Annals of DAAAM for 2010 & Proceedings of the 21st International DAAAM Symposium, Volume 21, No. 1, ISSN 1726-9679
ISBN 978-3-901509-73-5, Editor B. Katalinic, Published by DAAAM International, Vienna, Austria, EU, 2010
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Annals of DAAAM International

ADAPTIVE CONTROLLER WITH NEURAL NETWORK IDENTIFICATION

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Abstract: *In adaptive control is synthesis of the controller made on the basis of process's linear approximation. In identification based on neural network (NN) the approximation can be get direct from weights of linear NN or via linearization of nonlinear NN. In this article prosperities of closed loop if the nonlinear NN with it's linearization was verified in control of real process with LQ controller.*
Key words: *Neural networks, linear approximation, linearization, LQ controller*

1. INTRODUCTION

Most of the controlled processes are in fact nonlinear. Because the processes are usually control in the neighbourhood of few its operating point therefore linear controllers can be used. Controller's synthesis is mostly realized by linear model of the process in its actual operating point. In adaptive control the linear models are usually get by LS of RLS or as in this article via method based on NN (Nelles, 2001). Parameters of the linear model are dependent directly on NN's weights if the network is linear. In this article the nonlinear NN was used. If nonlinear NN is use the NN model can give better approximation of the real process. In this case linear model have to be achieved via linearization of the NN in its operating point equal the process operating point.

2. CONTROLLED PROCESS BLOCK DIAGRAM

The Controller contains three main separated parts identification, state observer and controller Fig 1, *w(k)* denotes desired value, *u(k)* action value and *y(k)* controlled value of the plant. The model could by write as ARX model with transfer function (1) or in vector form as $\hat{y}(k) = \varphi^T(k)\theta(k) + e_0(k)$, where $\theta(k)$ are the linear parameters, φ^T is vector of measurement. In this case 2[th] order approximation was used.

$$F(z) = \frac{b_1 z^{-1} + b_2 z^{-2}}{1 + a_1 z^{-1} + a_2 z^{-2}}$$
$$\varphi(k) = \left[u(k-1)\;\; u(k-2)\;\; -y(k-1)\;\; -y(k-2)\right]^T \qquad (1)$$
$$\theta(k) = \left[b_1(k)\;\; b_2(k)\;\; a_1(k)\;\; a_2(k)\right]^T$$

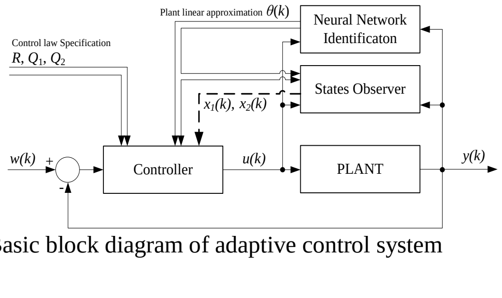

Fig 1. Basic block diagram of adaptive control system

2.1 Neural network identification

Structure of used NN is show Fig. 2.

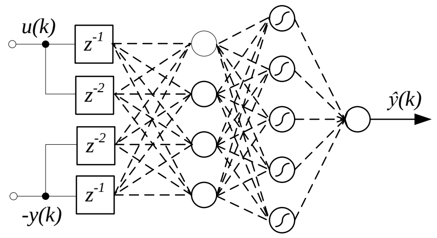

Fig 2. Identified model with three layer NN, neurons with logistictic actionvation function in hidden layer

Learning of NN is realized by Lavenberq-Marqurt algorithm (2), where *W* are weights of NN, *m* is number of

$$W(m) = W(m-1) - \eta\left[J^T J + \lambda I\right]^{-1} JE \qquad (2)$$

iterations in each step, η is line search parameter and was set as η=1, λ is regularization parameter and was set as λ=1, *E* is vector of prediction errors,

$$E = \left[e(k-n)\; e(k-n+1) \quad \cdots \quad e(k)\right]^T$$
$$e(k) = y(k) - \hat{y}(k) \qquad (3)$$

and *J* is jacobian of *E*, *n* is number of patterns.

$$J = \left[\frac{\partial e(k-n)^T}{\partial W} \quad \cdots \quad \frac{\partial e(n)^T}{\partial W}\right]^T \qquad (4)$$

Jacobian for the nonlinear network is more complex so isn't shown. In practice, the matrix inversion in (2) isn't usually performed explicitly but by solving (5) (Nelles, 2001), in this case solution using Cholesky factorization was used.

$$\left[J^T J + \lambda I\right]p = J^T E \qquad (5)$$

Because nonlinear network was used, ARX model parameters had to be obtain via the linearization of the network in its operating point (Narrendra, 1997). Then linear approximation closed to operation point could by compute as (6). The operating point is determined by measurement vector.

$$\hat{y}(k) = f(W, \varphi(k))$$
$$b_i = \frac{\partial f(W,\varphi(k))}{\partial u_i} \qquad a_i = \frac{\partial f(W,\varphi(k))}{\partial y_i} \qquad (6)$$

2.2 Adaptive controller algorithms

The purpose of adaptive controller is to adapt parameters of control law to changes of the controlled system. Controller based on LQ approach is implemented, so its parameters synthesis is based on minimizing cost function (7). Where u is

$$J = \sum_{k=0}^{\infty}\left(x^T(k)Qx(k) + u^T(k)Ru(k)\right) \qquad (7)$$

process input, *x* are states of the optimized system, *Q* is positive definite states penalization matrix, R is positive semidefinite penalization of input. Optimized system is given by (8).

