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ADAPTIVE LINEAR NETWORK IN MODEL PREDICTIVE CONTROL OF CONTINUOUS CHEMICAL REACTOR

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ABSTRACT
The contribution is aimed at predictive control of nonlinear processes with the help of adaptive linear artificial neural network as the predictor. Since this methodology is relatively wide, paper only concentrates on the prediction via artificial neural networks. Special attention is paid to the on-line adaption of the predictor. The proposed method is tested in simulations on a nonlinear system.
Keywords: ADALINE, artificial neural network, model predictive control, CSTR

1. INTRODUCTION
Model predictive control (MPC) [2] is a very attractive concept for the development and tuning of nonlinear controllers in the presence of input, output or state constraint. Many predictive control techniques based on MPC that use artificial neural network (ANN) as a predictor are established on multilayer feed-forward neural networks [3], [4]. In spite the multilayer feed-forward neural networks (MFFNNs) have many advantages such as simple design and scalability they have also many drawbacks such as long training times and choice of an appropriate learning stop time (the overlearning versus the early stopping). Nevertheless, there are quite a number of types ANNs suitable for the modelling and prediction [5], [6], [7]. Moreover, features of these ANNs exceed abilities of the MFFNN in many cases. One of these ANNs is ADALINE (ADAptive LInear Neuron).

2. ADAPTIVE LINEAR NETWORKS
ADALINE contains just one neuron with a few inputs and additional unit signal. As a transfer function is used linear function. Though, this structure has limited skills, so Widrow and Hoff connected more of ADALINEs together and gave it a name MADALINE (Multiple ADALINE).

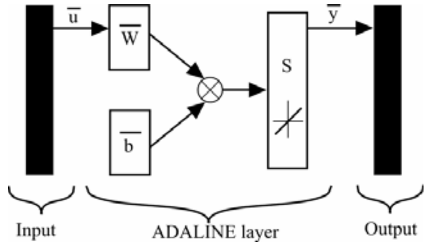

Figure 1. Schema of Adaptive linear network

Despite the fact that MADALINEs are able to solve only linearly separable problems, in practise has been shown that they can approximate nonlinear functions with sufficient accuracy while using enough number of neurons. Because of their main advantage, that is very fast learning, they have many practical applications, e.g. noise reduction, signal processing and signal prediction in control and communication systems.

3. MODEL PREDICTIVE CONTROL USING ARTIFICIAL NEURAL NETWORK

There are various approaches to predictive control by artificial neural networks. Generally we can say that these methods use ANN as the plant model in order to get its output predictions. The most used approach is model predictive control [2]. MPC is a broad control strategy applicable to both linear and nonlinear processes. The main idea of MPC algorithms is to use a dynamical model of process to predict the effect of future control actions on the output of the process. Hence, the controller calculates the control input that will optimize the performance criterion over a specified future time horizon:

$$J = \sum_{j=N_1}^{N_2} \left[y_r(k+j) - \hat{y}(k+j) \right]^2 + \rho \sum_{j=1}^{N_u} \left[u_t(k+k-1) - u_t(k+j-2) \right]^2 , \qquad \text{... (1)}$$

where N_1, N_2 and N_u define horizons over which the tracking error and the control increments are evaluated. The u_t variable is the tentative control signal, y_r is the desired response and $\hat{y}$ is the network model response. The ρ determines the contribution that the sum of the squares of the control increments has on the performance index.

There is usually assumed that after a certain interval $N_u < N_2$ there is no variation in the proposed control signals, that is:

$$\Delta u(k+i) = 0 \qquad for \quad i \in \left\langle N_u, N_2 - 1 \right\rangle . \qquad \text{... (2)}$$

This is equivalent to giving infinite weights to the changes in the control from a certain instant. This approach is adopted in this paper.

Typically the receding horizon principle is implemented, which means that after the computation of optimal control sequence, only the first control action is implemented. Then the horizon is shifted forward one sampling instant and the optimization is again restarted with new information from measurements. This methodology is adopted in this paper. In cases where the model of the process is given as a nonlinear combination of the process inputs (e.g. ANN), the solution of the standard constrained MPC is necessarily more complex. Due to nonlinear nature of ANN prediction model a nonlinear optimization problem must be solved through some numerical algorithm.

4. SIMULATIONS AND RESULTS

To demonstrate the controller, we use it for control of a catalytic Continuous Stirred Tank Reactor (CSTR) [1]. The dynamic model if the system is:

$$\frac{dh(t)}{dt} = q_1(t) + q_2(t) - 0.2 \cdot \sqrt{h(t)} \qquad \text{... (3)}$$

$$\frac{dC_b(t)}{dt} = \left(C_{b1} - C_b(t)\right)\frac{q_1(t)}{h(t)} + \left(C_{b2} - C_b(t)\right)\frac{q_2(t)}{h(t)} - \frac{k_1 C_b(t)}{\left(1 + k_2 C_b(t)\right)^2} , \qquad \text{... (4)}$$

where $h(t)$ is the liquid level, $C_b(t)$ is the product concentration at the output of the process, $q_1(t)$ is the flow rate of the concentrated feed C_{b1}, and $q_2(t)$ is the flow rate of the diluted feed C_{b2}. The input concentrations are set to C_{b1} = 24.9 mol/cm^3 and C_{b2} = 0.1 mol/cm^3. The constants associated with the rate of consumption are $k_1 = 1$ and $k_2 = 1$. To simplify the demonstration, the input flow q_2 was constant $q_2(t)$ = 0.1 cm^3/s. The task of the controller is to control the product concentration C_b by adjusting the flow rate q_1. The level of the tank $h(t)$ is not controlled for this experiment.

