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Neuro-fuzzy Control of the Three Tank System

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Abstract: This paper presents the control design via the combination of the neural predictive controller and the neuro-fuzzy controller type of ANFIS. The neuro-fuzzy controller works in parallel with the predictive controller. This controller adjusts the output of the predictive controller, in order to enhance the predicted inputs. The performance of our proposal is demonstrated on the three tank system control problem with disturbance. Simulation results demonstrate the effectiveness and robustness of the proposed approach.

1. INTRODUCTION

The aim of process control is to achieve the target value of the given variable. This is mainly the task of the properly designed controller. The controller should also provide some flexibility in case an unexpected failure, change of conditions, etc.

Today, there are many methods for designing intelligent controllers, such as fuzzy control, neural networks or expert systems. Appropriate combinations of these methods offer a number of other design possibilities.

This paper describes the above mentioned combination of two methods of intelligent system controlling. By the parallel connection of predictive and neural-fuzzy controller, we aimed to obtain better results of the reference variable in terms of lowering its overshooting and reducing the control time. The designed system with two connected controllers was tested using a three tank system. The tank system introduces one of the nonlinear type of the chemical-technological processes.

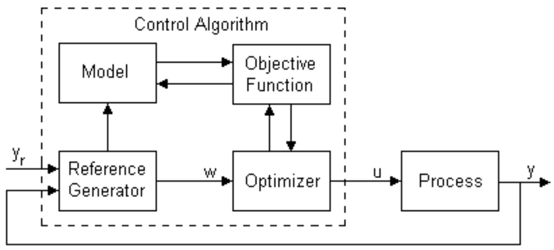

Fig. 1. Model-based predictive control scheme

2. PREDICTIVE CONTROL

MBPC (Model-Based Predictive Control) is a name of a several different control techniques (A. Vasičkaninová 2008). All are associated with the same idea. The prediction is based on the model of the process (Figure 1).

The controller uses a neural network model to predict future plant responses to potential control signals. An optimization algorithm then computes the control signals that optimize future plant performance. The neural network plant model is trained offline, in bath form, using any of the training algorithms. The controller, however, requires a significant amount of online computation, because an optimization algorithm is performed at each sample time to compute the optimal control input. The model predictive control method is based on the receding horizon technique. The neural network model predicts the plant response over a specified time horizon. The predictions are used by a numerical optimization program to determine the control signal that minimizes the following performance criterion over the specified horizon.

$$J(t,u(k)) = \sum_{i=N_1}^{N_2} (y_m(t+i) - y_r(t+i))^2 + \lambda \sum_{i=1}^{N_u} (\Delta u(t+i-1))^2 \qquad (1)$$

where N_1, N_2 and N_u define the horizons over the tracking error and the control increments are evaluated. The Δu variable is the tentative control signal, y_r is the desired response and y_m is the network model response. The λ value determines the contribution that the sum of the squares of the control increments has on the performance index.

The controller consists of the neural network plant model and the optimization block. The optimization block determines the values of u that minimize J, and then the optimal u is input to the plant.

Equation (1) is used in combination with input and output constraints:

$$\begin{array}{ccccc} u_{\min} & \le & u & \le & u_{\max} \\ \Delta u_{\min} & \le & \Delta u & \le & \Delta u_{\max} \\ y_{\min} & \le & y & \le & y_{\max} \\ \Delta y_{\min} & \le & \Delta y & \le & \Delta y_{\max} \end{array} \quad (2)$$

3. NEURO-FUZZY CONTROLLER

The neural predictive controller can be extended with neuro-fuzzy controller, connected in parallel (Figure 2).

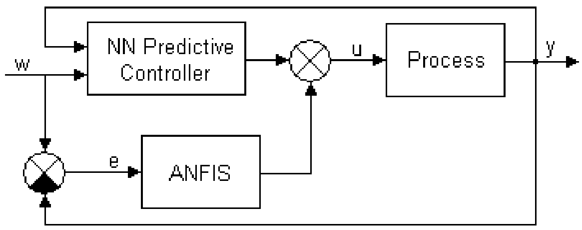

Fig. 2. Neuro-fuzzy control scheme

Neuro-fuzzy systems, which combine neural networks and fuzzy logic, have recently gained a lot of interest in research and application. A specific approach in neuro-fuzzy development is the ANFIS (Adaptive Network-based Fuzzy Inference System) (M. Agil 2007). ANFIS uses a feed forward network to search for fuzzy decision rules that perform well on a given task. Using a given input-output data set, ANFIS creates an Fuzzy Inference System for which membership function parameters are adjusted using a combination of a backpropagation and least square method. The ANFIS architecture of the first-order Takagi-Sugeno inference system is shown in Figure 3.

