Adaptive Predictive Control of Laboratory Heat Exchanger

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Abstract: - Heat exchange belongs to the class of basic thermal processes which occur in a range of industrial technologies, particularly in the energetic, chemical, polymer and rubber industry. The process of heat exchange is often implemented by through-flow heat exchangers. It is apparent that for an exact theoretical description of dynamics of heat exchange processes it is necessary to use partial differential equations. Heat exchange is namely a process with distributed parameters. It is also necessary to take into account its nonlinear and stochastic character. In spite of these facts, most of thermal equipment is controlled by digital modifications of PID controllers at present. This paper deals with identification of a dynamic behaviour of a through-flow heat exchanger and a design of a self-tuning predictive controller for its control. The designed controller was verified by a real-time control of an experimental laboratory heat exchanger.

Key-Words: - Model predictive control; Adaptive control; CARIMA model; ARX model; Least squares method; Process identification; Time-delay system; Heat exchanger

1 Introduction

A heat exchanger is a specialized device that exchanges heat between two streams, heating one and cooling the other. Heat exchangers are divided into three basic groups: *direct contact exchangers, recuperators* and *regenerators.* Recuperating (through-flow) heater exchangers are surely used in industrial practice. Their principle consists in following: the hot and cold fluids are separated by a wall and heat is transferred by conduction through the wall. This class includes double pipe (hairpin), shell and tube, and compact (plate and frame, etc.) exchangers. Heat exchangers are typical systems with time-delay (dead-time) and therefore their good function is dependent on the design and implementation of the optimal control system.

The problem of control time-delay processes can be solved by several control methods (e.g. using PID controllers, time-delay compensators, model predictive control techniques). In practice the implementation of the time-delay controllers on analog equipment was difficult. In spite of the fact that all these algorithms are implemented in digital platforms, most of the works analyze only the continuous case (see e.g. [1 - 6]).

When a high performance of the control process is desired or the relative time-delay is very large, a usage of the predictive control strategy is one of possible approaches to control processes with reaching of the good control quality. The predictive control strategy includes a model of the process in the structure of the controller. The first time-delay compensation algorithm was proposed by Smith in 1957 [7]. This control algorithm known as the Smith Predictor (SP) contained a dynamic model of the time-delay process and it can be considered as the first model predictive algorithm. First versions of Smith Predictors were designed in the continuous-time modifications. Because most of modern controllers are implemented on digital platforms, the discrete versions of the time-delay controllers are more suitable for time-delay compensation in industrial practice. Most authors designed the digital time-delay compensators with fixed parameters [8-10]. However, the time-delay compensators are more sensitive to process parameter variations and therefore require an auto-tuning or adaptive (self-tuning) approach in many practical applications. Two adaptive modifications of the digital Smith Predictors are designed in [11, 12] and implemented into MATLAB/SIMULINK Toolbox [13, 15, 16].

One of the possible approaches to control processes with time-delay is Model Predictive Control (MPC) [16-21] method. MPC is becoming increasingly occurring in industrial process control where time-delays are component parts of the system. However, an accurate appropriate model of the process is required to ensure the benefits of MPC.

The aim of the paper is design of an adaptive predictive controller for control of a laboratory heat exchanger. The second-order model with time-delay was used for the recursive identification and it was also applied in the control part of the GPC (Generalized Predictive Control) algorithm [16, 17].

The paper is organized in the following way. The experimental laboratory heat equipment containing the heat exchanger is described in Section 2. The basic principle of MPC is presented in Section 3. Problems of implementation of GPC method is described in Section 4. The computation of the predictor for time-delay systems is derived in Section 5. The experimental identification of the laboratory heat exchanger is introduced in Section 6. The implementation of the predictive control algorithm for a control of the laboratory heat exchanger in real-time conditions is demonstrated in Section 7. Section 8 concludes the paper.

2 Experimental Laboratory Heat Equipment

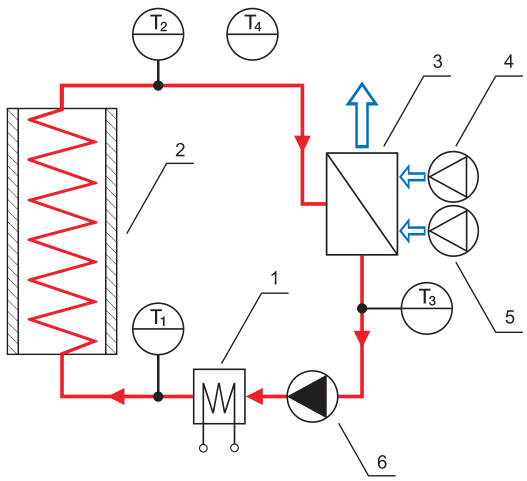

Fig. 1.Scheme of laboratory heat equipment

A scheme of the laboratory heat equipment [22] is depicted in Fig. 1. The heat transferring fluid (e.g. water) is transported using a continuously controllable DC pump (6) into a flow heater (1) with max. power of 750 W. The temperature of a fluid at the heater output T_1 is measured by a platinum thermometer. Warmed liquid then goes through a 15 meters long insulated coiled pipeline (2) which causes the significant delay (20 – 200 s) in the system. The air-water heat exchanger (3) with two cooling fans (4, 5) represents a heat-consuming appliance. The speed of the first fan can be continuously adjusted, whereas the second one is of on/off type. Input and output temperatures of the cooler are measured again by platinum thermometers as T_2, respective T_3. The platinum thermometer T_4 is dedicated for measurement of the outdoor-air temperature. The laboratory heat equipment is connected to a standard PC via technological multifunction I/O card MF 624. This card is designed for the need of connecting PC compatible computers to real world signals. The card is designed for standard data acquisition, control applications and optimized for use with Real Time Toolbox for SIMULINK. The MATLAB/SIMULINK environment was used for all monitoring and control functions.

