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# Advanced Control of a Mixing Process

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## Abstract

Two advanced approaches to control of a laboratory process are compared in the paper. The first approach is robust one and is based on design of robust PI controllers for systems with parametric uncertainty. The design method is based on plotting the stability boundary locus in the controller-parameter plane and the sixteen plant theorem. The stability boundaries obtained for sixteen Kharitonov plants split the controller-parameter plane in stable and unstable regions. The parameters of robust PI controllers are chosen from the stable region common for all sixteen plants. The second approach combines the neural-network based predictive controller and the neuro-fuzzy controller. The neuro-fuzzy controller works in parallel with the neural-network predictive controller and corrects its output in order to enhance the control response**.** Both methods are applied for control of a laboratory chemical continuous stirred tank reactor that is used as a mixer. NaCl solution with desired concentration is prepared in the equipment. The conductivity of the solution is the controlled variable and the volumetric flow rate of water is the manipulated variable.

**Keywords**: process control, uncertainty, robust PI controller, neuro-fuzzy controller

## Introduction

Operation of plants in chemical industry is connected with many different problems. Some of them arise from varying or not exactly known parameters, non-linear behaviour of controlled processes, varying operation points. Various types of disturbances also affect operation of chemical processes. The model based control strategies suffer from the inaccurateness of mathematical models of controlled processes. All these problems can cause poor control responses or even instability of classical closed-loop control systems and various advanced control strategies are developed in last decades to overcome all above mentioned problems, as e.g. adaptive control (Dostál et al. (2011)), robust control (Bakošová et al. (2009), Gerhard et al.s (2004), Méndez-Acosta et al. (2010)), model-based predictive control (Mohammadi et al. (2010), Yu and Yu (2007)) and others.

Two of advanced approaches to control of a laboratory process are compared in the paper, the robust approach and the neuro-fuzzy one. A simple method for design of robust PI controllers is presented (Tan and Kaya (2003)). The method is based on plotting the stability boundary locus of the closed-loop control system in the plane of controller parameters that is called $(k_p, k_i)$-plane and on the sixteen plant theorem. Parameters of a stabilizing PI controller are determined from the stability region (Závacká et al. (2009)). The PI controller stabilizes a controlled system with interval parametric uncertainty, when the stability region is found for sufficient number of Kharitonov plants (Barmish et al. (1992)).

Presented neuro-fuzzy control is combination of two methods of intelligent control. The parallel connection of neural-network based predictive controller (Sámek and Macků (2008)) and neuro-fuzzy controller (Vasičkaninová and Bakošová (2007)) leads to better results in the reference variable tracking. Using this approach brings lowering overshoots in control responses and reducing settling times.

Both approaches are used for control of a laboratory continuous stirred tank reactor that is used as a mixer for preparing the NaCl solution with demanded concentration. Composition of the solution is determined by measurement of the solution conductivity and the conductivity is the controlled variable. The volumetric flow rate of water that is used for diluting of NaCl solution is the manipulated variable. The process is nonlinear and influenced by disturbances caused e.g. by pressure variations in the water distribution. These facts are reasons for application of advanced control techniques.

## Theoretical

### Robust PI controller design

Consider a SISO control system with an uncertain controlled system and a PI controller. The controlled system is a system with parametric uncertainty that can be modelled in the form of an uncertain interval system

$$G(s,b,a)=\frac{N(s,b)}{D(s,a)}=\frac{b_m s^m+b_{m-1}s^{m-1}+\cdots+b_0}{a_n s^n+a_{n-1}s^{n-1}+\cdots+a_0} \tag{1}$$

where $b_i\in\left[b_i^-,b_i^+\right]$, $i=0,1,2,\ldots,m$, and $a_j\in\left[a_j^-,a_j^+\right]$, $j=0,1,2,\ldots,n$. Let the Kharitonov polynomials associated with $N(s,b)$ and $D(s,a)$ are (Barmish, 1994)

