (for the rest of variables, correlation coefficient is not greater than 0.5).

Variables	Delay [s]	Correlation coefficient
FEEDER_LOAD	150	0.393
FAN_DMPR	80	0.390
MILL_IN_PRESS	130	0.369
P_AIR_FLOW_kgs	130	0.347
DELTA_PA_mbar	130	0.340
FUEL_DMD	150	0.289
P_AIR_FLOW_DMD	90	0.287
SUPPLIED_HEAT	30	0.282
FUEL_DMD_REG	20	0.281
MW	20	0.281
MW_DMD	30	0.281
STEAM_FLOW	30	0.276
P_AIR_FLOW	20	0.239
PRESS_CORR	300	0.220
HOT_AIR_DMPR	20	0.208
TURB_PRESS	10	0.199
COLD_AIR_DMPR	300	0.195

Table 3. Variable delays best correlated with AMPS.

Variables	Delay [s]	Correlation coefficient
MILL_OUT_TEMP_DMD	300	0.926
COLD_AIR_DMPR	300	−0.497
TEMP_MILL_IN	300	0.467
P_AIR_FLOW_kgs	300	−0.362
TEMP_OUTSIDE	300	−0.327
DELTA_PA_mbar	10	−0.269
MILL_IN_PRESS	10	−0.259
P_AIR_FLOW_DMD	200	−0.247
P_AIR_FLOW	300	−0.240
TEMP_ON_LOAD	300	−0.202

Table 4. Variable delays best correlated with MILL_OUT_TEMP.

4. Feature selection

So far, input data set used to evaluate models contains all parameters. Obviously, not all of them have the impact on modeling parameters. The process of feature selection has been made to extract all variables with the influence on modeling output. This process is also developed to:

1. simplify the model. Simple models are easier to interpret and maintain;
2. increase the generalization of the model by limiting overfitting, and by that, increasing the quality of the modeling;
3. decrease the model training time.

The main assumption during feature selection is that the initial data set contains variables which are redundant, strongly correlated with one another or irrelevant and, therefore, can be deleted without information losses [10, 11].

The wage of model improvement is determined by model accuracy coefficient, and in this chapter, the root mean square (RMS) coefficient has been used. Forward feature selection has been made with the usage of author algorithms. The comparison between various developed models has been made by comparing calculated model accuracy coefficients. For each model, the following model fitting parameters have been calculated: coefficient of determination (R^2), root mean square (RMS) and mean average percentage error (MAPE). Those parameters have been calculated with the usage of threefold cross-validation technics [12]. Comparison between models has been made by comparing RMS coefficient value.

The determination of unknown regression coefficient has been made with linear and ridge regression usage [13].

In **Table 5**, the reference model is presented. The reference model has been fitted to initial data set containing variables presented in **Tables 1** and **2** and their means (no feature selection process).

Depended variables	R^2	RMS	MAPE
AMPS	0.256	0.707	1.903
MILL_OUT_TEMP	0.85	2.21	1.43

Table 5. Reference models.

Features	Accuracy coefficients	
MILL_IN_PRESS_mean3–120, P_PP_IN_AVG_kPa-30, FUEL2POWER-10, FUEL2POWER_mean3–10	MAPE [%]	1.965
	RMS [A]	0.622
	R^2 [−]	0.179

Table 6. AMPS model.

In **Table 6**, the best model evaluated for AMPS independent variable after feature selection process is presented; the number of features has been decreased from 55 to 4 with minor model accuracy diminution.

The model variables have been chosen from the RFECV feature selection method, with ridge regression model fitting estimator ($\propto$ =1e 07).

In **Table 7**, the best model evaluated for MILL_OUT_TEMP independent variable is presented. The feature number has been decreased from 55 to 15, and the model accuracy has been improved. The features have been chosen from the RFECV feature selection method. The model accuracy has been improved in comparison with the reference model.

The autoregressive models have not been considered because of future model's use that is fault detection. Autoregressive models in case of fault development will model malfunction, and consequently, the fault will be undetected.

Afterwards, few additional hypotheses have been investigated:

Hypothesis 1: Continuous historical data updating can improve model fitting. An assumption has been made that if we will train model progressively based on defined period of historical data, the accuracy of the model will be improved in comparison with model based on all historical data. The hypothesis has been tested by algorithm that idea is presented in **Figure 4**. First model is trained on data located in history window, then the model output prediction is made for samples located in prediction window. Afterwards, data widow is moved by the length of prediction window; then, process of model training and output prediction is repeated. The windows are moved after each iteration until the end of data set.

The algorithm has been implemented to forward feature selection but without particular success (the feature selection algorithm has stopped after first iteration). Furthermore, the algorithm has been used to obtain model coefficient for models presented in **Tables 6** and **7**; for this model, numerous configurations of data history window and data prediction window have been examined. The summary of results is presented in **Table 8**.

