SOME APPROACHES TO ADAPTIVE CONTROL OF NON-LINEAR PHYSICAL LABORATORY SERVO-SYSTEM DR 300

Vladimír Bobál, Petr Chalupa, Marek Kubalčík and Petr Dostál

Department of Process Control, Faculty of Applied Informatics
Tomas Bata University in Zlin
Czech Republic
bobal@fai.utb.cz

Abstract

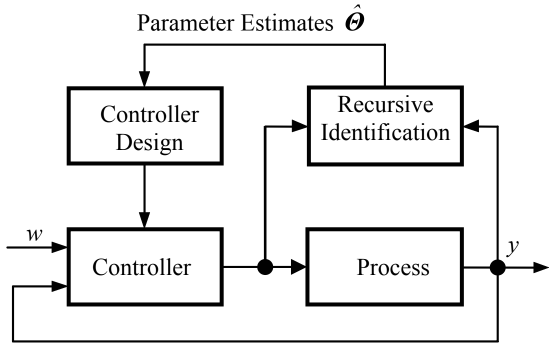
The majority of processes met in the industrial practice have stochastic characteristics and eventually they embody nonlinear behaviour. Traditional controllers with fixed parameters are often unsuitable for such processes because their parameters change. The changes of process parameters are caused by changes in the manufacturing process, in the nature of the input materials, fuel, machinery use (wear) etc. One possible alternative for improving the quality of control for such processes is the use of adaptive control systems. Different approaches were proposed and utilized. One successful approach is represented by self-tuning controller (STC). The standard STC approach based on the Linear Quadratic (LQ) method is verified and compared with two STC based on the Model Predictive Control (MPC). The verification of both methods was implemented by the real-time control of a highly nonlinear laboratory model, the Amira DR300 Speed Control with Variable Load.

Key words

Non-linear system, servo-system, CARIMA model, adaptive control, predictive control, real-time control.

1 Introduction

Self-tuning controllers (STC) use the combination of the recursive process identification on base of a selected model process and the controller synthesis based on knowledge of parameter estimates of controlled process (see [Åström and Wittenmark, 1995; Isermann *et al.*, 1991; Welstead and Zarrop, 1991; Landau, 1998 and Bobál *et al.*, 2005]). Like this STCs that use in a synthesis part estimates of the process model parameters are called explicit. Block diagram of an explicit STC (with direct identification) is shown in Fig. 1.



$y(k)$ - process output, $u(k)$ - controller output (manipulated variable), $w(k)$ - reference signal, $\hat{\Theta}(k)$ - process model parameter estimates

Figure 1. Block diagram of an explicit self-tuning controller

Model Predictive Control (MPC) is one of the control methods which have developed considerably over a few past years. Predictive control is essentially based on discrete or sampled models of processes. Computation of appropriate control algorithms is then realized especially in the discrete domain. The term Model Predictive Control designes a class of control methods, see e. g. [Maciejowski, 2002; Rossiter, 2003; Camacho and Bordons, 2004; Mikleš and Fikar, 2008]. The basic structure of the MPC is shown in Fig. 2. A model is used to predict the future process outputs y, based on the past and current values and on the proposed optimal future actions (manipulated variables) u. These actions are calculated by the optimizer taking into account the cost function (where the future tracking error is considered) as well as the constraints [Camacho and Bordons, 2004].

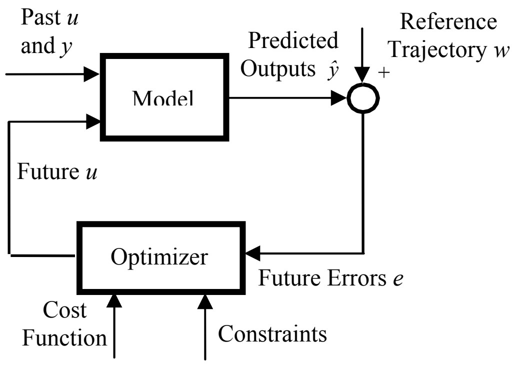


Figure. 2. Block diagram of basic structure of MPC

One of the major advantages of predictive control is its ability to do on-line constraints handling in a systematic way. Almost all practical applications hold constraints of input, output and state space variables. This is also the case of the laboratory model DR300.

