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NEURO-FUZZY CONTROL OF CHEMICAL TECHNOLOGICAL PROCESSES

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Abstract: By continuous improvement of the intelligent control systems achieves more accurate values of the controlled parameters which lead to the more effective control, entirely. This paper presents the intelligent control system design via the combination of the predictive 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 Continuous Stirred-Tank Reactor (CSTR) control problem. Experimental results confirmed control quality improvement in the combined controller over the original predictive and PID controller.

Keywords: Intelligent control, predictive controller, neuro-fuzzy controller, chemical reactor.

1 INTRODUCTION

Process control aims at achieving 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. raises.

Nowadays, there is an increasing interest in enforcing the productivity of work and hence finding the optimal control system. Regarding this issue, we often speak about intelligent system. This was seen as the best way to good results since the beginning of the very idea of the intelligent control system. Fundamentally, it is the closest step towards the man himself and his excellence. The development of regulators followed this line to a large extent.

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.

One common method of controller designing is via fuzzy control and neural networks. Both methods possess good properties and complement each other. Therefore the effect is increased by combining them. The controller designed by these methods is appropriate for controlling more complex and difficult to describe processes. Chemical-technological processes belong to this kind of processes as well. One important property of neural networks is the ability to generalize the rules between the input and output variables. Further on, these rules are applied to any value of the input variable. Therefore this method is applicable to control and simulation techniques. To achieve the most accurate reference value, we search appropriate extensions and improvements in the intelligent control system.

For this purpose, the predictive control seems to be a promising candidate. Its properties are suggested by the name. The prediction is a form of prognoses of future model states. Using these states and suitable optimization criterion, it is possible to get more accurate values and the controlling becomes overall more effective.

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 the chemical reactor. The chemical reactor introduce one of the complicated type of the chemical-technological processes where be needed that the control to have been full sail and without expressive overshooting.

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 (fig. 1).

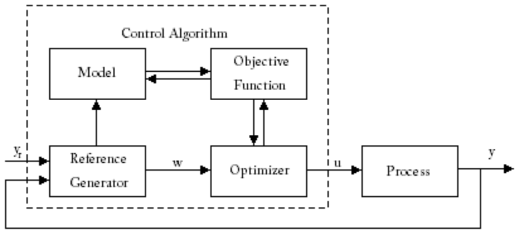

Fig. 1. Model-based predictive control scheme

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.

$$J\big(t,u(k)\big) = \sum_{i=N_1}^{N_2}\big(y_m(t+i) - y_r(t+i)\big)^2 + \\ +\lambda \sum_{i=1}^{N_u}(u'(t+i-1) - u'(t+i-2))^2 \qquad (1)$$

where N1, N2 and Nu define the horizons over the tracking error and the control increments are evaluated. The u' variable is the tentative control signal, yr is the desired response and ym 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 nad output constraints:

$$\begin{aligned} u_{min} &\le u \le u_{max} \\ \Delta u_{min} &\le \Delta u \le \Delta u_{max} \\ y_{min} &\le y \le y_{max} \\ \Delta y_{min} &\le \Delta y \le \Delta y_{max} \end{aligned} \qquad (2)$$

2.1 *System modeling using neural network*

Neural network needs the system input and output data (fig.2) (V. Bucko (2004)). Neural network is connected parallel to system and they share input. Second input to neural network is error between system and neural network output. Based on this error, new parameters of neural network are adjusted. Sampling period of input and output data, network architecture, training algorithm and train periods number affect quality of trained neural network.

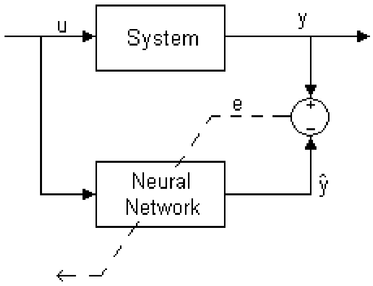

Fig. 2. Generation the neural model

The neural model of the system is given by:

$$y_k = f(u_{k-1}, u_{k-2}, u_{k-3}, y_{k-1}, y_{k-2}, y_{k-3}) \qquad (3)$$

3 NEURO-FUZZY CONTROLLER

The neural predictive controller can be extended with neuro-fuzzy controller, connected in parallel (fig. 4). 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 Fig. 3.