3 Principle of MPC

Model Predictive Control attracts considerable research attention because of its unparalleled advantages. These include:

- Applicability to a broad class of systems and industrial applications.
- Computational feasibility.
- Systematic approach to obtain a closed-loop control and guaranteed stability.
- Ability to handle hard constraints on the control as well as the system states.
- Good tracking performance.
- Robustness with respect to system modeling uncertainty as well as external disturbances.

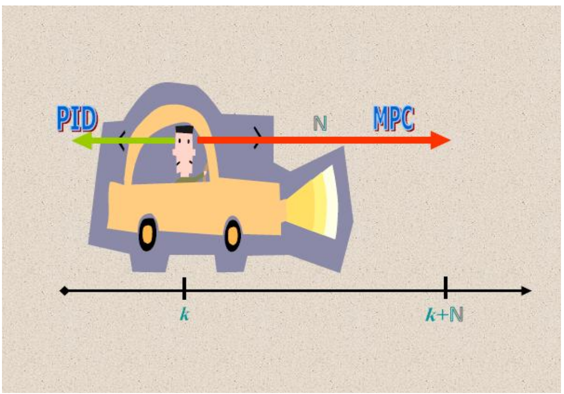

Fig. 2. Difference between the MPC and PID control

The MPC strategy performs the optimization of a performance index with respect to some future control sequence, using predictions of the output signal based on a process model, coping with amplitude constraints on inputs, outputs and states.

For a quick comparison of MPC and traditional control scheme, such as PID control, Fig. 2 shows the difference between the MPC and PID control schemes in which "anticipating the future" is desirable while a PID controller only has capacity of reacting to the past behaviours. The MPC algorithm is very similar to the control strategy used in driving a car [23].

At current time k, the driver knows the desired reference trajectory for a finite control horizon, say (k, k + N), and the taking into account the car characteristics to decide which control actions (accelerator, brakes, and steering) to take in order to follow the desired trajectory. Only the first control action is adopted as the current control law, and the procedure is then repeated over the next time horizon, say (k + 1, k + 1+ N). The term "*receding horizon*" is introduced, since the horizon recedes as time proceeds.

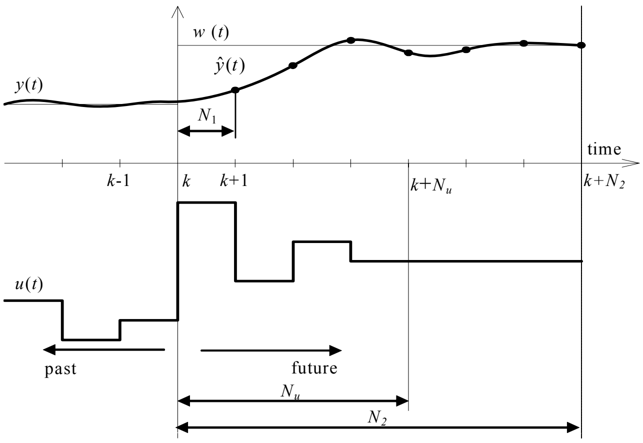

Fig. 3. Principle of MPC

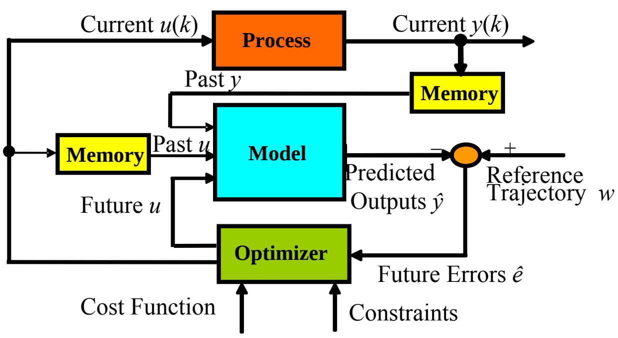

Fig. 4. Block diagram of MPC

4 MPC Based on Minimization of Quadratic Criterion

The designed control algorithm is based on the GPC method. The standard cost function used in GPC contains quadratic terms of control error and control increments on a finite horizon into the future [20, 21]

$$J=\sum_{i=N_1}^{N_2}\left[\hat{y}(k+i)-w(k+i)\right]^2+\sum_{i=1}^{N_u}\left[\lambda(i)\Delta u(k+i-1)\right]^2 \tag{1}$$

where $\hat{y}(k+i)$ is the process output of i steps in the future predicted on the base of information available upon the time k, $w(k+i)$ is the sequence of the reference signal and $\Delta u(k+i-1)$ is the sequence of the future increments of the manipulated variable that have to be calculated. Parameters N_1, N_2 and N_u are called minimum, maximum and control horizon. The parameter $\lambda(i)$ is a sequence which affects future behaviour of the controlled process. The output of the model (predictor) is computed as the sum of the free response $\boldsymbol{y}_0$ and forced response $\boldsymbol{y}_n$

$$\hat{\boldsymbol{y}}=\boldsymbol{y}_0+\boldsymbol{y}_n \tag{2}$$

The free response is that part of the prediction, which is determined by past values of the manipulated variable and past values of the systems output. The forced response is determined by future increments of the manipulated variable and is computed as the multiplication of the matrix $\boldsymbol{G}$ (Jacobian Matrix of the model) and the vector of future control increments $\Delta\boldsymbol{u}$, which is generally a priori unknown

$$\boldsymbol{y}_n=\boldsymbol{G}\Delta\boldsymbol{u} \tag{3}$$

where

$$\boldsymbol{G}=\begin{bmatrix} g_1 & 0 & 0 & \cdots & 0 \\ g_2 & g_1 & 0 & \cdots & 0 \\ g_3 & g_2 & g_1 & \cdots & 0 \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ g_{N_2} & g_{N_2-1} & g_{N_2-2} & \cdots & g_{N_2-N_u+1} \end{bmatrix} \tag{4}$$

is matrix containing values of the step sequence.

