Design of Intelligent Controllers for Biotechnological Process

Alojz Mészáros, Juraj Vörös*

Institute of Information Engineering, Automation and Mathematics, Faculty of Chemical and Food Technology Faculty of Chemical and Food Technology, Slovak University of Technology, Radlinského 9, 812 37 Bratislava, Slovakia

**juraj.voros@stuba.sk*

Abstract

This paper deals with intelligent controller design using artificial neural networks (ANN) in the role of feedback controllers. Neural controllers are built up and trained as inverse neural process models. Their performance and robustness are, gradually, improved and augmented by introducing, first, an adaptive simple integrator and, then, a controller with fuzzy integrator part. The proposed ANN control system performance is demonstrated a non-linear continuous biochemical process model with simulated uncertainties. MATLAB programme package environment has been used to build up and train the ANN feedback controllers.

Keywords: biochemical process, intelligent control, neural networks

Introduction

Non-linear and the time-varying behavior is the characteristic attribute for many industrially important fermentation processes. Moreover, as the cultivation medium consists of living microorganisms, the application of standard controllers as well as modern control techniques, is embarrassed by overcoming such effects as substrate inhibition, catabolite repression, product inhibition, glucose effect and so on. In order to eliminate these negative effects, maintaining the key variables of the process in desired range is the main goal of control. Conventional methods of controller design require detailed information about the controlled system, especially time constants, time delays and steady-state gains. The non-linearity and time-dependence variation of plant parameters can cause incorrect identification of system as well as controller parameters. This parameters mismatch usually leads to degradation of control performance resulting in oscillations, overshoot or long regulation times. An alternative way of process modeling is to utilize an artificial neural network (ANN) as a black-box model of the process. It has been shown that any function can be approximated as precisely as required by a neural network having enough neurons, at least one hidden layer, and an appropriate set of weights using data samples, since they are universal function approximators (Hornik et al. 1989). Neural black-box models have been successfully used in chemical and biochemical applications (Thibault 1990). Control system based on inverse neural model and augmented by robust term has been applied to control dissolved oxygen concentration in laboratory fermenter (Andrášik 2003).

Artificial neural networks have good general approximation capabilities for modeling complex non-linear processes because they are able to match the input/output behavior of any continuous non-linear system (Omidvar and Elliott 1997). Many results, well-known in modeling or other scientific fields, have been re-discovered in neural networks context. The use of ANNs in identification and control, which has been recognized as an effective tool for handling difficult non-linear problems, has recently attracted a great deal of attention, because ANN appear to provide a convenient means for modeling complicated non-linear processes at low cost.

A neural network can be trained to develop an inverse model of the plant. The network input is the process output, and the network output is the corresponding process input. Typically, the inverse model is a steady-state/static model, which can be used for feedforward control (Morari and Zafiriou 1989). Obviously, an inverse model exists only when the process behaves monotonically as a „forward“ function at steady state. If not, this approach is inapplicable. In principle, an inverse neural network model can learn the inverse dynamics under some restrictions (e.g. minimum phase and causality are required). Then, the inverse model is arranged in a way similar to an internal model control (IMC) structure (Ramasamy et al. 1995).

In this paper, neural network based feedback controllers are designed and trained off-line as inverse models of the plant controlled. However, the control behaviour is deteriorated in case of perturbation. The reason is that for a stable and strictly proper system, the simple inverse neural model based controller (INMC) exhibits a PD-like behaviour. To achieve offset free control responses, this controller has to be augmented by an adaptive integral term, which modifies the neural bias at output layer. As the simulation experiments confirm, the result is a PID-like control with robust performance.

Another way to improve INMC is to extend the feedback by a full integral part with fuzzy tuning. The resulting control structure is more sophisticated, however, it shows much improved behaviour in presence of unmeasured disturbances and unpredictable uncertainties.

Robustness of the proposed strategies is tested in simulation experiments where a continuous flow stirred biochemical reactor is chosen as a case study. The main goal of the resulting control system is to maintain a desired profile of dissolved oxygen concentration in the fermenter by manipulating the dilution rate. Simulation results demonstrate the usefulness of the fuzzy integrating term and the robustness of the proposed control system.

