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ARTIFICIAL AND COMPUTATIONAL INTELLIGENCE

The identification method of the coal mill motor power model with the use of machine learning techniques

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Abstract. The article presents an identification method of the model of the ball-and-race coal mill motor power signal with the use of machine learning techniques. The stages of preparing training data for model parameters identification purposes are described, as well as these aimed at verifying the quality of the evaluated model. In order to meet the tasks of machine learning, additive regression model was applied. Identification of the additive model parameters was performed on the basis of iterative backfitting algorithm combined with nonparametric estimation techniques. The proposed models have predictive nature and are aimed at simulation of the motor power signal of a coal mill during its regular operation, startup and shutdown. A comparative analysis has been performed of the models structured differently in terms of identification quality and sensitivity to the existence of an exemplary disturbance in the form of overhangs in the coal bunker. Tests carried out on the basis of real measuring data registered in the Polish power unit with a capacity of 200 MW confirm the effectiveness of the method.

Key words: coal mill motor power; nonlinear model identification; machine learning; additive regression model; process monitoring.

1. Introduction

Economic development of a country is dependent on its access to energy, that is why energy security is a strategic matter for every country. Despite the CO2 emission requirements [1], the coal power industry is still developing dynamically. The basis of the energy sector in Poland are steam units burning coal fuels. At the moment, 80% of electric energy in Poland is generated by two types of fuels – hard coal and brown coal [2]. The condition for constant and effective supply of energetic units in fuel is the correct operation of coal mills which are responsible for pulverizing, drying and transport of coal dust to the boilers. The pulverised coal combustion process in power boilers is a complex technological process [1].

Operation of the mill depends on the quality of the fuel (coal or a blend of coal and biomass) and the wear of exploitation elements, as well as the implemented diagnostic system, whose purpose is early detection of any disturbances and preventing them by undertaking actions securing the power unit without the need to stopp the mill. An example of a disturbance destabilising the operation of the control system is a disruption in the fuel supply to the mill. A low level of the coal in the bunker or its lack may lead to overheating of the mill and, as a consequence to the fire of the mill and the carburizing installation. Monitoring of the crucial parameters of pulverizing process may significantly affect its exploitation security and maintaining continuity in delivery of electric energy [1, 3, 4].

The models simulating the operation of coal mills are crucial during the implementation of control, optimization or diagnostic tasks. The models commonly used in the power industry are analytical models based on the laws of physics and chemistry, occurring when pulverizing raw coal and delivering a dust-air mixture to the boiler. Such models are based on the balance of the coal physical mass and thermal balance dependencies [5–7]. Due to the complexity of the processes occurring in the pulverizing, drying and burning of the coal processes, the construction of such models is often very difficult.

Modelling of undetermined processes occurring in complex energetic installations requires the use of simplified models using multimodal parameters distribution depending on the distinguished space of the object. In order to recreate the behaviour of a coal mill in different pulverizing conditions, the paper [8] proposes the use of dynamic model where the internal area of the mill is divided into 4 zones and carbon particles are divided into 10 size groups. The authors of [9] in turn suggested the division of the internal area of a mill and carbon particles into 5 zones and 5 size groups. Paper [10] also describes a simple model determining 11 parameters of the model. The authors of [11] developed a six-segment model of a coal mill for different operating stages (startup, steady state, shutdown and stopping). The models of thermal balance and the balance of the coal mass are then constructed depending on the particular zones and stages of mill operation.

Analytical models can be difficult to implement due to some parameters such as calorific value and moisture level of raw coal delivered to the mill being determined experimentally [12, 13]. Literature describes numerous improvements of balance models [11, 14, 15], which when basing on genetic algorithms allow for efficient estimation of these parameters, which

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are difficult to calculate analytically. However, due to the simplified modelling and a huge set of parameters, the possibilities to use such models are limited.

The development of metrological technologies and computational methods allowing for collecting, storing and processing of a large amount of process data, provided new possibilities in testing thermal-flow energetic installations. Among the intelligent computational methods, a crucial role is played by artificial neural networks and fuzzy logic systems, which may be used in monitoring and optimization of the processes occurring in a coal mill, its control or fault diagnostics [16–18]. High accuracy of neural and neural-fuzzy models is usually obtained at the expense of the appearance of dimensionality problems. The increase of the number of process variables rapidly increases computational inputs in neural modelling and the number of rules in fuzzy modelling.

The paper presents an alternative technique overbearing limitation related to nonlinear multidimensional modelling. These are additive models [19] used to estimate and predict the motor power signal of a mill during its regular operation, startup and shutdown.

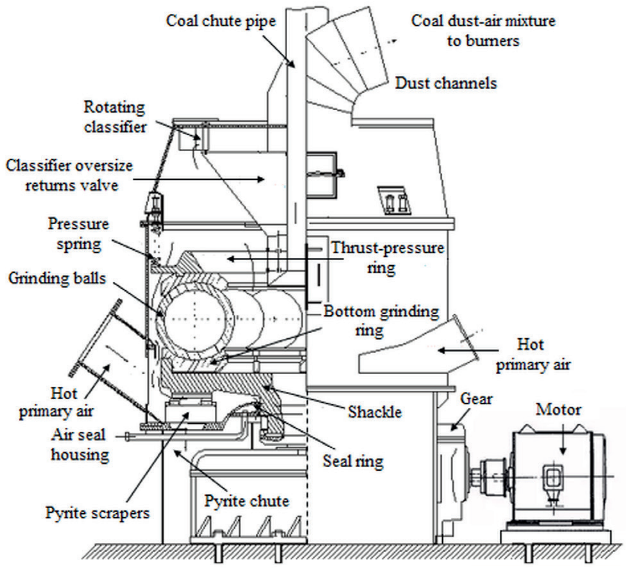

Fig. 1. A schematic drawing of a ball-and-race MKM type coal mill

2. Description of a pulverized coal-fired boiler and its principle of operation

Tests were carried out on the basis of real measuring data. These are the archival data from DCS control system from a Polish power unit with a capacity of 200 MW. The power station is equipped with an OP-650 boiler drum with a natural circulation of water, hard coal dust-fired.

