An Application of Identification and Control Design to the Experimental Calorimeter

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The application of an identification and control design to the continuous laboratory plant is presented. The reason of identification is given by the necessity to design the controller, which provides the suitable tracking of the reference signal described by given temperature profile. Used identification algorithm is based on the least-squares prediction error estimation. As a result of identification the parameters of the linear model of continuous system are estimated. This model is further used for computation of the transfer function of the unknown controller. Since in this case at the beginning no controller is available, the identification must be performed in the open-loop configuration.

A key problem in control system design is to handle uncertainties associated with a plant. Two main techniques for the analysis and design of systems with uncertainties are robust control [1] and adaptive control [2]. In the robust control approach a controller is designed based on a nominal model of the plant with the associated model uncertainties. This has motivated the development of identification techniques that estimate an upper boundary on the deviations between a plant and its nominal model. For high-performance control design a well-suited nominal model is needed. Traditional adaptive control systems that invariably invoke the principle of certainty equivalence have an unsatisfactory property of robustness.

In recent years, a revival of interest in the plant model identification occurred in the context of the iterative combination of identification in closed loop and control redesign [3, 4]. The identification of dynamic models from experimental data has very often been motivated and supported by the presumed ability to use the resulting model as a basis for model-based control design. A number of identification methods have been developed and analyzed [5, 6].

The main task of this contribution is to design the controller that provides temperature stabilization of plant and good tracking of reference signal. In this case, the plant is represented by a multikilogram scale combustion calorimeter. Based on an energy and water balance over the whole calorimeter the (upper and lower) energy value of heterogeneous materials of solid fuels is measured. Since the exact mathematical model of calorimeter is unknown, the mentioned controller must be designed from its estimated linear model. The estimation of this model is realized by the black-box identification based on data collected by experiments performed on the experimental calorimeter.

Here the estimation, based on the least-squares (LS) prediction error identification, is performed in the open-loop configuration. Directly identified linear model is further used to design the parameters of the controller with proportional and integral part (PI controller). The parameters of the controller can be designed by different ways [7]. The control design strategy, in this paper, is based on the linear quadratic (LQ) control approach. Here the poles of closed loop are not designed by the user, like in standard pole placement approach [7], but they are computed from identified model *via* spectral factorization. The advantage of this approach is that the controller is tuned by setting of two weight factors.

IDENTIFICATION AND COTROL DESIGN

Controlled System

Fig. 1 shows the major components of the plant, which consists of a combustion chamber 3 with internal combustion chamber for afterburning, heat ex-

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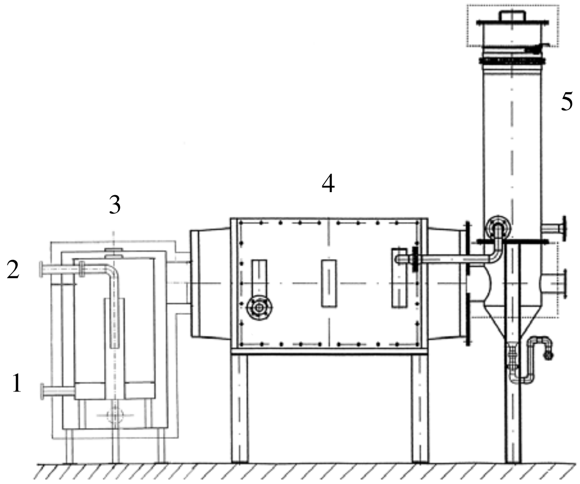

Fig. 1. Multikilogram capacity calorimeter.

changer 4, and condenser 5, where condensable products are collected. The capacity of the combustion chamber 3 is from 10 to 20 kg of tested material. The inlets 1 and 2 represent the primary and secondary air inlet. The flue gas 6 consists of O_2, CO_2, CO, NO, C_xH_y, H_2O. The constitution of flue gas is analyzed automatically. CO_2 and CO are analyzed by BINOS 1.1 (Leybold—Heraeus) and O_2 is analyzed by OXYNOS 1C (Rosemount). Analyzer VE 7 (JUM Engineers) is used for detection of C_xH_y. The temperatures are measured by Ni/Cr/Ni thermocouples. Gas meters G4/G6 and G2 measure the amount of natural gas. The flow of cooling water is measured by a magnetic-inductive flowmeter MAGFLO.