All controllers use 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 [Kulhavý, 1987 and Bobál *et al*., 2005]. 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.

This paper is organized in the following way. The description of DR300 laboratory servo model and analysis of its static and dynamic properties are introduced in Section 2. Implementation of standard STCs and experimental results by real-time control of the DR300 model are described in Section 3. Problems of implementation of self-tuning predictive control and its application on the above mentioned laboratory model are the content of Section 4. Section 5 concludes the paper.

2 Description of Laboratory Model DR 300

The self-tuning algorithms were designed for a real-time control of the laboratory model DR300 (see Fig. 3). A block scheme of this system is shown in Fig. 4.

The plant is represented by a permanently exited DC-motor (M1) of which the input signal (armature current) is provided by a current control loop. Its servo amplifier allows the 4-quadrant mode. The sensors for the output signal (speed) are a tachogenerator (T) and an incremental encoder (I). The free end of the motor shaft is fixedly coupled (K) to the shaft of a second, identical motor (M2).

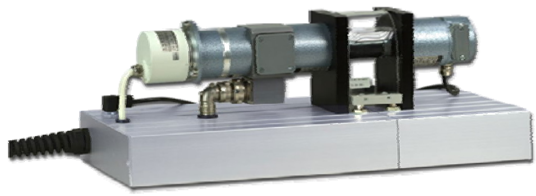


Figure 3. Laboratory model Amira DR300

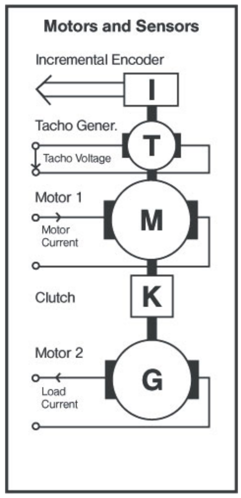


Figure 4. Block scheme of Amira DR300 servomotor.

This motor is used as a generator. Its output current is freely adjustable.

The rotation speed of the motor M1 is driven by voltage u. The motor shaft rotations per minute (rpm) are measured by tachogenerator T. The aim of the control process is to control the rotation speed of the shaft ω with the control voltage u.

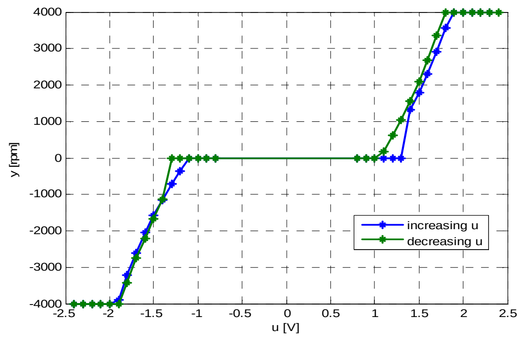


Figure 5. Static characteristics of Amira DR300 servomotor

From the control point of view, the Amira DR300 is a non-linear system. Some characteristics of the nonlinearity (gain with dead zone and hysteresis) can be observed from the static characteristics shown in Fig. 5.

3 Implementation of LQ STC

Due to nonlinearities of the DR300 system, self-tuning controllers were used for its control. The laboratory model was connected with a PC equipped with a control and measurement PC card. MATLAB and Real Time Toolbox were used to control the system.

Several controllers from the Self Tuning Controlles Simulink Library (STCSL) [Bobál *et al.*, 2005; Bobál and Chalupa, 2008], were applied to the control problem and different settings of controller parameters were tested. Most of these controllers were able to cope with the control of DR300 system.