Theoretical

Inverse neural models

Application of neural networks in role of controller is mostly connected with inverse neural models (Mészáros et al. 1997), (Andrášik et al. 2003). In this case, a neural network is trained in such a way that it represents inverse dynamics of the controlled system. Then, the proposed system uses the inverse neural model as a direct feedback controller, as it is depicted in Fig.1.

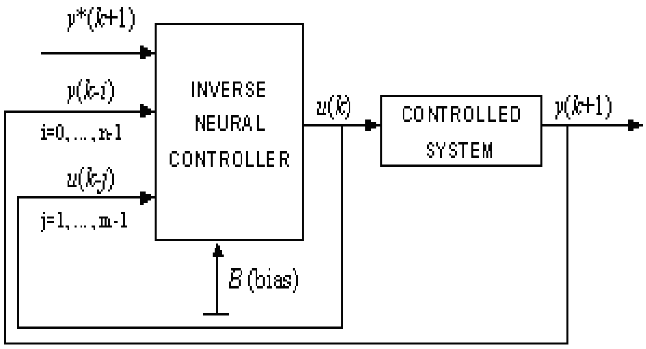

Fig.1. The simple inverse neural model based control system structure (INMC).

The neural model in a role of controller has to be trained accurately to avoid model mismatch problems. However, the well trained direct neural controller gives satisfactory and offset-free results for the nominal plant only. In practice, it is not effective to train the ANN as long as to achieve the exact inverse dynamics because achieving zero training error may be a strongly time-consuming process. Moreover, most of the plants in chemical or biochemical technologies exhibit strongly non-linear characteristics and may be corrupted with unpredictable disturbances and parameter uncertainties. As a result, the nominal performance cannot be achieved and some adaptation of the pure inverse controller is required. There are different ways how to make the neural controller adaptive, but the methods to be preferred are those, which adjust only few parameters. Then, the neural model is usually trained off-line and only the required parameters are tuned on-line (Mészáros et al. 2002).

A different method of neural controller adaptation is through additive adapter adjusting the output from neural network through bias neuron (Bhat and McAvoy 1990). In comparison with other adaptive methods based on on-line network training, these concepts require low computational time and, therefore, they can be used in real-time applications.

The above scheme follows from the IMC concept. IMC schemes have been proposed for ANN models (Demuth and Beale 1994), but the model dynamics and the model inverse dynamics of the plant were identified with two separate ANN models that did not match and, therefore, could not account for modeling errors.

Robust neural controller

In practice, especially for discrete-type dynamic models, the inverse model may not be able to learn precisely the desired inverse dynamics. In many cases, a process inverse is in fact non-causal even if the process behaves monotonically, as mentioned above. The non-causality (or improperness) of a process inverse can result from dead time or discretization of a continuous process in a sampled-data system. Even if an inverse model does exist, the use of a dynamic inverse model as a feedback controller will not result in a strictly proper control system.

The ANN model in role of controller has to be trained precisely to avoid model mismatch problems. The well trained direct feedback neural controller gives satisfactory and offset-free results for the nominal system. However, most of the plants in chemical or biochemical technologies exhibit strongly non-linear characteristics and may be corrupted with unpredictable disturbances and parameter uncertainties. The idea of adaptation of inverse neural model into exact inverse system dynamics, comes out from adjusting the input into threshold (bias) neuron. Assuming that the cause of deviation in the process output from the set point is the improper value of the bias neuron input, it may be surmised that by properly adjusting the bias neuron, the set point error can be eliminated. It has been shown that adaptation of the bias on the network output layer only, is sufficient. The proper signal for adjustment is of course the integral of the set point error. As long as a finite set point error exists, the output of the adapter, a pure integral controller, will continue to change and the neural network controller will undergo continuing adjustment. The adjustment will cause the error to diminish over time and when the set point error vanishes, the adjustment will cease and the exact inverse of the forward model is found. The exact adapter equation is

$$B = B_0 + \beta\left[\sum\left(y^* - y\right)\right] \tag{1}$$

where B_0 is the initial value of the bias input (unity), y^* is the set point, and y is the process output. The term β is an adaptation gain which may vary in the range $(-\infty,\infty)$. The actual range for a given application may be limited by stability considerations. A value of $\beta = 0$ means no adaptation. For some applications β may be positive, while for others it may be negative. As β is increased (or reduced) beyond a certain value, oscillations and instability occur. Proper values of β may be found by trial and error. The control structure described can be seen in Fig.2.

