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MATHEMATICAL MODELING AND IDENTIFICATION OF THERMAL PLANT

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Abstract: The paper discusses identification of the laboratory model of thermal-plant. Due to the presence of several non-linearities the non-linear model is used to describe the plant's dynamics. Recursive method of consecutive integral (RMOCI) is employed for the identification.

Keywords: thermal-plant, non-linear model, identification

1 INTRODUCTION

The identification of the process to be controlled is one of the basic tasks in the control design. In this paper the laboratory model of thermal plant is identified. Due to the presence of several non-linearities the non-linear model is used to describe the plant's dynamics. The paper is organized as follows: In chapter 2, the thermal plant is introduced. The identification of the plant is presented in chapter 3. The results are summarized in the conclusion.

2 THERMO-OPTICAL PLANT MODEL

The thermo-optical plant laboratory model (Fig.1) offers measurement of 8 process variables: controlled temperature, its filtered value, ambient temperature, controlled light intensity, its derivative and filtered value, the fan speed of rotation and current. The temperature and the light intensity control channels are interconnected by 3 manipulated voltage variables influencing the bulb (heat & light source), the light-diode (the light source) and the fan (the system cooling). Besides these, it is possible to adjust two parameters of the light intensity differentiator. Within Matlab/Simulink or Scilab/Scicos schemes the plant is represented as a single block and so limiting needs on costly and complicated software packages for real time control. The (supported) external converter cards are necessary just for sampling periods below 50ms. Currently, more than 30 such plants are used in labs of several EU universities.

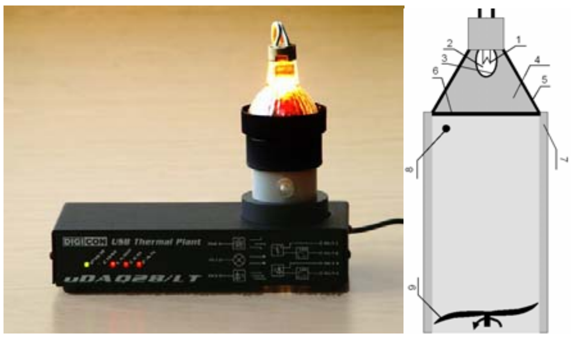

Fig. 1. The thermo-optical plant and scheme of its thermal channel

The thermal plant consists of a halogen bulb 12V DC/20W (elements 1-6), of a plastic pipe wall (element 7), of its internal air column (element 8) containing the temperature sensor PT100, and of a fan 12V DC/0,6W (element 9 that can be used for producing disturbances, but also for control).

2.1 Mathematical modeling of running processes

These processes can be characterized as follows:

Electrical current makes the filament hot and generates light and heat.

The filament temperature depends on the current intensity and on the heat exchange with surrounding area.

Glowing filament distributes heat by conducting and radiation.

Sum of the energy/heat amounts entering the system is equal to the sum of outgoing energy/heat amounts and the energy accumulated within the system. The process can be described as

$$\frac{dQ_v}{dt} = RI^2 - Q_1 - Q_2, \quad (1)$$

whereby

Q_v - heat of filament [J]

Q_1 - heat flow dissipated by conduction [W]

Q_2 - heat flow dissipated by radiation [W]

RI^2 - heat generated by current and filament resistance

Heat of the filament is given as

$$Q_V = m_V C_{PV} T_V, \quad (2)$$

whereby

m_V - filament mass [kg],

C_{PV} - specific heat capacity of filament [J.kg^{-1}.K^{-1}]

T_V - filament temperature [K]

For heat flow transferred by conduction it holds

$$Q_1 = K_1(T_V - T_{OUT}) \quad (3)$$

K_1 - constant of heat flow by conduction [W.K^{-1}]

T_V - filament temperature [K]

T_{OUT} - temperature of filament surroundings [K]

For the heat flow transferred by radiation it holds

$$Q_2 = eA\sigma T_V^4 - K_2 T_{OUT}^4 \quad (4)$$

, whereby

e - emissive power [1]

A - emissive surface [m^2]

σ - Stefan-Boltzman constant (5,67.10^{-8}Wm^{-2}.K^{-4})

K_2 - complex coefficient expressing ability of surrounding to [W.K^{-4}]