2.1. Description of a coal mill. The object separated from the technological installation is one of the 4 ball-and-race MKM type coal mills with a nominal capacity of 33 t/h. Its air demand is 34÷55 kNm^3/h, and the maximum permissible air temperature is 370°C. This is a medium speed mill powered by a 400 kW and 37.3 rev./min. electric motor.

The MKM-33 mill consists of the base on which the mill chamber is located, with a sifter mounted on it with an outlet head. A gear is attached to the foundation plate of the mill. The gear's task is to transfer torque from electric driving motor to the coal mill. The main shaft of the gear is connected to the shackle to which pyrite scrapers are attached in the lower part. A crushing ring with balls is located on the shackle. A thrust-pressure ring with 4 sets of pressure springs rests on the balls. A through ring is placed inside the mill's chamber. The rotating classifier is mounted on the cover of the mill chamber. A coal chute pipe runs through the centre of the mill. An example of a ball-and-race mill is presented in Fig. 1.

Torque is transferred from the asynchronous motor through the clutch, first and second gear stage to the main transmission shaft, from where the lower and upper shackle to the lower ring attached to it causing the entire shackle assembly to rotate. The movement of the lower ring makes the balls roll down the race. The coal falling in the central chute pipe access the rotating ring and under the rolling balls. The pressure of 4 sets of pressure springs on the pressure ring results in the coal pulverizing. The pulverized coal is lifted by a stream of hot air and directed to the sifter, where the separation of too large coal fractions is performed and they go back to pulverizing. The final coal dust-air mixture is supplied to the output head and then – through the dust channels – to the mill burners where it is burnt.

3. Identification of the coal mill motor signal model

The description of the actions aimed at developing a statistical model is called model identification and is conducted on the basis of measuring data, thus it is based on the data mining and machine learning methods. Each stage, starting from data preparation and analysis, the choice and transformation of the variables, through the choice of the structure of the model and the technique of its estimation, ending with the evaluation ensures its correct course. The quality of the measuring data determines the success of calculations and the quality of the resulting model.

3.1. Data preparation and analysis. The available real data come from a few months period (February 2016–May 2016) of the coal mill operation in different conditions – during regular operation, startup and shutdown. Among the available measuring signals, those have been distinguished that describe the model of the mill motor power. The symbols of the particular signals along with the description and measuring range are included in Table 1. The sampling time for all data is the same – 5 seconds (average number of samples obtained in 1 second).

The correlation between power of the mill's motor and height of the coal level in the bunker was very week. Our research studies have demonstrated that instead of developing an explicit recurrent dependency may use rescaling of the signals.

Table 1
The description of the selected control signals and process variables

Symbol	Description	Range	Unit
P_{eng}	Power of the mill's motor	0-400	kW
H_{coal}	Height of the coal level in the bunker	0–12	m
F_{coal}	Quantitative fuel flow to the mill	0–80	t/h
P_{air}	Air pressure to the mill	0–20	kPa
F_{air}	Quantitative air flow to the mill	0–55	kNm^3/h
T_h	Temperature of hot air to the mill	0–400	°C
T_{out}	Temperature of the dust-air mixture on the outlet of a mill	0–200	°C
V_c	Feeder speed	0-100	%
P_{set}	Set power unit (regular operation, no deep disturbances)	0–200	MW
P_{sel}	Chosen power unit (regular operation, no deep disturbances)	0–200	MW

The three new most important variables were selected and added to the database:

$$
\begin{aligned}
F_{coal}^{MOD} &= F_{coal} \cdot P_{eng}\,, \\
H_{coal}^{MOD1} &= H_{coal} \cdot P_{eng}\,, \\
H_{coal}^{MOD2} &= H_{coal} \cdot P_{air}\,,
\end{aligned} \tag{1}
$$

which are the rescaling of the values of the original signals by the corresponding values of the mill's motor power and air pressure inside the mill. The modifications of the signals were aimed at improving the quality of modelling and increasing the sensitivity of the model to the disturbances in the form of overhangs in the coal bunker.

The criterion for the selection of training and testing data were the largest possible ranges of input and output data. The training set consisted of the data registered during the startup, regular operation (with no disturbances) and shutdown between 1–2.03.2016, approximately 31 thousand samples in total. Test sets cover 7 days of the object operation (13–17.03, 10.02 and 01.04). The last two contain information on the occurrence of the disturbance.

The results and measurements from measuring transducer are usually encumbered with noise-derived errors. In practice, when using reconstruction or prediction algorithms, satisfactory results reducing the noises are achieved by the use of filtering as a form of signal smoothing. In the tests a locally weighted scatterplot smoothing [20] was used. For each measuring point, a locally adjusted simple regression in the neighbourhood of 5% of data was used. Smoothing was applied to the most noisy signals: P_{eng}, P_{air}, F_{air}. Moreover, data with negative values of the motor power registered during the startup of the mill were eliminated.

3.2. The choice of the machine learning algorithm. Machine learning is a branch of artificial intelligence, which on the basis of the knowledge in the samples attempts to imitate intelligent behaviours that can be described by numerical algorithms. The solution of the task of machine learning consists in the use of learning algorithm and transferring training data in order to develop a model. The developed model describes the relations between the variables and is of predictive nature. Its quality is validated on the basis of testing data. The general scheme of machine learning is presented in Fig. 2.

