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Neuro-fuzzy control design of processes in chemical technologies

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The paper presents design of neuro-fuzzy control and its application in chemical technologies. Our approach to neuro-fuzzy control is a combination of the neural predictive controller and the neuro-fuzzy controller (Adaptive Network-based Fuzzy Inference System - ANFIS). These controllers work in parallel. The output of ANFIS adjusts the output of the neural predictive controller to enhance the control performance. Such design of an intelligent control system is applied to control of the continuous stirred tank reactor and laboratory mixing process.

Key words: neuro-fuzzy control, chemical reactor, neural predictive controller, ANFIS, laboratory process

1. Introduction

Processes in chemical technology are usually complicated and exhibit large variations in their behavior and control. Some issues can be caused by nonlinear behavior of the controlled processes or by not exactly known parameters, and other reasons. Disturbances can also affect the operation of such processes. Model based control strategies can suffer from inaccuracy of mathematical models of the controlled processes. Various control techniques have been proposed and employed for control of chemical processes, such as adaptive control [4, 7, 11], robust control [6, 20], predictive control [12, 14], intelligent control etc. Nowadays, intelligent control has gained a lot of attention as a design control method.

There are different methods of intelligent controllers design, such as fuzzy control, neural networks, genetic algorithms or expert systems. Appropriate combinations of these methods provide another design possibilities. Known approach to controller design is combination of fuzzy control and neural networks. Both methods provide good properties and complement each other well. Resulting controllers are suitable for the control

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of complex or difficult processes, such as chemical reactors, distillation columns, heat exchangers, etc.

This paper describes neuro-fuzzy control which is a combination of two methods of intelligent system control [15, 18]. Parallel connection of the neural predictive controller [21] and the neural-fuzzy controller [5] should provide better performance in terms of smaller overshoots and better tracking. Predictive control strategies employ a model of the process to predict the future response over a specified horizon [9, 16]. The model designed by artificial neural network does not need exact mathematical description of the plant. ANFIS is the neuro-fuzzy controller. This control method represents a neural network approach to the design of fuzzy inference systems and bases on the input-output data of the system under consideration [13, 22]. In our case, ANFIS is used mainly as an assistant controller, which can improve set-point tracking properties.

Suitability of the proposed control system is shown in this paper by simulation results and a real-time control application to the laboratory mixing process. For the simulation purposes, CSTR was chosen as the controlled process, and serves as an example to illustrate properties of the proposed control system. In the second case, a laboratory continuous stirred tank reactor was controlled and used as a mixer to prepare of NaCl solution with a required concentration.

2. Neuro-fuzzy control

Our design of an intelligent control system comprises two controllers. These controllers are connected in parallel to a feedback control loop as shown in Fig. 1, where w represent the reference value, e is the set-point error, u is the input to the process and y is the output of the process. The first controller is the neural predictive controller and the second one is the neuro-fuzzy controller of the ANFIS type. These controllers are designed separately to achieve better regulatory performance than the control performance of the neural predictive controller.

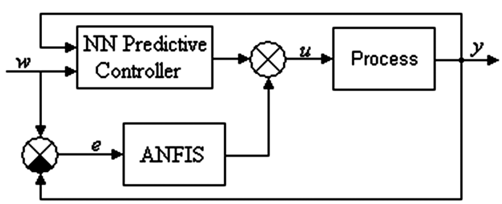

Figure 1. Neuro-fuzzy control scheme.

The neural predictive controller is considered as the main controller. ANFIS in this system is an assistant controller improving the performance of the independent predictive neural controller.

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2.1. Neural predictive control

The term MBPC (Model-Based Predictive Control) concerns several different control techniques [16, 23]. All of them bases on the same idea. The block diagram in Fig. 2 illustrates the model predictive control process.

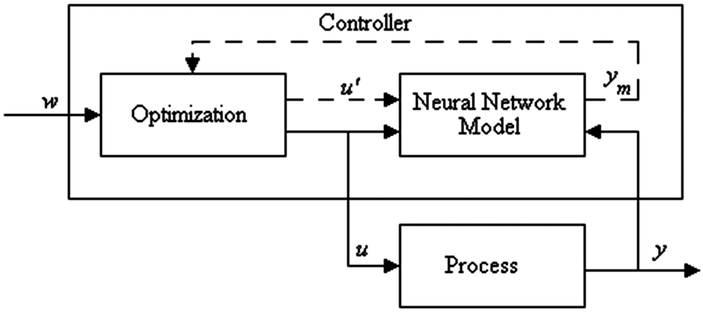

Figure 2. Model-based predictive control scheme.

The controller uses a neural network (NN) model to predict future process responses to potential control signals. The NN model is trained off-line, in batch, using training algorithms which uses data collected from the operation of the plant. The procedure of the network parameters selection is called training of the network. NN model of the controlled plant is two-layered network with a sigmoid transfer function of the neurons in the hidden layer and a linear transfer function in the output layer. This structure is shown in Fig. 3, where $u(t)$ is the system input, $y(t)$ is the plant output, $y_m(t+1)$ is the NN plant model output, TDL blocks are the tapped delay lines where the previous values of the input signals are stored, $IW^{i,j}$ is the weighting matrix from the input layer j to the layer i, $LW^{i,j}$ is the weighting matrix from the layer j to the layer i. The prediction error between the plant output and the NN output is used as the NN training signal. The NN model uses previous inputs and previous plant outputs to predict future values of the plant output.