It follows from (2) and (3) that the predictor in a vector form is given by

$$\hat{\boldsymbol{y}}=\boldsymbol{G}\Delta\boldsymbol{u}+\boldsymbol{y}_0 \tag{5}$$

The cost function (1) can be modified to the form

$$\begin{aligned} J&=(\hat{\boldsymbol{y}}-\boldsymbol{w})^T(\hat{\boldsymbol{y}}-\boldsymbol{w})+\lambda\Delta\boldsymbol{u}^T\Delta\boldsymbol{u}= \\ &=(\boldsymbol{G}\Delta\boldsymbol{u}+\boldsymbol{y}_0-\boldsymbol{w})^T(\boldsymbol{G}\Delta\boldsymbol{u}+\boldsymbol{y}_0-\boldsymbol{w})+\lambda\Delta\boldsymbol{u}^T\Delta\boldsymbol{u} \end{aligned} \tag{6}$$

Minimisation of the cost function (6) now becomes a direct problem of linear algebra. The solution in an unconstrained case can be found by setting partial derivative of J with respect to $\Delta\boldsymbol{u}$ as zero and yields

$$\Delta\boldsymbol{u} = \left(\boldsymbol{G}^T\boldsymbol{G} + \lambda\boldsymbol{I}\right)^{-1}\boldsymbol{G}^T\left(\boldsymbol{w} - \boldsymbol{y}_0\right) \tag{7}$$

Equation (7) gives the whole trajectory of the future increments of the manipulated variable and such is an open-loop strategy. To close the loop, only the first element is applied to the system and the whole algorithm is recomputed at time k+1. If we denote the first row of the matrix $\left(\boldsymbol{G}^T\boldsymbol{G} + \lambda\boldsymbol{I}\right)^{-1}\boldsymbol{G}^T$ as $\boldsymbol{K}$ then the actual increment of the manipulated variable can be calculated as

$$\Delta u(k) = \boldsymbol{K}\left(\boldsymbol{w} - \boldsymbol{y}_0\right) \tag{8}$$

5 Computation of Predictor

An important task is computation of predictions for arbitrary prediction and control horizons. Dynamics of most of processes requires horizons of length where it is not possible to compute predictions in a simple straightforward way. Recursive expressions for computation of the free response and the matrix $\boldsymbol{G}$ in each sampling period had to be derived. There are several different ways of deriving the prediction equations for transfer function models. Some papers make use of Diophantine equations to form the prediction equations [20]. In [19] matrix methods are used to compute predictions. We derived a method for recursive computation of both the free response and the matrix of the dynamics [24].

Computation of the predictor for the time-delay system can be obtained by modification of the predictor for the corresponding system without a time-delay. At first we will consider the second order system without time-delay and then we will modify the computation of predictions for the time-delay system.

5.1 Second Order System without Time-Delay

The deterministic model is described by the discrete transfer function

$$G\left(z^{-1}\right) = \frac{B\left(z^{-1}\right)}{A\left(z^{-1}\right)} = \frac{b_1 z^{-1} + b_2 z^{-2}}{1 + a_1 z^{-1} + a_2 z^{-2}} \tag{9}$$

Model (10) can be also written in the form

$$A\left(z^{-1}\right)y(k) = B\left(z^{-1}\right)u(k) \tag{10}$$

A widely used model in GPC is the CARIMA model which can be obtained from the nominal model (11) by adding a disturbance model

$$A\left(z^{-1}\right)y(k) = B\left(z^{-1}\right)u(k) + \frac{C\left(z^{-1}\right)}{\Delta}n_c(k) \tag{11}$$

where $n_c(k)$ is a non-measurable random disturbance that is assumed to have zero mean value, constant covariance and $\Delta = 1 - z^{-1}$. Inverted Δ is then an integrator. The difference equation of the second order CARIMA model without the unknown term $n_c(k)$ can be expressed as

$$\begin{aligned} y(k) &= (1-a_1)y(k-1) + (a_1 - a_2)y(k-2) \\ &\quad + a_2 y(k-3) + b_1\Delta u(k-1) + b_2\Delta u(k-2) \end{aligned} \tag{12}$$

It was necessary to compute three step-ahead predictions in straightforward way by establishing of lower predictions to higher predictions. The model order defines that computation of one step-ahead prediction is based on three past values of the system output. The three step-ahead predictions are in detail derived in [25] and their matrix equation is

$$\begin{aligned}
\begin{bmatrix} \hat{y}(k+1) \\ \hat{y}(k+2) \\ \hat{y}(k+3) \end{bmatrix} &= \begin{bmatrix} g_1 & 0 \\ g_2 & g_1 \\ g_3 & g_2 \end{bmatrix}\begin{bmatrix} \Delta u(k) \\ \Delta u(k+1) \end{bmatrix} + \begin{bmatrix} p_{11} & p_{12} & p_{13} & p_{14} \\ p_{21} & p_{22} & p_{23} & p_{24} \\ p_{31} & p_{32} & p_{33} & p_{34} \end{bmatrix}\begin{bmatrix} y(k) \\ y(k-1) \\ y(k-2) \\ \Delta u(k-1) \end{bmatrix} \\
&= \begin{bmatrix} b_1 & 0 \\ b_1(1-a_1)+b_2 & b_1 \\ (a_1-a_2)b_1+(1-a_1)^2 b_1+(1-a_1)b_2 & b_1(1-a_1)+b_2 \end{bmatrix}\begin{bmatrix} \Delta u(k) \\ \Delta u(k+1) \end{bmatrix} \\
&+ \begin{bmatrix} (1-a_1) & (a_1-a_2) & a_2 & b_2 \\ (1-a_1)^2+(a_1-a_2) & (1-a_1)(a_1-a_2)+a_2 & a_2(1-a_1) & b_2(1-a_1) \\ (1-a_1)^3+2(1-a_1)(a_1-a_2)+a_2 & (1-a_1)^2(a_1-a_2)+a_2(1-a_1)+(a_1-a_2)^2 & a_2(1-a_1)^2+(a_1-a_2)a_2 & b_2(1-a_1)^2+(a_1-a_2)b_2 \end{bmatrix}\begin{bmatrix} y(k) \\ y(k-1) \\ y(k-2) \\ \Delta u(k-1) \end{bmatrix}
\end{aligned} \tag{13}$$