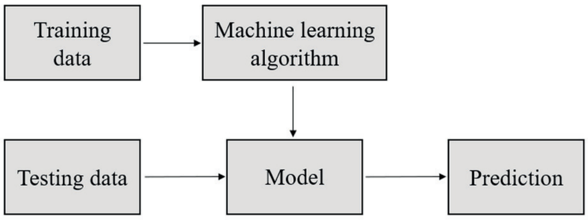

Fig. 2. The general scheme of machine learning

The tests utilized nonparametric regression included in the group of supervised training algorithms. Nonparametric regression methods is an alternative approach to the classic methods. Neither the knowledge of the analytical forms of the input and output signals, nor the knowledge of the random component distribution in the model is assumed. As a result, the described methods are characterized by greater flexibility and a wider range of applications.

In order to develop a model of a coal mill motor power signal, an additive regression model was proposed. For output variable Y and input variables X_i the additive model AD with k parameters is defined by:

$$
Y = \sum_{i=1}^{k} \phi_i(X_i) + \varepsilon_t\,, \tag{2}
$$

where ε_t is independent random error of zero expected value and constant variance, and $\phi_i(\cdot)$ are one-dimensional real functions, not necessarily linear. Hence prognosis models can be nonlinear towards input variables, but are still linear in regard to $\phi_i(X_i)$.

This method has not been used so far in the context of modelling energetic installations, but has potentially great possibilities and advantages [21,22]. First of all, it overcomes limitation related to nonlinear multidimensional modelling, as the regression function is modelled by the sum of the functions of particular input variables. Hence the estimation of the parameters of the additive model is much easier than when the model is a nonlinear function of the parameters.

To identify the parameters of an additive model, an iterative approach was applied through using backfitting algorithm. In order to achieve greater flexibility, the relations between output variable and input variables are estimated nonparametrically. For this purpose, the analysis of smoothing techniques was performed in the function of locally polynomial smoothers and spline smoothers. The right choice of the smoothing coefficient is of extreme importance f or the shape of the regression line as it controls the 'smoothness' of the estimator of a regression function [20].

3.3. The choice of the model's input variables. The accuracy of the identification, and as a consequence a reliable prediction of the model, depends to a large extent on the right choice of the structure of the model, mainly the choice of the variables describing the power of the motor. Moreover, when choosing the structure of the model, one should also be guided by its complexity level, thus – the computational complexity of the methods of its identification.

In order to choose the right input variables of the model, which significantly affect the signal of the mill's motor power, expert knowledge and correlation analysis were used. With their help, the input variables were selected in such a way to be the best correlated with the output variable P_{eng} and the least correlated to each other at the same time. It needs to be emphasized what we do not assume that input variables are independent [19]. For this purpose, Pearson correlation coefficient and Spearman's rank correlation coefficient were used allowing to ascertain any monotonic dependency. Figs. 3 and 4 present the correlation matrices of both methods for the chosen variables from the training set.

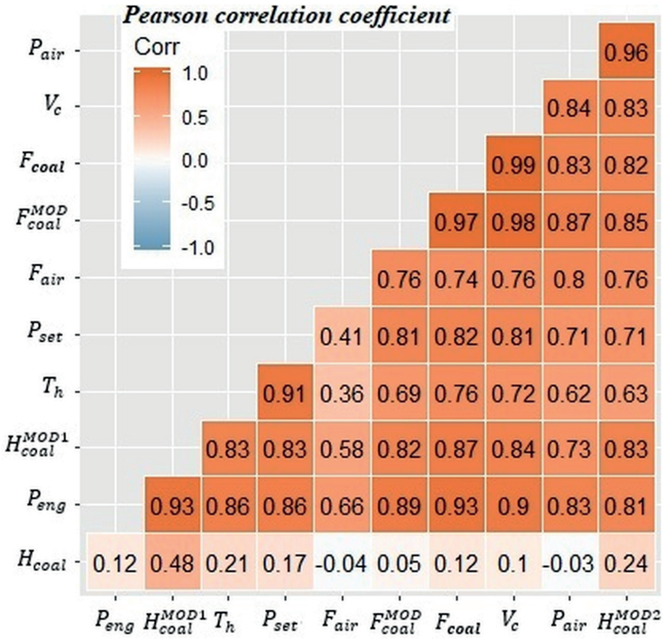

Fig. 3. Pearson correlation coefficient matrix

The largest mean value of a linear correlation coefficient of the 0.93 order has a quantitative flow of raw coal to F_{coal} and a modified height of the coal level in the bunker H_{coal}^{MOD1}. A strong relation with the mill's motor power is also exhibited by the feeder speed V_c. However, due to strong correlation with F_{coal} this signal was not used for modelling. Moreover, the obtained values of Spearman's rank correlation coefficient clearly confirm that correlation of the air pressure to the mill P_{air} and modified height of the coal level in the feeder H_{coal}^{MOD2} with the signal of the mill's motor power. The least correlated values were achieved for the coal level in the bunker H_{coal}.

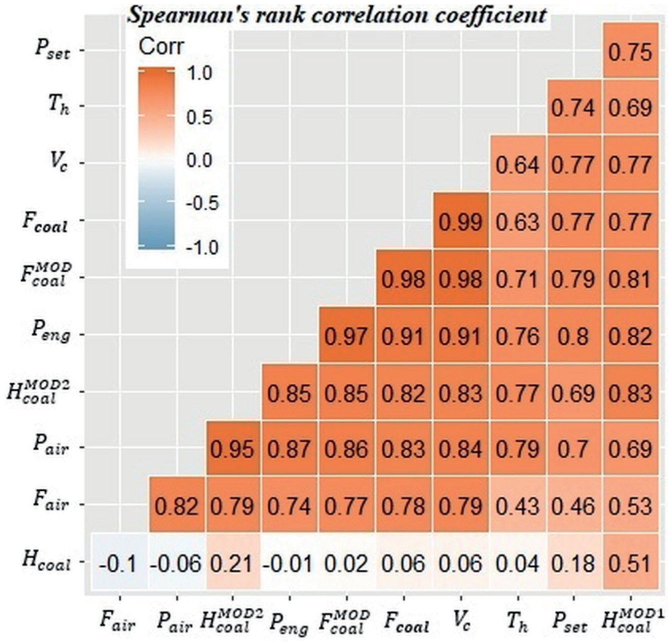

Fig. 4. Spearman's rank correlation coefficient matrix

In addition, because some of the input variables may affect the output variable with different time delay, the calculations of correlation were performed for different values of lags. The delay taken into account were from 5 to 360 seconds. When the correlation of signals is strong, the mill's motor power reacts to changes very quickly, with a minor delay – at most 15 seconds.