T_V - filament temperature [K]

T_{OUT} -temperature of filament ambient [K]

For a subsystem that is in contact with blowing filament the thermal balance depends on the heat amount accepted from the filament by conduction, from the heat amount accepted from the heat radiated by the filament and from the heat losses depending on the subsystem surrounding.

$$\frac{dQ_S}{dt} = L_1(T_V - T_S) + L_2 eA\sigma T_V^4 - \\ - L_{22} T_S^4 - L_3(T_S - T_{OUT,S}) \quad (5)$$

where

L_1 - constant of the heat flow by conduction [W.K^{-1}]

L_2- constant of the heat flow by radiation [1]

L_{22} - constant of subsystem for radiation [W.K^{-4}]

L_3 - constant of the heat flow by conduction [W.K^{-1}]

T_V - filament temperature [K]

T_S- filament temperature [K]

$T_{OUT,S}$ -temperature of subsystem ambient [K]

For Q_S it holds that

$$Q_S = m_S C_{PS} T_S \quad (6)$$

whereby

m_S – subsystem mass [kg]

C_{PS} - specific heat capacity of the subsystem [J.kg^{-1}.K^{-1}]

T_S - subsystem temperature [K]

Since the filament thermal capacity is small in comparing with that of the subsystem 8 (inner tube area) and, simultaneously, the time for reaching a steady state filament temperature is substantially smaller than time required for reaching steady-state temperature in the inner area 8 (fig. 1), it is possible to accept simplifying assumption that the steady state filament temperature is reached momentary.

The filament temperature can be determined by means of the V-A characteristic using the thermal dependance of metal resistance

$$R = R_0\left[1 + \alpha(T - T_0)\right] \quad (7)$$

whereby

R – metal resistance at temperature T [Ω]

R_0 - metal resistance at temperature T_0 [Ω]

α – temperature factor of electrical resistance [K^{-1}]

T, T_0 - filament temperature [K]

For a known resistance R_0, known temperature T_0 (indoor area) it is possible by means of the actual value of R to get the filament temperature using:

$$R = \frac{U}{I} \tag{8}$$

U - is the lamp voltage [V]

I - is the lamp current [A].

Then, for the filament temperature it holds

$$T = \frac{R - R_0 + R_0 \alpha T_0}{R_0 \alpha} \tag{9}$$

whereby for the tungsten filament there is α = 0,0053 [K^{-1}].

Regression made using measured data of the V-A characteristic yields law for computing the filament temperature as

$$T = T_{NORM} + T_{RED} = T_{NORM} + 1790{,}9819 I_T^{0{,}28817} \tag{10}$$

whereby

T - filament temperature [K]

T_{RED} - reduced filament temperature [K]

T_{NORM} - measurement temperature filament

293,15 [K]

I_T- interpreter value of temperature filament [1]

After assigning the inner tube area containing the temperature sensor as subsystem containing also the air column, the inner tube surface, the fun and the front bulb side. For derivation of its mathematical model it is necessary to accept some assumptions and simplifications regarding the running processes.

2.2 Assumptions for simplification of the mathematical model

For a switched off fan the air flow can be neglected and the air column be considered as quasi-stationary. The temperature changes will otherwise cause also changes in the air density leading to forced circulation. However, due to the relatively small gaps of the mechanical construction such a flow can be neglected. The existing flows can be further minimized e.g. by enclosing the fan outlet by an adhesive tape.

The heat is flowing from the lamp to the inner area by conduction and radiation. The stationary air column will absorb part of the radiated heat and simultaneously it will accept heat distributed by conduction. This process will cause increase of its temperature. Simultaneously, some heat of the air column is passed through the pipe wall to the surrounding space by the contact with the internal pipe surface. The thermal capacity of the temperature sensor will be considered in deriving the pseudo thermal capacity of the air column.

The inner pipe wall is from the material point of view reasonably different from the air column. Heat is distributed to its surface by conduction and radiation. The differences in material will cause that the temperature of the internal surface will be different from that of the air column both in dynamical and steady states. The wall is exposed to radiation to much less degree than the air column

The outer pipe wall is exposed to influence of surrounding air column that is also supposed to be stationary.

Due to the relatively small high of the pipe (9,5cm) zero gradient of radiation in dependence on the distance from the lamp will be supposed.

