MPC using adaline.

Abstract: This paper deals with model predictive control using artificial neural networks. After short introduction to the model predictive control approach this contribution presents an application of adaptive linear neural network for predictive control of nonlinear system. This paper shows ability of adaptive linear network to predict nonlinear system output and to be used for predictive control of these systems. Multilayer feed-forward neural networks are used as a comparative method.

Key words: artificial neural networks, ADALINE, model predictive control, prediction, MFFNN

1. INTRODUCTION

Many predictive control techniques that use artificial neural network (ANN) as a predictor are established on multilayer feed-forward neural networks (Kanjilal, 1995; Hagan et al., 2002). 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 prediction (Liu, 2001; Samek, 2003). 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. Linear function is used as a transfer function. Due to limited skills of this structure Widrow and Hoff connected more of ADALINEs together and gave it a name MADALINE (Multiple ADALINE).

Despite the fact that ADALINE is able to solve only linearly separable problems, in practise it 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. PREDICTIVE CONTROL USING ANN

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 controller then calculates the control input that will optimize the performance criterion over a specified future time horizon.

$$J = \sum_{j=N_1}^{N_2} [Y_r(k + j) - ??(k + j)]^2 + + \rho \sum_{j=1}^{N_u} [u_t(k + j - 1) - u_t(k + j - 2)]^2 \quad (1)$$

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 [??] is the network model response. The ρ parameter determines the contribution that the sum of the squares of the control increments has on the performance index.

4. SIMULATIONS AND RESULTS

To demonstrate presented method, we used a catalytic Continuous Stirred Tank Reactor (CSTR). The dynamic model of the system is (Brengel & Seider, 1989):

$$r_b = K_1 C_b / (1 + K_2 C_b)^2 \quad (2)$$

$$dh / dt = q_1 + q_2 - 0.2 \sqrt{h} \quad (3)$$

$$dC_b / dt = (C_{b1} - C_b) q_1 / h + (C_{b2} - C_b) q_2 / h - r_b \quad (4)$$

where r_b is rate of consumption of C_b, h is the liquid level, C_b is the product concentration at the output of the process, q_1 is the flow rate of the concentrated feed C_{b1}, and q_2 is the flow rate of the concentrated 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 $K_1 = K_2 = 1$. The objective of the controller is to maintain the product concentration by adjusting the flow q_2. To simplify the demonstration, we set q_1 = 0.1 cm^3/s. The allowable range for q_2 was assigned to be in the interval <0, 4>. The level of the tank h is not controlled for this experiment.

All simulations were done in Matlab 6.5 using Neural Network Toolbox, Optimization Toolbox and Simulink (Fig. 1). Off-line trained ADALINE model with 10 inputs (5 delayed control actions + 5 delayed values of C_b) was used for the ANN predictor.

The multilayer feed-forward neural network was used as a comparative method. The MFFNN had three hidden layers and its structure was 10 $\rightarrow$ 15 $\rightarrow$ 10 $\rightarrow$ 10 $\rightarrow$ 1. All neurons utilized hyperbolic tangent sigmoid transfer function.

The Levenberg-Marquardt algorithm was used as the optimization method of the controller.

[FIGURE 1 OMITTED]

At first, the system without noise (the Gain at the fig. 1 was 0) was examined. After number of simulations we found optimal settings for the controller: ρ = 0.1, N_1=1, N_2=5, N_u=3. For better comparability same setting was used for both predictors.

[FIGURE 2 OMITTED]

[FIGURE 3 OMITTED]

Furthermore, the noise was added to system output C_b (the Gain at the fig. 1 was 0.05). The noise power of Band-Limited White Noise block was 0.1. In order to at least partly reduce oscillation of control actions the parameter ρ was set to 0.5, other parameters remain the same. And again, for better comparability, same setting was used for both predictors.

[FIGURE 4 OMITTED]

[FIGURE 5 OMITTED]

5. DISCUSSION

As can be seen from results, the prediction of the nonlinear system by ADALINE was sufficient for both cases with and without noise, despite the network was trained for data without noise. Because of the noise influence the control signal tended to oscillate, thus the parameter [rho] had to be increased in case noise influence.

Presented 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. In case without noise figures 2 and 3) ADALINE provides better response without overshoots. However, in case of noise presence (figures 4 and 5) controller with ADALINE generates more oscillating control actions in comparison to MFFNN. Nevertheless, this behaviour can be reduced by increasing [rho] or [N.sub.u].

The main advantages of ADALINE are small memory requirements, fast training, adaptivity and simple usage. On the other hand, the disadvantage of this approach is that ADALINE predictor gives us more fluctuating control action in case of noise. So the subject of the future research will be to reduce this behaviour.

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