All controllers from the STCSL use ARX model of the controlled system which can be described by the following equation

$$y(k) = \boldsymbol{\Theta}^T(k)\boldsymbol{\Phi}(k) + n(k) \tag{1}$$

where

$$\boldsymbol{\Theta}^T(k) = \left[a_1\ a_2\ b_1\ b_2\right] \tag{2}$$

is the vector of the current model parameters and

$$\boldsymbol{\Phi}^T(k) = \left[-y(k-1) - y(k-2)\, u(k-1)\, u(k-2)\right] \tag{3}$$

is the regression vector, $u(k)$ and $y(k)$ are the manipulated variable and process output. The non-measurable random component $n(k)$ is assumed to have zero mean value $E[n(k)] = 0$ and constant covariance (dispersion) $R = E\left[n^2(k)\right]$.

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One of the controllers from the STCSL which produced satisfactory and reliable control results was LQ controller named *pp2lq*. Computation of the control sequence of this controller is based on minimization of a quadratic criterion in the following form

$$J = \sum_{k=0}^{\infty}\left\{\left[w(k) - y(k)\right]^2 + q_u\left[u(k)\right]^2\right\} \tag{4}$$

where q_u is a coefficient representing weight of control signals in the LQ criterion. The controller 2DOF (two degrees of freedom) was applied in the form

$$\begin{aligned} u(k) &= r_0 w(k) - q_0 y(k) - q_1 y(k-1) - q_2 y(k-2) + \\ &+ (1-p_1)u(k-1) + p_1 u(k-2) \end{aligned} \tag{5}$$

The expressions for computation of individual controller parameters are introduced in [Bobál *et al.*, 2005].

Control courses of the *pp2lq* controller are presented in Fig. 6. The sampling period of T_0=0.05 s was used and weighting coefficient q_u=1 was applied. Initial parameter estimates were calculated to match working point of y=0.7 (i.e. different from the initial phase of the control course).

The same controller was also applied for the constrained case – the control signal was restricted to the range of u[V] <-2, 2>. Resulting control courses are presented in Fig. 7.

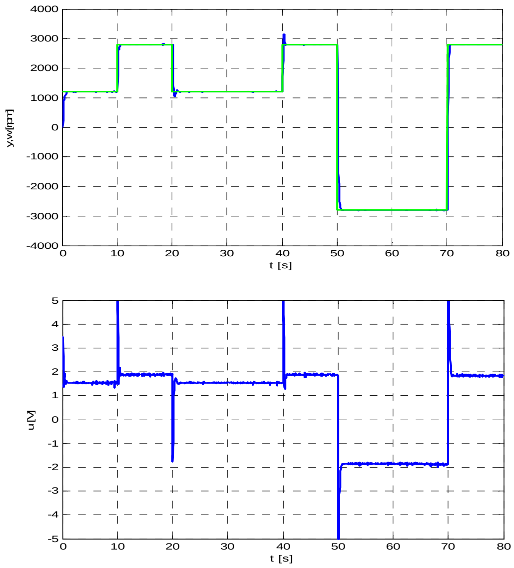

Figure 6. Control of DR300 using LQ STC (unconstrained case).

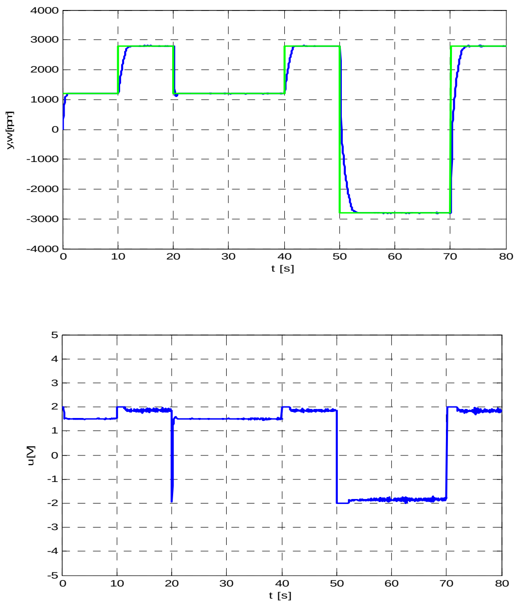

Figure 7. Control of DR300 using LQ STC (constrained case).