It is possible to divide computation of the predictions to recursion of the free response and recursion of the matrix of the dynamics. Based on the three previous predictions it is repeatedly computed the next row of the free response matrix in the following way:

$$\begin{aligned} p_{41} &= (1-a_1)p_{31} + (a_1 - a_2)p_{21} + a_2 p_{11} \\ p_{42} &= (1-a_1)p_{32} + (a_1 - a_2)p_{22} + a_2 p_{12} \\ p_{43} &= (1-a_1)p_{33} + (a_1 - a_2)p_{23} + a_2 p_{13} \\ p_{44} &= (1-a_1)p_{34} + (a_1 - a_2)p_{24} + a_2 p_{14} \end{aligned} \tag{14}$$

The first row of the matrix is omitted in the next step and further prediction is computed based on the three last rows including the one computed in the previous step. This procedure is cyclically repeated. It is possible to compute an arbitrary number of rows of the matrix.

The recursion of the dynamics matrix is similar. The next element of the first column is repeatedly computed in the same way as in the previous case and the remaining columns are shifted to form a lower triangular matrix in the way which is obvious from the equation (14). This procedure is performed repeatedly until the prediction horizon is achieved. If the control horizon is lower than the prediction horizon a number of columns in the matrix is reduced. Computation of the new element is performed as follows:

$$g_4 = (1 - a_1) g_3 + (a_1 - a_2) g_2 + a_2 g_1 \qquad (15)$$

5.2 Second Order System with Time- Delay

The nominal second order model with d steps of time-delay is considered as

$$G(z^{-1}) = \frac{B(z^{-1})}{A(z^{-1})} z^{-d} = \frac{b_1 z^{-1} + b_2 z^{-2}}{1 + a_1 z^{-1} + a_2 z^{-2}} z^{-d} \qquad (16)$$

where d is a number of time-delay steps.

The CARIMA model for time-delay system without the unknown term $n_c(k)$ takes the form

$$\Delta A(z^{-1}) y(k) = z^{-d} B(z^{-1}) \Delta u(k) \qquad (17)$$

In order to compute the control action it is necessary to determine the predictions from d+1 to d+N_2. The predictor (13) is then modified for an arbitrary number of time delay steps to

$$\begin{bmatrix} \hat{y}(k+3) \\ \hat{y}(k+4) \\ \hat{y}(k+5) \end{bmatrix} = \begin{bmatrix} p_{(1+d)1} & p_{(1+d)2} & p_{(1+d)3} \\ p_{(2+d)1} & p_{(2+d)2} & p_{(2+d)3} \\ p_{(3+d)1} & p_{(3+d)2} & p_{(3+d)3} \end{bmatrix} \begin{bmatrix} y(k) \\ y(k-1) \\ y(k-2) \end{bmatrix} + \begin{bmatrix} g_1 & 0 \\ g_2 & g_1 \\ g_3 & g_2 \end{bmatrix} \begin{bmatrix} \Delta u(k) \\ \Delta u(k+1) \end{bmatrix} + \begin{bmatrix} g_{1+d-1} & g_{2+d-1} & p_{(1+d)4} \\ g_{2+d-1} & g_{3+d-1} & p_{(2+d)4} \\ g_{3+d-1} & g_{4+d-1} & p_{(3+d)4} \end{bmatrix} \begin{bmatrix} \Delta u(k-1) \\ \Delta u(k-2) \\ \Delta u(k-3) \end{bmatrix} \qquad (18)$$

Recursive computation of the matrices is analogical to the recursive computation described for the second order system without time-delay [26].

6 Identification of Heat Exchanger

The heat exchanger has been identified using off-line methods (for simulation verification of the GPC algorithms and determination of the initial model parameter estimates) and recursive (on-line) method which was used in the adaptive GPC. Static and dynamic models of the laboratory heat exchanger were obtained from input (the power of a flow heater P [W]) and output (the temperature T_2 [^{o}C] of the cooler) data of the process (see Fig. 1).

6.1 Off-Line Process Identification

The number of time delay steps d is either approximately known on the basis of *a priori* information or it can be obtained by an off-line identification using the least squares method (LSM) [27]

$$\hat{\boldsymbol{\Theta}} = \left(\boldsymbol{F}^{\boldsymbol{T}} \boldsymbol{F}\right)^{-1} \boldsymbol{F}^{\boldsymbol{T}} \boldsymbol{y} \qquad (19)$$

where

$$\hat{\boldsymbol{\Theta}}^T = \begin{bmatrix} \hat{a}_1 & \hat{a}_2 & \cdots & \hat{a}_n & \hat{b}_1 & \hat{b}_2 & \cdots & \hat{b}_n \end{bmatrix} \qquad (20)$$