The energy balance consists of energy of natural gas, of cooling water, of combustion air, of exhaust gases, of unburned carbon monoxide and hydrocarbons and energy in the condensate.

The water mass balance consists of following partitions: water from the combustion of natural gas and from the combustion of test material, from the combustion air; water in the condensate and in the flue gas.

The on-line measurement of outlet temperature and quantities of a gas is provided. The control of the outlet temperature of the combustion chamber is guaranteed by the controllable gasburner. This temperature can be also influenced by the second uncontrollable gasburner, which represents a measurable disturbance. The second gasburner is used to heat the system to an initial temperature. Each measurement requires two test runs. The first run is called the measurement run and works with a fixed amount of test material. The second run is called the reference and works without the test material. Since the temperature conditions for both measurements must be equal, the suitable controller designed from identified model, which provides tracking of the defined temperature profile is required.

Estimation of Linear Model

To make things clear about the estimation of the linear model of the calorimeter, we shall make the following assumptions.

Assumption 1: The true plant will be assumed to be representable as follows

$$y = G(s)u + v \tag{1}$$

Here G is a scalar proper rational transfer function, u is the input signal, v is a possible unmeasurable disturbance acting on the output signal y.

Assumption 2: Consider that the true plant $G(s)$

$$G(s) = \frac{b(s)}{a(s)} \tag{2}$$

is stabilized by controller $C(s)$

$$C(s) = \frac{q(s)}{p(s)} \tag{3}$$

and following identity holds

$$a(s)p(s) + b(s)q(s) = n(s)g(s) \tag{4}$$

Here $b(s)$, $a(s)$, $q(s)$, $p(s)$, $n(s)$, and $g(s)$ are polynomials from $R(s)$. $R(s)$ denotes the set of stable polynomials. s is operator of the Laplace transformation.

Assumption 1 describes the true plant and it is standard for identification problem.

Assumption 2 is known from control theory and guarantees that the designed controller stabilizes the plant if and only if the polynomials $n(s)$ and $g(s)$ are stable, see *e.g.* [7].

We first recall the basic ingredients of predictor error identification. Consider that the identified model takes the form

$$\hat{y} = G(\boldsymbol{\theta}, s)u \tag{5}$$

Here $G(\boldsymbol{\theta}, s)$ is a transfer function with polynomials $\hat{b}(s)$, $\hat{a}(s)$ from $R(s)$ parametrized by arbitrary real vector $\boldsymbol{\theta}$. We notice that the true plant is given by *Assumption 1*. Consider that *Assumption 2* also holds for estimated model, which means that the transfer function $G(s)$ in this assumption is replaced by $G(\boldsymbol{\theta}, s)$. Notice that we shall use eqns (*1*) and (*5*) also as a system description for the sampled output values, keeping in mind that the computation of these values will involve numerical solution of a differential equation [5].

In LS prediction error identification, the estimation of the parameter vector $\boldsymbol{\theta}$ on the basis of N input-output data is obtained by minimizing the sum of the squares of the prediction error [5]

$$V_N = \frac{1}{N}\sum_{t=1}^{N}(\varepsilon(\boldsymbol{\theta}))^2 \tag{6}$$

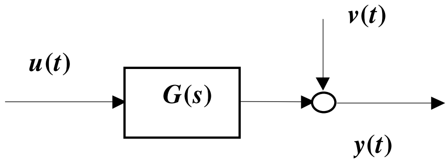

Fig. 2. Open-loop configuration.

where

$$\varepsilon(\boldsymbol{\theta}) = y - \hat{y} = (G(s) - G(\boldsymbol{\theta}, s))u + v \qquad (7)$$

The parameter estimate is then defined as

$$\boldsymbol{\theta} = \arg\min_{\boldsymbol{\theta} \in D} V_N(\boldsymbol{\theta}) \qquad (8)$$

where D is a predefined set of admissible values.