4 Implementation of MPC STC

The aim of this Section is implementation of the self – tuning predictive controller handling constraints of the manipulated variable for control of the objective laboratory equipment. As a model describing the controlled process was chosen an input-output CARIMA (Controlled Auto-

Regressive Integrated Moving Average) model. A quadratic cost function was used in the optimization part of the algorithm. The Generalized Predictive Control (GPC) method [Clarke *et al.*, 1987] was applied. A recursive algorithm which enables computation of predictions for arbitrary horizons was designed.

4.1 MPC based on minimization of quadratic criterion

The standard cost function used in GPC contains quadratic terms of control error and control increments on a finite horizon into the future

$$J=\sum_{i=N_1}^{N_2}\left[\hat{y}(k+i)-w(k+i)\right]^2+\sum_{i=1}^{N_u}\left[\lambda(i)\Delta u(k+i-\mathbf{1})\right]^2 \quad (6)$$

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*, $w(k+1)$ is the sequence of the reference signal and $\Delta u(k+i-1)$ is the sequence of the future control increments that have to be calculated. 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, generally, it is chosen in the form of constants or exponential weights. The output of the model (predictor) is computed as the sum of the forced response $\boldsymbol{y}_n$ and the free response $\boldsymbol{y}_0$

$$\hat{\boldsymbol{y}}=\boldsymbol{y}_n+\boldsymbol{y}_0 \quad (7)$$

It is possible to compute the forced response as the multiplication of the matrix $\boldsymbol{G}$ (Jacobian Matrix of the model) and the vector of future control increments $\boldsymbol{\Delta u}$, which is generally a priori unknown

$$\boldsymbol{y}_n=\boldsymbol{G\Delta u} \quad (8)$$

where $\boldsymbol{G}$ is matrix containing step responses.

It follows from equations (7) and (8) that the predictor in a vector form is given by

$$\hat{\boldsymbol{y}}=\boldsymbol{G\Delta u}+\boldsymbol{y}_0 \quad (9)$$

Minimization 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 $\boldsymbol{\Delta u}$ to zero and yields

$$\boldsymbol{\Delta u}=-\left(\boldsymbol{G}^T\boldsymbol{G}+\lambda\boldsymbol{I}\right)^{-1}\boldsymbol{G}^T\left(\boldsymbol{y}_0-\boldsymbol{w}\right)=-\boldsymbol{H}^{-1}\boldsymbol{g} \quad (10)$$

where $\boldsymbol{H}$ and $\boldsymbol{g}$ are the Hesse-Matrix and the gradient.

Detailed derivation of the predictive controller and its application for the control of the laboratory model DR300 is introduced in [Bobál *et al.*, 2009].

In case of the Amira DR300 laboratory model, the actuator has a limited range of action. The voltage applied to the motor can vary between fixed limits. As it was mentioned in the Section 1, 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:

$$\min_{\boldsymbol{\Delta u}} 2\boldsymbol{g}^T\boldsymbol{\Delta u}+\boldsymbol{\Delta u}^T\boldsymbol{H\Delta u} \quad (11)$$

owing to

$$\boldsymbol{A\Delta u}\le\boldsymbol{b} \quad (12)$$

The inequality (12) expresses the constraints in a compact form. In our case of the constrained input signals particular matrices can be expressed as

$$\boldsymbol{A}=\begin{bmatrix}-\boldsymbol{T}\\ \boldsymbol{T}\end{bmatrix};\quad \boldsymbol{b}=\begin{bmatrix}-\boldsymbol{1u}_{min}+\boldsymbol{1u}(k-1)\\ \boldsymbol{1u}_{max}-\boldsymbol{1u}(k-1)\end{bmatrix} \quad (13)$$

where $\boldsymbol{T}$ is a lower triangular matrix whose non - zero elements are ones and $\boldsymbol{1}$ is unit vector.