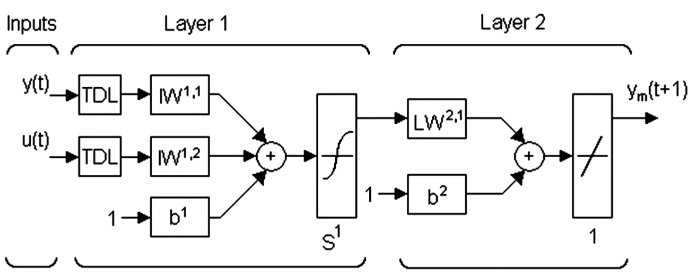

Figure 3. Structure of the neural network plant model.

The controller requires enough amount of computational resources because optimization algorithm is performed at each sample time to determine the optimal control input. The model predictive control method is based on the receding horizon technique. The neural network model predicts the process response over a specified time horizon. The predictions are used by a numerical optimization program to determine the control signal which minimizes the following performance criterions

$$J(t,u(k)) = \sum_{i=N_1}^{N_2} (w(t+i) - y_m(t+i))^2 + \lambda \sum_{i=1}^{N_u} \left(u'(t+i-1) - u'(t+i-2)\right)^2 \tag{1}$$

Here N_1, N_2 and N_u define the horizons over which the tracking error and the control increments are calculated. Variable u' is the tentative control signal, w is the desired response and y_m is the network model response. Parameter λ determines the relation of the control increments and the tracking errors in the criterion index.

The controller consists of the neural network model and the optimization block. The optimization block determines the values of u' which minimizes J, and then the optimal u is the input into the process.

2.2. ANFIS

Neuro-fuzzy systems combine neural networks and fuzzy logic and have recently gained a lot of interest in research and application. A specific approach in the neuro-fuzzy development is ANFIS (Adaptive Network-based Fuzzy Inference System) [13]. ANFIS uses a feed-forward network to search for fuzzy decision rules that perform well for a given task. Using input-output data set, ANFIS creates a Fuzzy Inference System for which the membership function parameters are adjusted using a combination of back propagation and the least squares method. ANFIS architecture of the first-order Takagi-Sugeno inference system is shown in Fig. 4 [22]. Output f of the ANFIS controller is the response to input x and y, w_i are the firing strengths and $\bar{w}_i$ are the normalized firing strengths.

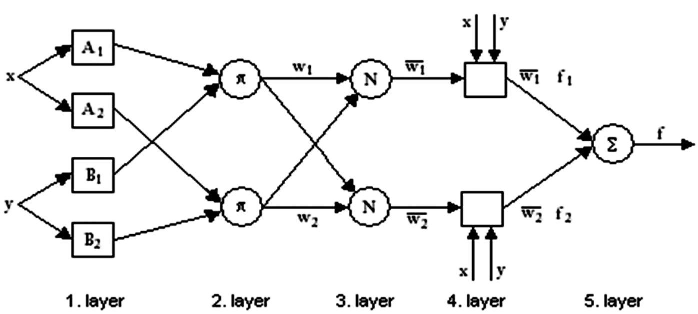

Figure 4. ANFIS system architecture.

3. Simulations and experimental results

In this section we apply the proposed control approach to two examples of chemical technology. The first is simulator of CSTR control and the second is real-time control of a laboratory process.

3.1. Simulation control of CSTR

Process model

Consider CSTR (Fig. 5) [16] with a first-order irreversible parallel reaction according to scheme:

$$\begin{aligned} A &\xrightarrow{k_1} B \\ A &\xrightarrow{k_2} C \end{aligned} \tag{2}$$

A simplified dynamic mathematical model of such CSTR can be represented as follows:

$$\frac{dc_A}{dt} = \frac{q}{V}c_{vA} - \frac{q}{V}c_A - k_1 c_A - k_2 c_A \tag{3}$$

$$\frac{dc_B}{dt} = \frac{q}{V}c_{vB} - \frac{q}{V}c_B + k_1 c_A \tag{4}$$

$$\frac{dc_C}{dt} = \frac{q}{V}c_{vC} - \frac{q}{V}c_C + k_2 c_A \tag{5}$$

$$\frac{d\vartheta}{dt} = \frac{q}{V}\vartheta_v - \frac{q}{V}\vartheta - \frac{Ak}{Vc_p\rho}[\vartheta - \vartheta_c] + \frac{Q_r}{Vc_p\rho} \tag{6}$$

$$\frac{d\vartheta_c}{dt} = \frac{q}{V_c}\vartheta_{vc} - \frac{q}{V_c}\vartheta_c + \frac{Ak}{V_c\rho_c c_{pc}}[\vartheta - \vartheta_c] \tag{7}$$

Rate of the reaction strongly depends on the temperature

$$k_i = k_{i\infty} e^{\frac{-E_i}{R\vartheta}} \tag{8}$$

The reaction heat can be calculated as follows:

$$Q_r = k_1 c_A V(-\Delta_r H_1) + k_2 c_A V(-\Delta_r H_2) \tag{9}$$

Temperature of the reaction mixture ϑ [K] is a controlled variable and volume flow rate of the coolant, q_c [m^{3}min^{-1}] is the input variable. The process state variables are: molar concentrations of A, B and C (c_A, c_B and c_C [kmol m^{-3}]), temperatures of the reaction mixture ϑ [K], and the coolant ϑ_c [K]. Model parameters are summarized in Tab. 1.