As we mentioned above, the data have been collected while the process operates in the open loop (Fig. 2). In such case, signals u and v are uncorrelated and the prediction error is given by eqn (*7*). Here the input signal u is considered as step change signal.

Assume now fixed structure of the unmeasurable noise (*i.e.* $v(t) = H(\sigma)e_{\mathrm{w}}(t)$) where $H(\sigma)$ is $\boldsymbol{\theta}$-independent transfer function and e_{w} represents white noise and σ is operator of differentiation. The expression (*7*) shows that the convergence point of $\boldsymbol{\theta}$ is independent of the actual noise distribution. It depends only on the noise model $H(\sigma)$ [3].

Controller Design

Our main task that we consider here is to design a feedback controller, based on the model that is to be identified from experimental data. This controller must stabilize the calorimeter and provide expected control performance. A typical control design type situation is that the designer has a minimization of some control performance criterion in mind. The standard feedback configuration is shown in Fig. 3. Here r represents the reference signal, uncorrelated to the disturbance v. In the standard LQ control design the following performance criterion is minimized [8].

$$J_{\mathrm{LQ}} = \int_0^\infty \{\mu e^2(t) + \varphi \tilde{u}^2(t)\} \mathrm{d}t \qquad (9)$$

where signals $e = r - y$ and $\tilde{u}$ are control error and derivative of input signal u and where μ and φ are positive weighting factors that reflect the respective importance given to the tracking error and the control effort.

This criterion cannot be minimized directly because it depends on the unknown transfer function $G(s)$ through the dynamic relationship that links r, u, and y. Instead, one designs a controller on the basis of an estimate $G(\boldsymbol{\theta}, s)$ of $G(s)$, which we shall in this paper consider to obtain from plant data by identification. Based on the procedure presented in [9], we can compute the parameters of designed controller from eqn (*4*). Here the polynomials $b(s)$ and $a(s)$ are replaced by estimated $\hat{b}(s)$, $\hat{a}(s)$. In standard LQ approach deg $n \geq$ deg a and deg $g =$ deg $(a+1)$ (deg = degree). These polynomials are given by the following spectral factorization [9].

$$n^* n = a^* a$$

$$(\hat{a}s)^* \varphi \hat{a}s + \hat{b}^* \mu \hat{b} = g^* g \qquad (10)$$

Here exponent * represents conjugated polynomial [7]. The values of weighting factors are designed by the user and depend on the claimed control performance. Eqn (*10*) shows that the right hand (the poles of closed loop) of eqn (*4*) depends on identified polynomials $\hat{b}(s)$, $\hat{a}(s)$ and mentioned weighting factors. Based on this information we can say that the complexity of designed controller directly depends on the complexity of identified model. Consider now that the first-order model is identified with the structure $G(\boldsymbol{\theta}, s) = \dfrac{\hat{b}_0}{s + \hat{a}_0}$. Here $\hat{b}_0$, $\hat{a}_0$ are coefficients of polynomials $\hat{b}(s)$, $\hat{a}(s)$. Using eqns (*10*) and (*4*) we can design the controller with the structure $C(s) = \dfrac{q_1 s + q_0}{s(p_1 s + p_0)}$. Here q_1, q_0 and p_1, p_0 are coefficients of polynomials $q(s)$ and $p(s)$, respectively. For detail information about LQ control design strategy we refer readers to [8].

