



archives of thermodynamics Vol. **37**(2016), No. 1, 31–46 DOI: 10.1515/aoter-2016-0003

# On line diagnostics and self-tuning method for the fluidized bed temperature controller

### JAN PORZUCZEK<sup>1</sup>

Cracow University of Technology, Institute of Thermal Engineering and Air Quality Protection, Warszawska 24, 31-155 Cracow, Poland

**Abstract** The paper presents the method of on-line diagnostics of the bed temperature controller for the fluidized bed boiler. Proposed solution is based on the methods of statistical process control. Detected decrease of the bed temperature control quality is used to activate the controller self-tuning procedure. The algorithm that provides optimal tuning of the bed temperature controller is also proposed. The results of experimental verification of the presented method is attached. Experimental studies were carried out using the 2 MW bubbling fluidized bed boiler.

**Keywords:** Fluidized bed boiler; Bed temperature; Temperature control; Statistical process control

#### Nomenclature

e	—	control deviation, K
$e_{acc}$	-	upper acceptable limit of control deviation, K
EWMA	_	exponentially weighted moving average, K
EWDEV	_	exponentially weighted mean deviation, K
$G_P$	_	transfer function of the controlled process
$G_R$	_	transfer function of the controller
IMC	_	internal model control method
ISE	_	integral of squared error, K <sup>2</sup>
$K_o$	_	proportional gain of the process model, ${\rm K}/\%$

<sup>1</sup>E-mail: porzuk@pk.edu.pl



J. Porzuczek

$K_p$	_	proportional gain of the controller
N	-	coefficient for derivative term filtration
OVR	_	overshoot, $\%$
s	-	complex number frequency
t	_	variable of integration, time, s
$t_o$	_	averaging period, s
$T_1, T_2, T_3$	_	time constant of the process model, s
$T_d$	_	derivative time, s
$T_i$	_	integral time, s
$T_o$	-	period of control deviation averaging, s
$T_{st}$	_	steady state time, s
u	_	control signal, $\%$
$u_{max}$	-	maximum value of controller output, $\%$

Greek symbols

$\alpha$	_	weighting coefficient
$\vartheta_z$	_	bed temperature, <sup>°</sup> C
$\lambda$	_	tuning method time constant, s
$\sigma$	_	standard deviation, K
$\sigma_{acc}$	_	upper acceptable limit of standard deviation, K
au	_	transport delay of the process model, s

### 1 Introduction

In small, autonomous heating systems (e.g., for housing estate or factory) fluidized bed boilers are increasingly being considered nowadays as an alternative to stoker-fired boilers which are to be withdrawn from the use. As the main reason is regarded the possibility of efficient combustion of low quality (and therefore cheap) fuels while reducing emissions of substances such as  $SO_2$  and  $NO_x$  to the atmosphere. In prospect of rising fuel prices and rigorous requirements for emission standards, these advantages can contribute to dissemination of this technology. High quality of combustion in a fluidized bed, defined as efficiency maximization at the lowest possible emission rates, is expected to be provided by properly designed and tuned automatic control system.

The bed temperature is known to be one of the fundamental parameters of the fluidized bed boilers operation. Both the efficiency of energy conversion and emission parameters depend on the bed temperature [2] thus the need for its proper control is essential. The lower limit of the bed temperature (700–750 °C) is determined by increased emission of the CO and hydrocarbon ( $C_xH_y$ ), and thus decrease of the efficiency of energy conversion. There is also possibility of interruption of combustion process. The upper limit of the bed temperature (950–1000 °C) is the limit of ash





On line diagnostics and self-tuning method for the fluidized bed...

melting point. Exceeding this value threatens the possibility of formation the bed material agglomeration and even interruption of the fluidization. Depending on the sort of fuel burned and additional process conditions (e.g., use of reacting substances for desulphurization), this range may be further limited. For example when limestone is use for flue gas desulphurization, bed temperature should be maintained at 850 °C because at this temperature sulfur capture efficiency is highest. Time-varying properties of the fuel (e.g., calorific value or moisture content) increase the difficulty of effective control of bed temperature contributing to the occurrence of high amplitude oscillation proving that stability limit has been reached. This phenomenon can be significantly reduced by the use of control algorithms that are able to adapt to the nonstationary nature of the process.