is the vector of parameter model estimates of dimension (2n),

$$\boldsymbol{F} = \begin{bmatrix} -y(n+d) & -y(n+d-1) & \cdots & -y(d+1) \\ -y(n+d+1) & -y(n+d) & \cdots & -y(d+2) \\ \vdots & \vdots & \cdots & \vdots \\ -y(N-1) & -y(N-2) & \cdots & -y(N-n) \\ u(n) & u(n-1) & \cdots & u(1) \\ u(n+1) & u(n) & \cdots & u(2) \\ \vdots & \vdots & \cdots & \vdots \\ u(N-d-1) & u(N-d-2) & \cdots & u(N-d-n) \end{bmatrix} \qquad (21)$$

is the data matrix of dimension (N-n-d, 2n) and

$$\boldsymbol{y}^T = \begin{bmatrix} y(n+d+1) & y(n+d+2) & \cdots & y(N) \end{bmatrix} \qquad (22)$$

is the output vector of dimension (N-n-d).). N is the number of samples of measured input and output data, n is the model order [12].

Consider that model (16) is the deterministic part of the stochastic process described by the ARX (regression) model

$$y(k) = -a_1 y(k-1) - a_2 y(k-2) + \\ + b_1 y(k-1-d) + b_2 y(k-2-d) + n_c(k) \quad (23)$$

where $n_c(k)$ is the random non-measurable component. The vector of parameter model estimates is computed by solving equation (19)

$$\hat{\boldsymbol{\Theta}}^T(k) = \begin{bmatrix} \hat{a}_1 & \hat{a}_2 & \hat{b}_1 & \hat{b}_2 \end{bmatrix} \quad (24)$$

and is used for computation of the prediction output

$$\hat{y}(k) = -\hat{a}_1 y(k-1) - \hat{a}_2 y(k-2) + \\ \hat{b}_1 u(k-1-d) + \hat{b}_2 u(k-2-d) \quad (25)$$

The quality of identification can be considered according to error, i.e. the deviation

$$\hat{e}(k) = y(k) - \hat{y}(k) \quad (26)$$

In this paper, the error was used for suitable choice of the time-delay dT_0. The LSM algorithm (19) – (22) is computed for several time-delays dT_0 and the suitable time-delay is chosen according to quality of identification based on the prediction error (26).

Except LSM the MATLAB function from the Optimization Toolbox

$$x = \text{fminsearch}('name\_fce', x_0) \quad (27)$$

was also used for the off-line process identification. This function find minimum of an unconstrained multivariable function using derivative-free method. Algorithm “fminsearch” uses the simplex search method of [28]. This is a direct search method that does not use numerical or analytic gradients.

It is obvious that the quality of time-delay systems identification is very dependent on the choice of a suitable input exciting signal $u(k)$. Therefore the MATLAB function from the System Identification Toolbox

$$u = \text{idinput}(N, type, band, levels) \quad (28)$$

was used [29]. This MATLAB code generates input signals u of different kinds, which are typically used for identification purposes. N determines the number of generated input data. *Type* defines the type of input signal to be generated. This argument takes one of the following values:

type = 'rgs': Gives a random, Gaussian signal.
type = 'rbs': Gives a random, binary signal. This is the default.
type = 'prbs': Gives a pseudorandom, binary signal.
type = 'sine': Gives a signal that is a sum of sinusoids.

6.2 Recursive Identification Algorithm

The regression (ARX) model of the following form

$$y(k) = \boldsymbol{\Theta}^T(k)\boldsymbol{\Phi}(k) + n_c(k) \quad (29)$$

is used in the identification part of the designed controller algorithms, where

$$\boldsymbol{\Theta}^T(k) = \begin{bmatrix} a_1 & a_2 & b_1 & b_2 \end{bmatrix} \quad (30)$$

is the vector of model parameters and

$$\boldsymbol{\Phi}^T(k-1) = \begin{bmatrix} -y(k-1) & -y(k-2) & u(k-d-1) & u(k-d-2) \end{bmatrix} \quad (31)$$

is the regression vector. The non-measurable random component $n_c(k)$ is assumed to have zero mean value $E[n_c(k)] = 0$ and constant covariance (dispersion) $R = E[n_c^2(k)]$.

The digital adaptive GPC controller uses the algorithm of identification based on the Recursive Least Squares Method (RLSM) extended to include the technique of directional (adaptive) forgetting. Numerical stability is improved by means of the LD decomposition [30], [31]. This method is based on the idea of changing the influence of input-output data pairs to the current estimates. The weights are assigned according to amount of information carried by the data.

When using the adaptive principle, the model parameter estimates must approach the true values right from the start of the control. This means that as the self-tuning algorithm begins to operate, identification must be run from suitable conditions – the result of the possible *a priori* information. The role of suitable initial conditions in recursive identification is often underestimated.

6.3 Off-Line Identification of Laboratory Heat-Exchanger

The dynamic off-line model of the laboratory heat exchanger was obtained from processed input (the power of a flow heater P [W]) and output (the temperature of a T_2 [^{o}C] of the cooler) data (see Fig. 1). The input signal $u(k)$ was generated using the MATLAB function “idinput” and discrete parameter estimates of model (25) for sampling period T_0 = 100 s and time-delay T_d = 200 s were computed using off-line LSM and MATLAB function “fminsearch”.

The graphical variable courses of individual identification experiments are shown in Figs. 5 – 7.