For the sake of further model simplifications it can be supposed that the temperature sensor is integrated into the air column and that the outer temperature can be simply measured. These simplifications lead to simplified model with just two simply measurable state variables. One will be taken as the air column temperature, the 2nd one as the outer pipe surface temperature. In deriving model with 2 state variables it is yet required to eliminate from the description the temperature of the inner pipe surface and some plant parameters. The elimination can be based on introducing new pseudo variables.

The resulting mathematical model is

$$T(t) = T_{NORM} + T_{RED}(t) = \\ = T_{NORM} + 1790{,}9819 I_T(t)^{0{,}28817}$$

$$\frac{dT_{VS}(t)}{dt} = K_{11}(T(t) - T_{VS}(t)) + K_{12}(T(t)^4 - T_{VS}(t)^4) - \\ - K_{13}(T_{VS}(t) - T_{OUT,S}(t)) - \\ - f(I_V)(T_{VS}(t) - T_{OUT})$$

$$\frac{dT_{OUT,S}(t)}{dt} = K_{21}(T_{VS}(t) - T_{OUT,S}(t)) - \\ - K_{22}(T_{OUT,S}(t) - T_{OUT})$$

$$y(t) = T_{VS}(t) \tag{11}$$

$T_{VS}(t)$ - temperature of the inner air column [K]

$T_{OUT,S}(t)$ - temperature of the outer tube wall [K]

T_{OUT} - ambient temperature [K]

K_{11}, K_{13},K_{21}, K_{22} - constants characterizing heat transfer by conduction [s^{-1}]

K_{12} - constants characterizing heat transfer by radiation [$s^{-1}K^{-3}$]

$f(I_V)$ - fan air flow as a function of its control variable I_V [s^{-1}]

$I_T(t)$ - control variable for bulb [1]

$y(t)$ - (measured) output temperature [K].

Under switched-on fan the air flow will cause that the difference of the temperature of the inner tube surface and the air column temperature will be smaller as in the stationary case. From the practical point of view it is, however, simpler to include this effect into the function $f(I_V)$ with input variable changing in the range 0 – 5V, whereby it will be supposed that the outgoing air flow has temperature of the air column and the input air has temperature equal to the ambient temperature. Of course, by increasing the air flow the differences of the temperatures of the ingoing and of the outgoing flows decrease. Simultaneously, fan speed has especially for the relatively low speed of rotation high hysteresis. All these specific properties may be compensated by appropriate design of $f(I_V)$.

3 PLANT IDENTIFICATION

Identification will be carried out by recursive method of consecutive integral (RMOCI). This method [9] enables to identify parameters of the nonlinear model. It is based on LS recursive algorithms [5-7], whereby RMOCI broadens its possibility to be applied in identification of nonlinear model parameters without using plant linearization or other approximative approaches. This extension is based on preparation of the vector of input data so that the resulting vector may be used for identification of unknown parameters of the nonlinear model. In preparing data for LS recursive algorithm RMOCI method [9] achieves this by nonlinear state transformation [8] and modified method of consecutive integration [1-4]. In this way the vector of input data can be processed both for the linear systems (by using structure of the input-output model represented by the transfer function) and by nonlinear systems using the state-space description. Characteristic features of such modified vector are its integral functions. In contrast to using data produced by differentiation this approach does not require use of filters. Linear combinations of vector data occur in practical application just scarcely. Under some assumptions it is e.g. possible to identify by a single step response also higher order transfer function. Among other advantages one could mention better convergence under high measurement noise and the fact that due to numerous publications the particular methods combined within the solution are well known, together with their properties and constraints.

In this special case RMOCI is used by considering measurement of just single state variable, when due to special structure of the plant model it is not required to use nonlinear state transformation (when it is possible step-by-step integrate and substitute particular state variables).