The best growth of MAPE coefficient has been observed for short historical data windows (from 14 to 28 days) though training model on such short period of time can be dangerous. If

Features	Accuracy coefficients	
MILL_OUT_TEMP_DMD_mean3–300,FUEL2POWER_mean3–300, P_AIR_FLOW_DMD_mean3–190,COLD_AIR_DMPR-300, TEMP_MILL_IN_mean3–300,P_AIR_FLOW_BIAS_mean3–10, FEEDER_LOAD_mean3–180,COLD_AIR_DMPR_mean3–300, HOT_AIR_DMPR-300, FQUALITY_mean3–300, MW-300,TURB_PRESS_mean3–300, P_AIR_FLOW_DMD-200,PRESS_CORR-300, P_AIR_FLOW_BIAS-10,MW_DMD_mean3–300, STEAM_FLOW-10,P_AIR_FLOW-300, PRESS_FAN_IN_L-300,FUEL_DMD_mean3–300,	R^2[−]	0.930
	RMS[°C]	1.831
	MAPE[%]	1.253

Table 7. MILL_OUT_TEMP model.

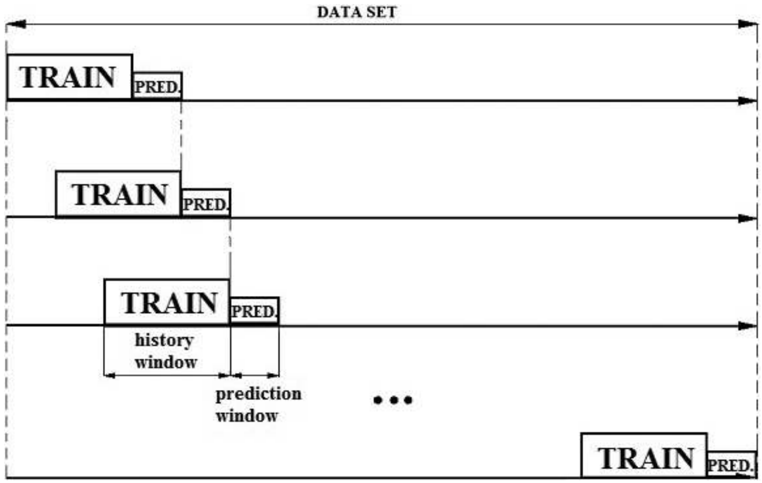

Figure 4. The idea of progressive prediction.

abnormal condition has occurred during this period, the model will fit coefficients into these data obviously; furthermore, model would not achieve its function. It has been assumed that safe historical data length is greater than 800,000 s (around 3 months). For such cases, model accuracy has not improved significantly, and this is why the algorithm has been rejected. Nevertheless, it has to be kept in mind that after some periods, the model coefficient has to be updated, for example in case of mill or boiler renovation. In such cases, it is recommended to train the model on at least 2-month history data set.

Hypothesis 2: The fuzzy regression will improve model accuracy. As shown in Section 3.3, some parameters have bimodal distribution; in such cases, fuzzy regression can be successfully implemented. An algorithm has been developed which creates two linear models, model for high load and model for low load. The model output is the sum of those sub model outputs, multiplied by wages that are depended on load. The formula for wages is presented in Eqs. (2) and (3):

$$\mu_{low\ demand} = \begin{cases} 1 & for\ x < 150 \\ \dfrac{190 - x}{190 - 150} & for\ x\ \epsilon < 150, 190 > \\ 0 & for\ x > 190 \end{cases} \tag{2}$$

$$\mu_{high\ demand} = \begin{cases} 1 & for\ x < 150 \\ \dfrac{x - 150}{190 - 150} & for\ x\ \epsilon < 150, 190 > \\ 0 & for\ x > 190 \end{cases} \tag{3}$$

where x is the unit power. As presented in **Table 9**, the model accuracy has not been improved.

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History window (s)	Prediction window (s)	R^2 [−]	RMS [A]	MAPE [%]
50,000	100	0.495	0.488	1.551
100,000	100	0.375	0.543	1.732
100,000	500	0.317	0.568	1.755
5,000,000	100	0.184	0.590	1.890
5,000,000	500	0.164	0.597	1.890
5,000,000	1000	0.142	0.605	1.891

Table 8. AMPS moved historical window.

	RMS	MAPE
AMPS	0.719	1.922
MILL_OUT_TEMP	9.428	1.224

Table 9. Fuzzy regression.

Hypothesis 3: Non-linear input variable transformation may increase model accuracy. Since the processes occurring in the mill are non-linear, some input parameters' manipulation has been investigated. To perform, an algorithm has been created which was adding a new parameter that was obtained by changing selected parameters values according to defined manipulation; however, during one iteration, only one parameter with one manipulation has been investigated; after iteration, the algorithm was returning to initial data set. The parameter modifications have been based on functions such as quadratic function, cubic function, square, natural logarithm, decimal logarithm and exponential function. The results show that for none of the parameter's modification, the model accuracy coefficients have improved significantly.

5. Coal moisture content

To improve model accuracy and abnormal working conditions' detection ability, the estimation of the moisture content has been evaluated. Two main processes, coal gridding and moisture evaporation from the coal dust, are taking place in the mill, and the quality and performance of those processes are highly depended on coal milling quality and moisture content. Online measurements of those parameters are not possible; however, the moisture content can be determined by evaluating the energy balance.

A simple energy balance model of the coal mill is derived based on [2, 3]. The coal mill is considered as one body with the mass m_m, as illustrated in **Figure 5**.