$$\begin{aligned}
N_1(s)&=b_0^-+b_1^-s+b_2^+s^2+b_3^+s^3+\ldots\\
N_2(s)&=b_0^++b_1^+s+b_2^-s^2+b_3^-s^3+\ldots\\
N_3(s)&=b_0^++b_1^-s+b_2^-s^2+b_3^+s^3+\ldots\\
N_4(s)&=b_0^-+b_1^+s+b_2^+s^2+b_3^-s^3+\ldots
\end{aligned} \tag{2}$$

and

$$\begin{aligned}
D_1(s)&=a_0^-+a_1^-s+a_2^+s^2+a_3^+s^3+\ldots\\
D_2(s)&=a_0^++a_1^+s+a_2^-s^2+a_3^-s^3+\ldots\\
D_3(s)&=a_0^++a_1^-s+a_2^-s^2+a_3^+s^3+\ldots\\
D_4(s)&=a_0^-+a_1^+s+a_2^+s^2+a_3^-s^3+\ldots
\end{aligned} \tag{3}$$

By taking all combinations of $N_i(s)$ and $D_j(s)$ for $i, j$ = 1,2,3,4, the following family of sixteen Kharitonov plants can be obtained

$$G_K(s)=G_{ij}(s)=\frac{N_i(s)}{D_j(s)},\qquad i,j=1,2,3,4;\ K=1,\ldots,16 \tag{4}$$

The PI controller $C(s)$ is described by the transfer function in the form

$$C(s)=k_p+\frac{k_i}{s}=\frac{k_p s+k_i}{s} \tag{5}$$

The problem is to find the parameters of the PI controller (5) that stabilize the system (1).

Decomposing the numerator and the denominator polynomials in (4) (Tan and Kaya (2003)) into their even and odd parts, and substituting $s=j\omega$, where $\omega$ is the frequency, gives

$$G_K(j\omega)=\frac{N_{ie}\left(-\omega^2\right)+j\omega N_{io}\left(-\omega^2\right)}{D_{je}\left(-\omega^2\right)+j\omega D_{jo}\left(-\omega^2\right)} \tag{6}$$

The closed loop characteristic equation can be written as

$$\begin{aligned}
\Delta(j\omega)=&\left[k_i N_{ie}\left(-\omega^2\right)-k_p\omega^2 N_{io}\left(-\omega^2\right)-\omega^2 D_{jo}\left(-\omega^2\right)\right]+\\
&+j\left[k_p\omega N_{ie}\left(-\omega^2\right)+k_i\omega N_{io}\left(-\omega^2\right)+\omega D_{je}\left(-\omega^2\right)\right]=0
\end{aligned} \tag{7}$$

Then, equating the real and the imaginary parts of $\Delta(j\omega)$ to zero, one obtains

$$k_p\left(-\omega^2 N_{io}\left(-\omega^2\right)\right)+k_i\left(N_{ie}\left(-\omega^2\right)\right)=\omega^2 D_{jo}\left(-\omega^2\right) \tag{8}$$

and

$$k_p\left(N_{ie}\left(-\omega^2\right)\right)+k_i\left(N_{io}\left(-\omega^2\right)\right)=-D_{je}\left(-\omega^2\right) \tag{9}$$

Let

$$\begin{aligned}
F(\omega)&=-\omega^2 N_{io}\left(-\omega^2\right)\\
G(\omega)&=N_{ie}\left(-\omega^2\right)\\
H(\omega)&=N_{ie}\left(-\omega^2\right)\\
I(\omega)&=N_{io}\left(-\omega^2\right)\\
J(\omega)&=\omega^2 D_{jo}\left(-\omega^2\right)\\
F(\omega)&=-D_{je}\left(-\omega^2\right)
\end{aligned} \tag{10}$$

Then, (8) and (9) can be written as

$$\begin{aligned}
k_p F(\omega)+k_i G(\omega)&=J(\omega)\\
k_p H(\omega)+k_i I(\omega)&=K(\omega)
\end{aligned} \tag{11}$$

From (11), parameters of the PI controller (5) are

$$k_p=\frac{J(\omega)I(\omega)-K(\omega)G(\omega)}{F(\omega)I(\omega)-G(\omega)H(\omega)} \tag{12}$$

and

$$k_i=\frac{K(\omega)F(\omega)-J(\omega)H(\omega)}{F(\omega)I(\omega)-G(\omega)H(\omega)} \tag{13}$$

Solving these two equations simultaneously for $\omega \geq 0$, the set of parameters $k_p$ and $k_i$ is obtained. Then, it is possible to plot the dependence of $k_i$ on $k_p$, and the stability boundary locus $l(k_p, k_i, \omega)$ in the $(k_p, k_i)$-plane is obtained. The stability boundary divides the parameter plane into stable and unstable regions. The stability region is found by the choice of testing points inside the regions.