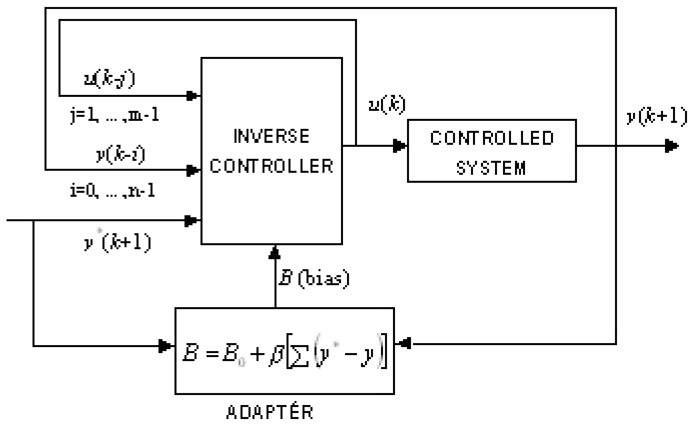

Fig.2. The robust neural control system structure (RINMC).

Fuzzy-neural controller

In (Bhat and McAvoy 1990) it was shown, that presence of some integration term is inevitable in a neural control loop. However, even involving this, the control performance may turn up unsatisfactory in terms of regulation time and overshoot. It has been shown that these negative effects may result from self-characteristic of adapter (pure integrator) and incorrect timing of adaptation. In effort to improve the pure inverse controller performance, the simple integrator is replaced by a fuzzy one, resulting in the structure shown in Fig.3.

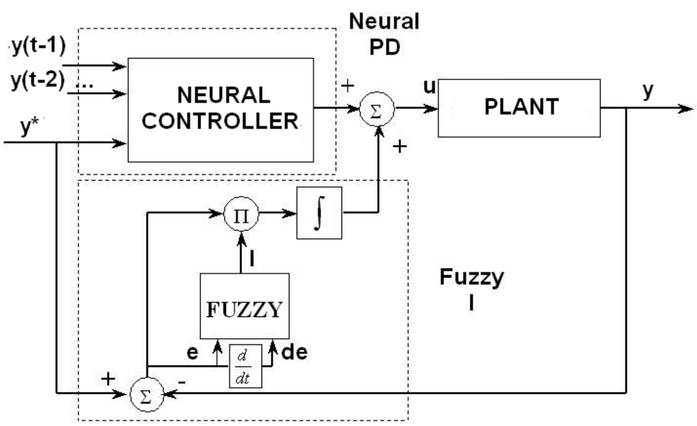

Fig.3. The fuzzy-neural control system structure (FRINMC).

Then the manipulated variable is computed according to the equation

$$u = f_{NET}\left(y^{*}, y\right) + f_{FUZZY}\left(e, de\right) \tag{2}$$

where $f_{NET}(y^*,y)$ is a nonlinear function of reference, y^*, and system output, y, which represents the inverse dynamics neural model. The term $f_{FUZZY}(e,de)$ is a fuzzy integrator represented by nonlinear function of control error, e, and its derivation, de, as follows

$$f_{FUZZY}\left(e, de\right) = \int_0^t \left[I\left(e(t), de(t)\right).e(t)\right]dt \tag{3}$$

where the element $I(e(t),de(t))$ corresponds to fuzzy controller output with inputs e and de. Assuming (2) to be the control law of a parallel PID controller, then the term $f_{NET}(y^*,y)$ can be considered as a PD component and the term $f_{FUZZY}(e,de)$ as the I component of a PID controller. Moreover, it is evident from (3), that the „speed“ of integral term can be easily adjusted through I parameter of the fuzzy integrator.