Forms of the matrices for an arbitrary control horizon were computed and can be expressed as follows:

$$\begin{bmatrix}-1 & 0 & \cdots & 0\\ \vdots & \vdots & \cdots & \vdots\\ -1 & -1 & \cdots & -1\\ 1 & 0 & \cdots & 0\\ \vdots & \vdots & \cdots & \vdots\\ 1 & 1 & \cdots & 1\end{bmatrix}\begin{bmatrix}\Delta u(k)\\ \Delta u(k+1)\\ \vdots\\ \Delta u(k+N_u-1)\end{bmatrix}\le\begin{bmatrix}-\begin{bmatrix}1\\1\\ \vdots\\1\end{bmatrix}u_{\min}+\begin{bmatrix}1\\1\\ \vdots\\1\end{bmatrix}\left[u(k-1)\right]\\ \begin{bmatrix}1\\1\\ \vdots\\1\end{bmatrix}u_{\max}-\begin{bmatrix}1\\1\\ \vdots\\1\end{bmatrix}\left[u(k-1)\right]\end{bmatrix} \quad (14)$$

The control sequence is computed from expression (11), equations (13) and inequations (12) and (14).

The optimization problem is solved numerically by quadratic programming in each sampling period. The first element of the resulting vector $\boldsymbol{\Delta u}$ is then applied as the increment of the manipulated variable.

Courses of the reference signal contain step changes in both directions. This is one of the most unfavourable situations which can occur in a closed loop control system. Within the steps also changes the operational range. This is one of the reasons for application of self – tuning controllers.

An approximate sampling period was found based on measured step responses so that ten samples cover important part of the step response. The best sampling period T_0=0.05 s was then tuned according to experiments.

The tuning parameters that are the prediction and control horizons and the weighting coefficient λ were tuned experimentally. There is a lack of clear theory relating to the closed loop behaviour to design parameters. The prediction horizon, which should cover the important part of the step response, was set to N_2 = 15. The control horizon was also set to N_u = 15. The coefficient λ was taken as equal to 50.

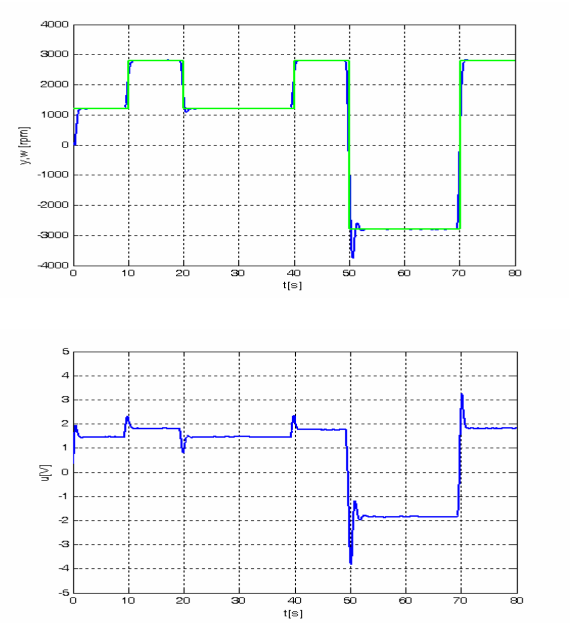

Figure 8. Control of DR300 using MPC STC (unconstrained case).

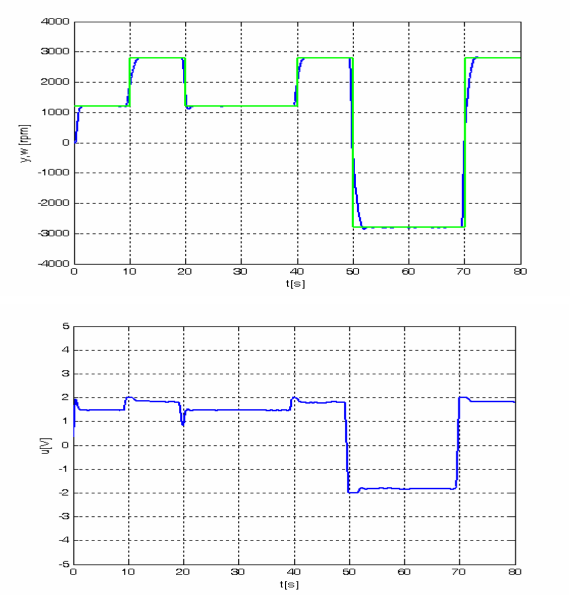

Figure 9. Control of DR300 using MPC STC (constrained case).

