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ADAPTIVE PREDICTIVE CONTROL OF OIL PRESSURE

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ABSTRACT
The paper deals with a control of oil pressure in a car tube test room during material endurance testing. Car tube test room is equipment designed for mechanical and pressure testing of car tubes for cooling water circuit. In the test room there it is simulated an engine compartment. In the primary circuit the oil circulates by tube specimen in agreement with given pressure characteristic, liquid and ambient temperature. The aim of control was pressure control in primary pressure circuit of the equipment. The controlled process is described as the second order system. The self – tuning control approach is applied for control of this nonlinear process. The used controller is based on predictive control. The test room is controlled by multifunctional I/O card NI PCI-6221which is placed in real-time PC target. Process visualization is established by remote desktop PC. Control and visualization are assured by LabView.
Keywords: predictive control, oil pressure, recursive identification, LabView

1. INTRODUCTION
The car tube test room is equipment designed for mechanical and pressure testing of car tubes for cooling water circuits. It is required so that oil pressure in tested tubes tracks sinusoidal and ramp reference signals for a long time during executed tests. Detailed description of this apparatus is in [1]. It is a nonlinear stochastic process with variable parameters. A suitable approach to the control of nonlinear processes is application of self – tuning controllers [2].
The nonlinear dynamics is described by a linear model in the neighbourhood of a steady state. A suitable model of the real object for control with self – tuning controllers is an input – output model. This is a standard approach in self tuning controller area. Instead of often tedious construction of a model from the first principles and then calculating its parameters from plant dimensions and physical constants, general type of model is chosen and its parameters are identified from data. Advantages of this kind of model are its simplicity and accuracy in an operational range in which the input – output dependence is measured.
In this paper, a self – tuning controller based on model predictive control (MPC) approach [8] was applied to control the process. In the identification part of the self – tuning controller the recursive least squares method [5] supported by adaptive directional forgetting [7], [6] was applied. Control is performed by means of LabView 8.2.

2. DESCRIPTION OF THE TEST ROOM
The test room consists of an isolated test chamber, vibration unit which generates signals with specified amplitudes and frequencies, hydraulic system, heating circuit with liquid circulation which simulates cooling mixture, a heating circuit which heats air inside the chamber and a control panel. The heating circuit and the vibration unit are controlled by PLC. The test room is depicted in Figure 1. The test chamber with a tube sample is shown in Figure 2.

Figure 1. The test room

Figure 2. Test chamber and tube samples

Second ends of tube samples are mounted to a supporting grid of chamber and are connected to steel tubes which transfer liquid to an output cube. Secondary circuit is parallel connected to a closed circuit of liquid. The hydraulic system provides required pressure in tubes. The hydraulic system consists of primary and secondary circuits. A source of pressure is a hydraulic unit. The primary circuit consists of a proportional valve, main and auxiliary hydraulic cylinder. The pressure is set up by main hydraulic cylinder (piston) which compresses the liquid. Position of the piston and consequently value of the pressure are set up by the auxiliary cylinder (piston). The aim of control is manipulating of this auxiliary piston by speed of inflow and outflow of oil in the cylinder. This is performed by a proportional valve Rexroth 4WRA6 which is controlled by current signal.
It is not possible to measure static characteristics of the process because the pressure in the primary circuit always stabilizes on the same value. We control speed of inflow and outflow of oil, the piston is always stopped at the end position or at the time when the pressure of the oil is not able to overcome forces of the main piston.
The process is nonlinear and sample properties and oil temperature vary in time during a test. These facts justify application of a self – tuning predictive controller.
The test room is controlled by real-time target PC with multifunctional DAQ card NI PCI-6221. Visualization is assured by desktop PC which is connected to real-time target by ethernet. Visualization and control of the test room are performed by graphic object-oriented system LabView 8.2.