The method is very fast and effective, but one problem consists in finding a proper interval of frequency $\omega$. However, the Nyquist plot (Mikleš and Fikar (2007)) can be used for $\omega$ scaling. It is only necessary to find real values of $\omega$ that satisfy condition

$$\mathrm{Im}[G(j\omega)]=0 \tag{14}$$

All found stability regions represent values of the PI controller parameters for which the given controlled plant $G_K(s)$ with interval parametric uncertainty is Hurwitz stable.

Define the set $S_{ij}(C(s)G_{ij}(s))$ that contains all values of the parameters of the controller $C(s)$ that stabilize $G_{ij}(s)$. Then the set of all the stabilizing parameters of the PI controller that stabilize the interval plant (1), can be written

$$S(C(s)G(s,b,a)) = S_{11}(C(s)G_{11}(s)) \cap S_{12}(C(s)G_{12}(s)) \cap \cdots \cap S_{44}(C(s)G_{44}(s)) \tag{15}$$

**Neuro-fuzzy control**

Design of an intelligent control system includes two independent controllers. These controllers are connected in parallel in a feedback control loop according to the scheme shown in Fig. 1. The first controller is a neural predictive one (NNPC) and the second controller is a neuro-fuzzy one of ANFIS type.

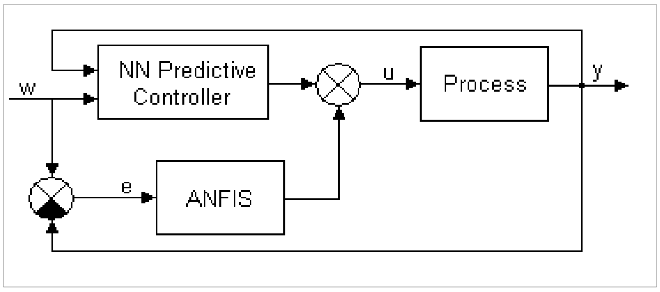


**Fig. 1.** Neuro-fuzzy control scheme.

*Neural-network predictive controller*

Model-based predictive control (MPC) is a common name for several different control techniques (Vasičkaninová et al., 2008). They all are connected by the same idea. The prediction of control inputs is based on a model of the controlled process (Fig. 2).

The neural-network predictive controller (NNPC) uses a neural network model to predict future plant responses to potential control inputs. An optimization algorithm then computes the control signals that optimize future plant performance. The neural network plant model is trained offline in batch mode using some of the training algorithms. The controller requires also significant amount of online computations, because an optimization algorithm is performed at each sample time to compute the optimal control input.

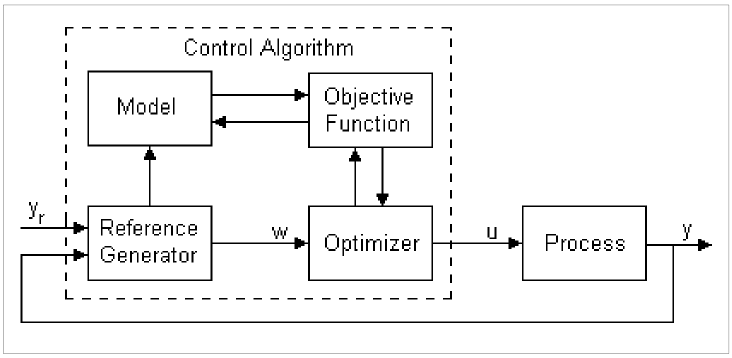


**Fig. 2.** Model-based predictive control scheme.

The MPC method is based on the receding horizon technique. In the NNPC, 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 performance criteria (16) over the specified horizons.