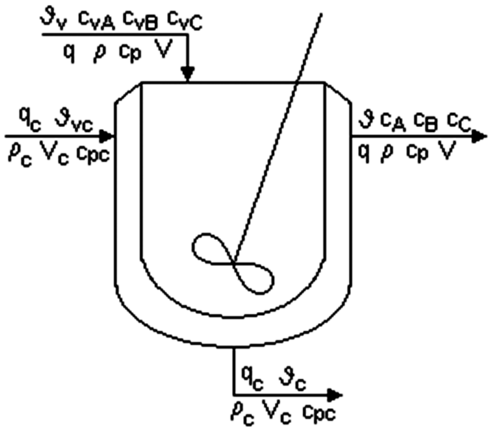

Figure 5. Scheme of the chemical reactor.

Table 11. Parameters of the chemical reactor.

Variable	Unit	Value	Variable	Unit	Value
c_{vA}	kmol m^{-3}	4.22	c_{pc}	kJ kg^{-1}K^{-1}	4.182
c_{vB}	kmol m^{-3}	0	V_c	m^3	0.21
c_{vC}	kmol m^{-3}	0	A	m^2	1.51
q	m^{3}min^{-1}	0.015	K	kJ min^{-1}m^{-2}K^{-1}	42.8
ϑ_v	K	328	E_1/R	K	9850
ρ	kg m^{-3}	1020	$\delta_r H_1$	kJ kmol^{-1}	-8.6 $\cdot 10^4$
c_p	kJ kg^{-1}K^{-1}	4.02	$k_{1\infty}$	min^{-1}	1.55$\cdot 10^1$1
V	m^3	0.23	E_2/R	K	22019
q_{vc}	m^{3}min^{-1}	0.004	$\delta_r H_2$	kJ kmol^{-1}	-1.82$\cdot 10^4$
ϑ_{vc}	K	298	$k_{2\infty}$	min^{-1}	4.55$\cdot 10^{25}$
ρ_c	jg m^3	998			

Control of CSTR in the nominal state

Firstly CSTR was simulated with a neural predictive controller (NNPC). To set-up this controller, a neural network model was designed. Neural network model of CSTR was trained off-line by the Levenberg-Marquardt back propagation method [14] based on nonlinear process input and output data. Input data represented the volume flow rate of the coolant, q_c [m^{3}min^{-1}], and the output data were the temperatures of the reaction mixtures, ϑ [K]. NN model had two delayed plant inputs, two delayed plant outputs and

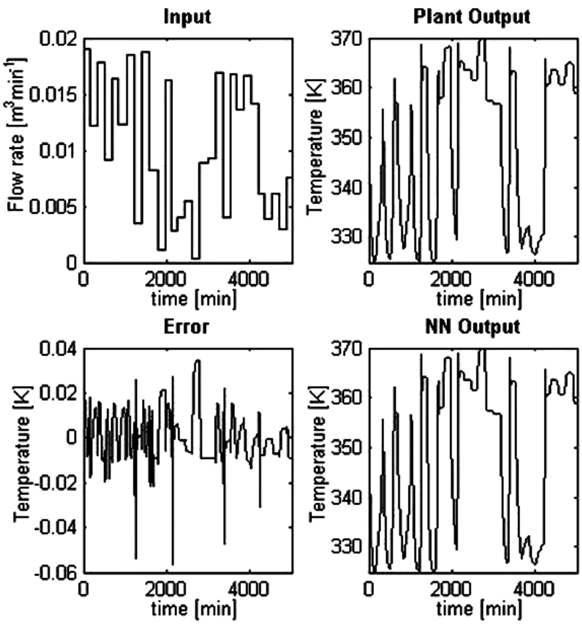

Figure 6. Training data for NN model of CSTR.

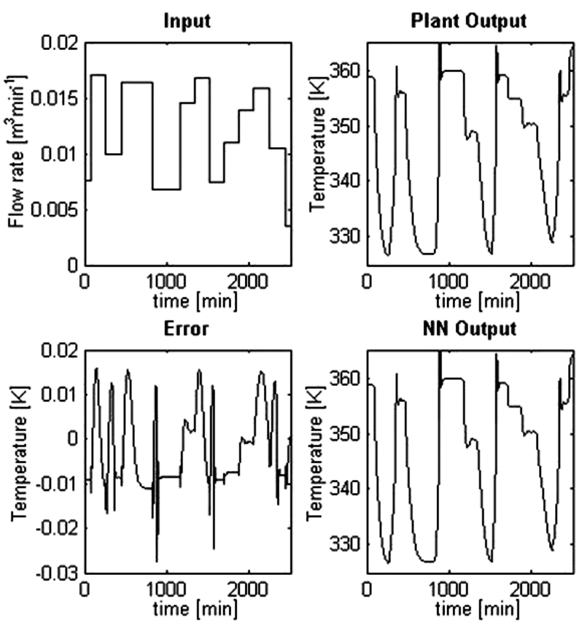

Figure 7. Validation data for NN model of CSTR.

four neurons in the hidden layer. Results of the training for the training data are shown in Fig. 6. Results of validation presents Fig. 7. Validation for test data is shown in Fig. 8. In every case, the prediction error was sufficiently small and the process output and the NN model output fitted well.