$$\begin{bmatrix} x_P(k+1) \\ x_3(k+1) \\ x_4(k+1) \end{bmatrix} = \begin{bmatrix} A_P & 0 & 0 \\ 0 & 1 & 0 \\ C_P & -1 & 1 \end{bmatrix} \begin{bmatrix} x_P(k) \\ x_3(k) \\ x_4(k) \end{bmatrix} + \begin{bmatrix} B_P \\ 0 \\ 0 \end{bmatrix} u(k) \quad (8)$$

Where x_P is plant's states vector, A_P plant's system matrix and B_P plant's input matrix, C_P plant's output matrix. Plant state space description may by realized form linear approximation (1) by (9). State x_3 is model of request value process, x_4 is control deviation summation for constant disturbance cancelling.

$$x_P(k+1) = \begin{bmatrix} x_1(k+1) \\ x_2(k+1) \end{bmatrix}, \quad A_P = \begin{bmatrix} 0 & a_2 \\ 1 & a_1 \end{bmatrix}$$
$$B_p = \begin{bmatrix} b_2 \\ b_1 \end{bmatrix}, \quad C_P = \begin{bmatrix} 0 & 1 \end{bmatrix} \quad (9)$$

Control law and simultaneously closed loop properties are influenced indirect via penalization in cost function (7) where Q is given by (11).

$$Q = \begin{bmatrix} C_P^T Q_1 C_P & -C_P^T Q_1 & 0 \\ -Q_1 C_P & Q_1 & 0 \\ 0 & 0 & Q_2 \end{bmatrix} \quad (10)$$

R, Q1, Q2 are scalar values, R is action value's penalization, Q1 is control deviation's penalization, Q2 penalized sum of control deviation.

Control law is given in the form $u(k) = -Kx(k)$. Feedback gains K are obtained by minimizing of the cost function (7). Algebraic Riccati equation is solve by iteration Kleinman algorithm (11). Start setting of feedback gains was set to ones and start setting of $P=Q$. Only the one iteration of (11) was realized in every step.

$$P = Q + K^T R K + (A - BK)^T P (A - BK)$$
$$K = \left[R + B^T P B\right]^{-1} B^T P A \quad (11)$$

A is system matrix, B input matrix both of optimized system (9).

2.3 States observer

Plant's states x_1 and x_2 were reconstructs by simple death beat observer realized as simple dynamic system (13).

$$\begin{bmatrix} \hat{x}_1(k) \\ \hat{x}_2(k) \end{bmatrix} = \begin{bmatrix} 0 & 0 \\ 1 & 0 \end{bmatrix} + \begin{bmatrix} b_2 & a_2 \\ b_1 & a_1 \end{bmatrix} \begin{bmatrix} u(k-1) \\ y(k-1) \end{bmatrix} \quad (12)$$

2.4 Control of real process

Controlled plant was electronic system realized by operating amplifier. The plant can by consider as linear system and transfer function change is capable. Two transfer functions (13) were choose for adaptive control. Sample time for controller and identification was both choose T_s=0.5s, controller's settings R=2, Q_1=2, Q_2=2.5, three iterations of (2) and , λ=0.1 during open loop identification and one iteration (2) and , λ=1 during closed loop. Before controller was connected into to the process F_1, the open-loop identification from double step response is realized between 0-80 s in the Fig. 3. After this closed loop control of F_1 was ON. Controller's adaptive properties show Fig 4. The process's transfer function change was realized from F_1 to F_2 at 370 s. Step disturbance rejection show Fig. 4. at 620 s and 670 s.

$$F_1(s) = \frac{1}{(4s+1)(2s+1)(0.5s+1)}$$
$$F_2(s) = \frac{1}{(7s+1)(2s+1)(0.5s+1)} \quad (13)$$

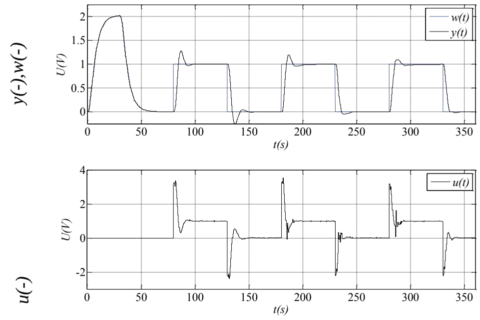

Fig 3. Model controlled by adaptive controller, 0-80 s identification in open loop, 80-350 s on-line identification and control of F_1

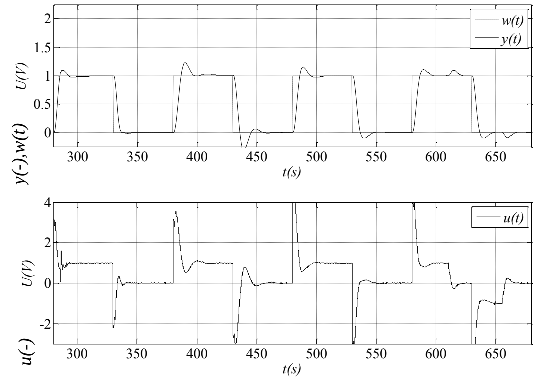

Fig 4. On-line identification and control with plant's transfer function change from F_1 to F_2 in 370 s. Constant disturbance rejection in 620 s and 670 s.

3. CONCLUSION

In this article algorithms for on-line identification and adaptive control were implemented into PLC and verified by real model. Getting of the linear model from nonlinear NN was check. Good linear model of the process was obtained only if the network was exactly learned so time-consuming teaching had to be used. Time-consuming and correctness of algorithm's implementation was check via linear process control. Obtained results are corresponding with expectations and nonlinear NN can by use for on-line identification in adaptive control.

4. ACKNOWLEDGEMENTS

This work was supported by grant „Modern Methods and Approaches in Automation" from the Internal Grant Agency of Brno University of Technology (grant No. FEKT-S-10-12).

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