Thus, the system is regarded as single input-single output (SISO). The allowable range for $q_1(t)$ was assigned to be in <0, 4> cm^3/s. The initial conditions are $C_b(0) = 22$ mol/cm^3 and $h(0) = 30$ cm.

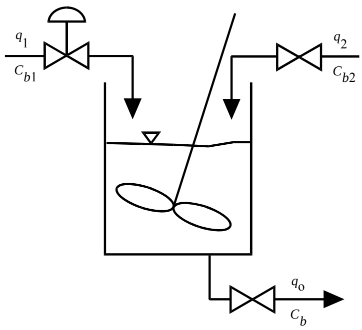

Figure 2. Scheme of the continuous stirred tank reactor

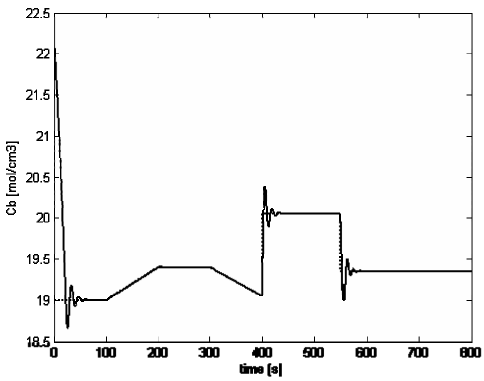

Figure 3. Simulation results without presence of noise (system output - continuous line, reference value – dotted line)

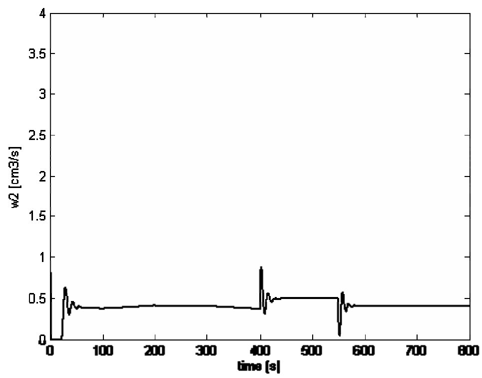

Figure 4. Simulation results without presence of noise (control signal)

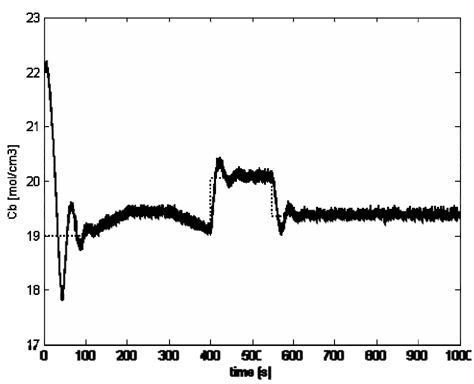

Figure 5. Simulation results witht presence of noise (system output - continuous line, reference value – dotted line)

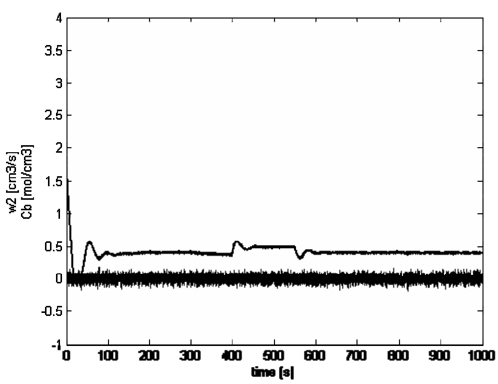

Figure 6. Simulation results with presence of noise (control signal)

The model for simulations as well as the controller was prepared in Matlab and Simulink. Band-Limited White noise block has been included to find out the behaviour without noise and while noise is present, the gain of noise was set to 0 and 0.05 respectively.
The controller has used quasi-Newton method as a numerical optimization algorithm. The setting of the controller was: ρ = 40, N_1 =1, N_2 = 10, N_u = 5 in case of no noise and ρ = 500, N_1 =1, N_2 = 10, N_u = 5 in case of influence of noise. The sampling period for both simulations was 0.1s.
In spite of ADALINE's ability to adapt the off-line identification was used in order to get rid of starting inaccuracies. However, the predictor was adapted at each sampling period so as to improve predictions. For the off-line identification was used input-output data generated by pulses of random amplitude and duration. Duration and amplitude of the pulses must be chosen carefully to produce accurate identification. The amplitudes in range <0;4> cm^3/s and duration from 1s to 100s were used. Results are presented in figures 3 - 6.

5. CONSLUSION

As can be seen from figures 3 - 6 usage of ADALINE as a predictor in model predictive control is possible for both cases, despite the predictor was trained for data without noise. Due to influence of noise, the parameter ρ had to be increased to reduce the jittering of control actions. However, oscillations of output value (C_b) could not be removed because of placement of noise at the output of the CSTR.
The simulations proved that simple one-neuron network with linear transfer function is able to predict the nonlinear system output with moderate deviations. Moreover, it was shown that the ADALINE can be used for sufficient predictive control of this kind of systems.
The main advantages of ADALINE are small memory requirements, fast training and simple usage. As a result of fast training time can be ADALINE easily adapted on-line, what increases the accuracy of control.
Of course, the presented method has also disadvantages. The first drawback comes from the simplicity of ADALINE. Linear nature of ADALINE may result in not so exact predictions in comparison to predictions to be obtained from more complex ANN. On the other hand, MPC is quite tolerant to small predictor inaccuracy and on-line adaptation may also decrease the prediction error. The second disadvantage is the computational demands of optimization algorithm.

6. ACKNOWLEDGEMENT

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