The issues of automatic control of fluidized bed boilers have been widely discussed in scientific studies. The detailed review of automatic control methods for fluidized bed boilers was presented in the monograph [14]. The most common approach, reported in scientific publications, is based on fuzzy logic [1,5,8,9]. Some of commercial available DCS (distributed control system), e.g., metsoDNA (fluidized bed boiler combustion optimizer) [17] developed by MetsoAutomation also uses fuzzy logic. Although, fuzzy logic controllers, sometimes so-called 'soft computing' solutions: artificial neural networks [3,10] or genetic algorithms [6], allow to achieve potentially a higher control quality but their practical application (especially in small plants) is at least difficult. The effects of newly developed methods are usually being compared to the classical PID control. Unfortunately, in most studies such comparisons are based solely on computer simulations, and are not verified experimentally. Furthermore, it is hard to justify the correctness of a newly developed method with operation of the proportional integral derivative controller (PID controller) tuned by the oldest known Ziegler-Nichols methods [1]. By now there are more than 1000 rules known for tuning PID controllers [13]. It allows the selection of a proper method for more precise shaping of the characteristics of the automatic control system. Likewise, they are not computationally complex which allows their practical application even in relatively simple systems based on PLC (programmable logic controller). The aim of this work is to demonstrate that the significant improvement in the quality of the bed temperature control is possible using a simple adaptive algorithm, performing tuning of the classical PID controller in case of decline in the control quality.





# 2 On line diagnostics of the bed temperature controller

The primary task for the controller is tracking the bed temperature setpoint, therefore, it is required to adjust the static control deviation as close to zero as possible. In the absence of disturbances the above-mentioned requirement is met for each stable control systems comprising an integrator. In real systems which are always exposed to disturbances the statistical parameters of the control deviation are often being analyzed. In the presence of disturbances it is usually required that the absolute mean value of the control deviation (for the averaging period  $T_o$ , usually experimentally adopted) was not greater than the acceptable limit (1):

$$\left|\bar{e}\right| = \left|\frac{1}{T_o} \int_t^{t+T_o} e\left(t\right) dt\right| \le \bar{e}_{acc} .$$

$$\tag{1}$$

The standard deviation of the control deviation should not exceed the acceptable value

$$\sigma(e) \le \sigma_{acc}(e) . \tag{2}$$

The requirements formulated in (1) and (2) are of static character thus they do not allow to infer about the trend of statistical parameters of the control deviation which are the measure of the process quality. In the issues of statistical process control (SPC) there are known methods (first introduced by Shewhart in the thirties of the last century) allowing to track the changes in the statistical parameters of the process [12]. These methods provide an objective assessment of whether the process is subject to an acceptable variation or starts behaving 'abnormally'.

In this study, to reflect the variations of control deviation, it is proposed to use the exponentially weighted moving average (EWMA) which can be described as

$$EWMA_i = (1 - \alpha)EWMA_{i-1} + \alpha e_i . \tag{3}$$

This indicator is calculated after each (*i*th) measurement, based on the previous average value ( $EWMA_{i-1}$ ), and the current control deviation value,  $e_i$ . The parameter  $\alpha \in (0, 1)$ , determines the rate of decrease in the weight of the previous value. Using the EWMA the ability to detect the decline in the quality of the process was examined. The value  $\pm 10$  K was assumed as the acceptable control deviation limit, exceeding of which the control performance is regarded as unacceptable. The value of the adopted threshold





On line diagnostics and self-tuning method for the fluidized bed...

results of operating experience. It is difficult to achieve significantly lower values of average control deviation during combustion of typical solid fuels. On the other hand, the higher value of the threshold could have a negative impact on boiler efficiency and emission factors.

The graph (Fig. 1) shows an example of the bed temperature control deviation and its averaged values for  $\alpha = 0.005$  and 0.001. The appearance of high amplitude oscillations can be seen after time  $t_0$  as well as the resulting change of averaged control deviation. It was found that the cause of this phenomenon was the change of fuel consignment. This is a typical case of situation requiring adjustments of the controller. The boiler, working near the stability limit, is exposed to uncontrolled growth of control deviation and consequently the risk of an emergency shutdown. As can be seen, the quickness of disturbance detection is significantly dependent on the value of parameter  $\alpha$ . For  $\alpha = 0.005$  exceeding the limit occured 63 s after the disturbance while for  $\alpha = 0.001$  detection of quality deterioration was found after 454 s.



Figure 1: The influence of parameter  $\alpha$  on the rate of detection of the control quality decrease.