Following control theory, the inversion of a stable invertible system leads to a system with proportional-derivative properties. Previous experiments have confirmed similarity of inverse neural model and PD controller e.g. existence of offset. Let the control problem be divided into two tasks. First, if the inverse neural model is utilized as a PD controller then we can suppose that the neural controller drives the system output close to the reference value. In the second part of regulation, when the offset appears, the task of the fuzzy tuner is to adjust I-parameter of integral term in order to remove offset. Thus, the main task of the resulting fuzzy robust inverse neural model based controller (FRINMC) is the correct timing of adaptation of the overall control system with respect to the value of set-point error and its derivation.

The rules and membership functions of fuzzy controller were designed in order to satisfy the following two principles:

1. Adaptation speed has to be minimal after step change of set-point value (minimal value I)
2. As offset appears, adaptation speed reaches maximal value (maximal value I)

The fuzzy system satisfying the above two principles, can be defined as follows:

Input variables: e - set-point error; de – derivation of set-point error

Output variable: I – integration parameter

Rule base:

If e is zero and de is zero, then I is maximal
If e is zero and de is non-zero, then I is middle

If *e* is non-zero a *de* is zero, then *I* is middle
If *e* is non-zero a *de* is non-zero, then *I* is minimal

Seven fuzzy sets are defined: two for variable *e*, two for variable *de* and three for variable *I*. In fact, defining five membership functions (Fig. 4) is enough because fuzzy set non-zero is the complement of fuzzy set zero for both *e* and *de* variables. Gaussian MF were chosen for input variables, triangular and trapezoid MF define membership to output fuzzy set. The output surface of fuzzy controller is depicted in Fig. 5.

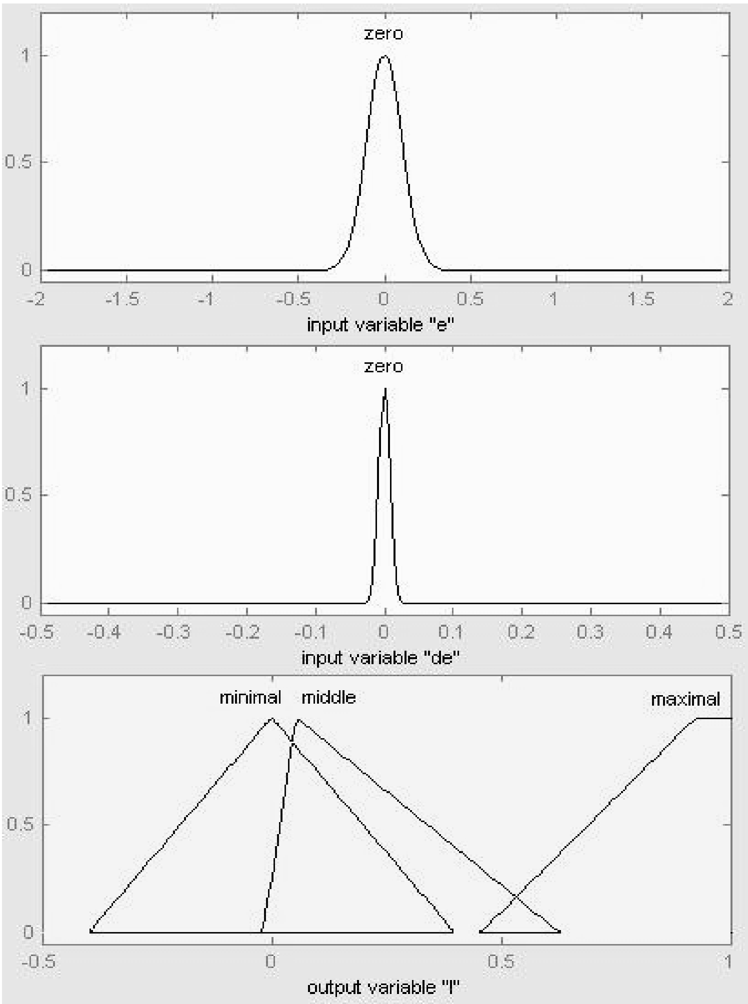

Fig.4. Membership functions.