In **Figure 5**, T(t) is the temperature in the mill, Q_air (t) is the energy in the primary air flow, Q_coal (t) is the energy in the coal flow, Q_moisture (t) is the energy in moisture, Q_e (t) is energy losses to environment, Q_pf (t) is energy in air-fuel mixture, Q_steam (t) is energy in steam, Q_evap (t) is energy used to evaporate moisture and Q_cum (t) is accumulated energy

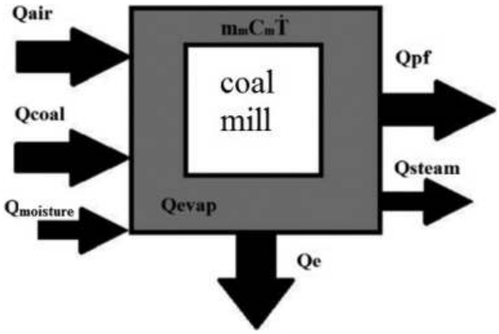

Figure 5. Scheme of coal mill heat balance.

in the mill. The specific heat capacity of the mill is C_m. Even though this assumption is only entirely true for steady state, it is assumed in this chapter for simplifying the model.

The energy balance is given by [2, 3](4):

$$Q_{air}(t) + Q_{coal}(t) + Q_{moisture}(t) = \quad Q_{pf}(t) + Q_{cum}(t) + Q_e(t) + Q_{steam}(t) \tag{4}$$

The Q_cum (t) + Q_e (t) + Q_steam (t) coefficients have been neglected due to relatively small influence into balance or lack of information. The heating and evaporation of the moisture in the coal are modeled by combined heating coefficients. The latent energy of the evaporation dominates the energy required for a few degrees of heating of the moisture. The combined heat coefficient, H_st, is defined as follows: H_st = C_w + L_steam/100, where C_w is the specific heat of the water and L_steam is the latent heat. This combined heat coefficient does not deal with the fact that the specific heats of water and steam are different. However, the model error is due to heat if steam to a couple of degrees above 100°C is negligible in this context. The moisture content has been determined by [4](5):

$$\gamma = \frac{m_{air} Cp_{air} * (T_{air_{in}} - T_{out}) + m_{coal}\, Cp_{coal}\left(T_{on_{load}} - T_{out}\right)}{m_{coal}\, Cp_{coal}\left(T_{on_{load}} - T_{out}\right) + m_{coal}(T_{out} - T_{on\ load}) + m_{coal} h_{ev}} \tag{5}$$

where m_{air} is the primary air flow, m_{coal} is the coal flow into mill, Cp_{air}, Cp_{coal} are specific heat of air and coal, $T_{air_{in}}$ is primary air flow temperature,T_{out} is outlet temperature of pulverized fuel, and $T_{on_{load}}$ is temperature in coal bunker. The modeling results are presented in **Figure 6**.

The moisture content together with the heat accumulation determined by (6) has been added to AMPS model selected features.

$$Q_{acumulated} = Q_{air} + Q_{coal} - Q_{coal\_dust} \tag{6}$$

The model accuracy has been slightly improved, and it has also been noticed that the model presents high differences from measurements during faults.

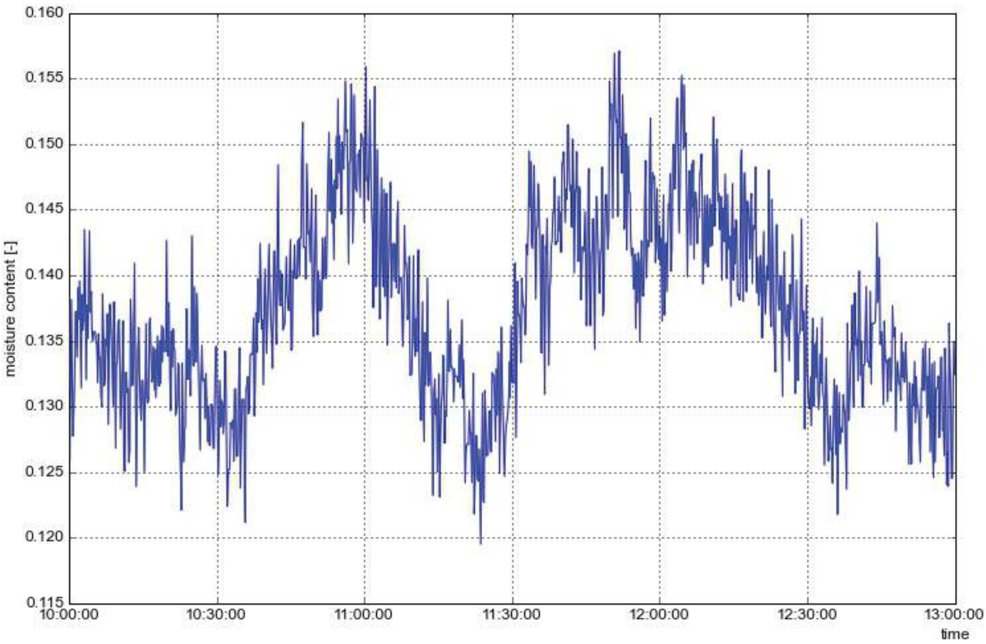

Figure 6. The plot of moisture content estimation.

6. Modeling results

The best obtained models have been based on variables presented in **Tables 7** and **10**. The predicted values are compared with the measured values in **Figures 7** and **8**. From this figure, it can be seen that the models are quite similar to the dynamical changes as the measurements show. However, for periods with co-milling the biomass, model behavior with comparison to measurements is not sufficient. The analyzed power plant does not continue co-firing of biomass with such way; therefore, these periods are not the main focus of this algorithm. It has also been noticed that during fault occurring in data sets, the models have been presenting a noticeable difference from the measurements.