In our case we need to design the PI controller with the structure $C(s) = \dfrac{q_1 s + q_0}{p_0 s}$. This structure of controller can be designed if the standard pole placement method is used [7] and plant is identified in the

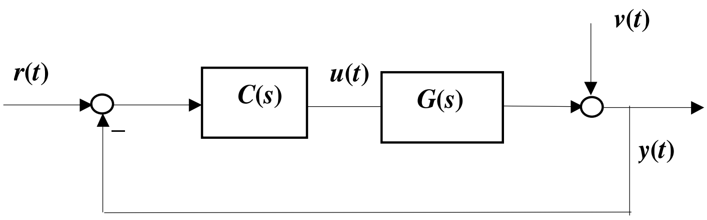

Fig. 3. Closed-loop configuration with negative feedback. – Negative feedback.

form $G(\boldsymbol{\theta}, s) = \dfrac{\hat{b}_0}{s + \hat{a}_0}$. As we mentioned above if the pole placement approach is applied, the right hand of eqn (*4*) depends on the user choice. Our idea is to use the spectral factorization for design of the right hand of eqn (*4*). It is impossible if the polynomial $n(s)$ is given by eqn (*10*). As we will show in the next section, if we want to design PI controller then we have to identify the first-order model and define the polynomial $n(s)$ like $n(s) = 1$. Then it is possible to calculate the polynomial $g(s)$ by spectral factorization (*10*) and finally the parameters of PI controller using relation (*4*).

Based on the theoretical background presented above, we can formulate the following steps of identification and control design strategy:

Step 1: Collect a data set $\{u(t), y(t)\}$ of length N (Fig. 2).
Step 2: Use these signals in LS identification algorithm with prediction error (*6*), considering y as an output signal and u as an input signal, and identify the transfer function $G(\boldsymbol{\theta}, s)$.
Step 3: Choose the weighting factors and polynomial $n(s)$.
Step 4: Compute the polynomial $g(s)$ from relation (*10*).
Step 5: Compute the parameters of designed controller $C(\boldsymbol{\theta}, s)$ from eqn (*4*).

In this case the LS algorithm is applied for control-relevant system identification [10, 11]. The model parameters are recursively estimated in discrete time intervals [12]. For more information about identification of continuous system in discrete intervals we refer readers to [5]. In this part of this contribution the formulated algorithm of identification and control design (Step 1—Step 5) is applied for the laboratory calorimeter.

RESULTS AND DISCUSSION

Identification – Steps 1 and 2

In this section the application of identification and control design is presented. Our task is to design the controller that provides the tracking and stabilization of the temperature in the combustion chamber 3 shown in Fig. 1. This temperature is influenced by the controllable and uncontrollable gasburner. On the other hand, this temperature is not strongly influenced by the unmeasurable noise v. This is the reason why we considered that $v = 0$ and the transfer function $H(\sigma)$ was not identified. Moreover, the identification is performed in open-loop configuration and input signal u is independent of the noise signal. It means that the convergence point of $\boldsymbol{\theta}$ is independent of the actual noise distribution.

The voltage for controllable gasburner gives the measurable input signal u and y is equal to the outlet temperature of the combustion chamber. The measurable input signal for uncontrollable gasburner u_{un} is given by the rate of methane flow. In this experiment both gasburners were identified. The resulted transfer functions of both gasburners had the following forms. Controllable gasburner

$$G(\boldsymbol{\theta}, s) = \frac{\hat{b}_1 s + \hat{b}_0}{\hat{a}_3 s^3 + \hat{a}_2 s^2 + \hat{a}_1 s + \hat{a}_0} \qquad (11)$$

Uncontrollable gasburner

$$G_{\mathrm{un}}(\boldsymbol{\theta}, s) = \frac{\hat{b}_1^{\mathrm{un}} s + \hat{b}_0^{\mathrm{un}}}{\hat{a}_3^{\mathrm{un}} s^3 + \hat{a}_2^{\mathrm{un}} s^2 + \hat{a}_1^{\mathrm{un}} s + \hat{a}_0^{\mathrm{un}}} \qquad (12)$$

The parameters of eqns (*11*) and (*12*) were identified using routines programmed in the Matlab.

At first, the transfer function of uncontrollable gasburner was measured. The process was excited by a step change of u_{un} from 0 to 5.8 $\mathrm{m^3\ h^{-1}}$. After stabilization of outlet temperature at the value approximately equal to 593 ℃ the second excitation was made and the transfer function for controllable gasburner was measured. Here the step change of u was from 0 to 1.73 V. For both cases the length of collected data was $N = 360$.