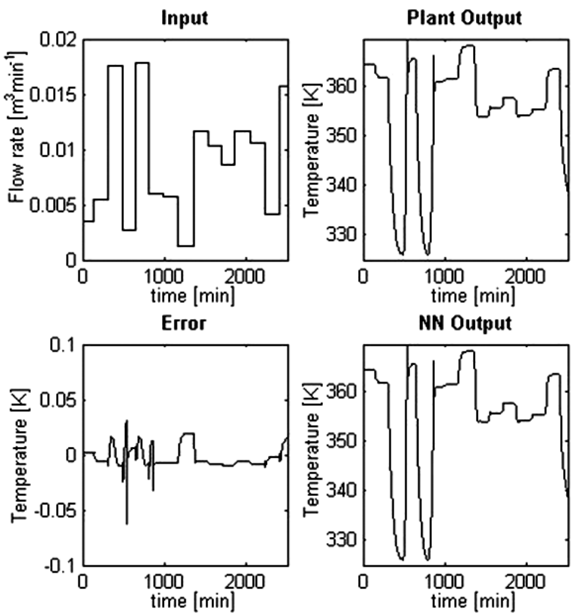

Figure 8. Test data for NN model of CSTR.

In the next step parameters of the neural predictive controller were set up. Prediction horizon for the neural model output variable (N_2) was set to the value of 10 and the prediction horizon for the control variable (N_u) was assumed 8, and the weighting parameter (λ) was set to the value of 0.05. Line search function for the predictive control optimization was selected as the backtracking search [8] and sample time was 1 min. Simulating tool was MATLAB Neural Network Toolbox NNPC. Parameters of the simulator were set experimentally to achieve best quality of the control performance. Constraints of the control signal and the controlled variable were set based on the neural network model: for control variable from 0 to 0.02 m^3min^{-1} and for controlled variable from 320 to 380 K. The designed neural predictive controller was used to control CSTR. The controlled variable $y(t)$ was the temperature of the reaction mixture, ϑ [K], and the reference $w(t)$ was the temperature of the reaction mixture to be achieved. Obtained results are presented in Fig. 9.

Further step was experiments of CSTR control using neuro-fuzzy control consisting of the neural predictive controller and the ANFIS controller. The ANFIS controller was trained by a PID controller to ensure integration and differentiation properties in the ANFIS. PID parameters were designed by the Smith-Murrill method in five training periods and obtained mean square error value was $3.32 \cdot 10^{-6}$. The ANFIS controller had

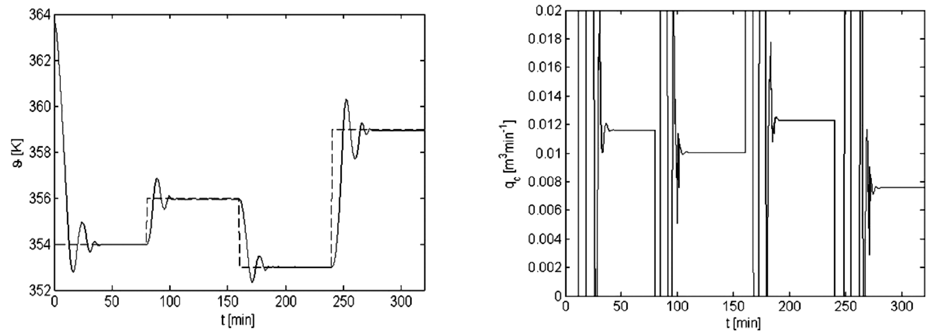

Figure 9. Trajectory of the controlled variable $y(t)$ (temperature of the reaction mixture, solid line) with a neural predictive controller, reference variable $w(t)$ (dashed line) (left) and the trajectory of the control variable $u(t)$ (volume flow rate of the coolant) with a neural predictive controller (right).

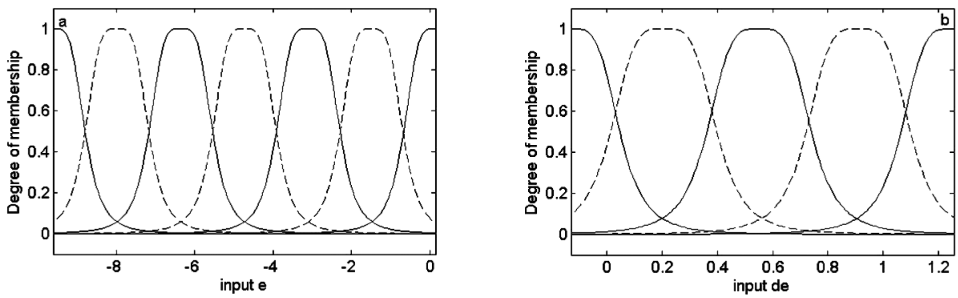

Figure 10. Membership functions for input variables e (a) and de (b) of the control of the CSTR.

two inputs: set-point error e, and difference of the set-point error de. Twelve bell shaped membership function were chosen for the ANFIS input: seven for variable e and five for variable de (Fig. 10). The controller had 35 rules and all ANFIS controller parameters were chosen experimentally. Obtained simulation results are presented in Fig. 11.