On the basis of the performed analysis, the following sets of input data X were proposed, used during the identification of the signal of the mill's motor power Y:

$$Y = P_{eng}, \qquad X = \left(F_{coal}, F_{coal}^{MOD}, H_{coal}^{MOD1}, H_{coal}^{MOD2}\right), \tag{3}$$

$$Y = P_{eng}, \qquad X = (P_{eng}, F_{coal}, H_{coal}, P_{air}), \tag{4}$$

The second set uses the signal of the mill's motor power as an input variable thus developing an explicit recurrent dependency. Such models are characterized by higher estimation accuracy, but greater tendency to overtraining at the same time. In such case, they may be insensitive to the occurring disturbances.

3.4. The criteria for the model's quality estimation. The objective estimation of the model of the signal of the mill's motor power is the use of the determined model for the simulation of the output for the set of test data. It allows us to validate its operation for conditions different than those in which it was finally refined and tuned. For training data, a separate verification procedure can be performed giving only a general view of the quality of the model.

As the model's quality estimation criteria, mean square error (MSE), mean absolute error (MAE), normalized mean absolute error (NMAE) and standard deviation (SD) were used:

$$\begin{aligned}
\mathrm{MSE} &= \frac{1}{N}\sum_{t=1}^{N}\left(Y_t-\hat{Y}_t\right)^2,\\
\mathrm{MAE} &= \frac{1}{N}\sum_{t=1}^{N}\left|Y_t-\hat{Y}_t\right|,\\
\mathrm{NMAE} &= \frac{1}{N}\sum_{t=1}^{N}\frac{\left|Y_t-\hat{Y}_t\right|}{(\max(Y_t)-\min(Y_t))}\cdot 100\%,\\
\mathrm{SD} &= \sqrt{\frac{1}{N-1}\sum_{t=1}^{N}(e_t-\bar{e})^2},
\end{aligned} \tag{5}$$

where Y_t and $\hat{Y}_t$ are properly measured and estimated values of the signal of the motor power in t time, $e_t = Y_t - \hat{Y}_t$ is the value of the fitting error in t time, $\bar{e}$ is the mean error and N is the number of data points.

It needs emphasizing that data aimed at determining the model are of a statistical nature, and therefore the error itself will be statistical and such should also be its evaluation.

3.5. The choice of the model's structure. The models with more developed structure usually have more accurate estimation, but at the same time they have more predisposition to overtraining. In such case, they can react impulsively to the disturbances. The models with oversimplified structure in turn, may give unreliable prediction. To choose the structure of the model, comparative analysis was also applied of a few models describing the changeability of a given output variable with the use of final prediction error (FPE) criterion. Assuming that the model includes k number of parameters in the model and N number of data points, FPE criterion utilizes the dependency:

$$\mathrm{FPE}(k) = J\cdot\frac{N+k}{N-k}, \tag{6}$$

where J is the sum of the squares of errors. Using the multiplier $(N+k)/(N-k)$, which increases with a number of variables in the model, this test imposes penalty for the models with a large number of the parameters, causing some protection against the excessively expanded structure of the model.

Let the additive models $\mathrm{AD}_1(4,l_1)$ and $\mathrm{AD}_2(4,l_2)$ have input variables X from set (3) and (4) respectively, but acknowledged with different order of delay l_1 and l_2. Then, the number of the parameters of particular models is $4\cdot l_1$ and $4\cdot l_2$ respectively. Table 2 gathers $\mathrm{FPE}(k)$ values and model accuracy coefficients (5) calculated on the basis of the training test for a few selected models depending on the used input variables.

On the basis of the obtained results, a conclusion could have been provided that for the proper modelling of the dynamics of the signal of the mill's motor power, it is enough to use $\mathrm{AD}_1(4,3)$ structure, or alternatively $\mathrm{AD}_2(4,1)$. Increasing the order of the model did not result in the significant improvement of the results of identification in relation to the increase of the model's complexity.

Table 2
$\mathrm{FPE}(k)$ values and model accuracy coefficients for the training set

Model	k	FPE	MSE	MAE	NMAE	SD
$\mathrm{AD}_1(4,1)$	4	50886.62	1.6421	0.8425	0.3649%	1.2815
$\mathrm{AD}_1(4,2)$	8	27064.76	0.8746	0.6268	0.2715%	0.9352
$\mathrm{AD}_1(4,3)$	12	19477.87	0.6291	0.5368	0.2325%	0.7932
$\mathrm{AD}_1(4,4)$	16	17687.91	0.5059	0.4829	0.2091%	0.7112
$\mathrm{AD}_2(4,1)$	4	363.82	0.0115	0.058	0.0251%	0.1073
$\mathrm{AD}_2(4,2)$	8	0.4359	0.0001	0.0024	0.001%	0.0037

4. The results of the verification studies

Verification studies were performed in terms of the prediction quality for the testing data from the period of startup, regular operation and shutdown, as well as for data with a registered disturbance in the form of overhangs in the coal bunker.

The paper compares the values of the accuracy indicators of particular models, and graphic interpretation of the modelled value of the model's output in comparison to the real value of the modelled variable and fitting errors. Identification of the model was performed with the use of R-project program dedicated to the advanced statistical calculations and data visualization [23].