The results of identification in an open loop are depicted in Figs. 4 and 5. These figures compare the step responses of the uncontrollable and controllable gasburners with responses of their identified models for given step changes of the input signals (solid line – measured data from the process, dotted line – data from the identified model). From the prediction error (*6*) point of view we can say that selected structures of controllable and uncontrollable gasburners provided suitable approximation of real ones (the prediction error (*6*) reached the minimal value).

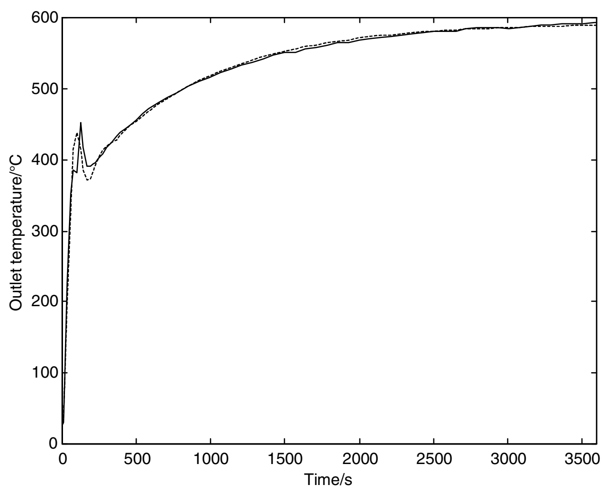

Fig. 4. Step responses of uncontrolled gasburner.

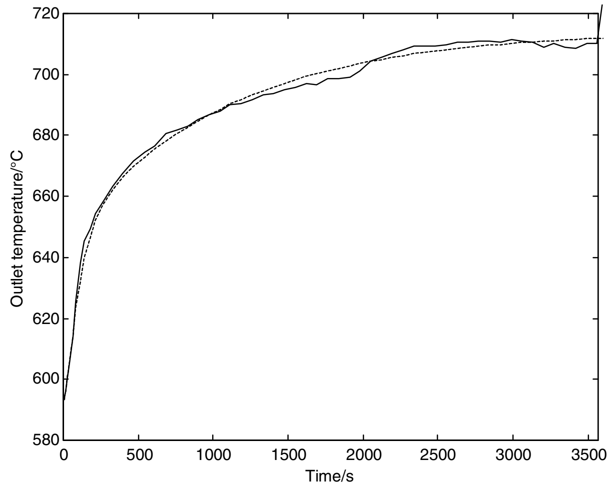

Fig. 5. Step responses of controlled gasburner.

Controller Design – Steps 3, 4, 5

The identified transfer function $G(\boldsymbol{\theta}, s)$ was further used in control design step, while the model of uncontrollable gasburner $G_{\mathrm{un}}(\boldsymbol{\theta}, s)$ was used during simulation of controlling outlet temperature of the combustion chamber. The structure of designed controller was in the form

$$C(s) = \frac{q_1 s + q_0}{p_0 s} \qquad (13)$$

Since the structure of the controller was strictly given, then with respect to eqn (*4*) the identified transfer function (*11*) was reduced to the following relation

$$G^{\mathrm{r}}(\boldsymbol{\theta}, s) = \frac{\hat{b}_0^{\mathrm{r}}}{s + \hat{a}_0^{\mathrm{r}}} \qquad (14)$$

This operation was realized *via* model reduction algorithm based on a Pade approximation [13] in Matlab. With respect to eqns (*4*) and (*10*) the polynomial $n(s)$ has been chosen as $n(s) = 1$. Step 4 was realized through the following equations, derived from eqn (*10*)

$$g_2 = \sqrt{\varphi}$$

$$g_0 = \sqrt{(\hat{b}_0^{\mathrm{r}})^2 \mu} \qquad (15)$$

$$g_1 = \sqrt{(\hat{a}_0^{\mathrm{r}})^2 \varphi + 2 g_0}$$

Here the weighting factors φ and μ were selected by the user in step 3. Finally the parameters of the controller were computed from relations (*16*) – step 5.

$$p_0 = g_2$$

$$q_1 = \frac{g_1 - p_0 \hat{a}_0^{\mathrm{r}}}{\hat{b}_0^{\mathrm{r}}} \qquad (16)$$

$$q_0 = \frac{g_0}{\hat{b}_0^{\mathrm{r}}}$$

Before application to the real plant the designed controller was tested *via* simulation in Matlab/Simulink software. The scheme of simulated closed loop is depicted in Fig. 6.