To assess the suitability of the proposed intelligent control system, its performance was compared with that of the neural predictive controller and a conventional PID controller based on the normalized integration quality criteria of control (Tab. 2). Integral squared error (ISE) and integral absolute errors (IAE) [16] are often used criteria for the evaluation of the control performance quality and they were also used for the comparison of the proposed controllers. Fig. 12 shows output behavior for all three approaches.

Control of CSTR in the perturbed state

Tracking abilities of controllers proposed in the presence of disturbances is of utmost importance. Disturbances were applied as step changes of the input concentration of substance A (c_{vA}), input temperature of the reaction mixture (ϑ_v), input temperature

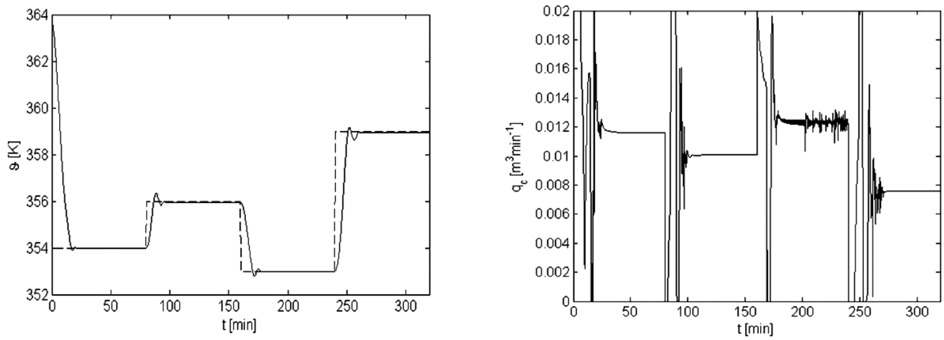

Figure 11. Trajectory of the controlled variable $y(t)$ (temperature of the reaction mixture, solid line) with a neuro-fuzzy control, reference variable $w(t)$ (dashed line) (left) and the trajectory of the control variable $u(t)$ (volume flow rate of the coolant) with a neuro-fuzzy control (right).

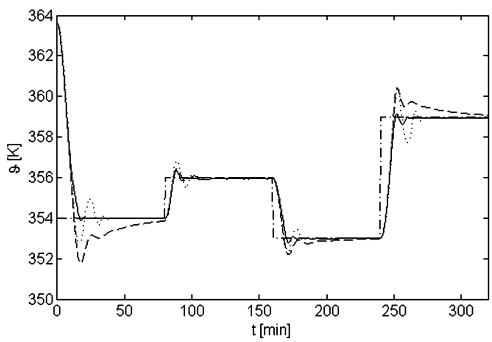

Figure 12. Comparison of controlled variable $y(t)$ (temperature of the reaction mixture): reference variable $w(t)$ (dash-dotted line), controlled variable $y(t)$ with a PID controller (dashed line), controlled variable $y(t)$ with an NNPC controller (dotted line), and controlled variable $y(t)$ with an NFC controller (solid line).

Table 12. Comparison of integral absolute error and integral square error of CSTR control.

Type of control	IAE	ISE
NFC	0.7838	0.9861
NNPC	0.9115	1.0500
PID	1.0000	1.0000

of the coolant (ϑ_{vc}), and the flow rate of the reaction mixture (q). Input concentration of substance A (c_{vA}) was changed in the range of $\pm 10\%$ of the nominal value. Input temperature of the reaction mixture (ϑ_v) was changed in the range of ± 8 K from the nominal value. Input temperature of the coolant (ϑ_{vc}) was changed in the range of ± 8 K from the nominal value. Flow rate of the reaction mixture was changed in the range of $\pm 15\%$ from the nominal value.

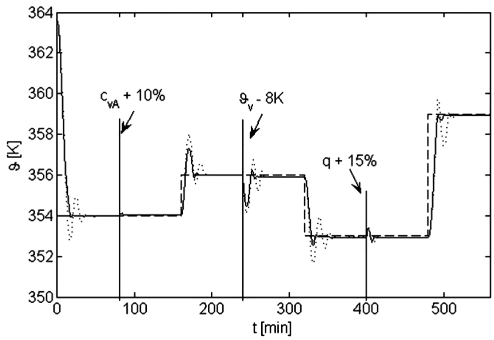

Figure 13. Comparison of the trajectory of the controlled variable $y(t)$ (temperature of the reaction mixture) for perturbed state; reference variable $w(t)$ (dash-dotted line), controlled variable $y(t)$ with an NNPC controller (dotted line), and controlled variable $y(t)$ with an NFC controller (solid line).

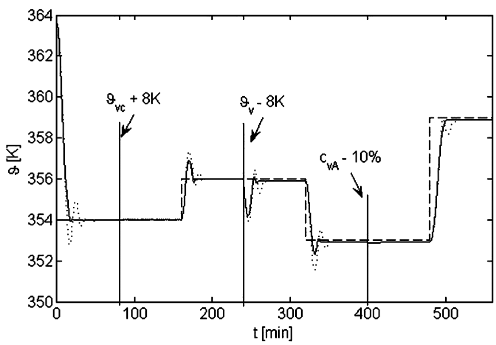

Figure 14. Comparison of the trajectory of the controlled variable $y(t)$ (temperature of the reaction mixture) for perturbed state; reference variable $w(t)$ (dash-dotted line), controlled variable $y(t)$ with an NNPC controller (dotted line) and controlled variable $y(t)$ with an NFC controller (solid line).