3.1RMOCI description

Mathematically RMOCI can be formulated as follows:

The first step is nonlinear transformation according to Sommer [8]. When considering the following non-transformed mathematical model

$$\begin{aligned} \frac{d\mathbf{x}(t)}{dt} &= \mathbf{f}(\mathbf{x}(t)) + \mathbf{g}(\mathbf{x}(t))\mathrm{u}(t) \\ y(t) &= h(\mathbf{x}) \end{aligned} \tag{12}$$

whereby

$\mathrm{x}(t) = (x_1, x_2, ..., x_n)^T$ is the vector of state variables

f -vector function of state space variable

u -input signal

y -output signal

h -output function of the system.

after transformation one gets

$$\begin{aligned} \frac{d\mathbf{z}(t)}{dt} &= \mathbf{A}(\mathbf{x})\mathbf{z}(t) + \mathbf{B}(\mathbf{x})u(t) \\ y(t) &= z_1(t) = T_1(\mathbf{x}) = h(\mathbf{x}) \end{aligned} \tag{13}$$

whereby

$$\mathbf{A}(\mathbf{x}) = \begin{pmatrix} 0 & 1 & 0 & 0 \\ \vdots & \ddots & \ddots & 0 \\ 0 & \cdots & 0 & 1 \\ p_{A1}(\mathbf{x}) & \cdots & \cdots & p_{An}(\mathbf{x}) \end{pmatrix}$$

$$\mathbf{B}(\mathbf{x}) = \begin{pmatrix} p_{B1}(\mathbf{x}) \\ \vdots \\ p_{Bn}(\mathbf{x}) \end{pmatrix}, \quad \mathbf{C}(\mathbf{x}) = \begin{pmatrix} 1 & 0 & \cdots & 0 \end{pmatrix} \tag{14}$$

$$\begin{aligned} &\frac{\partial T_1(\mathbf{x})}{\partial \mathbf{x}} \mathbf{f}(\mathbf{x}) = T_2(\mathbf{x}) = z_2(t) \\ &\vdots \\ &\frac{\partial T_{n-1}(\mathbf{x})}{\partial \mathbf{x}} \mathbf{f}(\mathbf{x}) = T_n(\mathbf{x}) = z_n(t) \\ &\frac{\partial T_n(\mathbf{x})}{\partial \mathbf{x}} \mathbf{f}(\mathbf{x}) = p_{A1}(\mathbf{x}) T_1(\mathbf{x}) + p_{A2}(\mathbf{x}) T_2(\mathbf{x}) + \\ &\cdots + p_{An}(\mathbf{x}) T_n(\mathbf{x}) \end{aligned} \tag{15}$$

$$\begin{aligned} p_{A1}(\mathbf{x}) &= \frac{\frac{\partial T_n(\mathbf{x})}{\partial x_1} f_1(\mathbf{x})}{T_1(\mathbf{x})}, \\ p_{A2}(\mathbf{x}) &= \frac{\frac{\partial T_n(\mathbf{x})}{\partial x_2} f_2(\mathbf{x})}{T_2(\mathbf{x})}, \\ p,_{An}(\mathbf{x}) &= \frac{\frac{\partial T_n(\mathbf{x})}{\partial x_n} f_n(\mathbf{x})}{T_n(\mathbf{x})}, \\ p_{B1}(\mathbf{x}) &= \frac{\partial T_1(\mathbf{x})}{\partial \mathbf{x}} \mathbf{g}(\mathbf{x}), \\ p_{B2}(\mathbf{x}) &= \frac{\partial T_2(\mathbf{x})}{\partial \mathbf{x}} \mathbf{g}(\mathbf{x}), \\ p_{Bn}(\mathbf{x}) &= \frac{\partial T_n(\mathbf{x})}{\partial \mathbf{x}} \mathbf{g}(\mathbf{x}). \end{aligned} \tag{16}$$

The equation represents transformed quasi-linear system.

In the second step this quasi-linear system will be integrated by the modified method of consecutive integral (MMOCI).

$$\begin{aligned} \mathbf{z}(t) &= \int_0^t \mathbf{A}(x)\mathbf{z}(\tau)d\tau + \int_0^t \mathbf{B}(x)u(\tau)d\tau + \mathbf{z}(0) \\ y(t) &= z_1(t) \end{aligned} \tag{17}$$

Atfer modification it yields one regression equation in integral form

$$\begin{aligned} z_1(t) = \hat{y}(t) = \begin{bmatrix} c_1 & \cdots & c_r \end{bmatrix} \begin{bmatrix} f_1(\mathbf{x}_m, t) \\ \vdots \\ f_r(\mathbf{x}_m, t) \end{bmatrix} + \\ + \begin{bmatrix} c_{r+1}(\mathbf{x}(0)) & \cdots & c_{r+m}(\mathbf{x}(0)) \end{bmatrix} \begin{bmatrix} f_{r+1}(t) \\ \vdots \\ f_{r+m}(t) \end{bmatrix} \end{aligned} \tag{18}$$

whereby

$\hat{y}(t)$ -computed output variable

$f_i(x_m,t)$ -integral function dependent on the measured state variables

$f_j(t)$ -function dependent on the time only

c_i -identified parameter

$c_j(x(0))$ -identified parameter dependent on the initial values of state vector $x(t)$.