From this scheme it is clear that the simulated closed loop consists of designed controller (*13*), estimated transfer function of controllable gasburner (*11*), and of the measurable disturbance represented by the estimated transfer function of uncontrollable gasburner (*12*). We notice that the reduced model of controllable gasburner $G^{\mathrm{r}}(\boldsymbol{\theta}, s)$ was not used directly in the scheme shown in Fig. 6. The reason was that the model described by eqn (*11*) provides better approximation of laboratory calorimeter than its reduced version (*14*).

Two simulations have been realized for two different step changes of input signal u_{un} at the beginning of the simulation. In the first case the input signal for uncontrollable gasburner was changed from 0 to 5.8 $\mathrm{m^3\ h^{-1}}$ and in the second case it was from 0 to 2.6 $\mathrm{m^3\ h^{-1}}$. In both cases, at the beginning of the simulation, the outlet temperature had a value 24.5 °C and the input signal of the controllable gasburner was 0 V. The initialization temperature, the lowest temperature of given temperature profile, was 266 °C. If the outlet temperature was lower than initialization temperature, the manual control has been activated. On the other hand, if the controlled outlet temperature was equal or higher than initialization temperature, then the designed controller has been activated

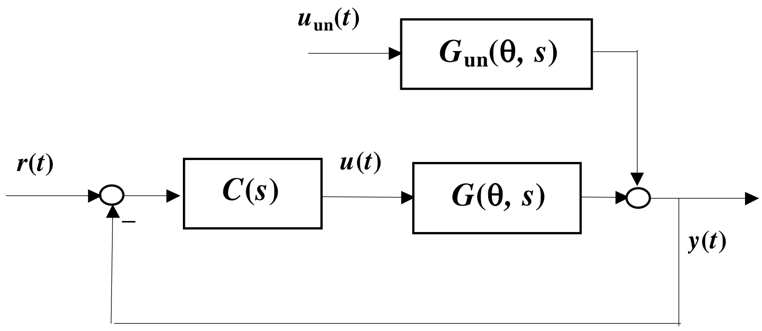

Fig. 6. Simulated closed-loop configuration with negative feedback. – Negative feedback.

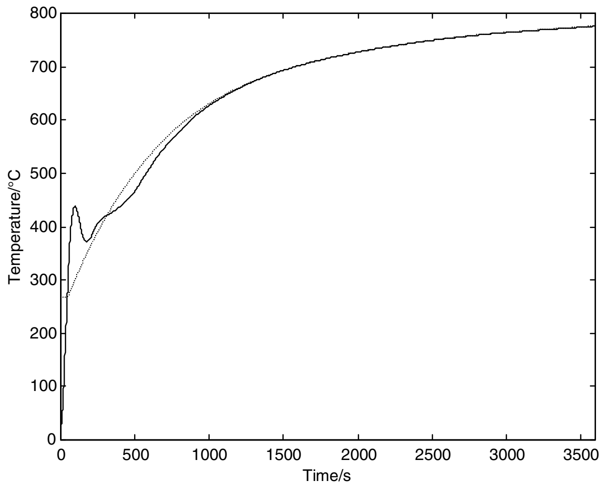

Fig. 7. Controlled temperature – the first simulation, temperature profile (solid line), outlet temperature (dotted line).