4.1. Models of the signal of the mill's motor power. All of the input data from set (3) were taken into account in the model with a 5-, 10- and 15-second delay, which corresponds to displacement of 1, 2 and 3 samples. In set (4) the delay was of a 1 sample order. The forms of the particular additive models are the following:

$\mathrm{AD}_1(4,3)$:

$$\begin{aligned}
P_{eng,t} &= f_1\left(F_{coal,t-1}\right)+f_2\left(F_{coal,t-2}\right)+f_3\left(F_{coal,t-3}\right)\\
&\quad+f_4\left(F^{MOD}_{coal,t-1}\right)+f_5\left(F^{MOD}_{coal,t-2}\right)+f_6\left(F^{MOD}_{coal,t-3}\right)\\
&\quad+f_7\left(H^{MOD1}_{coal,t-1}\right)+f_8\left(H^{MOD1}_{coal,t-2}\right)+f_9\left(H^{MOD1}_{coal,t-3}\right)\\
&\quad+f_{10}\left(H^{MOD2}_{coal,t-1}\right)+f_{11}\left(H^{MOD2}_{coal,t-2}\right)\\
&\quad+f_{12}\left(H^{MOD2}_{coal,t-3}\right)+\varepsilon_{1,t}\,,
\end{aligned} \tag{7}$$

$\mathrm{AD}_2(4,1)$:

$$\begin{aligned}
P_{eng,t} &= g_1\left(P_{eng,t-1}\right)+g_2\left(F_{coal,t-1}\right)+g_3\left(H_{coal,t-1}\right)\\
&\quad+g_4\left(P_{air,t-1}\right)+\varepsilon_{2,t}\,,
\end{aligned} \tag{8}$$

where $\varepsilon_{1,t}$, $\varepsilon_{2,t}$ are independent random errors of zero expected value and constant variance and $f_i(\cdot)$, $g_j(\cdot)$ are one-dimensional real functions. On the basis of models (7) and (8), the fitting error can be calculated:

$$e_t = P_{eng,t} - \hat{P}_{eng,t}\,, \tag{9}$$

which is the approximation of $\varepsilon_{1,t}$ and $\varepsilon_{2,t}$ errors respectively. The values $P_{eng,t}$ and $\hat{P}_{eng,t}$ are properly measured and estimated values of the signal of the motor power in t time.

4.2. The results of the identification of the models. In order to identify additive models (7) and (8), the backfitting algorithm with natural cubic spline function was applied with a smoothing parameter $df = 4$ aliasing with a number of the degrees of freedom [20]. The choice of the technique and parameter of smoothing was dictated as a compromise between obtaining high quality identification and overfitting the model to the training data.

Fig. 5 presents the estimated values of the mill's motor power (red color) along with the measured values of the motor's power (black color). The plots were prepared for data registered during startup, regular operation and shutdown.

The results obtained for the training set were the best for $\mathrm{AD}_2(4,1)$. The estimated values of the mill's motor power almost perfectly kept up with the measured values. Detailed statistical analysis for both models $\mathrm{AD}_2(4,1)$ and $\mathrm{AD}_2(4,1)$ is presented in Table 2. The obtained identification quality did not exceed 0.5% and 0.05% of the range of changeability of the modelled output respectively.

The test sets were used to verify the obtained models. Figs. 6–9 show estimated and measured values for selected mill operation days with no deep disturbances. For good data visualization the e_t values have been normalized to the range $[-1,1]$. The plots of the normalized error along with the marked limits calculated for training data, prove the correct identification of the model of the motor power signal. Upper (green color) and lower (blue color) limits were calculated as follows:

$$\max(\tilde{e}_t) + p \cdot sd(\tilde{e}_t), \qquad \min(\tilde{e}_t) - p \cdot sd(\tilde{e}_t), \tag{10}$$

where $\tilde{e}_t$ is the normalized error and $sd(\tilde{e}_t)$ is standard deviation of the normalized error. For the models $\mathrm{AD}_1(4,3)$ and $\mathrm{AD}_2(4,1)$, $p = 3$ and $p = 5$ were accepted respectively.

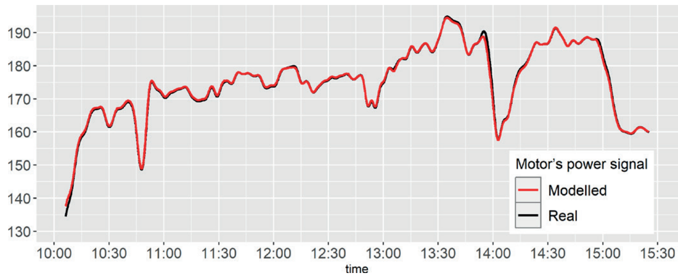

Fig. 6. The modelled and real signal of the motor's power for test data registered on 13.03.16 during regular operation of the mill: $\mathrm{AD}_1(4,3)$

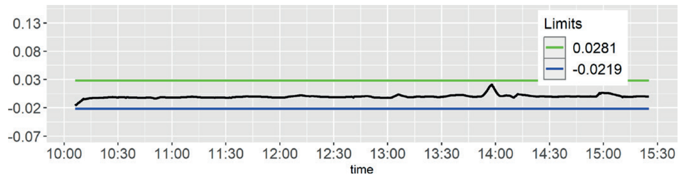

Fig. 7. The simulation error with upper and lower limits for test data registered on 13.03.16 during regular operation of the mill: $\mathrm{AD}_1(4,3)$

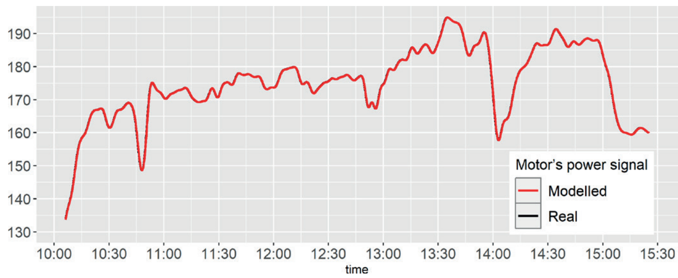

Fig. 8. The modelled and real signal of the motor's power for test data registered on 13.03.16 during regular operation of the mill: $\mathrm{AD}_2(4,1)$