Both constrained and unconstrained cases were considered. Control results when constraints of the manipulated variable were not considered are presented in Fig. 8. In the subsequent experiment the manipulated variable was constrained within lower and upper limits and the algorithm considering the constraints was applied. The results are shown in Fig. 9.

4.2 MPC based on minimization of linear criterion

Not only the quadratic criterion was used in the model predictive control, the absolute value based criterion of MPC was also applied to the control problem.

$$J=\sum_{i=N_1}^{N_2}\left|\hat{y}(k+i)-w(k+i)\right|+\sum_{i=\mathbf{1}}^{N_u}\lambda(i)\left|\Delta u(k+i-\mathbf{1})\right| \quad (15)$$

Solution of the criterion (15) leads to the linear programming which can cope with constraints in the same way as the quadratic programming described in section 4.1.

Control course for the settings of N_1 = 1, N_2 = 15 and N_u = 5 are presented in Fig. 10. The coefficient λ was equal to 0.2 in this case.

Utilization of linear criterion leads to faster response of the controller to the step changes of reference signal. On the other hand, small changes of the control error caused by noise have greater influence to the control signal when comparing control courses with the the control courses obtained by MPC based on quadratic criterion.

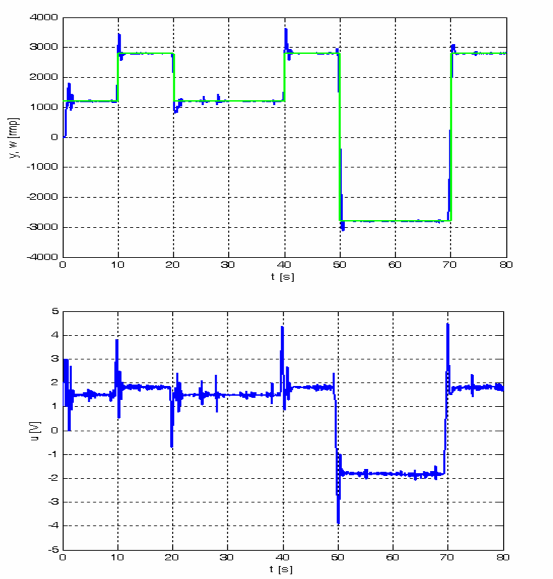

Figure 10. Control of DR300 using MPC STC (linear ceiterion).

5 Conclusion

Criteria of the quality of control are summarized in Table I. The criteria are sum of powers of tracking errors and sum of increments of the manipulated variable.

It is obvious that selection of an appropriate model for control in particular operational ranges is a difficult task in case of nonlinear or stochastic processes. One of the possible approaches to the solution of this problem is utilization of adaptive control. This paper deals with the proposal and application of two adaptive approaches to control of the nonlinear time varying system – the laboratory model DR300. The first approach is based on the standard LQ self – tuning controller. In the second case the predictive self – tuning controller was proposed. Control with both unconstrained and constrained input signal was tested. The control tests gave satisfactory results for both controllers. According to comparison of results in Table I it is evident that better quality of control was achieved with the predictive self – tuning controller.

Table I. Control quality criteria

controller	$\sum e^2$	$\sum \Delta u^2$	$\sum \lvert e \rvert$	$\sum \lvert \Delta u \rvert$
LQ STC - unconstrained case	13.0058	3.6929	19.3884	11.3535
LQ STC - constrained case	29.3412	0.4975	52.5267	5.6708
MPC quadratic - unconstrained case	8.0985	0.0561	26.4681	2.8453
MPC quadratic - constrained case	11.9377	0.0302	36.8594	1.8496
MPC absolute values - unconstrained case	7.0411	0.7683	27.3585	14.0666

The objective laboratory model simulates a process, which frequently occur in industry. It was proved that the examined method could be implemented and used successfully to control such processes.

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