Notice that $(r+m)$ can not be equal n.

This regression can also be written as

$$\begin{aligned} \hat{y}(t) &= c_1 f_1(t) + c_2 f_2(t) + \ldots + c_r f_r(t) + c_{(r+1)} f_{(r+1)}(t) + \\ &+ c_{(r+2)} f_{(r+2)}(t) + \ldots + c_{(r+m)} f_{(r+m)}(t) \end{aligned} \tag{19}$$

In the third step one has to apply minimization of the Gauss criterion

$$J = \sum_i \begin{pmatrix} y_m(i) - c_1 f_1(i) - c_2 f_2(i) - \ldots - c_r f_r(i) - c_{(r+1)} f_{(r+1)}(i) - \\ - c_{(r+2)} f_{(r+2)}(i) - \ldots - c_{(r+m)} f_{(r+m)}(i) \end{pmatrix}^2 . \to \min \tag{20}$$

Here i represents the number of sampled data. For this purpose it is possible to use recursive least-square method, whereby the data and parameter vectors take the form

$$\begin{aligned} \mathbf{Z}^T &= \begin{pmatrix} f_1(t) & f_2(t) & \cdots & f_{r+m}(t) \end{pmatrix} \\ \mathbf{C}^T &= \begin{pmatrix} c_1 & c_2 & \cdots & c_{r+m} \end{pmatrix}. \end{aligned} \tag{21}$$

3.2 *Deriving regression equation*

$$\begin{aligned} \frac{dT_{VS}(t)}{dt} &= K_{11}(T(t) - T_{VS}(t)) + \\ &+ K_{12}(T(t)^4 - T_{VS}(t)^4) - K_{13}(T_{VS}(t) - T_{OUT,S}(t)) \end{aligned} \tag{22}$$

$$\frac{dT_{OUT,S}(t)}{dt} = K_{21}(T_{VS}(t) - T_{OUT,S}(t)) - -K_{22}(T_{OUT,S}(t) - T_{OUT}) \quad (23)$$

$$y(t) = T_{VS}(t) \quad (24)$$

equation (2) is used for expressing $T_{OUT,S}(t)$

$$T_{OUT,S}(t) = \frac{1}{K_{13}}\left[\frac{dT_{VS}(t)}{dt} - K_{11}(T(t) - T_{VS}(t)) - -K_{12}(T(t)^4 - T_{VS}(t)^4) + K_{13}T_{VS}(t)\right] \quad (25)$$

By integrating (25) one gets

$$\int_0^\tau T_{OUT,S}(t)dt = \frac{1}{K_{13}}\left[T_{VS}(t) - T_{VS}(0) - -K_{11}\int_0^\tau (T(t) - T_{VS}(t))dt - K_{12}\int_0^\tau (T(t)^4 - T_{VS}(t)^4)dt + K_{13}\int_0^\tau T_{VS}(t)dt\right] \quad (26)$$

Similarly, by integrating (23) and expressing $T_{OUT,S}(t)$:

$$T_{OUT,S}(t) = K_{21}\int_0^\tau T_{VS}(t)dt + +(-K_{21} - K_{22})\int_0^\tau T_{OUT,S}(t)dt + +K_{22}T_{OUT}\int_0^\tau 1dt + T_{OUT,S}(0) \quad (27)$$

In (27) $T_{OUT,S}(t)$ and $\int_0^\tau T_{OUT,S}(t)dt$ are substituted by (25) and (26). By consecutive integration and manipulation one gets