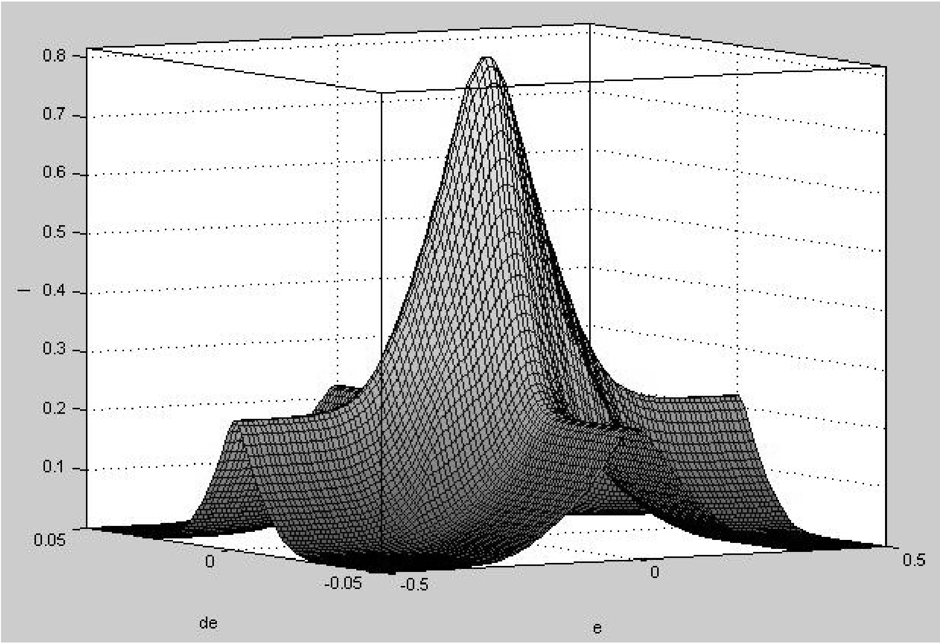

Fig.5. Output surface of fuzzy controller.

Experimental

Case Study: Non-linear bioprocess model

The non-linear model describing the response of Saccharomyces cerevisiae, known as baker's yeast, has been used for the non-linear process control simulation. This mathematical model, adopted in dynamical structure from (Mészáros et al. 1995) is based on limited oxidation capacity of yeast leading to a switch-over from oxidative to oxido-reductive metabolism.

Regarding the law of the conservation of mass, the model for continuous process can be expressed by the following set of ordinary differential equations:

cell mass concentration

$$\frac{dX}{dt} = \mu X - \frac{q}{V_l} X \tag{4}$$

where X is biomass concentration, μ is specific biomass growth rate, q is flow rate, and V_l is liquid phase volume.

substrate concentration

$$\frac{dS}{dt} = \frac{q}{V_l}\left(S_{in} - S\right) - Q_s X \tag{5}$$

where S is substrate concentration, S_{in} is input substrate concentration, and Q_s is substrate specific consumption.

ethanol (product) concentration

$$\frac{dE}{dt} = \frac{q}{V_l}\left(E_{in} - E\right) + \left(Q_{e,pr} - Q_e\right)X \tag{6}$$

where E is ethanol concentration, E_{in} is input ethanol concentration, and Q_e is ethanol specific consumption.

carbon dioxide concentration

$$\frac{dC}{dt} = D_g\left(C_{in} - C\right) - Q_c X \tag{7}$$

where C is carbon dioxide concentration, D_g is gas phase dilution rate, C_{in} is input carbon dioxide concentration, and Q_c is carbon dioxide specific consumption.

dissolved oxygen concentration

$$\frac{dO}{dt} = \frac{q}{V_l}\left(O_{in} - O\right) + Na - Q_o X \tag{8}$$

where O is dissolved oxygen concentration, O_{in} is input dissolved oxygen concentration, Na is oxygen transfer, and Q_o is oxygen specific consumption.

gas phase oxygen concentration

$$\frac{dG}{dt} = D_g\left(G_{in} - G\right) - Na\frac{V_l}{V_g} \tag{9}$$

where G is gas phase oxygen concentration, D_g is gas phase dilution rate, G_{in} is input gas phase oxygen concentration, and V_g is gas phase volume.