Features	Accuracy coefficients	
MILL_IN_PRESS_mean3–120, P_PP_IN_AVG_kPa-30, FUEL2POWER-10, FUEL2POWER_mean3–10 $\gamma = Q_{acumulated}$	MAPE [%]	1.946
	RMS [A]	0.601
	R^2 [−]	0.21

Table 10. Adding moisture content.

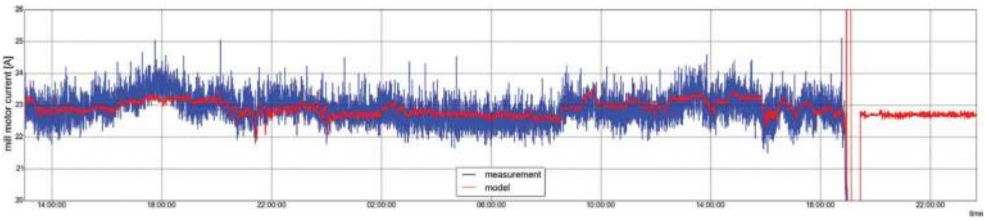

Figure 7. The plot of measured and modeled values of mill motor current (AMPS) date: 15 Feburary 2015, fuel: Coal.

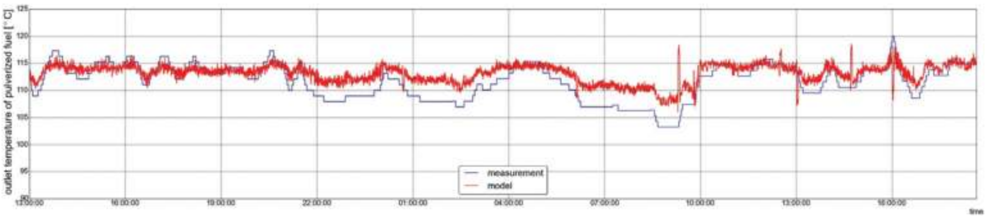

Figure 8. The plot of measured and modeled values of mill outlet temperature (MILL_OUT_TEMP) AMPS 15 Feburary 2015, fuel: Coal.

7. Comparison with artificial neural network and physical model

As presented in Section 1, the mill models have been the subject of investigation by many researches; nevertheless, the main scope of models creation is to develop model as simple as possible without significant model accuracy losses. Processes occurring in the coal mill are dynamic and nonlinear; this is why so many methods have been investigated. The model based on linear regression has been compared with the model based on artificial neural network and the model based on physical equations with genetic algorithm usage to determine unknown parameters.

7.1. Model based on artificial neural network

Artificial neural network (ANN)-based modeling is non-linear statistical technique [14]. Recently, there has been increasing interest in neural network modeling of industrial processes such as gridding in coal mills [19]. The design of ANN includes the choice of architecture, training function and training algorithm. The architecture of a network is determined by the number of hidden layers in the network, the number of neurons and the transfer function in each layer, and how the layers are connected to one another. The basic neural network is shown in **Figure 9**.

The multi-layer perception neural network (MLPNN) is one of the most widely applied neural network topologies, and this topology has been applied to develop non-linear models. The input variables are the features selected and presented in Sections 4 and 5. The values of data

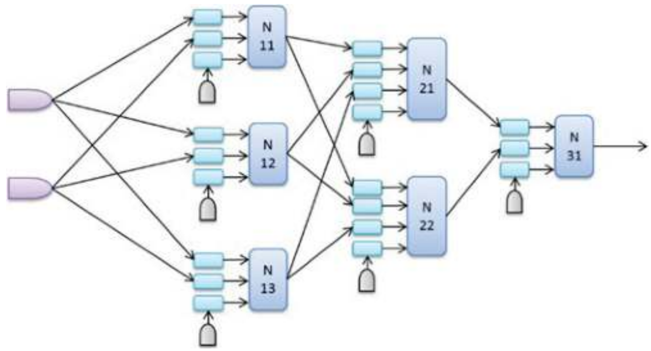

Figure 9. Example of artificial neural network architecture.

Number of neurons		MAPE [%]	
First hidden layer	Second hidden layer	AMPS	MILL_OUT_TEMP
11	8	1.961	1.12
20	6	1.959	1.10
8	2	1.984	1.18
15	0	1.971	1.15
4	0	2.21	1.29

Table 11. ANN modeling results.

set have been standardized [15, 16]. The MPLPNN hidden and output layers are activated with tangent-sigmoid function. Numerous combinations of architecture have been investigated to develop the best possible model. The architecture combinations are presented in **Table 11**. During training and testing procedures, the accuracy parameters have been calculated with cross-validation [12] technique usage. The ANN has been trained with usage of backpropagation supervised ANN learning algorithm. The ANN consists also the bias coefficients. The best obtained structure and results are presented in **Table 11**.