$$J(t,u(t)) = \sum_{i=N_1}^{N_2} \left(y_m(t+i) - y_r(t+i)\right)^2 + \lambda \sum_{i=1}^{N_u} \left(\Delta u(t+i-1)\right)^2 \qquad (16)$$

In (16), $N_1$, $N_2$ define the horizon over the tracking error, $N_u$ defines the control horizon and the control increments are evaluated. The variable $u$ is the control signal, $y_r$ is the desired response and $y_m$ is the network model response. The parameter $\lambda$ determines the contribution of the sum of squares of the control increments to the performance index (16). The values of $u$ that minimize $J$ are inputs to the plant. Minimisation of (16) is done with respect to input and output constraints

$$\begin{aligned} & u_{\min} \leq u \leq u_{\max} \\ & \Delta u_{\min} \leq \Delta u \leq \Delta u_{\max} \\ & y_{\min} \leq y \leq y_{\max} \\ & \Delta y_{\min} \leq \Delta y \leq \Delta y_{\max} \end{aligned} \qquad (17)$$

Minimal and maximal parameters of (17) are specified based on input and output data for a neural network.

*Neuro-fuzzy controller*

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 adaptive network-based fuzzy inference system (ANFIS) (Jang, 1993). ANFIS uses a feed forward neural network to search for fuzzy decision rules that perform well on a given task. Using a given input-output data set, ANFIS creates a fuzzy inference system (FIS), for which membership function parameters are adjusted using a combination of the back propagation and the least square methods. The ANFIS architecture of the first-order Takagi-Sugeno inference system is shown in Fig. 3.

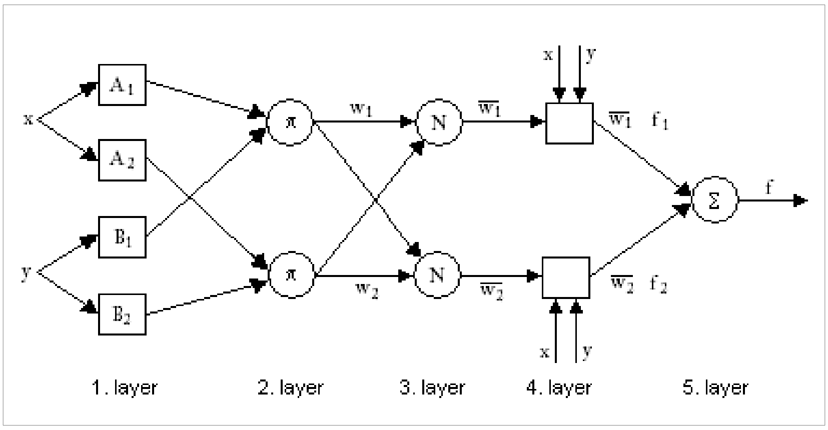


**Fig. 3.** System architecture of ANFIS.

## Results and discussion

### Description of the laboratory process

The controlled process is a part of a multifunctional process control teaching system - the Armfield PCT40 (Armfield (2005), Vojtešek et al. (2007). Armfield PCT40 and additional equipments PCT41 and PCT42 represent the system that enables to control a wide class of technological processes, as a tank, a heat exchanger, a continuous stirred tank reactor and their combinations (Armfield (2006a), Armfield (2006b)). From these processes, the reactor was chosen as a controlled plant. The equipment was used as a mixer for preparing NaCl solution with demanded concentration. The connection to the control computer was realized via an I/O connector, which is connected to the PCL card. The card used is the MF624 multifunction I/O card from Humusoft. This connection enables use of MATLAB Real-time Toolbox and Simulink or data entry from the MATLAB command window.

During experiments, NaCl solution with the concentration 0.8555 mol/dm$^3$ was fed into the tank by a peristaltic pump (PP). The performance of the pump could be set in the range 40-100%, because for the pump performance less than 40%, revolutions of the rotor were very small and the produced force was not high enough to transport the fluid from the barrel. For all experiments, the PP performance was 40% and this performance represented the volumetric flow rate of the NaCl solution 0.00175 $dm^3/s$. The volume of the solution in the tank was kept constant with the value 1 $dm^3$ during all experiments.