The mathematical description of the kinetic model mechanisms is arranged in Table 1,

Table 1. Kinetic model mechanisms of the bioprocess.

Mechanism	Description
Glucose uptake	$Q_s = Q_{s,\max} \frac{S}{k_s + S}$
Oxidation capacity	$Q_{o,\lim} = Q_{o,\max} \frac{O}{k_o + O}$
Oxidative glucose metabolism	$Q_{s,ox} = \min\begin{cases} Q_s \\ Y_{os} Q_{o,\lim} \end{cases}$
Reductive glucose metabolism	$Q_{s,red} = Q_s - Q_{s,ox}$
Ethanol uptake	$Q_e = Q_{e,\max} \frac{E}{k_e + E} \frac{k_I}{k_I + S}$
Oxidative ethanol metabolism	$Q_{e,ox} = \min\begin{cases} Q_e \\ (Q_{o,\lim} - Q_{s,ox} Y_{so}) Y_{oe} \end{cases}$
Ethanol production	$Q_{s,pr} = Y_{se} Q_{s,red}$
Growth	$\mu = Y_{sx}^{ox} Q_{s,ox} + Y_{sx}^{red} Q_{s,red} + Y_{ex} Q_e$
Carbon dioxide production	$Q_c = Y_{sc}^{ox} Q_{s,ox} + Y_{sc}^{red} Q_{s,red} + Y_{ec} Q_e$
Oxygen consumption	$Q_o = Y_{so} Q_{s,ox} + Y_{eo} Q_{e,ox}$
Oxygen transfer	$Na = k_L a \left(\frac{G}{m} - O \right)$
Maximum consumption rates	$\frac{dQ_{i,\max}}{dt} = \frac{1}{T_i} \left(Q_{i,\max}^p f_{ic} - Q_{i.\max} \right)$
where induction or repression factors are as follows	$f_{oc} = \frac{O}{k_o + O} \frac{2S + E}{k_m + 2S + E}$ $f_{sc} = \frac{S}{k_n + S}$ $f_{ec} = \frac{E}{k_e + E} \frac{k_I}{k_I + S} \frac{O}{k_o + O}$

where k is saturation constant, Y_{ij} is yield of component j on i, $k_L.a$ is volumetric mass transfer coefficient based on liquid volume, T is time constant for the induction of the production of consumption capacity, m is gas liquid distribution coefficient, f is induction or repression factor, and subscript and supercsript c is carbon dioxide,e is ethanol, g is gas phase, i is component i, in is input, I is inhibition, l is liquid phase, lim is limited capacity, max is maximum, o is oxygen, ox is oxidative, and red is reductive.

The main goal is to maintain a desired profile of dissolved oxygen concentration (DO) in the fermenter by manipulating the process inlet air flow rate (Dg).

Results and Discussion

To demonstrate the robust performance, first, for the robust INMC controller, and, then, for fuzzy-neural controller, parameter perturbation is applied to the process as variations in inlet substrate concentration, Sin, with a deviation of ±20% from the mean value.

Two-layer feedforward neural network of structure {4,3,1} (4 input neurons, 3 hidden neurons with sigmoidal activation functions, 1 output neuron with linear activation function) is designed and trained off-line to get ANN model of plant inverse dynamics on a training set of data, containing 1500 pairs of samples, taken in periods of 0.5h. For network training, a combined method of back-propagation and conjugate gradients is used. The input vector is fed by values of DO(t+1), DO(t), DO(t-1), DO(t-2), the output vector contains values of Dg(t). Training was finished after 1000 iteration runs and training error had gone beyond 4.10^{-4}. In Fig.6, we can find the nominal regulator performance in cases of nominal and perturbed plant control. Parameter perturbation in extent of ±20% over the nominal value has been applied onto inlet substrate concentration. The same system was controlled by the controller, augmented by robust term (RINMC). The influence of adaptation gain, β, is evaluated in Fig.7. A comparison of performance of the three new proposed controllers is given for the same plant in Fig.8. The simulation experiments confirm the theoretical expectations as to increasing control system robustness and disturbance rejection abilities in cases of RINMC and FRINMC.