A comparison of the neural predictive controller and the neuro-fuzzy controller performance tested in the presence of process parameter perturbations is shown in Figs. 13 and 14 (arrows point the time instants of the disturbances influence). As one can see, the proposed controller performs significantly better in all considered cases.

3.2. Real-time control of a laboratory process

Process description

Multi-functional process control teaching system - Armfield PCT40 [1] is a system enabling to test a wide range of technological processes, as a tank, heat exchanger, continuous stirred tank reactor and their combinations [2, 3]. The PCT40 unit consists of two process vessels, several pumps, sensors, and connection to the computer. Additional equipment PCT41 and PCT42 constitute chemical reactor with a stirrer and a cooling/heating coil. The plant is shown in Fig. 15.

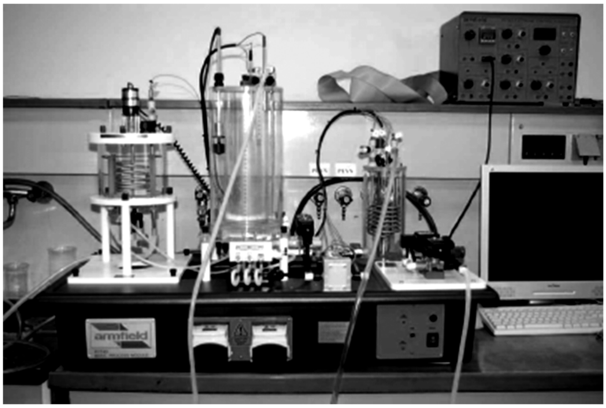

Figure 15. Multi-functional process control teaching system - Armfield.

Reactants can be injected into the reactor via normally closed solenoid valve or by a proportional solenoid valve (PSV). Third possibility of feeding water into the reactor is using one of the two peristaltic pumps.

The connection to the computer is realized via an I/O connector connected to MF624 multifunction PCL I/O card from Humusoft company. This configuration enables the use of Matlab Real-time Toolbox and Simulink.

NaCl solution of 0.8555 mol/dm^3 concentration is fed into the reactor by a peristaltic pump. The performance of the pump can be set in the range of 0-100%. But for the pump performance lower than 40% revolutions of the rotor are to small to transport the fluid from the barrel. Volumetric flow rate of NaCl solution for all measurements was 0.00175 dm^3/s. This represents 40% of the pump performance.

Water was dosed into the reactor by PSV. Application of PSV allowed for use of flow-meter. The PSV can be set in the range of 0-100%, but the volumetric flow rate of water for the PSV opening in the range of 0-30% was negligible.

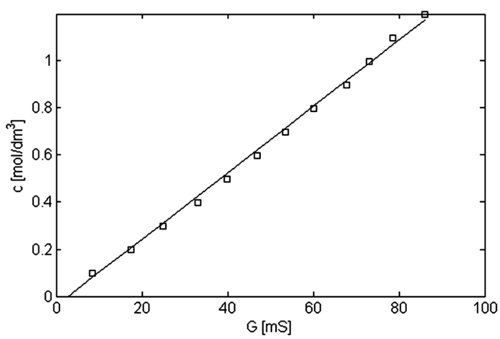

Figure 16. Calibration curve for NaCl solution.

For control purposes, the laboratory continuous stirred tank reactor is a system with single input and single output. The control variable is the volumetric flow rate of water (F) and the controlled variable is the conductivity of NaCl solution (G) inside the reactor. The concentration c of NaCl was determined on basis of the measured conductivity and the calibration curve (Fig. 16) as shown by equation (10). Used water was cold water from the standard water distribution system. The volume of the solution in the reactor was kept constant, 1 dm^3 during all experiments.

$$c = 0.0144\,G - 0.0576 \tag{10}$$

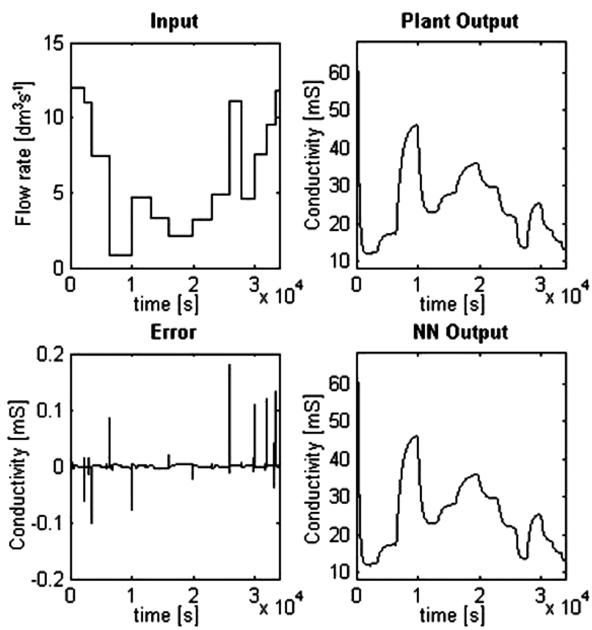

Figure 17. Training data for NN model of the laboratory process.