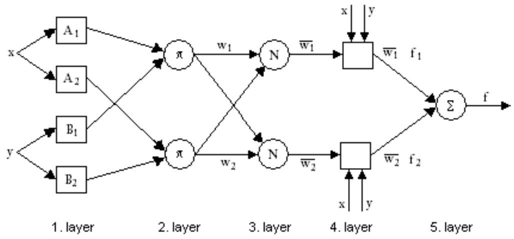

Fig. 3. System architecture ANFIS

The entire system consist of five layers, and the relationship between the input and output of each layers is summarized follows:

Layer1: Every node i in this layer is an adaptive node with a node output defined by

$$O_{1,i} = \mu_{A_i}(x) \quad for\ i = 1,2 \quad or \tag{4}$$

$$O_{1,i} = \mu_{B_{i-2}}(y) \quad for\ i = 3,4 \tag{5}$$

where x (or y) is the input to the node; A_i (or B_{i-2}) is a fuzzy set associated with this node, characterized by the shape of the membership function in this node. Parameters in this layer are referred to as premise (antecedent) parameters.

Layer 2: Every node in this layer is a fixed node labeled Π, which multiplies the incoming signals and output product.

$$O_{2,i} = w_i = \mu_{A_i}(x) \times \mu_{B_i}(y),\ i = 1,2. \tag{6}$$

Each output node represents the firing strength of a rule.

Layer 3: Every node in this layer is a circular node labeled N. The ith node calculates the ratio of the ith rule's firing strength to the sum of all rule's firing strengths

$$O_{3,i} = \overline{w} = \frac{w_i}{w_1+w_2},\ i = 1,2. \tag{7}$$

Output of this layer is called normalized firing strengths.

Layer 4: Node i in this layer computes the contribution of the ith rule towards the model output, with the following node function:

$$O_{4,i} = \overline{w}_i f_i = \overline{w}_i(p_i x + q_i y + r_i) \tag{8}$$

where $\overline{w}_i$ is the output of layer 3 and $\{p_i, q_i, r_i\}$ is the parameter set. Parameters in this layer are referred to as consequent parameters.

Layer 5: The single node in this layer is a fixed node labeled Σ that computes the overall output as the summation of all incoming signals.

$$Overal\ output = O_5 = \textstyle\sum_i \overline{w}_i f_i. \tag{9}$$

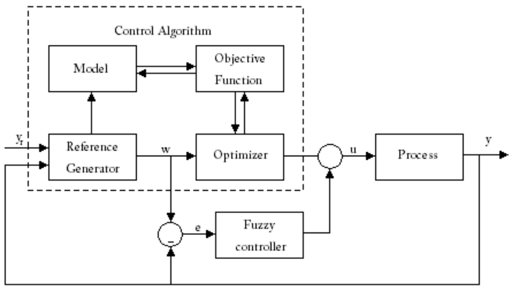

Fig. 4. Neuro-fuzzy control scheme

4 ILUSTRATIVE EXAMPLE

4.1 *CSTR*

Consider CSTR (Mikleš and Fikar (2007)) with first-order irreversible parallel reaction according to the scheme

$$A \xrightarrow{k_1} B$$
$$A \xrightarrow{k_2} C$$

The mathematical model of CSTR is:

$$\frac{dc_A}{dt} = \frac{q}{V}c_{vA} - \frac{q}{V}c_A - k_1 c_A - k_2 c_A \tag{10}$$

$$\frac{dc_B}{dt} = \frac{q}{V}c_{vB} - \frac{q}{V}c_B + k_1 c_A \tag{11}$$

$$\frac{dc_C}{dt} = \frac{q}{V}c_{vC} - \frac{q}{V}c_C + k_2 c_A \tag{12}$$

$$\frac{d\upsilon}{dt} = \frac{q}{V}\upsilon_v - \frac{q}{V}\upsilon - \frac{Ak}{V\rho c_p}[\upsilon - \upsilon_c] + \frac{Q_r}{V\rho c_p} \tag{13}$$

$$\frac{d\upsilon_c}{dt} = \frac{q}{V_c}\upsilon_{vc} - \frac{q}{V_c}\upsilon_c + \frac{Ak}{V_c\rho_c c_{pc}}[\upsilon - \upsilon_c] \tag{14}$$

The rate of reaction is a strong function of temperature:

$$k_1 = k_{1\infty}e^{-\frac{E_1}{R\upsilon}} \quad k_2 = k_{2\infty}e^{-\frac{E_2}{R\upsilon}} \tag{15}$$

For reaction heat gives:

$$Q_r = k_1 c_A V(-\Delta_r H_1) + k_2 c_A V(-\Delta_r H_2) \tag{16}$$

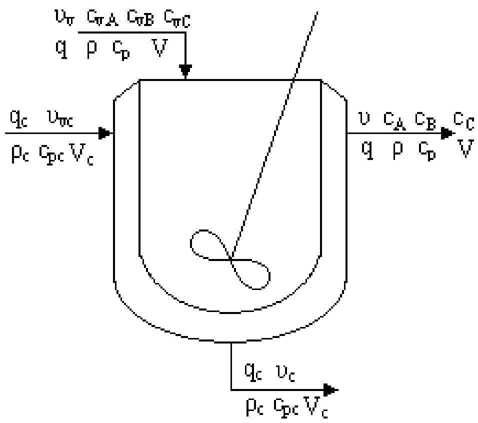

Fig. 5. Signification scheme of chemical reactor

Temperature of reaction mixture υ is controlled variable and volumetric flow rate of coolant q_c is input variable. The process state variables are molar concentration of A, B and C (c_A, c_B and c_C) and temperatures of reaction mixture υ *and* coolant υ_c. The model parameters are summarized in Table 1.