The obtained results of the simulation of the signal of the coal mill's motor power are satisfactory. The developed models accurately reflect the dynamics of the process, which is con-

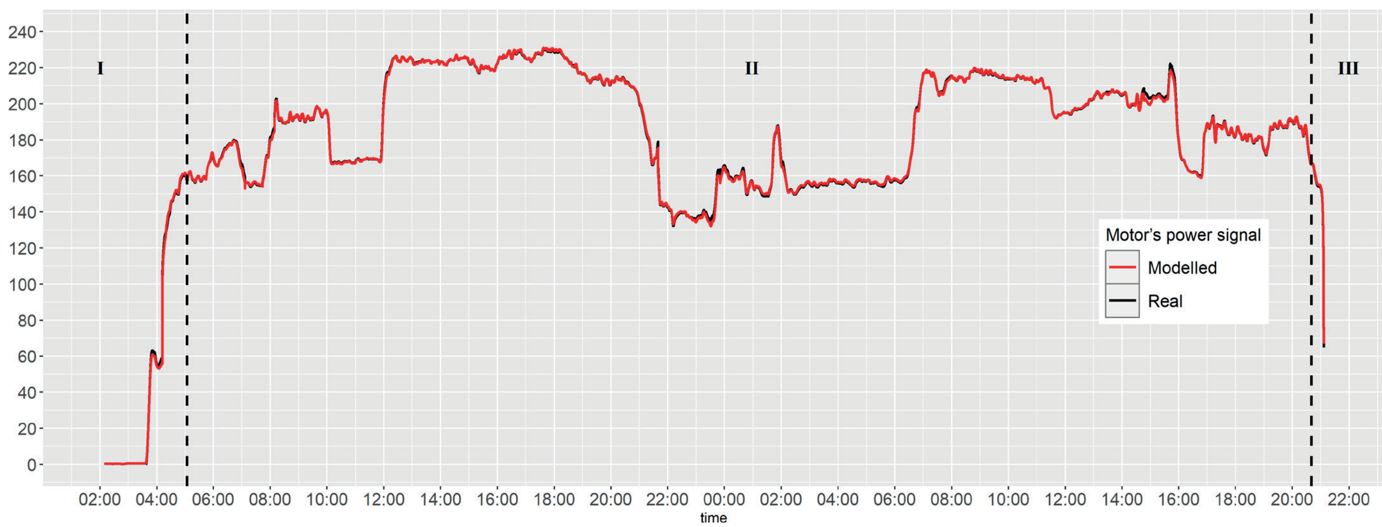

Fig. 5. The modelled and real signal of the motor's power for training data registered between 1–2.03.16 during startup (I), regular operation (II) and shutdown (III): $\mathrm{AD}_1(4,3)$

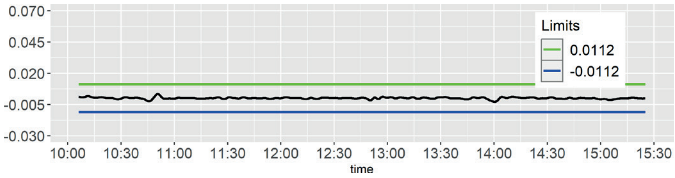

Fig. 9. The simulation error with upper and lower limits for test data registered on 13.03.16 during regular operation of the mill: $AD_2(4,1)$

firmed by the results presented in Table 3. For the rest of the test data, registered with no deep disturbances, fitting errors did not exceed 0.5% of the range of the changeability of the mill's motor power as well.

Table 3
Model accuracy coefficients for the test set from 13.03.2016

Model	MSE	MAE	NMAE	SD
$AD_1(4,3)$	0.2645	0.3042	0.5033%	0.5084
$AD_2(4,1)$	0.0132	0.0721	0.1182%	0.1138

A phenomenon often encountered during exploitation of the boiler installation are disturbances occurring as a result of coal overhanging in the coal bunker. Such overhangs lead to false information on the current state of the bunker filling, thereby to destabilization of the operation of the majority of control systems. Such disturbances may lead to underrepresenting of electric and thermal power of the unit, as well as blowthrough of hot air from the mill to the bunker, and as a consequence – to the fire of the mill and carburizing installation. The signal of the mill's motor power is proportional to the signal of the feeder control. That is why the analysis of the course of simulation error may support the operators in diagnosing the lack of coal in the mill and thus deciding on relieving or shutdown. The plots in Figs. 10–17 were prepared on the basis of data containing information on the occurrence of disturbance in the form of overhangs in the coal bunker.

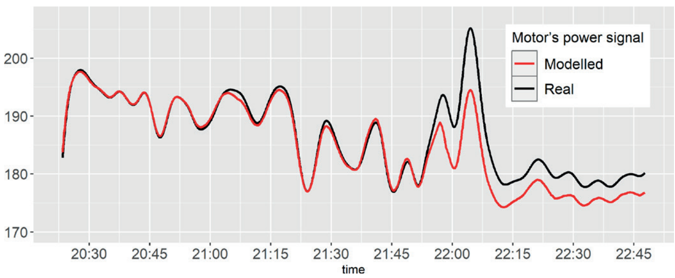

Fig. 10. The modelled and real signal of the motor's power for test data registered on 10.02.16 during overhang in the coal bunker: $AD_1(4,3)$

According to the predictions, $AD_2(4,1)$ model proved to be insensitive to disturbance and thereby not very useful in the tasks of industrial processes diagnostics. However, due to high level of its simulation for test data registered with no deep disturbances – such as overhangs in the coal bunker (Fig. 8), this model can be used to implement the tasks of model predictive