Control of the laboratory process

Similarly to simulations presented above, a neural network model of the laboratory process was obtained. The neural network model of the laboratory process was trained off-line by the Levenberg-Marquardt back propagation method [14] based on the input and output data. Input data represent the flow of water into the process and output data are the conductivity of NaCl solution. The structure of NN model was the same: two delayed plant inputs, two delayed plant outputs and four neurons in the hidden layer. Results of the training for the training data are shown in Fig. 17, for the validation data in Fig. 18 and for test data in Fig. 19. In every case, the prediction error was sufficiently small and the process output and the NN model output fitted well.

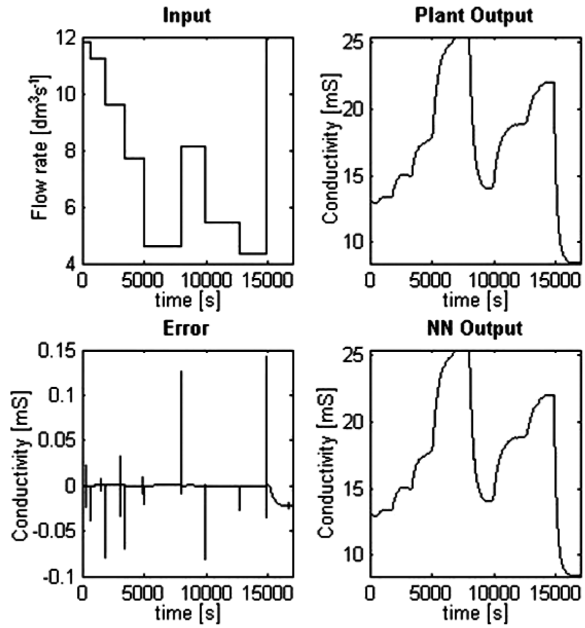

Figure 18. Validation data for NN model of the laboratory process.

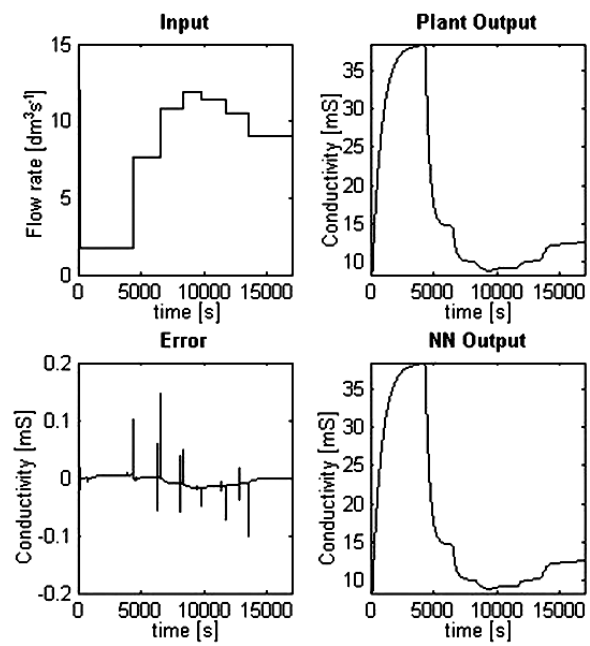

Figure 19. Test data for NN model of the laboratory process.

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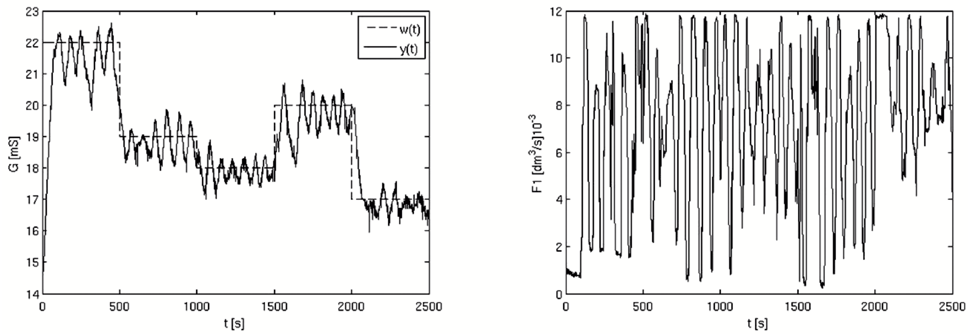

Figure 20. Trajectory of the controlled variable $y(t)$ (conductivity of NaCl solution, solid line) with a neural predictive controller, reference variable $w(t)$ (dashed line) (left) and the trajectory of the control variable $u(t)$ (water flow rate) with a neural predictive controller (right).

Firstly the neural predictive controller was set up. Prediction horizon N_2 for the output was 4, the prediction horizon for the control (N_u) was 2, the weighting parameter λ was 0.05. Line search function for the predictive control optimization was selected as the backtracking search [8] and sample time was 1 s. MATLAB Neural Network Toolbox NNPC was used and all parameters were set experimentally to achieve the best quality of the control performance. Boundary values of the control and the controlled variable were set based on the neural network model: for control variable from 0 to $12{\cdot}10^{-3}$ dm^3s^{-1} and for controlled variable from 0 to 70 mS. The controlled variable $y(t)$ was the conductivity G [mS] of NaCl solution, control variable $u(t)$ was the water flow rate F [dm^3/s], and the reference $w(t)$ was the conductivity of NaCl solution which corresponded to the required concentration of NaCl solution (see eqn. (10)). Obtained results are presented in Fig. 20.