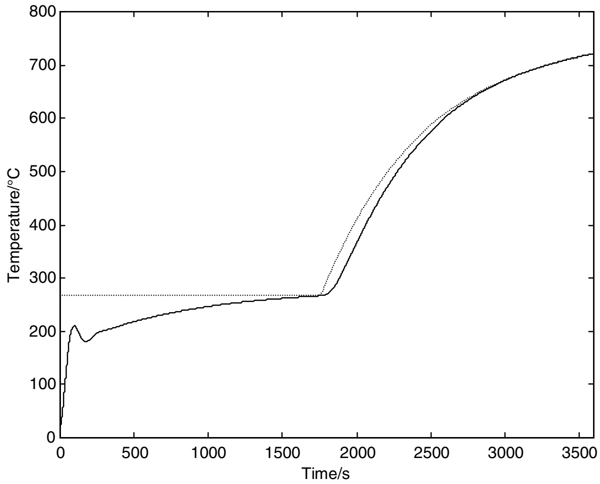

Fig. 9. Controlled temperature – the second simulation, temperature profile (solid line), outlet temperature (dotted line).

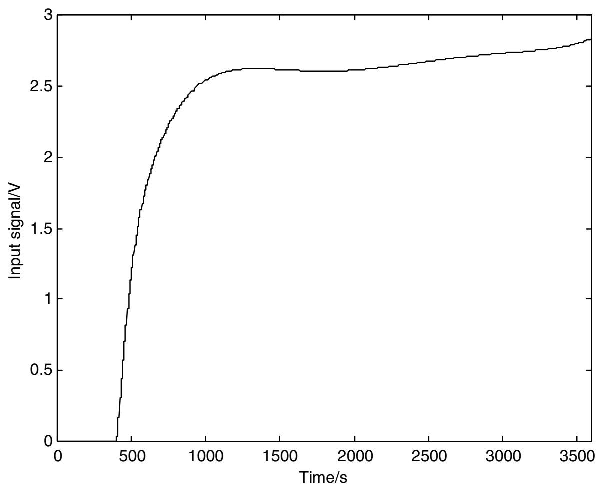

Fig. 8. Input signal of controllable gasburner – the first simulation.

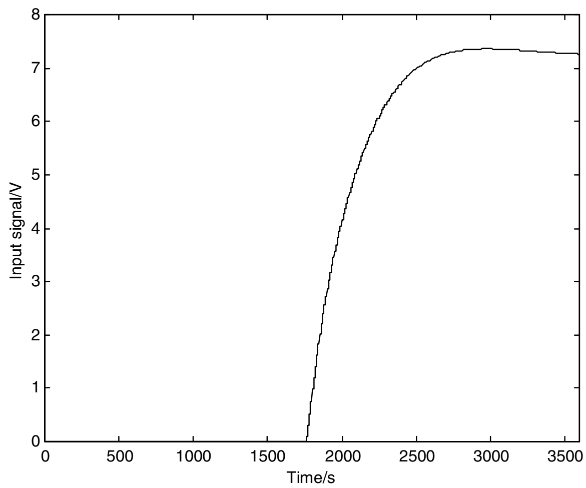

Fig. 10. Input signal of controllable gasburner – the second simulation.

and outlet temperature was controlled according to defined temperature profile. The range of the signal u was from 0 to 10 V.

The results from the first simulation are presented in the following figures. Fig. 7 shows that the outlet temperature of the combustion chamber was not controlled for time interval from 0 to 450 s, although the initial temperature (266 ℃) was reached in very short time (t = 45 s, see differences between temperature profile and controlled temperature). This problem was caused by the fact that the input signal u had the lowest possible value and so it was not possible to cool the combustion chamber by used controllable gasburner. Fig. 8 illustrates that the controller began to control the temperature approximately after t = 450 s. In the time interval from 0 to 450 s the input signal u had a constant value 0 V. This condition can be improved by decreasing the step change of the input signal u_{un} at the beginning of the simulation, as it is shown in the following results.

Fig. 9 shows that the heating of the combustion chamber was longer, approximately 1750 s, than it was in the first simulation. On the other hand, the controller began to control the outlet temperature immediately after the initial temperature was reached. Similarly as in the first simulation also in this case the input signal u had the value 0 V for time lower than 1750 s (Fig. 10).