Variable	Unit	Value
c_{vA}	kmol m^{-3}	4,22
c_{vB}	kmol m^{-3}	0
c_{vC}	kmol m^{-3}	0
Q	m^{3}min^{-1}	0,015
υ_v	K	328

P	kg m^{-3}	1020
c_p	kJ $kg^{-1}K^{-1}$	4,02
V	m^3	0,23
q_{vc}	m^3min^{-1}	0,004
υ_{vc}	K	298
ρ_c	kg m^{-3}	998
c_{pc}	kJ $kg^{-1}K^{-1}$	4,182
V_c	m^3	0,21
A	m^2	1,51
K	kJ $min^{-1}m^{-2}K^{-1}$	42,8
E_1/R	K	9850
ΔrH_1	kJ $kmol^{-1}$	$-8{,}6.10^4$
$k_{1\infty}$	min^{-1}	$1{,}55.10^{11}$
E_2/R	K	22019
ΔrH_2	kJ $kmol^{-1}$	$-1{,}82.10^4$
$k_{2\infty}$	min^{-1}	$4{,}55.10^{25}$

Table 1. Parameters of the chemical reactor

4.2 *Neural predictive control*

Proposed neural predictive controller was tested in MATLAB/SIMULINK environment using neural network toolbox. NN predictive controller block was used. Neural network model of CSTR was trained offline based on nonlinear process input and output data by Levenberg-marquardt backpropagation method. Simulation results are shown in Fig.6.

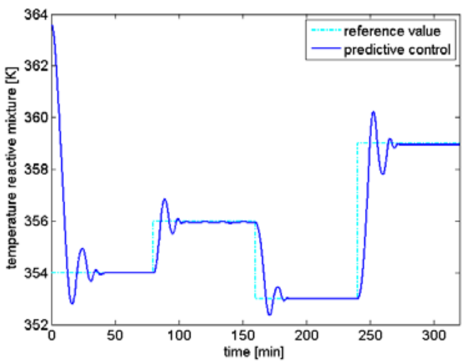

Fig. 6. Control response of chemical reactor with neural predictive controller

4.3 *Neuro-fuzzy predictive control*

In this approach neuro-fuzzy controller ANFIS was trained based on PID controller. PID parameters was designed by Smith-Murrill method in five training periods. 7 for „e“ input and 5 for „de“ input membership function bell shape were chosen for ANFIS input. Fig.7. depicts neuro-fuzzy predictive control.

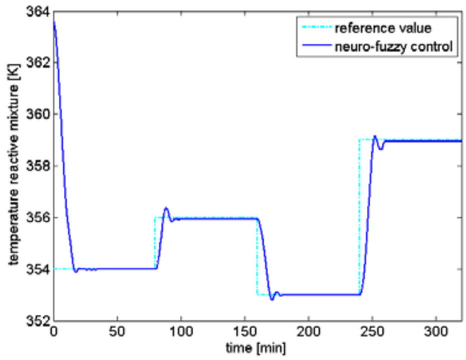

Fig. 7. Control response of chemical reactor with combinative control

4.4 *Performance of controllers comparison*

Our proposed design of neuro-fuzzy controller was benchmarked with conventional PID controller and neural predictive controller. From fig.8 it is observed, that performance of conventional PID controller is lowest. The performance of neuro-fuzzy controller is higher than neural predictive controller, because of better quality of integral criteria.

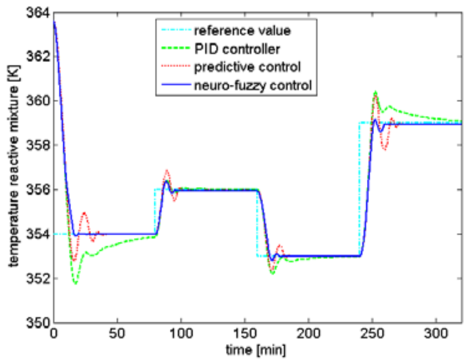

Fig. 8. Comparison of neuronal predictive controller, combinative controller and conventional PID controller

5 CONCLUSION

In this paper, we present intelligent control of the continuous stirred-tank reactor. The results reported here indicate, that from neural predictive controller, neuro-fuzzy controller and PID controller, neuro-fuzzy control scheme shows the best performance.

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