Used water was cold water from the standard water distribution. Water was dosed into the reactor by the proportional solenoid valve (PSV) and the volumetric flow rate of water was measured by the flow-meter. The PSV opening could be set in the range 0-100%, but the volumetric flow rate of water for the PSV opening in the range 0-30% was negligible.

From the control point of view, the controlled process was a single-input single-output (SISO) system. The manipulated variable was the volumetric flow rate of water ($F$) and the controlled variable was the conductivity of NaCl solution ($G$).

**Process identification**

Identification of the controlled process was necessary for robust PI controller design and it was based on measured step responses. The constant flow rate 0.00175 $dm^3/s$ of NaCl solution dosed into the reactor was assured by the peristaltic pump with performance 40% in all experiments. Fourteen various step changes of water flow rate were realized between 0.0032 – 0.01145 $dm^3/s$ which represented the PSV opening 50-100%. The step responses were measured repeatedly. The resultant transfer function of the laboratory process was identified in the form of the transfer function (18)

$$G(s) = \frac{b_1 s + b_0}{a_2 s + a_1 s + a_0} \qquad (18)$$

with the values of parameters given in Table 1. So, the controlled laboratory processes can be considered as an uncertain system with the interval parametric uncertainty. The software LDDIF (Čirka and Fikar (2007)) was used for identification, which was based on the least squares algorithm.

**Table 1.** Uncertain parameters.

| Parameter | Minimal value | Maximal value |
|---|---|---|
| $b_1$ | 0.0028 | 0.0428 |
| $b_0$ | -0.2776 | -0.0156 |
| $a_2$ | 1 | 1 |
| $a_1$ | 0.6349 | 5.5024 |
| $a_0$ | 0.2084 | 3.1351 |

## Design of a robust PI controller

Robust PI controller was designed using approach described in the theoretical section. For the controlled system in the form of the transfer function (18) with interval uncertainty (Table 1), the Kharitonov polynomials $N_i(s)$, $i$ = 1,2,3,4 for the numerator and $D_j(s)$, $j$ = 1, 2, 3, 4 for the denominator could be created, as it is seen in (19), (20)

$$\begin{aligned}N_1(s)&=b_1^- s+b_0^-\\N_2(s)&=b_1^+ s+b_0^+\\N_3(s)&=b_1^+ s+b_0^-\\N_4(s)&=b_1^- s+b_0^+\end{aligned} \tag{19}$$

and

$$\begin{aligned}D_1(s)&=a_2^- s^2+a_1^- s+a_0^+\\D_2(s)&=a_2^+ s^2+a_1^+ s+a_0^-\\D_3(s)&=a_2^+ s^2+a_1^- s+a_0^-\\D_4(s)&=a_2^- s^2+a_1^+ s+a_0^+\end{aligned} \tag{20}$$

where $b_k^-$ and $b_k^+$, $k$ = 0, 1, are lower and upper bounds of the intervals of the numerator parameters and $a_l^-$ and $a_l^+$, $l$ = 0, 1, 2, are lower and upper bounds of intervals of the denominator parameters. Using polynomials (19), (20), sixteen Kharitonov plants (4) could be obtained in the form

$$G_{ij}(s)=\frac{N_i(s)}{D_j(s)} \tag{21}$$

Consider one of the systems (21), where $i$ = 2 and $j$ = 3

$$G_{23}(s)=\frac{0.0428s-0.0156}{s^2+0.6349s+0.2084} \tag{23}$$

Then from equation (12), (13)

$$\begin{aligned}k_p&=\frac{a_2^+b_0^+\omega^2-a_0^-b_0^+-a_1^-b_1^+\omega^2}{\left(b_1^+\right)^2\omega^2+\left(b_0^+\right)^2}\\k_i&=\frac{a_1^-\omega^2+k_pb_1^+\omega^2}{b_0^+}\end{aligned} \tag{24}$$

The stability boundary of the closed loop with the system (23) in the $(k_p, k_i)$-plane for $\omega$ = [0, 0.6267] is driven in Fig. 4. Then parameters $k_p$ and $k_i$ of the stabilizing controller were chosen from the stable region.