CONCLUSION

In this paper the control design based on the identification of controllable and uncontrollable gasburner of experimental calorimeter is presented. The identification was realized in the open-loop configuration. The both gasburners were identified as third-order models. This structure provided the best approximation of the plant with respect to the minimization of identification criterion. The noise contribution was not identified because the input signal that was used during open-loop identification was independent of the noise signal. It means that the result of identification was not influenced by the actual noise. It depends only on the noise model $H(\sigma)$. Here the simplest model of noise was selected and identification provides satisfactory results.

The identified model of controllable gasburner was further used for PI controller design. The control design step was realized through eqns (*4*) and (*10*). The advantage of the used design method in comparison with the standard pole placement method is that the performances of designed controller are tuned by two weighting factors. Moreover, the properties of closed loop are not dependent on the user choice but they are function of identified linear model and the mentioned weighting factors *via* spectral factorization (*10*). Since the structure of resulted controller was strictly given, the structure of identified model of controllable gasburner was reduced from the third-order model to the first-order model. Without this reduction it is not possible to design the PI controller through relations (*4*) and (*10*). Reduction was realized *via* the method based on the Pade approximation. The final controller was designed by tuning of two weighting factors. The designed controller was tested in simulated closed loop. In this simulation the real gasburners were replaced by their identified models (third-order models were used).

Based on the results from simulation we can say that the designed controller had good tracking properties. High rate of methane flow for uncontrollable gasburner provided faster heating of the combustion chamber but the controller was not able to control the outlet temperature immediately after the initial temperature was reached. Lowering of the rate of the methane flow for uncontrollable gasburner increased the time necessary for heating the combustion chamber to the initial temperature.

Finally we can consider that the designed controller is suitable for controlling of the experimental calorimeter. The results from real experiment can be slightly different in comparison with the results obtained from realized simulations. This difference can be caused by possible nonlinear properties of the calorimeter. In this case the enhancement of designed controller will reside in application of advanced identification algorithms presented *e.g.* in [3], [4] or [14], which are based on the identification in closed-loop configuration.

SYMBOLS

u	input signal for controllable gasburner	V
$\tilde{u}(t)$	derivative of input signal for controllable gasburner	V s^{-1}
u_{un}	input signal for uncotrollable gasburner	m^3 h^{-1}
y	output signal – outlet temperature of combustion chamber	℃
$\hat{y}(t)$	estimated output signal	℃
r	reference signal	℃
e_{w}	white noise	
e	control error	℃
v	noise signal	
t	time	s
s	operator of the Laplace transformation	
σ	operator of differentiation	
$\varepsilon(\boldsymbol{\theta})$	prediction error	
$\boldsymbol{\theta}$	vector of estimated parameters	
$G(s)$	transfer function of controllable gasburner	
$G(\boldsymbol{\theta}, s)$	transfer function of estimated model of controllable gasburner	
$G^{\mathrm{r}}(\boldsymbol{\theta}, s)$	transfer function of reduced model of controllable gasburner	
$G_{\mathrm{un}}(\boldsymbol{\theta}, s)$	transfer function of uncontrollable gasburner	
$C(s)$	transfer function of controller	
$H(\sigma)$	transfer function of unmeasurable noise	
$a(s), b(s)$	polynomials of $G(s)$	
$\hat{a}(s), \hat{b}(s)$	polynomials of $G(\boldsymbol{\theta}, s)$	
$a^{\mathrm{r}}(s), b^{\mathrm{r}}(s)$	polynomials of $G^{\mathrm{r}}(\boldsymbol{\theta}, s)$	
$a^{\mathrm{un}}(s), b^{\mathrm{un}}(s)$	polynomials of $G_{\mathrm{un}}(\boldsymbol{\theta}, s)$	
$p(s), q(s)$	polynomials of $C(s)$	
R	stable polynomials	
φ, μ	weighting factors	

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