In the second step, the laboratory process was controlled with the neuro-fuzzy control. The ANFIS was trained by a PI controller which was designed according to the Strejc method [16] in five training periods with mean square error equal to 1.35. The ANFIS controller had two inputs: set-point error e, and difference of set-point error de. Seven bell shaped membership functions were chosen for the ANFIS input: four for variable e and three for variable de (Fig. 21). It had 12 rules and all ANFIS controller parameters were chosen experimentally. Obtained experimental results are presented in Fig. 22.

To assess the suitability of the proposed intelligent control system, the control trajectory was compared to that of the neural predictive controller and a conventional PI controller based on the normalized integration quality criteria of control (Tab. 3). Integral squared error (ISE) and integral absolute error (IAE) [16] were used for the comparison of the proposed controllers. In Fig. 23, the comparison of the controlled variables can be seen.

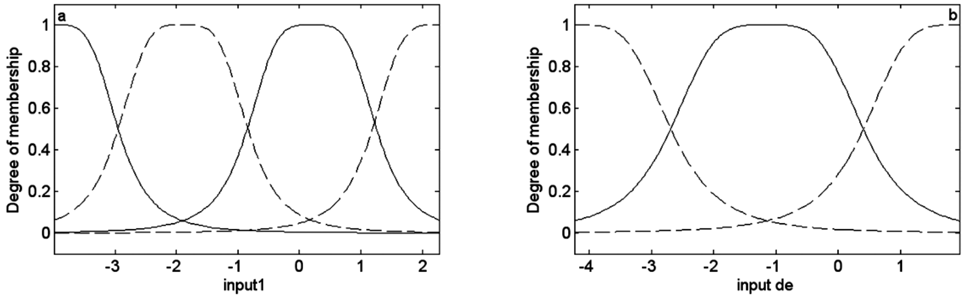

Figure 21. Membership functions for input variables *e* (a) and *de* (b) to the control of the laboratory process.

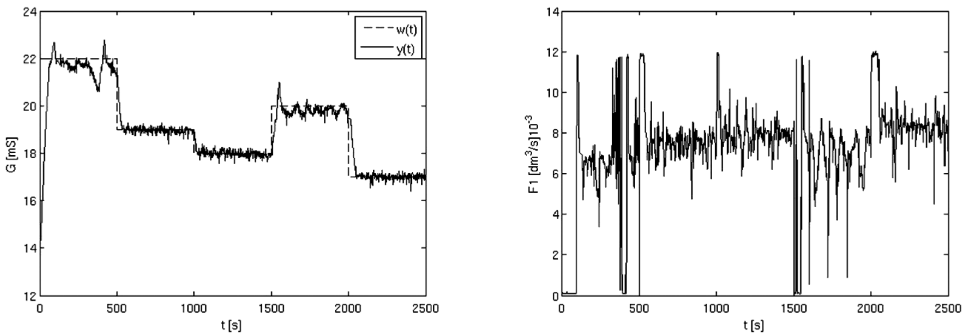

Figure 22. Trajectory of the controlled variable $y(t)$ (conductivity of NaCl solution, solid line) with a neuro-fuzzy control, reference variable $w(t)$ (dashed line) (left) and the trajectory of the control variable $u(t)$ (water flow rate) with a neuro-fuzzy control (right).

Table 13. Comparison of integral absolute error and integral square error of the control of the laboratory process.

Type of control	IAE	ISE
NFC	0.3858	0.2592
NNPC	0.6909	0.3640
PID	1.0000	1.0000

4. Conclusions

In this paper, an intelligent control system was proposed. It consists of two controllers: neural predictive controller and ANFIS controller. The main goal of the resulting control system was to enhance the profile of the controlled variable by manipulating the control variable. The results reported here indicate, that comparing the neural predictive controller, neuro-fuzzy controller and PI controller, the neuro-fuzzy control scheme shows the best performance.

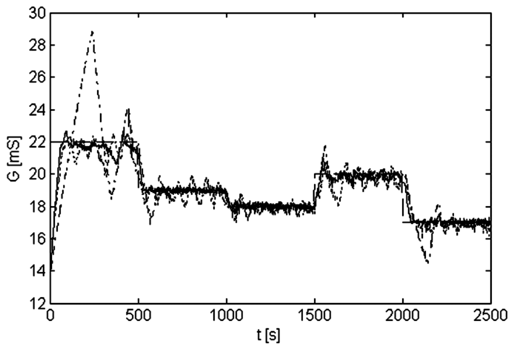

Figure 23. Comparison of the trajectory of the controlled variable $y(t)$ (conductivity of NaCl solution) of the proposed approach, reference variable $w(t)$ (dashed line), controlled variable $y(t)$ with a PID controller (dash-dotted line), controlled variable $y(t)$ with an NNPC controller (dotted line) and controlled variable $y(t)$ with an NFC controller (solid line).

Simulation and experimental results obtained demonstrate the usefulness and robustness of the proposed control system, and the general advantages of this technique in control applications.

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