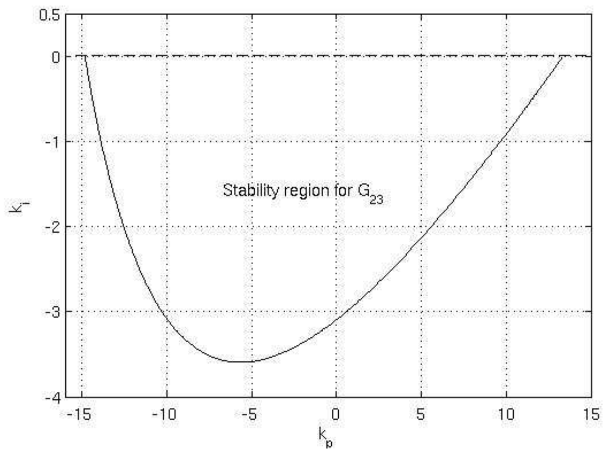


**Fig. 4.** Stability region of parameters $k_p$, $k_i$ for the system $G_{23}$.

Stable regions for all 16 Kharitonov systems were obtained alike. In Fig. 5, stable regions are shown for 16 Kharitonov plants (21). The controller that stabilizes all 16 Kharitonov plants had to be found as the intersection of all stable regions. The intersection is in detail displayed in Fig. 6.

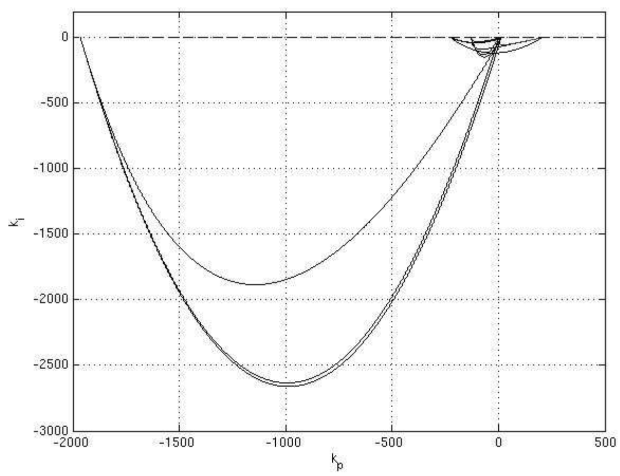


**Fig. 5.** Stability regions for 16 Kharitonov.

The parameters of the robust PI controller for control of the laboratory process were chosen from the stable region commo-n for all Kharitonov plants. Robust controller parameters $k_p$, $k_i$ for control experiments were chosen as the parameters, for which the best simulation results were obtained. The used robust PI controller was