4 (28)

whereby

$A = -K_{21} - K_{22}$

(28) has to be rewritten into the form

$$T_{VS}(t)_E = c_1 f_1(t) + c_2 f_2(t) + c_3 f_3(t) + +c_4 f_4(t) + c_5 f_5(t) + c_6 f_6(t) + +c_7 f_7(t) + c_8 f_8(t) + c_9 f_9 \quad (29)$$

whereby

$$c_1 = A - K_{13}; \quad c_2 = K_{11}; \quad c_3 = K_{12};$$
$$c_4 = K_{13}K_{21} - AK_{13}; \quad c_5 = -AK_{11}; \quad c_6 = -AK_{12}$$
$$c_7 = K_{13}T_{OUT,S}(0) - AT_{VS,E}(0);$$
$$c_8 = K_{13}K_{22}T_{OUT}; \quad c_9 = T_{VS,E}(0)$$

$$f_1(t) = \int_0^\tau T_{VS,M}(t)dt; \quad f_2(t) = \int_0^\tau (T(t) - T_{VS,M}(t))dt;$$

$$f_3(t) = \int_0^\tau (T(t)^4 - T_{VS,M}(t)^4)dt$$

$$f_4(t) = \int_0^\tau\int_0^\tau T_{VS,M}(t)dt; \quad f_5(t) = = \int_0^\tau\int_0^\tau (T(t) - T_{VS,M}(t))dt;$$

$$f_6(t) = \int_0^\tau\int_0^\tau (T(t)^4 - T_{VS,M}(t)^4)dt$$

$$f_7(t) = \int_0^\tau 1dt; \quad f_8(t) = \int_0^\tau\int_0^\tau 1dt; \quad f_9 = 1$$

$T_{VS,E}$ (t) - estimated inner air column temperature [K]

$T_{VS,M}$ (t) - measured inner air column temperature [K]

Data vector **Z** and the parameter vector **C** take forms

$$\mathbf{Z}^T = (f_1(t)\ f_2(t)\ f_3(t)\ f_4(t)\ f_5(t)\ f_6(t)\ f_7(t)\ f_8(t)\ f_9)$$
$$\mathbf{C}^T = (c_1\ c_2\ c_3\ c_4\ c_5\ c_6\ c_7\ c_8\ c_9)$$

Finally, RMOCI yields model of the thermal plant having coefficients shown in Tab.1.

c_1	c_2	c_3	c_4	c_6
-0,026	1,107 $.10^{-5}$	3,973 $.10^{-15}$	-2,911 $.10^{-5}$	1,234 $.10^{-17}$
K_{11}	**K_{12}**	**K_{13}**	**K_{21}**	**K_{22}**
1,107. 10^{-5}	3,973. 10^{-15}	0,023	0,002	0,001

In Fig. 2 the measured data used for identification are compared with data achieved by simulation using the resulting model.

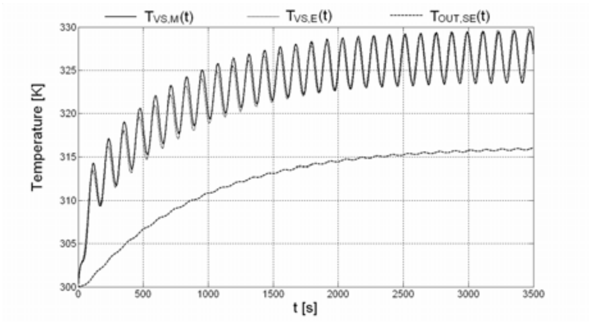

Fig.2 Comparing temperature $T_{VS,E}$ generated by the mathematical model (1) with the measured data $T_{VS,M}$ used for its identification and the corresponding response of $T_{OUT,SE}(t)$

The data used for identification were generated by the plant input consisting of a step at t=0 and of a sinusoidal function started at t=60 as

$$I_T(t) = 3.\mathbf{1}(t) + 3.\mathbf{1}(t-60)\frac{2}{3}\sin\left(\frac{\pi}{60}t\right) \quad (30)$$

As the quality criterion it was chosen the maximal absolute value of the difference of measured and simulated data that achieved its maximum 1,78 K for t=742,5s. In average this difference is 0,67 K.

4 CONCLUSION

The comparison of the identified model and the real data verifies the model structure and parameters. The possibility to run the identification on-line gives the advantage in the competition between the other identification algorithms.

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