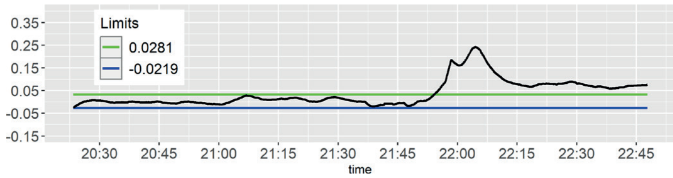

Fig. 11. The simulation error with upper and lower limits for test data registered on 10.02.16 during overhang in the coal bunker: $AD_1(4,3)$

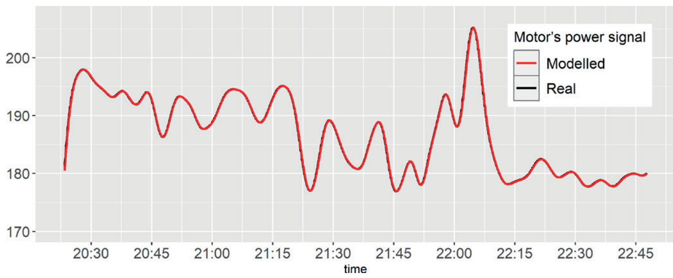

Fig. 12. The modelled and real signal of the motor's power for test data registered on 10.02.16 during overhang in the coal bunker: $AD_2(4,1)$

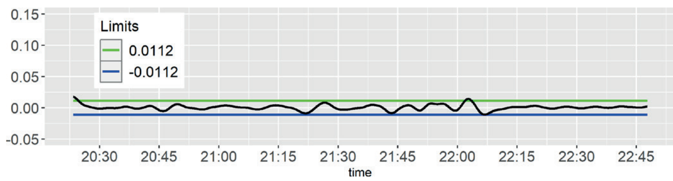

Fig. 13. The simulation error with upper and lower limits for test data registered on 10.02.16 during overhang in the coal bunker: $AD_2(4,1)$

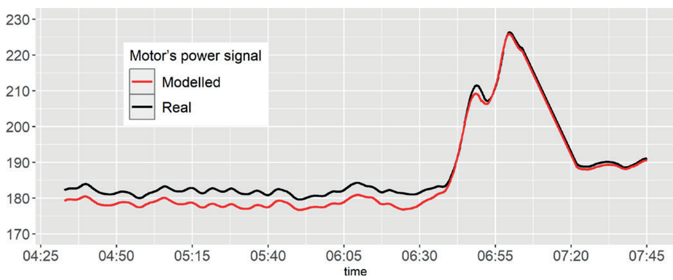

Fig. 14. The modelled and real signal of the motor's power for test data registered on 01.04.16 during overhang in the coal bunker: $AD_1(4,3)$

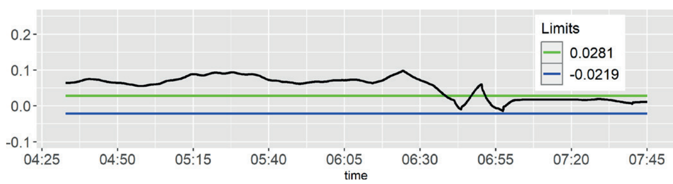

Fig. 15. The simulation error with upper and lower limits for test data registered on 01.04.16 during overhang in the coal bunker: $AD_1(4,3)$

control (MPC). Predictive control algorithms determine at any time of the sampling, control by optimization of a certain criterion function, defined on a finite horizon, on which the behaviour of the object model is predicted. There are many arti-

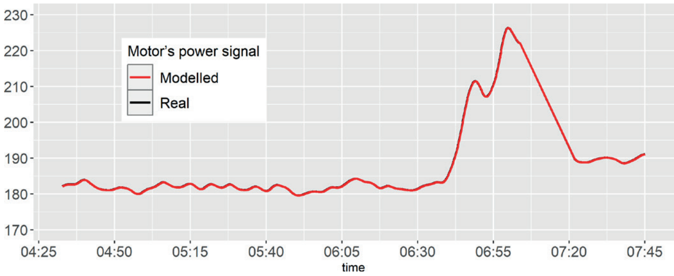

Fig. 16. The modelled and real signal of the motor's power for test data registered on 01.04.16 during overhang in the coal bunker: $\mathrm{AD}_2(4,1)$

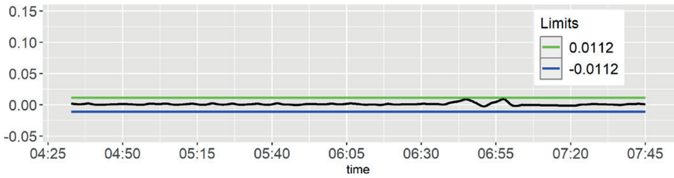

Fig. 17. The simulation error with upper and lower limits for test data registered on 01.04.16 during overhang in the coal bunker: $\mathrm{AD}_2(4,1)$

cles discussing the use of MPC for coal mills with quite promising results [5, 7, 24].

On the basis of the simulation error for model $\mathrm{AD}_1(4,3)$, a significant deviation from the zero value is clearly visible. Hence the model may be useful for developing diagnostic systems.

5. Summary

Modelling of the undefined processes occurring in complex energetic installations requires the use of simplified models which can be the cause of low quality of the object control, as well as generating false alarms by diagnostic systems. Additive models are an alternative technique in relation to the commonly used analytical models, enhancing the possibilities in the field of dynamic approximation and multidimensional nonlinear objects. This is a new approach that has not been used so far in the power industry.

In order to develop an additive model of the signal of a mill's motor power, its theoretical grounds as well as measuring data from the process have been used. Two alternative structures of the model were proposed – with the use of explicit recurrent dependency along with the use of the modified input signals. In the first case, the model including the delay line in the set in input data was characterized by much higher accuracy of identification and simulation, but at the same time – by the uselessness to detect disturbances in the form of overhangs in the coal bunker. The developed model very accurately reflected the dynamics of the process for the data during regular operation, startup and shutdown. The accuracy of the reconstructed values of the motor power ranged up to around 0.5 kW with and average value of the motor power of around 180 kW. In the case of the second, more developed structure, the introduced rescaling of the input signals improved the quality of modelling, and increased the sensitivity of the model on the analysed disturbances. The values of the simulation errors for test data including information on the disturbance occurrence were at least three times the assumed threshold values.