$$C(s) = \frac{k_p s + k_i}{s} = \frac{-7s - 1.5}{s} \tag{25}$$

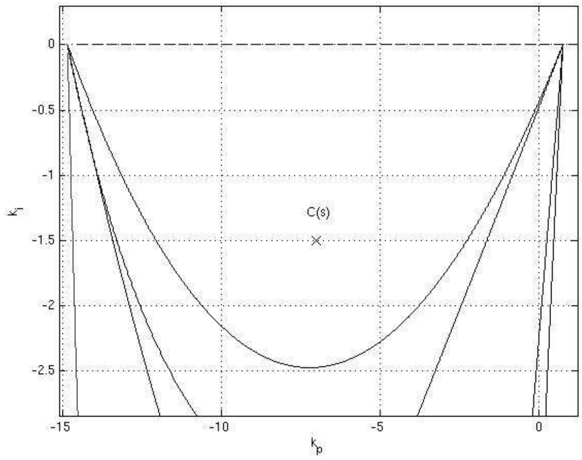


**Fig. 6.** Zoomed intersection of all stable regions.

## Design of a neuro-fuzzy control structure

At first, neural network model of the laboratory process was trained offline. The back propagation method was used based on Levenberg-Marquardt algorithm using the measured input and output data. Then, parameters of neural predictive controller were adjusted. NNPC was used of MATLAB Neural Network Toolbox and all parameters were set experimentally, so that control performance has the best quality. Secondly, ANFIS was trained as a PI controller in five training periods. The training data were obtained using classical PI control of the process and the parameters of the classical PI controller were designed using Strejc method (Mikleš and Fikar 2007). ANFIS had two inputs: set-point error *e* and derivation of set-point error *de*. Seven bell shaped membership functions were chosen for ANFIS inputs: four for variable *e* and three for variable *de* (Fig. 7). All ANFIS controller parameters were chosen experimentally.

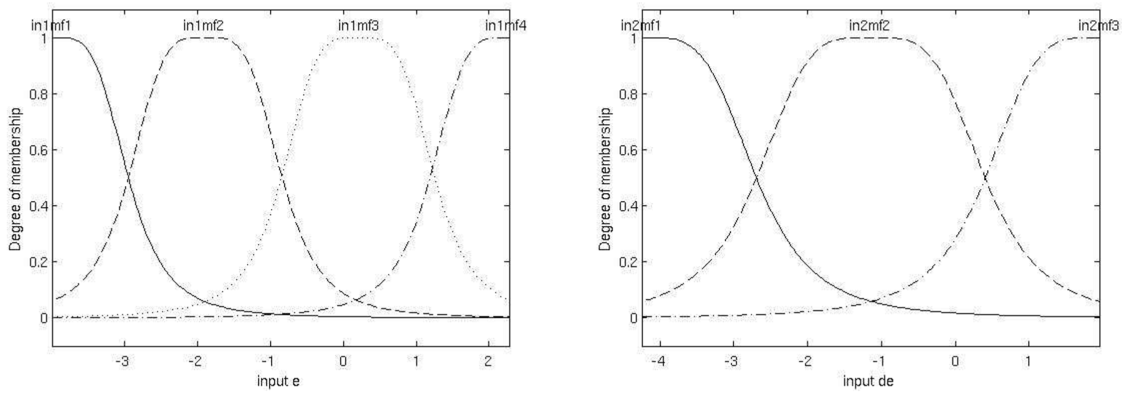


**Fig. 7.** Membership functions for input variables *e* and *de*.

### Comparison of robust PI controller with NFC

The designed robust PI controller (25) was compared with NFC while controlling the laboratory process. The controlled variable $y(t)$ was the conductivity $G$ [mS] of the NaCl solution, the manipulated variable $u(t)$ was the water flow rate $F$ [dm$^3$/s] and the reference $w(t)$ was the conductivity of the NaCl solution which corresponded to the required concentration of the NaCl solution.

Obtained experimental results are presented in Figs. 6 and 7. The ability to control real process using the designed robust PI controller (25) and NFC was tested by setting the reference value in a wider area. Control responses of the laboratory process obtained using robust controller are shown in Fig. 8 for $\omega \in$ [15; 35] and control responses obtained using NFC are shown in Fig. 9 for the same range of $\omega$.