Since the situation may occur in which the oscillation amplitude of con-







trol deviation increasing significantly but the average value is close to zero (which is also a symptom of improper operation) it was necessary to introduce the indicator describing the change in dispersion of results around the mean value. In analogy to Eq. (3), for the evaluation of the mean deviation of e(t) the indicator exponentially weighted mean deviation (EWDEV) can be proposed

$$EWDEV_i = (1 - \alpha) EWDEV_{i-1} + \alpha \sqrt{(e_i - EWMA_i)^2} .$$
 (4)

The graph (Fig. 2) shows an example of the bed temperature control deviation and calculated EWDEV indicator (for  $\alpha = 0.005$ ). For this indicator 5 K limit was taken as the threshold value. In the presented example, disturbance detection using EWDEV turned out to be about 41 s faster than using EWMA. Nonetheless, exceeding whichever indicator is a symptom of incorrect operation of the control system and should lead to a manual or automatic tuning of the controller.



Figure 2: Indicators EWMA and EWDEV during the exemplary test run.



On line diagnostics and self-tuning method for the fluidized bed...

# 3 The model of fluidized bed furnace and its identification

Design of the fluidized bed temperature controller has to be preceded by analysis of bed temperature dependence on other process parameters. Obviously, unreasonable (and virtually impossible) would be to create a model describing all the complex processes and reactions occurring in the fluidized bed and its surroundings. It is necessary only to indicate the fundamental relationships. In a broader sense, such representation implement multidimensional models MIMO (multiple input multiple output). These models may have a typical form of transfer function matrix [15,16], or use other methods for creating nonlinear models, such as genetic algorithms [6] or artificial neural networks [3]. Multidimensional approach, regardless of the methods used, is characterized by significant computational complexity and, at the moment, cannot be realized in the typical industrial PLC controller. In this practical matter it may be better to use single input single output (SISO) model, which parameters would be estimated in the current process conditions and recalculated subsequently after detection of the control quality decrease. Since the PID controller settings are based on the estimated model parameters, this will allow adaptation of the control system to nonstationary nature of the process.

From the perspective of process engineering, a fluidized bed boiler is a chemical reactor in which the series of chemical reactions and heat exchange processes occur. The bed temperature is dependent mainly on the flow of the supplied fuel, the primary air stream as well as a stream of ash removed. It can be presented descriptively as

BedTemperature = 
$$f$$
(FuelFeed, AirFlow, AshRemove). (5)

However, the bed temperature control is typically carried out by changing the flow rate of the fuel. Such operation is justified with a significant excess of primary air and other parameters fixed. It can be seen that step increase of the fuel flow rate will virtually immediate increase the heat flux needed to evaporate the moisture contained in the fuel and heat the fuel up to ignition. Therefore, in the initial phase of the reaction bed temperature will decrease. The value of this undershoot will be highly dependent on the fuel properties and will be deeper in case of higher moisture content and noncombustible solids in the fuel. Endothermic reactions (e.g., gasification of fuel or limestone sorbent calcination) occurring in the bed after introduction



PAN POLSKA AK ADEMIA NAUK

J. Porzuczek

of fuel also affect the bed temperature response. After ignition of fuel a surplus of combustion heat flux leads to increase in temperature and establish a new equilibrium state. On the contrary, the opposite course of the bed temperature will be observed in reducing flow of the supplied fuel.

Lixia *et al.* [11] proposed a representation of the dynamics of the bed temperature change, caused by the change of the fuel flow rate, by the transfer function model in the form

$$G_P(s) = K_o \frac{(1 - T_3 s)}{(1 + T_1 s)(1 + T_2 s)} \exp(-\tau s) .$$
(6)

In the considered narrow range of temperature variation and assuming the invariability of other process parameters, the model has been verified for example in [1,5,6,14]. It is linear, stationary and non-minimum phase model [7], which time constants  $T_1$ ,  $T_2$ ,  $T_3$  do not have a direct physical interpretation, however, their values strictly depend on the characteristics of the fuel, the thermal capacity of the bed and the heat exchange conditions. The transport delay,  $\tau$ , is the time after which the temperature change appears in response to a change in the fuel flow rate. The static gain,  $K_o$ , describes the steady state after changing the fuel flow rate (and thus the energy of supplied fuel); its value is highly dependent on, among others, the calorific value of the fuel and the characteristics of fuel feeders. Described factors cannot be directly calculated in practice and the only way to estimate their value requires experimental identification on a real boiler.