3. MODEL PREDICTIVE CONTROLLER

The basic idea of MPC is to use a model of a controlled process to predict *N* future outputs of the process. A trajectory of future manipulated variables is given by solving an optimization problem incorporating a suitable cost function and constraints. Only the first element of the obtained control sequence is applied. The whole procedure is repeated in following sampling period. This principle is known as the receding horizon strategy.
In our case of the SISO system, the model predictive controller is based on the model of the controlled process given by

$$\Delta \boldsymbol{A} \boldsymbol{Y}(z) = \boldsymbol{B} \Delta \boldsymbol{U}(z) \qquad \ldots(1)$$

where Δ is an integrator which ensures integrating properties of the controller, and A,B are polynomials in form

$$A(z^{-1}) = 1 + a_1 z^{-1} + a_2 z^{-2} \;,\; B(z^{-1}) = b_1 z^{-1} + b_2 z^{-2} \qquad \ldots(2)$$

The computation of a control law of MPC is based on minimization of the following criterion

$$J(k) = \sum_{j=1}^{N} \boldsymbol{e}(k+j)^2 + \lambda \sum_{j=1}^{N_u} \Delta \boldsymbol{u}(k+j)^2 \qquad \ldots(3)$$

where $\boldsymbol{e}(k+j)$ is a vector of predicted control errors, $\Delta\boldsymbol{u}(k+j)$ is a vector of future increments of manipulated variables. N is the prediction horizon, N_u is the control horizon and λ is a factor which represents ratio between weights of control errors and increments of manipulated variables. A predictor in a vector form is given by

$$\hat{\boldsymbol{y}} = \boldsymbol{G}\Delta\boldsymbol{u} + \boldsymbol{y}_0 \quad \ldots(4)$$

where $\hat{\boldsymbol{y}}$ is a vector of system predictions along the horizon N, $\Delta\boldsymbol{u}$ is a vector of control increments, $\boldsymbol{y}_0$ is the free response vector. $\boldsymbol{G}$ is a matrix of the dynamics given as

$$\mathbf{G} = \begin{bmatrix} g_0 & 0 & \cdots & \cdots & 0 \\ g_1 & g_0 & 0 & \cdots & 0 \\ \vdots & & \ddots & \ddots & \vdots \\ \vdots & & & g_0 & 0 \\ g_{N-1} & \cdots & \cdots & \cdots & g_0 \end{bmatrix} \quad \ldots(5)$$

Recursive expressions for computation of the free response and the matrix $\boldsymbol{G}$ in each sampling period had to be derived.

In case of the test room, actuators have a limited range of action. Current applied to the proportional valve can vary between fixed limits. MPC can consider constrained input and output signals in the process of the controller design. General formulation of predictive control with constraints is then as follows

$$\min_{\Delta\boldsymbol{u}} 2\boldsymbol{g}^T\Delta\boldsymbol{u} + \Delta\boldsymbol{u}^T\boldsymbol{H}\Delta\boldsymbol{u} \quad \ldots(6)$$

owing to

$$\boldsymbol{A}\Delta\boldsymbol{u} \le \boldsymbol{b} \quad \ldots(7)$$

Inequality (7) expresses the constraints in compact form. In our case of constrained input signals particular matrices can be expressed as

$$\boldsymbol{A} = \begin{bmatrix} \boldsymbol{T} \\ -\boldsymbol{T} \end{bmatrix} \quad \boldsymbol{b} = \begin{bmatrix} \boldsymbol{1u}_{\max} - \boldsymbol{1u}(k-1) \\ -\boldsymbol{1u}_{\min} + \boldsymbol{1u}(k-1) \end{bmatrix} \quad \ldots(8)$$

where 1 is a unit vector and T is lower triangular block matrix. The optimization problem is then solved numerically by quadratic programming in each sampling period.

4. SYSTEM IDENTIFICATION

The described controller was applied as a self - tuning controller with recursive identification of parameters of a model of the process. This approach is suitable for control of nonlinear processes and processes where parameters vary in time. The recursive least squares method proved to be effective for self – tuning controllers and was used as the basis for our algorithm.

The transfer function (1) can be transcribed into a difference equation which can be written in vector form

$$y(k) = \boldsymbol{\Theta}^T(k-1)\phi(k) + e_s(k) \quad \ldots(9)$$

$$\boldsymbol{\Theta}^T(k-1) = \left[\hat{a}_1, \hat{a}_2, \hat{b}_1, \hat{b}_2\right] \quad \ldots(10)$$

$$\phi^T(k) = [-y(k-1), -y(k-2), u(k-1), u(k-2)] \quad \ldots(11)$$

The vector $\Theta^T(k\text{-}1)$ contains the process parameter estimations computed in previous step and the vector $\Phi^T(k)$ contains output and input values for computation of current output y.