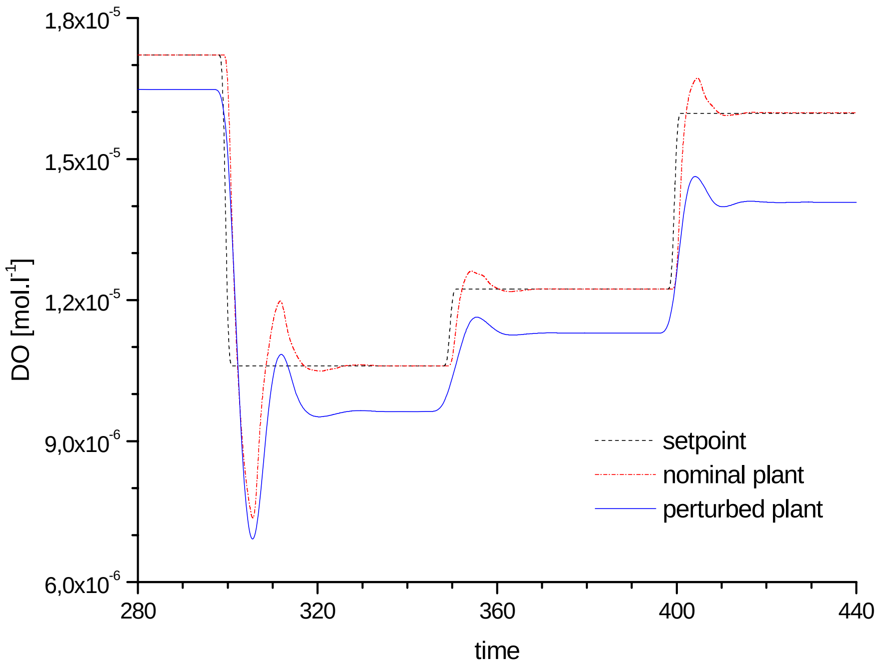

Fig.6. INMC performance for fermenter control.

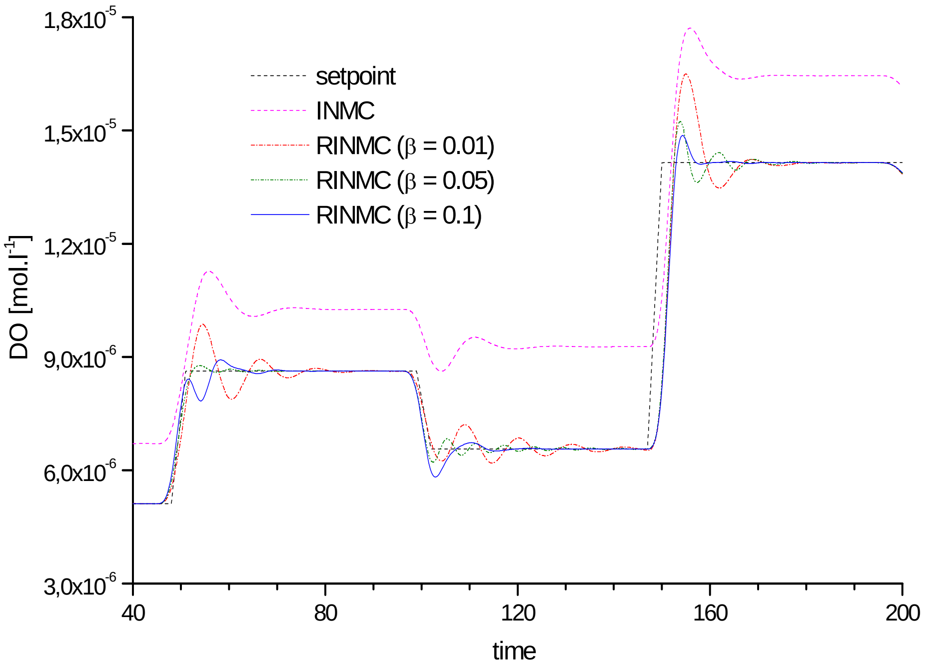

Fig.7. RINMC performance for fermenter control.