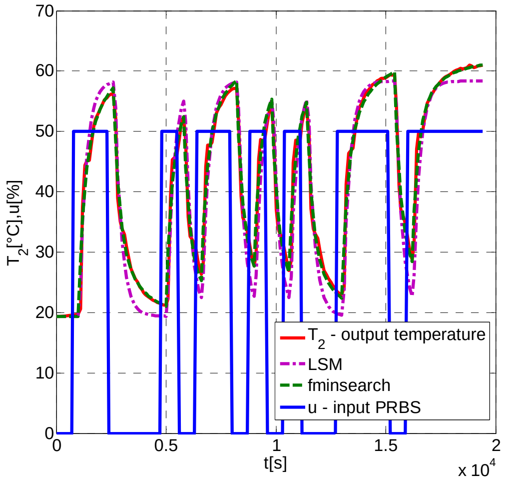

Fig. 5. Identification results: input PRBS

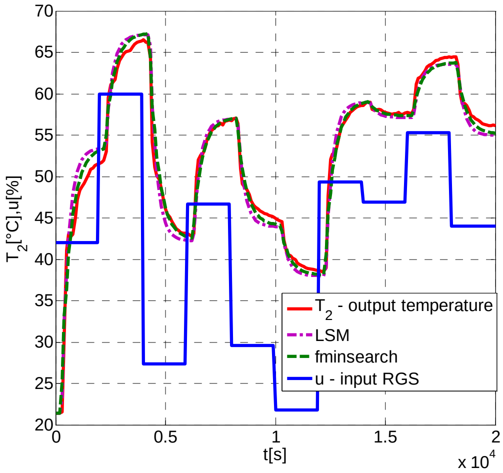

Fig. 6. Identification results: input RGS

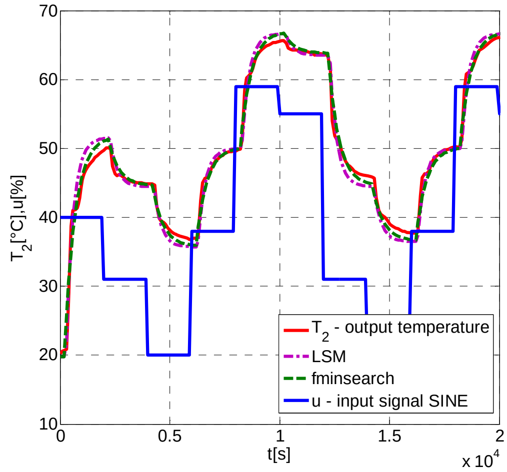

Fig. 7. Identification results: input SINE

Six discrete models which were obtained from individual experiments and criterions of identification quality are presented in [32]. The real output variable T_2 and the modelled output variables of the individual models were compared using criterion of identification quality

$$S_y = \frac{1}{N}\sum_{k=1}^{N}\left[y(k) - \hat{y}(k)\right]^2 \tag{32}$$

where $\hat{y}(k)$ is the predicted output and the estimate of static gain is

$$\hat{K}_g = \frac{\hat{b}_1 + \hat{b}_2}{1 + \hat{a}_1 + \hat{a}_2} \tag{33}$$

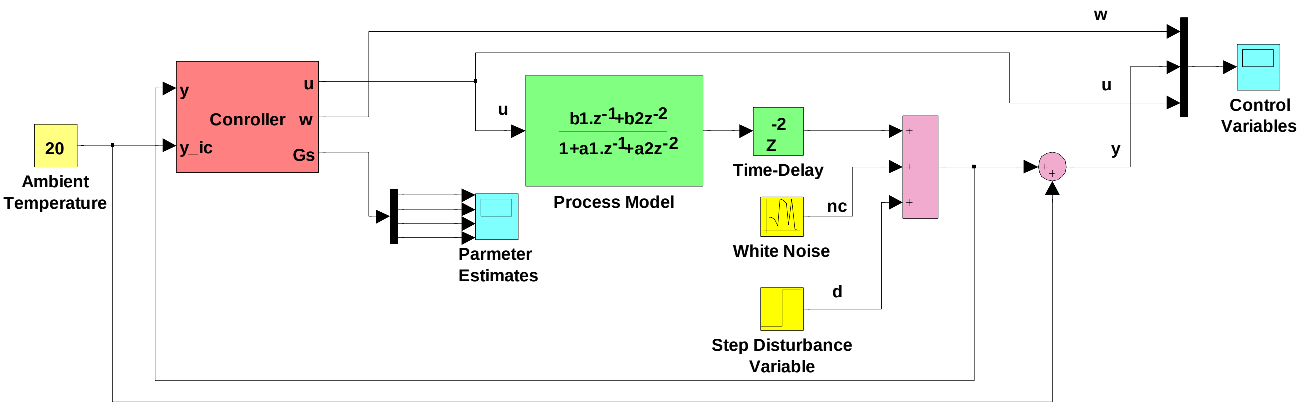

Fig. 8. General SIMULINK control scheme

7 Predictive Control of Heat Exchanger

On the basis of identification experiments, the discrete model in the form

$$G\left(z^{-1}\right) = \frac{0.1088z^{-1} + 0.1964z^{-2}}{1 - 0.0855z^{-1} - 0.5157z^{-2}} z^{-2} \tag{34}$$

was used for simulation verification of the designed predictive algorithm. A typical