The obtained results are satisfactory. Among the most important benefits coming from the use of additive models to identification of the signal of the coal mill's motor power are lack of assumptions on the forms of the functions linking the input and output signals, hence the use of nonparametric estimation methods allows for identification of the nonlinear systems when the number of initial information on them is so small that parametric methods cannot be used effectively. Moreover, their simple structure and low order significantly reduce training time, what is of key importance in large measuring databases available in the contemporary automation systems. Additive models-based methods do not require to use data with disturbances in the stage of identification. Particular models provide promising perspectives for the realization of the tasks of ontrol or diagnostics of the processes taking place in the coal mill (detecting the disturbances other than those described in the article).

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References

[1] W. Wójcik, "Application of fibre-optic flame monitoring systems to diagnostics of combustion process in power boilers", *Bull. Pol. Ac.: Tech.* 56(4), 177–196 (2008).

[2] Sprawozdanie z działalności Prezesa Urzędu Regulacji Energetyki w 2017 r. [Online]. https://www.ure.gov.pl

[3] W. Fennig, M. Kielian, M. Lipiński, A. Bielaczyc, M. Brzozowski, S. Lasota, and P. Sarnecki, "Układ do wykrywania i ostrzegania przed zakłóceniami w swobodnym spływie strumienia paliwa stałego w przykotłowym zasobniku węgla i jego praktyczne zastosowanie na obiekcie energetycznym", *Energetyka* 12, 757–760 (2014) [in Polish].

[4] M. Lipiński, "Detection and prevention systems of mills assembly emergency states", in *Advanced Solutions in Diagnostics and Fault Tolerant Control, DPS 2017; Advances in Intelligent Systems and Computing*, Eds. J. Kościelny, M. Syfert, A. Sztyber, Springer, Cham, 2018.

[5] A. Cortinovis, M. Mercangoz, T. Mathur, J. Poland, and M. Blaumann, "Nonlinear coal mill modeling and its application to model predictive control", *Control Eng. Practice* 21(3), 308–320 (2013).

[6] Y. Gao, D. Zeng, and J. Liu, "Modeling of a medium speed coal mill", *Powder Technol.* 17(5), 1–27 (2017).

[7] M. Mercangoez and J. Poland, "Coal mill modeling for monitoring and control", *IFAC Proc. Volumes*, 44(1), 13163–13166 (2011).

[8] N.W. Rees and G.Q. Fan, "Modeling and control of pulverized fuel coal mills", in *Thermal Power Plant Simulation and Control*, Ed. D. Flynn, IET, UK, 2003.

[9] G. Zhou, J. Si, and C.W. Taft, "Modeling and simulation of C-E deep bowl pulverizer", *IEEE Trans. Energy Convers.* 15(3), 312–322 (2000).

[10] P. Niemczyk, J.D. Bendtsen, T.S. Pedersen, P. Andersen, and A.P. Ravn, "Derivation and validation of a coal mill model for control", *Control Eng. Practice* 20(5), 519–530 (2012).

[11] J.L. Wei, J.H. Wang, and Q.H. Wu, "Development of a multisegment coal mill model using an evolutionary computation technique", *IEEE Trans. Energy Convers.* 22(3), 718–727 (2007).

[12] V. Agrawal, B.K. Panigrahi, and P.M.V. Subbarao, "A unified thermo-mechanical model for coal mill operation", *Control Eng. Practice* 44, 157–171 (2015).

[13] P.F. Odgaard and B. Mataji, "Observer-based fault detection and moisture estimating in coal mills", *Control Eng. Practice* 16, 909–921 (2008).

[14] M. Krośnicki, "Current diagnosis of coal mill using evolutionary algorithm", Warsaw University of Technology, Master thesis, 2015.

[15] P. Pradeebha, N. Pappa, and D. Vasanthi, "Modeling and Control of Coal Mill", *IFAC Proc. Volumes* 46(32), 797–802 (2013).

[16] T. Chai, L. Zhai, and H. Yue, "Multiple models and neural networks based decoupling control of ball mill coal pulverising systems", *J. Process Control* 21, 351–366 (2011).

[17] X. Han and X. Jiang, "Fault Diagnosis of Pulverizing System Based on Fuzzy Decision-Making Fusion Method", *Fuzzy Info. Eng.* 62, 1045–1056 (2009).

[18] Y.G. Zhang, Q.H. Wu, J. Wang, and X.X. Zhou, "Coal mill modeling by machine learning based on onsite measurements", *IEEE Trans. Energy Convers.* 17, 549–55 (2002).

[19] T. Hastie and R. Tibshirani, "Generalized additive models", *CRC Monographs on Statistics and Applied Probability*, Chapman & Hall/, 1990.

[20] Z.M. Łabęda-Grudziak, "Smoothing parameters selection in the additive regression models approach for the fault detection scheme", *Pomiary Automatyka Kontrola* 57(2), 197–200 (2010).

[21] Z.M. Łabęda-Grudziak, "Diagnostic technique based on additive models in the tasks of the ongoing exploitation of gas network", *Eksploatacja i Niezawodność – Maintenance and Reliability* 18(1), 50–56 (2016).

[22] Z.M. Łabęda-Grudziak, "Identification of dynamic system additive models by KDD methods", *Pomiary Automatyka Kontrola* 57(3), 249–252 (2010).

[23] R.K. Pearson, *Exploratory Data Analysis Using*, R, Chapman & Hall, 2018.

[24] V. Agrawal, B.K. Panigrahi, and P.M.V. Subbarao, "Review of control and fault diagnosis methods applied to coal mills", *J. Process Control* 32, 138–153 (2015).