7.2. Model based on physical equations with the use of a genetic algorithm to determine the unknown model coefficients

This method has been developed by [16, 17], and the model is derived through the analysis of energy transferring, heat exchange and mass flow balances. A non-linear mathematical model for a normal mill grinding process was developed in the previous work [16], which was based on the following assumptions: (1) the pulverizing mechanism in the mill is simplified, and coal classification is not considered; (2) grinding and pneumatic transport in the milling process are separated into two stages; and (3) coal size is grouped into only two categories, namely pulverized coal and unpulverized coal. The mill model for the steady-state milling process can be described by numerous equations [16, 17], containing five algebraic equations describing primary air flow based on pressure differences and air density, coal flow based on feeder speed, pulverized coal flow based on pressure differences and actual amount of pulverized fuel in mill and four differential equations describing mass balance in coal mill based on coal flow, actual coal content in mill, pulverized fuel flow and content in coal mill following equation describing mill motor current, mill pressure differences, and outlet temperature variability.

The main focus in developing this model is unknown coefficients K_i, where i ∈{1,2,3,…,17} definition is such way that the model has the lowest prediction error (the difference between measured and modeled values is minimalized). One approach [16] uses the genetic algorithm to determine unknown coefficients. The same method has been developed and applied to analyzed coal mill [18], and the results are presented in **Table 12**.

7.3. Comparison

In this chapter, three coal mill models' evaluation approaches are presented, and the methods are linear regression (Sections 4, 5 and 6), artificial neural network (Section 7.1) and physical equations with the use of a genetic algorithm to determine the unknown model coefficients (Section 7.2). All mentioned methods have been applied to data set containing values of operating parameters from 10 months of mill operation presented in Section 3. The results presented in **Table 13** show that the AMPS models have similar performance with the MAPE coefficient close to 2%, which is less than 0.5A mean error. The results presented in **Table 14** show that the MILL_OUT_TEMP models have more varied results.

Although ANN-based model of MILL_OUT_TEMP has the best accuracy, and the Ridge regression-based model has lower as it can be seen in **Figures 10** and **11**; the behavior of models, response to parameter changes and places of higher difference from measures are the same. The ANN better adapts to periods with high temperature increasing mainly in case of mill start-up. However, both models have the same sudden changes of predicted value as presented in **Figures 10** and **11**; ANN generates the valued bit proximal to measurement than ridge regression but without significant influence into further application to fault detection. It has been also tested that both models detect abnormal working condition present at nearly the same time. It seems reasonable to use Ridge regression-based models in algorithm since they are easier to train, maintain and adapt.

	MILL_OUT_TEMP [°C]	**AMPS [A]**
MAPE [%]	1.15	2.02

Table 12. Genetic algorithm.

Model based on	**MAPE**
Ridge regression	1.946
Artificial neural network	1.981
Physical equations	2.020

Table 13. AMPS comparison.

Model based on	MAPE
Ridge regression	1.26
Artificial neural network	1.10
Physical equations	1.15

Table 14. MILL_OUT_TEMP comparison.

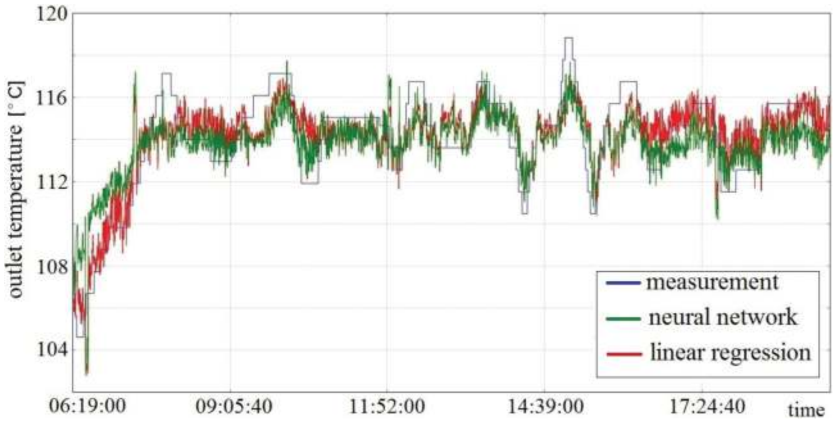

Figure 10. ANN and ridge regression comparison.

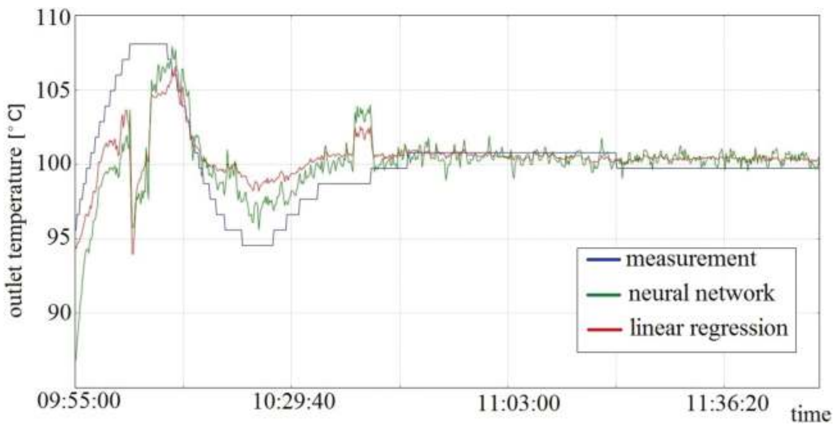

Figure 11. ANN and ridge regression comparison.