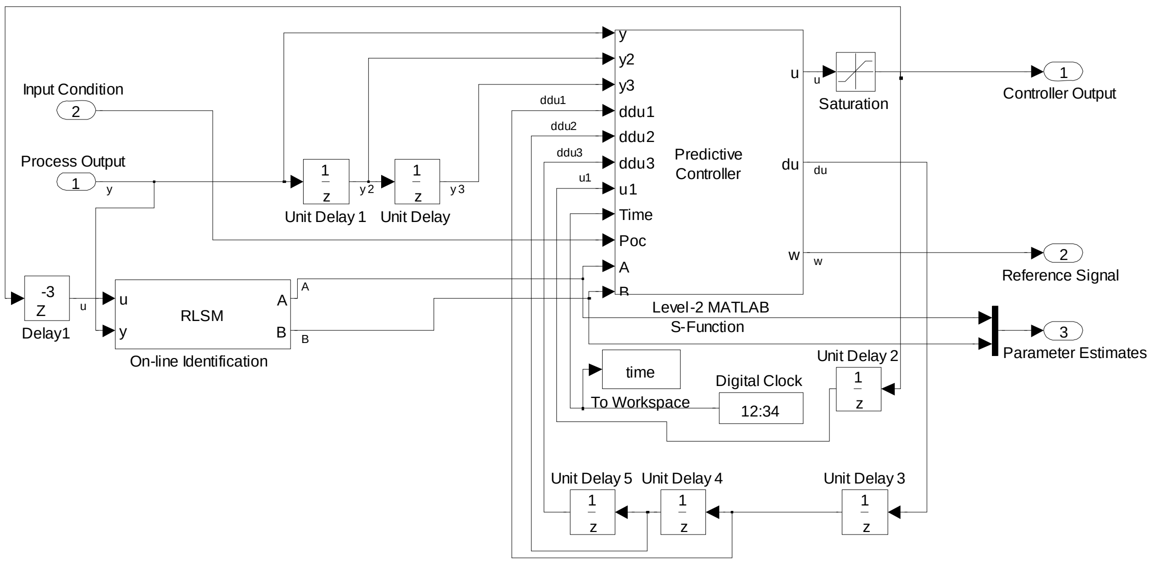

Fig. 9. SIMULINK scheme of subsystem Predictive Controller

SIMULINK scheme used for predictive control of second order systems with time-delay of two sample steps is depicted in Fig. 8. The general scheme consists of the constant block for setting of the Ambient Temperature, the Controller and Process Model with the Time-delay block. The SIMULINK scheme is completed by the White Noise Generator and the Step Disturbance. The main block Predictive Controller contains generating of the reference signal, the recursive identification part and own predictive controller (see SIMULINK scheme – Fig. 9). Following individual horizons were used:

$$N_1 = d + 1 = 3,\ N_2 = 30,\ N_u = N_2 - d = 28\,.$$

Two real-time control experiments for different values of the weighting factor λ were realized:

1) The model parameters of (32)

$$\hat{\boldsymbol{\Theta}}^T(0) = \begin{bmatrix} -0.0855 & -0.5157 & 0.1088 & 0.1964 \end{bmatrix}$$

were used as the initial model parameter estimates for the real-time control, it comes to this, that *a priori* information was used. Therefore elements of the main diagonal covariance matrix were chosen $C_{ii}(0) = 10^{-3}$ (an assumption, that the dispersions of the parameter estimates are in a narrow interval). The courses of the control variables are well including of the initial control interval – see Fig. 10. The evolution of the model parameter estimates in the individual sampling steps is shown in Fig. 11.

2) The model parameter estimates were chosen without *a priori* information

$$\hat{\boldsymbol{\Theta}}^T(0) = \begin{bmatrix} -0.0855 & 0.5157 & 0.1088 & 0.1964 \end{bmatrix}$$