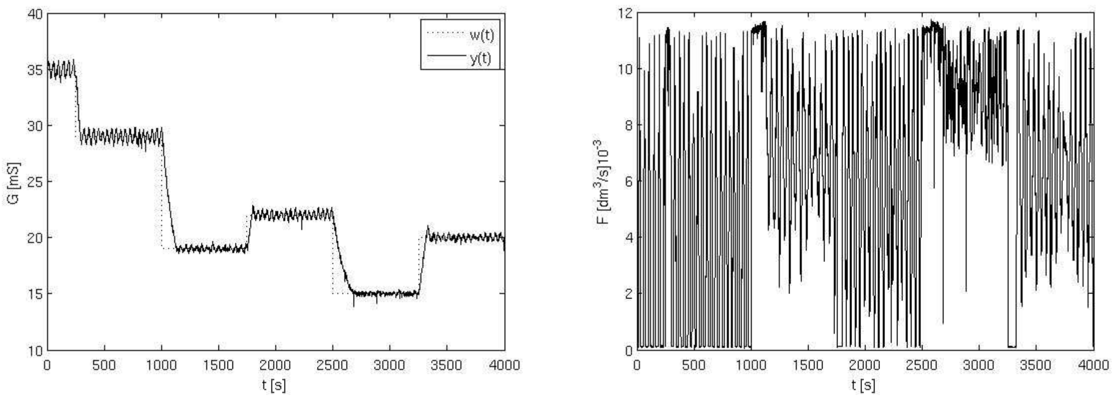


**Fig. 8.** Control of the laboratory process using robust PI controller.

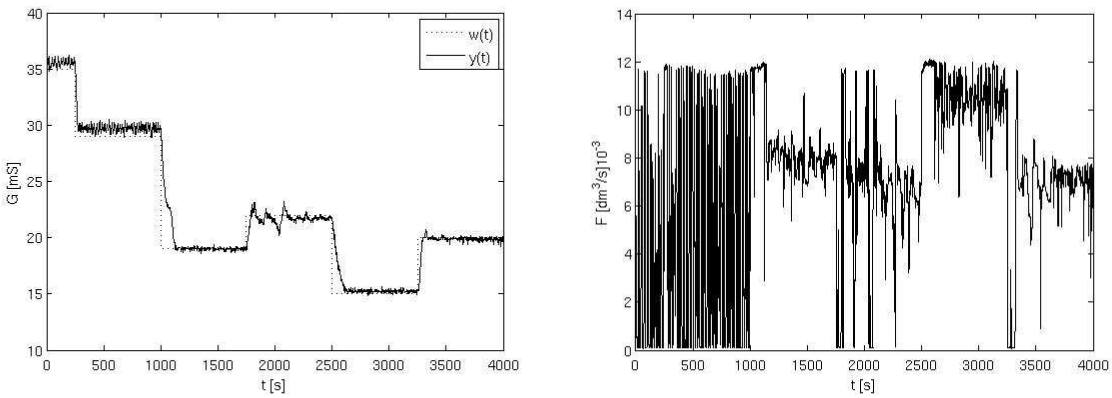


**Fig. 9.** Control of the laboratory process using NFC.

Integrated square error (ISE) (Mikleš and Fikar (2007)) is often used criteria for appraisal of control performance quality and it was used for comparison of robust PI controller and NFC. Obtained results are presented in Table 2. According to ISE, the neuro-fuzzy controller is able to assure better control responses then the robust PI controller. But the disadvantage of NFC is its much more complicated control structure.

**Table 2.** ISE for robust PI controller and NFC.

| Controller | ISE |
|---|---|
| Robust PI controller | 7844.9 |
| NFC | 6283.4 |

## Conclusion

In this paper, two advanced approaches to control of a laboratory process are compared, i.e. robust control and neuro-fuzzy control. The advantage of the first approach is that a simple PI controller is designed which has robust properties and is able to manage processes in the whole operation range. The robust PI strategy has guarantees of closed-loop stability, the proposed MPC approach does not. The importance of this approach corresponds to the fact that more that 90% controllers used in industry are up to now PID-like controllers. The other advantage is that the design procedure is simple and done off-line. But the controller is not optimal and the input and output constraints are not taken into account during the controller design. The advantage of the NFC approach is that it designs optimal control input sequence with respect to input and output constraints. But the design procedure is more complicated and it demands at first off-line training of models and then time demanding on-line calculations of control inputs.

Both designed controllers were tested experimentally by control of a laboratory process. Obtained experimental results confirmed that both designed controllers successfully controlled the laboratory process where controlled variable conductivity $G$ [mS] of NaCl solution was controlled by water flow rate $F$ [$dm^3/s$]. After comparison of control results, it can be stated that designed robust PI controller is able to assure set-point tracking in the whole range of set-point changes. The oscillations of the control input represent the disadvantage of this controller.

NFC left off-sets for higher values of set-points. The reason was not sufficient amount of data used in the off-line training phase of the algorithm that did not cover sufficiently the whole operation area and because an integrator is not including into the feedback arrangement.

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