It is necessary to emphasize that the model given by the Eq. (6) is a linear approximation of nonlinear process, therefore, after the estimation its parameters for a certain operating point of the boiler, it is possible to use the model only for a narrow surrounding of this operating point. Satisfactory compliance with the measurement results will be limited in practice to the temperature range of about 100 K [14], still, in most cases of the design of the controller it would be a sufficient range. Naturally, the model of such a structure will also not be adequate at a bed temperature lower than the fuel ignition temperature.



On line diagnostics and self-tuning method for the fluidized bed...

## 4 Optimization method for temperature controller tuning

Among the many possible, such as: series, pareallel, interacting, etc. [7,13], the PID controller structure can be defined by

$$G_R(s) = K_p \left( 1 + \frac{1}{T_i s} + \frac{T_d s}{1 + \frac{T_d s}{N}} \right) , \qquad (7)$$

where N denotes coefficient for filtration, with filtration in derivative term, has been adopted for further studies. This structure results from the fact that the ideal differentiation cannot be practically implemented and thus it must be subjected to inertia. In addition, many industrial controllers use such a structure and thus the calculated controller settings may be easily verified and used in practice. The values of the controller parameters  $K_p$ ,  $T_i$ ,  $T_d$  are critical to both the stability of the combustion process and the control quality of the combustion process, evaluated by the direct indicators of control quality (such as static and dynamic deviation, overshoot and time of control) and indirect integral square error (ISE) indicators (among others criterion). For this reason, the selection of these parameters should be carried out by optimization, using proper criterion of the control quality. In this paper the criterion of minimizing the integral of the squared control deviation ISE was applied

$$\min_{[K_p, T_i, T_d]} ISE = \min_{[K_p, T_i, T_d]} \int_0^{T_{st}} e^2(t) dt .$$
(8)

Since the  $T_d/N$  ratio is the time constant of the first order low pass filter the value of N will have a direct impact on the ability of the control system for the disturbance damping. The adopted value of the coefficient N = 10 results from the application of PID tuning method presented below. Therefore, the optimization problem will be searched for PID controller  $[K_p, T_i, T_d]$  minimizing the value of the ISE criterion (8) with the given constraints.

Minimizing a nonlinear function of three variables is characterized by the requirement of significant computing power. In addition, as stated in [14], the results obtained in this way may not be unambiguous. Also the robustness of the control system which settings was calculated with this method is, in general, unknown. Thus, in the present study it was sought







the optimization method for controller tuning focused on robustness (socalled 'robust controller' [7]).

For the controlled object model of the structure (6) with the controller given by (7) in [6] the novel PID tuning rule has been derived by Chien. According to [13], this is one of the few currently known PID tuning methods for non-minimum phase objects. Furthermore, it is the only currently known rule that leads to the synthesis of robust controller. This results from the fact that it was derived directly on the basis of the model (6) using the internal model control method (IMC) [7]. The formulas

$$K_p = \frac{T_1 + T_2 + \frac{T_3\tau}{\lambda + T_3 + \tau}}{K_o \left(\lambda + T_3 + \tau\right)} , \qquad (9)$$

$$T_i = T_1 + T_2 + \frac{T_3 \tau}{\lambda + T_3 + \tau} , \qquad (10)$$

$$T_d = \frac{T_3 \tau}{\lambda + T_3 + \tau} + \frac{T_1 T_2}{T_1 + T_2 + \frac{T_3 \tau}{\lambda + T_3 + \tau}} \,. \tag{11}$$

allowing for calculation of the controller settings. Moreover, it is required that:  $T_1 > T_2 > T_3$ ,  $\lambda \in \langle \tau, T_1 \rangle$ , and N = 10. From the above formulas it can be concluded that the only parameter optimized in this method is  $\lambda$  which value will determine the dynamic characteristics of the control closed-loop.

The solution of the optimization problem is therefore reduced to minimize a nonlinear functions of one variable, limiting the permissible variation of  $\lambda$  and limit the allowable overshoot (OVR). This problem can be written in the form

$$\min_{[\lambda]} ISE = \min_{[\lambda]} \int_0^{T_{st}} e^2(t) dt , \qquad (12)$$

$$\begin{cases} \lambda \in \langle \tau, T_1 \rangle \\ OVR(\lambda) \le OVR_{acc} \end{cases}$$
(13)

In addition, it is necessary to take into account nonlinear (saturation type) characteristics of fuel feeders, which can be represented by the formula

$$sat \{u(t), [0, u_{\max}]\} = \begin{cases} 0 & \text{for } u(t) < 0\\ u(t) & \text{for } u(t) \in \langle 0, u_{\max} \rangle \\ u_{\max} & \text{for } u(t) > u_{\max} \end{cases}$$
(14)

The procedure of the PID controller optimization was implemented in Matlab/Simulink [18] with additional package Optimization Toolbox [18]. The



On line diagnostics and self-tuning method for the fluidized bed...

block diagram of the optimized control system is shown in Fig. 3. To solve the optimization problem (12) the sequential quadratic programming (SQP) algorithm was used.