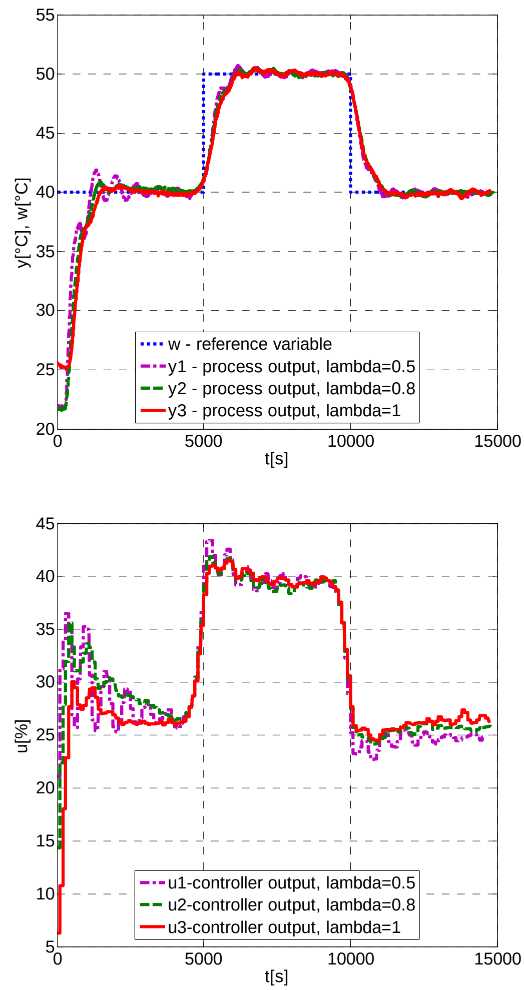

Fig. 10. Process control with *a priori* information

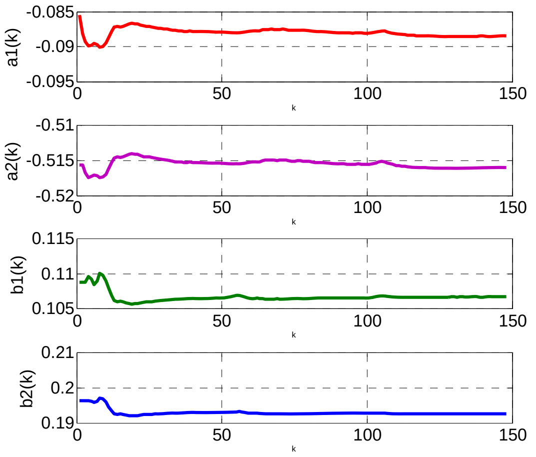

Fig. 11. Evolution of model parameter estimates, $C_{ii}(0) = 10^{-3}$

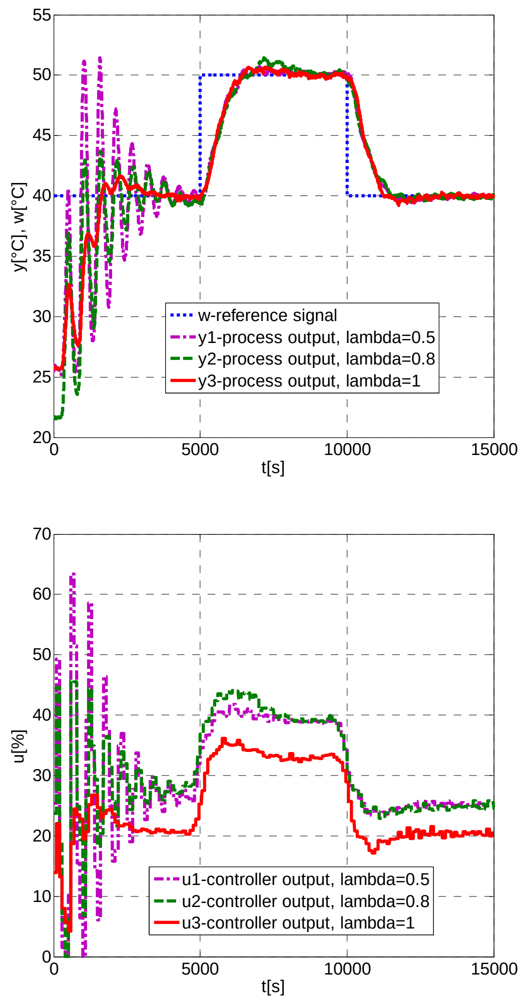

Fig. 12. Process control without *a priori* information

(by parameter estimate $\hat{a}_2$ was changed polarity). Therefore elements of the main diagonal covariance matrix were chosen $C_{ii}(0) = 10^3$ (an assumption, that the dispersions of the parameter estimates are in a wide interval). The courses of the control variables oscillate in the initial control interval, when the model parameter estimates are converged, the quality of the control process is very good – see Fig. 12. The evolution of the model parameter estimates in the individual sampling steps is shown in Fig. 13.

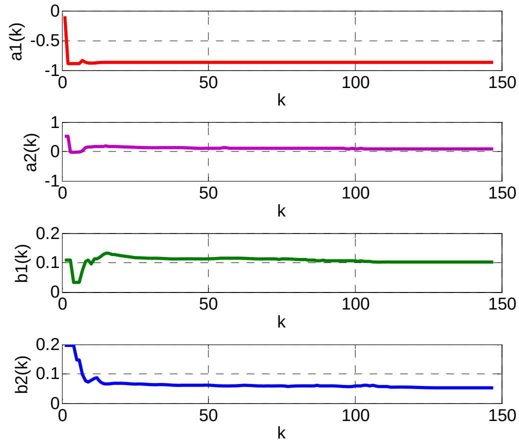

Fig. 13. Evolution of model parameter estimates, $C_{ii}(0) = 10^3$

The dependence of the process variables (process and controller outputs) on the weighting factor λ is obvious from Figs. 10 and 12. The experimental control results were influenced by variation of the outdoor temperature (see e.g. the courses of the control variables for $\lambda = 1$ in Fig. 12, where the experiment was realized for low outdoor temperature).

Some journal or conference papers deal with MPC of heat exchangers. Robust MPC of a heat exchanger network is designed and verified by simulation in [33]. The subject of paper [34] is a design of the MPC for a shell and tube heat exchanger. The designed MPC algorithm and its comparison with PID cotroller were realized only in simulation conditions. A cascade GPC for a heat exchanger process is proposed in [35]. The result of this paper is the simulation study of the effect of the cascaded GPC and basic GPC control algorithms on a model of heat exchangers. Adaptive GPC of a heat exchanger pilot plant is designed in [36]. The performance of the proposed controller is illustrated by a simulation example of a heat exchanger pilot plant.

From the above-mentioned citations it is obvious that most authors deal only with verification of the designed MPC algorithms by simulation and no by real-time control of real heat exchangers. It is also necessary to consider different structures of the individual equipments. Therefore a comparison of real-time control-loops is very problematic.

7 Conclusion

The contribution presents the adaptive predictive control applied to the time-delay process – the laboratory heat exchanger. The predictive controller is based on the recursive computation of predictions by direct use of the CARIMA model. The computation of predictions was extended for time-delay systems. A linear model with constant coefficients used in pure model predictive control can not describe the control system in all its modes. Therefore, an adaptive approach was applied. It consists of the recursive identification and the predictive controller. The model parameter estimates obtained from the identification procedure are used in the adaptive predictive controller. The GPC based on a minimisation of the quadratic criterion was derived and tested. For obtaining of a suitable model for simulation verification were used the experimental data measured on the laboratory heat exchanger system. This laboratory equipment was identified by combination of various input signals. Two off-line identification methods were used. The parameter estimates of one suitable discrete model from the point of view of quality identification were used in the initial part of the real-time control (the use *a priori* information). The designed adaptive GPC method was verified also in the case without *a priori* information. The real-time experiments confirmed that the predictive approach is able to cope with the given control problem. The real-time experiments demonstrated that the outdoor temperature has great influence up to dynamical behaviour of the laboratory heat exchanger. The following research will be directed to the extension of the designed predictive algorithm over the measurable disturbance.

Conclusion Remark:

This paper was included in the Special Issue on Multi-Models for Complex Technological Systems [37]. The Special Issues of the WSEAS Transactions on Systems [37] – [51] are very useful means for publication of monotematically focused contributions into an above mentioned journal. The Special Issues enable faster and easier access of interested academics and researches for the acquisition of partial necessary information in their research area.

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