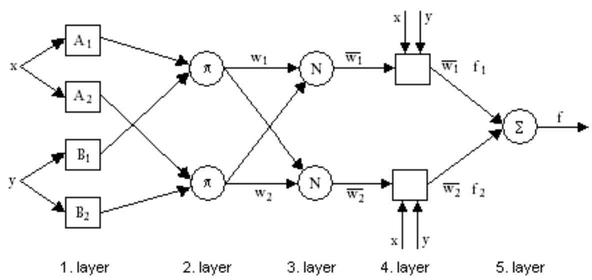

Fig. 3. System architecture ANFIS

4. EXPERIMENTAL

4.1 Process

We assume a non-linear system of three tanks shown in Figure 4 that is described by three sets of differential equations (Mikleš and Fikar 2007).

$$\frac{dh_1}{dt} = \frac{q_{01}}{S_1} - \frac{k_{11}}{S_1}\sqrt{h_1 - h_2} \quad (3)$$

$$\frac{dh_2}{dt} = \frac{q_{02}}{S_2} + \frac{k_{11}}{S_2}\sqrt{h_1 - h_2} - \frac{k_{22}}{S_2}\sqrt{h_2} \quad (4)$$

$$\frac{dh_3}{dt} = \frac{k_{22}}{S_3}\sqrt{h_2} - \frac{k_{33}}{S_3}\sqrt{h_3} \quad (5)$$

where S_1, S_2, S_3 [dm^2] are the cross-sectional areas of tanks, h_1, h_2, h_3 [dm] – heights of liquid in tanks, k_{11}, k_{22}, k_{33} [dm$^{2.5}$s^{-1}] – constants , q_{01} [dm^{3}s^{-1}] – inlet volumetric flow rate to the first tank, q_{02}, q_1 [dm^{3}s^{-1}] – inlet volumetric flow rate to the second tank, q_2 [dm^{3}s^{-1}] – inlet volumetric flow rate to the third tank, q_3 [dm^{3}s^{-1}] – outlet volumetric flow rate from the third tank and t [s] – time variable. The concrete values of the parameters are summarized in Table 1.

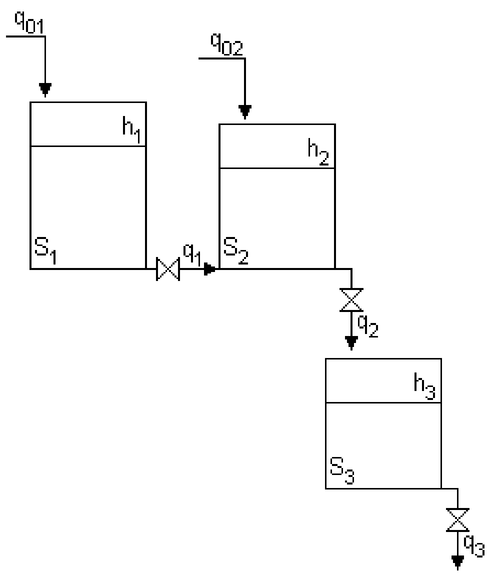

Fig. 4. Signification scheme of a three tank system

Table 1. Parameters of the tank system

Variable	Unit	Value
S_1	dm^2	3
S_2	dm^2	2.5
S_3	dm^2	2
k_{11}	dm$^{2.5}$s^{-1}	1.8
k_{22}	dm$^{2.5}$s^{-1}	1.3
k_{33}	dm$^{2.5}$s^{-1}	1.4
q_{01}	dm^{3}s^{-1}	1
q_{02}	dm^{3}s^{-1}	0.3

The height of liquid in the third tank h_3 is controlled variable and inlet volumetric flow rate to the first tank q_{01} is input variable. The process state variables are heights of liquid in tanks (h_1, h_2 and h_3).

4.2 Process control in the nominal state

Firstly, process was simulated with neural predictive controller (NNPC). To set this controller neural network process model was needed. Neural network model of three tanks system was trained offline based on non-linear process input and output data by Levenberg-Marquardt back propagation method. When optimization parameters were adjusted, tanks system was further controlled by NNPC controller.

Secondly, tanks system was controller with neuro-fuzzy controller (NFC) formed from neural predictive controller and ANFIS controller. ANFIS was trained by PID controller. PID parameters were designed by Strejc method (Bakošová et al. 2003) in five training periods. ANFIS have two inputs: set-point error *e* and derivation of set-point error *de*. Sixteen membership function bell shape were chosen for ANFIS input: nine for variable *e* and seven for variable *de* (Figure 5). The neural predictive and the neuro-fuzzy cotnroller were tested in MATLAB/SIMULINK ® environment using neural network toolbox and fuzzy logic toolbox. This experiment was designed to compare a neural predictive controller with neuro-fuzzy controller performance while controlling and nominal process.