Figure 3: The block diagram of the optimized control system: SP – setpoint, PV – process value.

The example calculation for optimization of PID controller was carried out with the model parameters listed in Tab. (1). As the maximum acceptable overshoot  $OVR_{acc} = 5\%$  was assumed. The graphical interpretation of the solution obtained is shown at the graph (Fig. 4).



Figure 4: Exemplary solution of the optimization problem.





Parameter	$K_o$	$T_1$	$T_2$	$T_3$	t
Unit	K/%	s	s	s	s
Value	55	200	60	20	10

Table 1: The values of the test model  $G_P(s)$  parameters.

#### $\mathbf{5}$ **Experimental** verification

In order to verify the effects of the developed method the verification tests were carried out using fluidized bed boiler with a capacity of 2 MW, located in a housing estate in the town of Goldap. The research was performed during the heating season. During the experiment, after finding deterioration of temperature control quality using indicators (3–4) the controller tuning was performed employing the method described above. Comparisons of control quality before and after the tuning was based on the approximation of the recorded data histogram with normal distribution (Fig. 5). Additionally, to investigate the effect of the controller tuning on the combustion process, the oxygen (Fig. 6) and  $NO_x$  (Fig. 7) concentration in the flue gas were analyzed before and after tuning procedure. The concentration of  $NO_x$  was converted to 6% oxygen content. The results of calculated average and standard deviation of obtained data are presented in Tab. (2).

Iten	$\vartheta_z$	e	$O_2$	$NO_x$	
Uni	$^{\circ}\mathrm{C}$	Κ	%	$\mathrm{mg}/\mathrm{m}^3$	
before optimization	average	882.0	12.0	12.40	1261
	std. dev.	13.3	13.3	1.96	290
after optimization	average	868.8	1.2	12.50	955
	std. dev.	5.1	5.1	0.73	81

Table 2: Summary of the results before and after optimization.

As may be noted from the experimental results, the optimization of the controller parameters significantly improved the quality of temperature control. With the bed temperature setpoint of  $870 \,^{\circ}$ C, the acceptable average control deviation  $\pm 10$  K was assumed. Before the optimization the average control deviation was greater than the limit and was equal to 12 K, while after the tuning the average deviation was ten times smaller. The



On line diagnostics and self-tuning method for the fluidized bed...



Figure 5: Distribution of the bed temperature before (1) and after optimization (2), SP – setpoint.

significant, positive effect of the operations carried out was also a decrease in bed temperature variations. After calculation of the standard deviation (as a measure of temperature variations), it was found that it has decreased as a result of tuning of the controller, more than 2.5 times, reaching a value of 5.1 K, while the initial value was 13.3 K.

As the results of tests have shown, the combustion process before and after the optimization occurs at virtually the same average oxygen content in the exhaust gases. However, it may be noticed a significant reduction in the dispersion of observed values. This result can be interpreted as an improvement in the stability of the combustion process. Before starting the tests it was expected that improving the stability of the process may also contribute to the improvement of emission factors. In case of the NO<sub>x</sub> concentration it was observed about 25% reduction in the mean concentration of these substances in the flue gas. It was also noted that the dispersion of observed values was significantly, 3.5 times decreased. This phenomenon may increase the efficiency of nitrogen oxide reduction systems (DeNOx).







Figure 6: Distribution of the oxygen concentration before (1) and after optimization (2).



Figure 7: Distribution of the NOx concentration before (1) and after optimization (2).



On line diagnostics and self-tuning method for the fluidized bed...

### 6 Conclusions

Time-varying fuel characteristics cause the significant impediment to effective control of the bed temperature. It has been found that the introduction of on-line diagnostics of the control system operation, with the use of proposed EWMA and EWDEV indicators, allows a sufficiently rapid detection of the control quality deterioration and consequently activate the tuning procedure. Detection rapidity of decrease in the control quality using the proposed indicators will depend on the weighing parameter  $\alpha$ . With the increase of this parameter it is possible to detect a decrease in the control quality more quickly. However, in the case of too high a value of  $\alpha$ , the naturally occurring oscillations will not be sufficiently damped, which can lead to too frequent retuning of the controller.