The models' application into industrial process control and fault detection usually depends on the model accuracy and the model complexity. As presented in the chapter, the three different approaches of AMPS model evaluations gave comparable model accuracy; however, their complexity differs. It seems natural that the model with the lowest complexity level is implemented, and still, furthermore, complex comparison tests should be performed. Model based on physical equation is the most understandable, but the process of unknown coefficient estimation is time-consuming and non-deterministic; the neural network-based model is the most complex and the least comprehensible; consequently, its implementation does not seem to be needed. The advantage of regression model is its simplicity and comprehension; therefore, it seems appropriate to implement model in algorithm designed to detect mill faults.

8. Fault detection algorithm

The models presented in **Tables 6** and **7** have been used to develop the algorithm and enabled to detect abnormal operation conditions and malfunction of analyzed mill. The algorithm during mill operation determines diagnostic signals (7) which represents the difference between measured y_measured and predicted y_predicted values of mill current and outlet temperature:

$$r = y_{predicted} - y_{measured} \tag{7}$$

If the value exceeds defined threshold, the algorithm infers about abnormal working condition presence. The predicted values are calculated based on coefficients determined for model presented in **Tables 8** and **10** with consideration of variable delays presented in **Tables 3** and **4**.

8.1. Threshold definition

The appropriate threshold value definition is crucial; if the threshold is low, the algorithm will often falsely infer the presence of abnormal condition; on the other hand, if threshold will be too high, the algorithm may not infer abnormal conditions while it occurs. The threshold values have been determined based on residual valued r, and the distribution of residuals is presented in **Figures 12** and **13**.

After analyzing the model behavior, it has been decided that the algorithm will infer with two levels:

LEVEL 1—abnormal operation conditions.

LEVEL 2—fault.

The thresholds for each level are presented in **Table 15**, and the alarm disabling will occur when the diagnostic signal value is decreased to determine value.

8.2. Fault cause distinction

When algorithm informs about appearance of abnormal working conditions, which mean that at least one diagnostic signal has exceeded the threshold, the most likely cause of these conditions is estimated and provided. There are three main fault causes that algorithm detects: feeder blockage, lack of coal in the mill and mill overload. Inference mechanism combines the algorithm performance and unit operator’s experience.

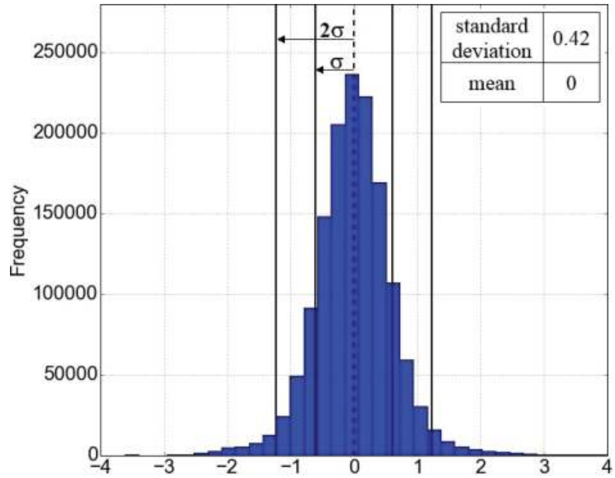

Figure 12. AMPS histogram of residuals.

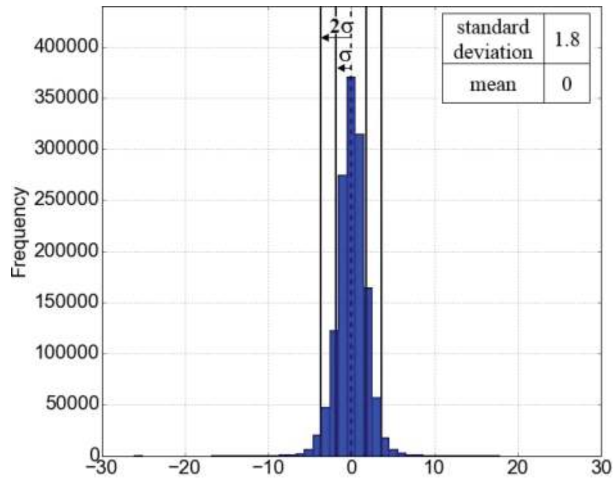

Figure 13. MILL_OUT_TEMP histogram of residuals.

Model	Threshold for level 1	Threshold for level 2	Threshold for disabling
AMPS	1,2	2	0,8
MILL_OUT_TEMP	8	15	6

Table 15. Thresholds.

First, algorithm determines whether in the mill there is too much ($r > 0$) or too little of coal ($r < 0$). If there is too little of coal, the second step is to compare temperature in coal bunker. If there is no coal in feeder, the temperature instantly is rising and the feeder motor current is lower that usually. In case of $r > 0$, the algorithm also is checking the mill inlet presser since it is main parameter observed by operators during mill diagnostic; if the pressure is significantly higher than usual, the algorithm also informs about it. Those mechanisms have been implemented in operator graphic which informs about current mill conditions and estimated risks.

8.3. Algorithm

Algorithm presented in **Figure 14** is designed to inform online about coal mill working conditions. History window contains the measurements from last 5 min (due to input signal time delay), and diagnostic signal is generated in way presented in Section 8. The operators are informed about actual coal mill conditions and estimated risk by dedicated operator graphic containing information about diagnostic signals and estimated risks presented in Section 8.2.