The main disadvantage of pure recursive least square method is an absence of original weighting. Each input and output affect result by the same weight, but actual process parameters can change in time. Thus newer inputs and outputs should affect output more than older values. This problem can be solved by directional forgetting method, which uses forgetting coefficient φ and decreases the weights of the data in previous steps. Parameter estimations are computed according to following equation:

$$\hat{\mathbf{\Theta}}(k) = \hat{\mathbf{\Theta}}(k-1) + \frac{\mathbf{C}(k-1)\boldsymbol{\varphi}(k-1)}{1+\xi(k-1)} \cdot \left(y_k - \Theta^T(k-1)\varphi(k)\right) \quad \ldots(12)$$

Recursive least squares method supported by the directional forgetting was applied.

5. REAL – TIME EXPERIMENTS

Speed of inflow and outflow of oil ranges from 0 to 11,4 l/min under the pressure to 10 bar in both directions. Control voltage ranges within ±10V. The pressure in the primary circuit always stabilizes on the same value. It is possible to control only speed of inflow and outflow of oil, the piston is always stopped at the end position or at the time when the pressure of the oil is not able to overcome forces of the main piston. The time response of the control when the initial parameter estimates were chosen without any prior information is shown in figures. It has to be supposed that the adaptive version would not work perfectly from very beginning. But it is possible to assume that the most important for practical use of an adaptive controller is its performance after adaptation phase. The figures shows that the time responses in the first two cycles are adapting while the time response in the third final cycle is already adapted. Time responses of this experiment are shown in Fig. 3 for the ramp shape of the reference signal and in Fig. 4 for the sinusoidal shape of the reference signal.

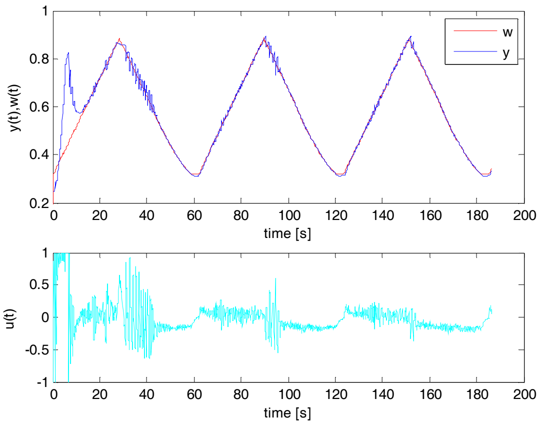

Figure 3. Adaptive predictive control of pressure (ramp shape)

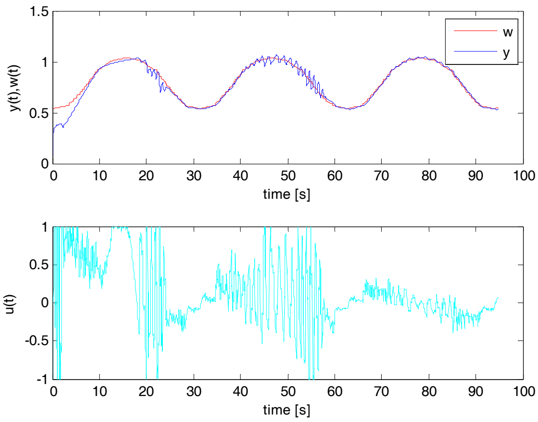

Figure 4. Adaptive predictive control of pressure (sinusoidal shape)

6. CONCLUSION

The adaptive predictive control of the test room for car tubes was realized. The tests require a long time control of pressure (one test takes 60 000 control loops, one loop takes 60 s). Typical shapes of reference signals for endurance testing are ramp and sinusoidal ones. Despite the fact, that the nonlinear dynamics of the process was described by the linear model, satisfactory results of control suitable for the endurance testing were achieved. Control application is used during car tube testing in company ITC Zlin.

7. ACKNOWLEDGMENTS

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