In this paper the optimization calculations were performed using Matlab Optimization Toolbox. Nevertheless, simplification of the controller optimization problem to minimization a function of one variable allows to transfer the calculations into automation devices such as industrial PC or PLC controllers. For this purpose it is necessary to develop an algorithm that can be implemented in such devices. This in turn enables the possibility to return the controller as frequent as it is necessary in the process of its adaptation to changing of the combustion conditions (e.g., changing of the fuel quality). After determination of the optimal controller settings they are fixed until detection the significant decrease of the control quality. The effectiveness of the presented solution is primarily limited by the simple linear representation of the complex combustion process. In the highly nonlinear systems it might cause too frequent re-tuning of the regulator, which would disturb the normal operation of the boiler. This problem seems to be a natural direction for further development of method presented in this paper. Combination of adaptive control, allowing adjustment of the control system to the current process conditions, with modeling based on fuzzy sets, would probably allow the significant reducing the impact of nonlinearities.

Received 23 June 2015

### References

 AYGUN H., DEMIREL H.: Comparison of PSO-PID, FLC and PID in a circulating fluidized bed boiler. In: Proc. 7th Int. Conf. on Electrical and Electronics Engineering (2011), 376–380.



J. Porzuczek

- [2] BASU P.: Combustion and Gasification in Fluidized Bed. CRC Press, Boca Raton 2006.
- [3] BUDNIK M., STANEK W., RUSINOWSKI H.: Application of neural modelling in hybrid control model of fluidized bed boiler fired with coal and biomass. In: Proc. 13th Int. Carpathian Control Conf. (2012), 69–74.
- [4] CHIEN I.-L.: IMC-PID controller design An extension. In: Proc. IFAC Adaptive Control of Chemical Processes Conf. (1988), 147–152.
- [5] FU P., YU X.-N., WANG H.: Research on fuzzy control algorithm for bed temperature control of circulating fluidized bed boiler. In: Proc. Fourth Int. Conf. Machine Learning and Cybernetics (2005), 825–828.
- [6] HOU G., ZHANG Y., ZHANG J.: Real-coding genetic algorithm-based model identification for bed temperature of 300 MW CFB boiler. Chinese Control and Decision Conf. (2011), 2019–2025.
- [7] JOHNSON M.A., MORADI M.H.: PID New Identification and Design Methods. Springer-Verlag, London 2005.
- [8] LIU X., WANG SH., XING L.: Fuzzy self-tuning PID temperature control for biomass pyrolysis fluidized bed combustor. In: Proc. 2nd IEEE Int. Conf. on Information Management and Engineering (2010), 384–387.
- [9] LIU CH.-Y., WANG J., LI Q., SONG X.-L., SONG Z.-Y.: The study of the control of the bed temperature in the circulating fluidized bed boiler based on the fuzzy control system. In: Proc. Int. Conf. on Computer and Communication Technologies in Agriculture Engineering (2010), 285–288.
- [10] LIUKKONEN M., HALIKKA E., HILTUNEN T., HILTUNEN Y.: Adaptive soft sensor for fluidized bed quality: Applications to combustion of biomass. Fuel Process. Technol. **105**(2013), 46-51.
- [11] LIXIA B., JUNXIA Z., SONG F.: Modeling and simulating of bed temperature control of circulating fluidized boiler. J. North China Electric Power Univ. **30**(2003), 1, 53 - 56.
- [12] OAKLAND J.S.: Statistical Process Control. Butterworth-Heinemann, Bodmin 2003.
- [13] O'DWYER A.: Handbook of PI and PID Controller Tuning Rules. Imperial College Press, London 2006.
- [14] PORZUCZEK J.: Optimization of the fluidized bed boilers operation in nonstationary states. Monograph 405, Environmental Engineering Ser., Cracow University of Technology, Krakow 2012 (in Polish).
- [15] PORZUCZEK J.: Dynamic model identification of the low-power fluidized bed boiler. Czasopismo Techniczne, 4-Ś/2012 (2012), 157–170 (in Polish).
- [16] PORZUCZEK J.: Transfer matrix model of the bubbling fluidized bed boiler. Arch. Thermodyn. 32(2011), 3, 245-26.
- [17] www.metsoautomation.com (acessed on 01.03.2016).