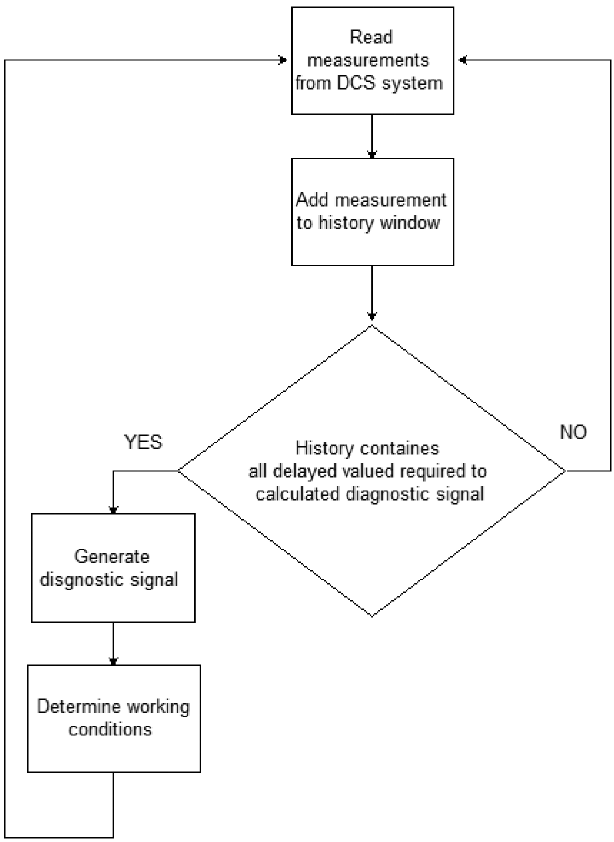

Figure 14. The idea of online diagnostic algorithm.

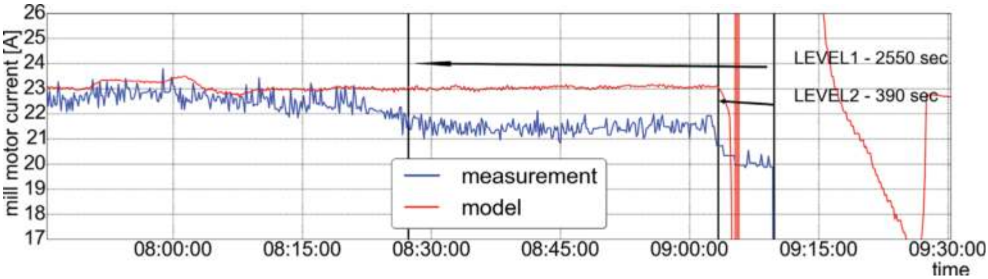

Figure 15. AMPS11 September 2014 fault: Screw blockage.

9. Fault detection performance

The algorithm has been tested to analyze its fault detection performance. In historical data set, the faults occur six times and were caused by lack of coal in coal bunker, feeder blockage and mill overload. For each malfunction type, the algorithm infers abnormal working conditions with some ahead of time. Particularly, the algorithm detects the feeder blockage. For fault in 11 September 2014, the algorithm infers abnormal working conditions around 40 min ahead the mill shutdown and 6 min before mill shutdown algorithm inferring about fault. More detailed times are presented in **Table 16**. It can be seen that the failure has been developing during period between first alarm occupancy at LEVEL1 and LEVEL 2. This gives the unit operators enough time to react safely.

In **Figures 15–16**, the comparison of measured and modeled values is presented. The same type of fault appeared in 22 January 2014, and the LEVELS 1 and 2 appeared at similar time around 11 min before emergency mill shutdown. Details are presented in **Table 17**, and

Model	Level 1	Level 2
AMPS	2550 s	390 s
MILL_OUT_TEMP	240 s	240

Table 16. 11 September 2014 fault: Screw blockage.

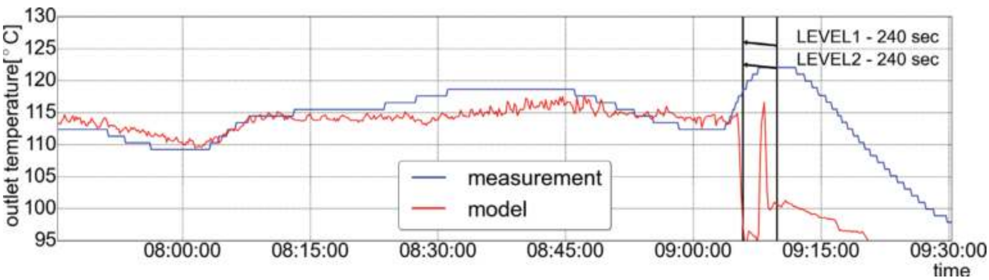

Figure 16. MILL_OUT_TEMP 2014.09.11 fault: Screw blockage.

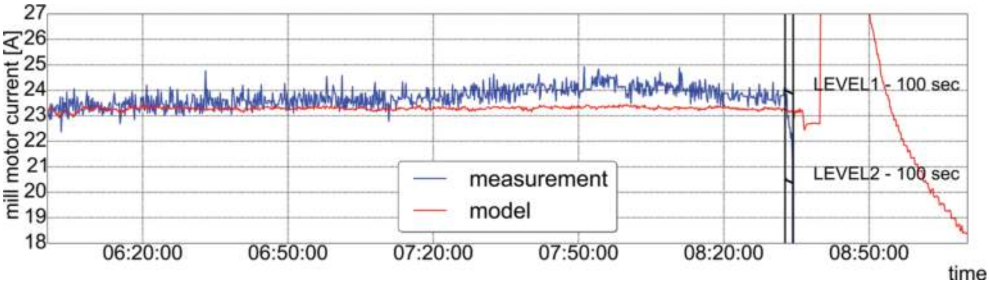

Figure 17. AMPS 12 July 2014 fault: Lack of coal in coal bunker.