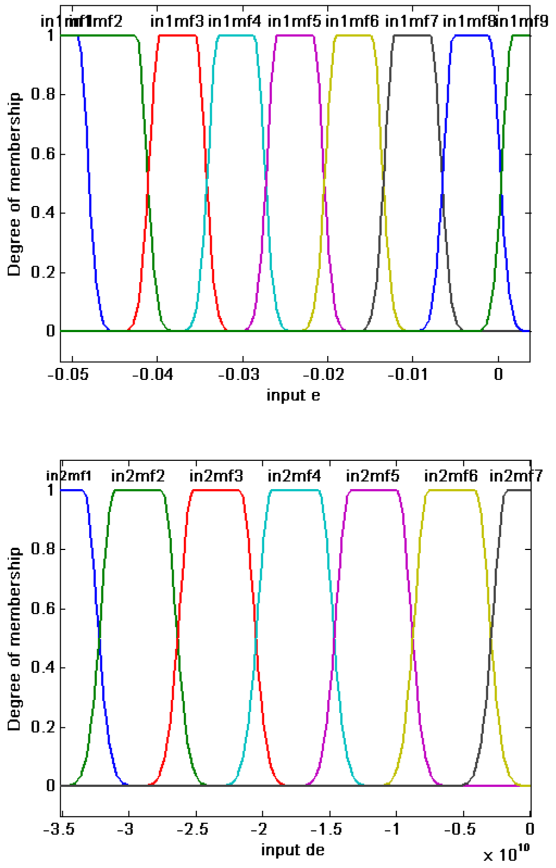

Fig.5. Membership functions for input variables *e* and *de*

For neural predictive controller had IAE criteria value 5.07 and for neuro-fuzzy controller had IAE criteria value 3.94. In Figure 6, set-point changes of the desired height profile were tracked with satisfactory result in both considered cases. However, it can be seen, that the controlled variable (h_3) profiles exhibit differences for both controllers compared. The neuro-fuzzy controller had more fainting performance that the neural predictive controller.

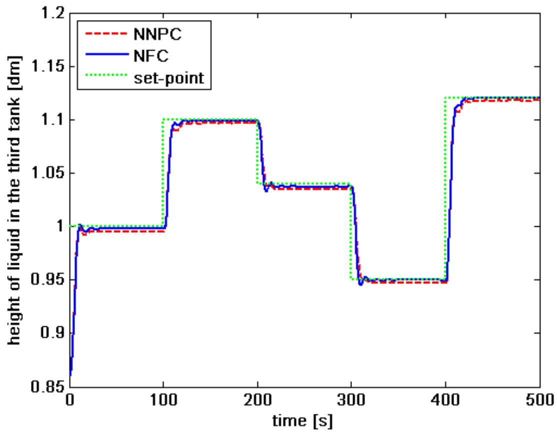

Fig.6. Comparison of NNPC and NFC performance for nominal plant

4.3 Process control in the perturbed state

Besides the good regulatory performance tested above, tracking abilities of controllers proposed in the presence of disturbances is of utmost importance. Disturbance was applied during the control curse and it was set as step change of inlet volumetric flow rate to the second tank (q_{02}). This disturbance was change in range ± 10% from nominal value q_{02}.

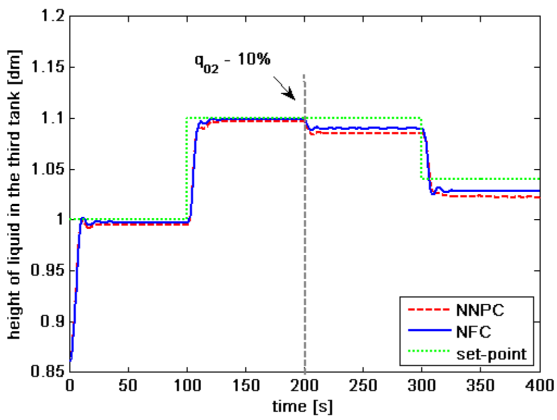

Fig.7. Comparison of NNPC and NFC performance for perturbed state – step change of q_{02} – 10% from nominal value

A comparison of the neural predictive controller and the neuro-fuzzy controller performance tested in the presence of process parameter is demonstrate in Figure 7,8 (the arrow is to show the time instants when disturbance was applied). IAE criteria values are shown in Table 2.

Table 2. Values of IAE criteria

Controller\Disturbance	q_{02} – 10% from nominal value	q_{02} + 10% from nominal value
NNPC	5.522	3.998
NFC	4.144	3.403

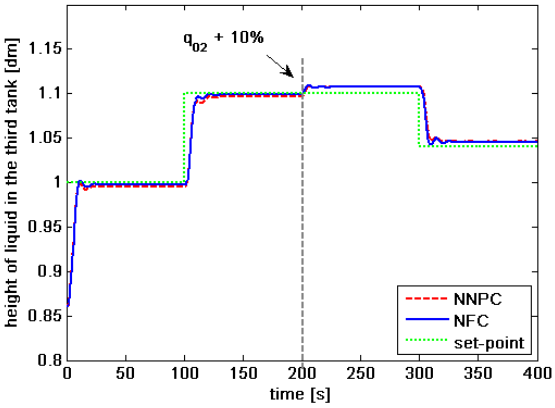

Fig.8. Comparison of NNPC and NFC performance for perturbed state – step change of q_{02} + 10% from nominal value

5. CONCLUSION

In this paper, we present intelligent control of a three tanks system. This intelligent control system is composed from two individual controllers: neural predictive controller and ANFIS controller.

The main goal of the resulting control system was to enhance a profile of height of liquid in the third tank by manipulating the inlet volumetric flow rate to the first tank. Simulation results and IAE criteria obtained demonstrated the usefulness and robustness of the proposed control system, and general advantages of the innovative technique in control application.

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