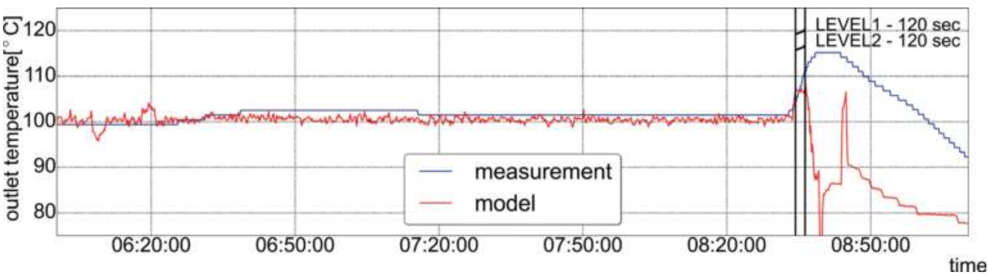

Figure 18. MILL_OUT_TEMP 12 July 2014 fault: Lack of coal in coal bunker.

MODEL	Level 1	Level 2
AMPS	670	600
MILL_OUT_TEMP	590 s	590

Table 17. 22 January 2014 fault: Screw blockage.

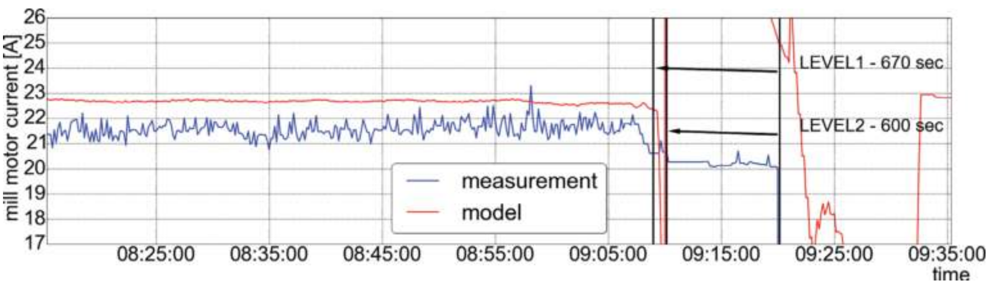

Figure 19. AMPS 22 January 2014. Fault: Screw blockage.

http://dx.doi.org/10.5772/intechopen.72952

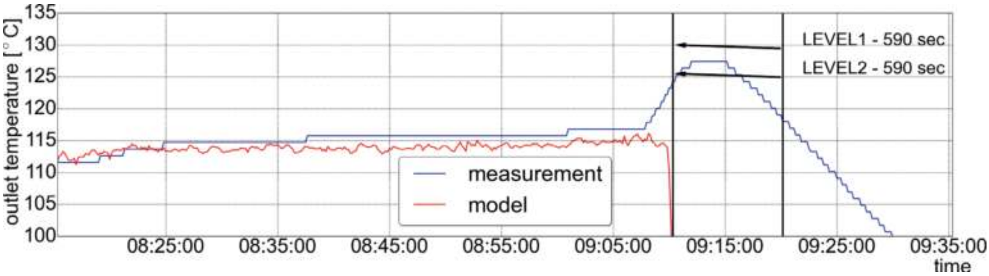

Figure 20. MILL_OUT_TEMP 22 January 2014. Fault: Screw blockage.

MODEL	Level 1	Level 2
AMPS	100	100
MILL_OUT_TEMP	120	120

Table 18. 12 July 2014 fault: Lack of coal in coal bunker.

comparison of modeled and predicted values is presented in **Figures 19** and **20**. It can be seen that the failure occurred suddenly unlike the failure on 11.09 where before failure the mill has been working with abnormal conditions for around 30 min; however, the algorithm has been informing at LEVEL 2 10 min before mill shut down. The fault caused by lack of coal in the bunker is presented in **Figures 17** and **18**, and the times of algorithm abnormal working condition inference are presented in **Table 18**. The algorithm infer at LEVEL 1 and LEVEL 2 around 2 min before emergency mill shutdown; although this is not a lot this types of faults forms and evolve relatively fast and inexpertly and algorithm allows inform and give for the operator a time for propel reaction.

10. Conclusion

This chapter presents the models of two coal mill operation parameters: motor current and outlet temperature of pulverized fuel, implemented in algorithm designed to detect faults and abnormal operating conditions in coal mills. During extended data analysis, it has been shown that some depended variables influence independent variables with certain delay. The models have been developed with usage of multiple regression theory and compared with model based on an artificial neural network and model based on physical equations. It has been demonstrated that regression-based models have comparable model accuracy and fault detection performance. Based on developed models, an algorithm that detects abnormal working conditions and faults of coal mill has been developed. Tests carried out on historical data show that this algorithm can be successfully used to detect certain abnormal conditions and malfunctions of the operating mill, such as feeder blockage, lack of coal and mill overload. The algorithm is implemented in the power plant on 200 MW power unit.

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