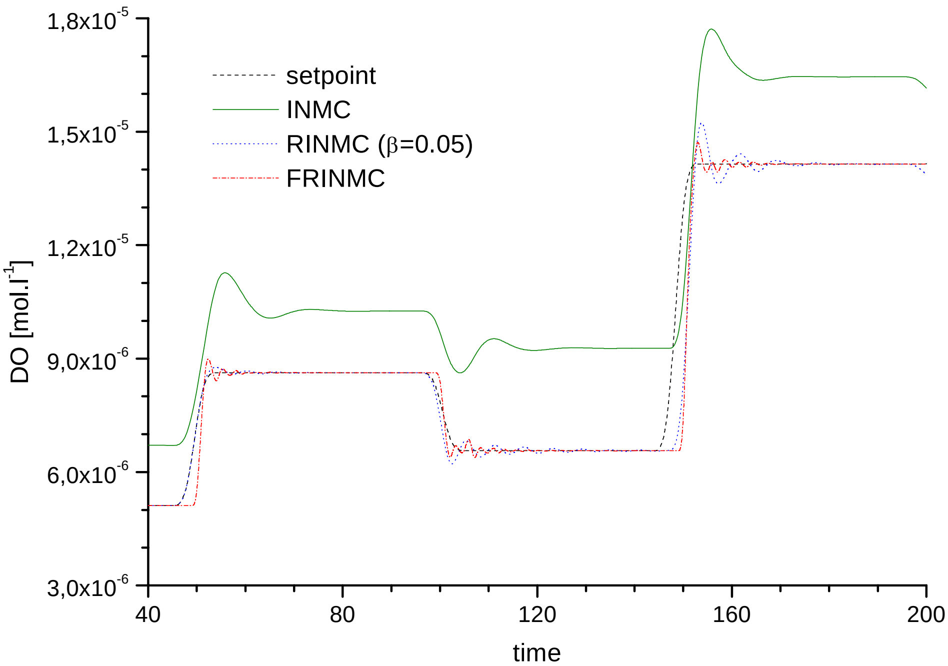

Fig.8. Comparison of INMC, RINMC and FRINMC performance in fermenter control.

It has been tested and confirmed that the proposed controllers are suitable to control non-linear fermentation plants with promising results. The nominal performance of the inverse neural model based regulators (INMC) has been demonstrated on biochemical process control with satisfactory results. However, the control behaviour was deteriorated in case of perturbation. This fact has comfirmed the PD-like behaviour of the INMC structure.

To overcome this, INMC was augmented by an adaptive integral term, resulting in a more robust, PID-like control structure (RINMC). Simulation experiments on non-linear perturbed systems have approved the increasing robustness in control performance. Eventually, INMC was extended by a full integral part with fuzzy tuning (FRINMC). The resulting control structure, according to simulation tests, has shown much improved behaviour in respect of elimination of unmeasured disturbances and unpredictable system uncertainties.

Acknowledgement

The authors highly acknowledge the financial support of the Scientific Grant Agency of the Slovak Republic under grants No. 1/3081/06 and 1/4055/07.

References

Andrášik A, Mészáros A, Bakošová M, Šperka Ľ (2003) In Proc. of the 30th International Conference SSCHE, SSCHE Bratislava, Tatranské Matliare (Slovakia), CD ROM P239.

Andrášik A, Mészáros A, Feyo de Azevedo S (2003) In Proc. of the 11th Mediterranean Conference on Control & Automation, Rhodes, Greece.

Bhat M, McAvoy TJ (1990) Comp. Chem. Engng. 14: 573-583.

Demuth H, Beale M (1994) Neural Network Toolbox. The Math Works Inc.

Hornik K, Stichcombe M, White H (1989) Neural Networks 2: 259-366.

Mészáros A, Andrášik A, Šperka Ľ (2002) In Proc. 5th International Scientifi -Technical Conference on Process Control. Kouty nad Desnou, Czech Republic, CD ROM R241a.

Mészáros A, Brdys' M, Tatjewski P, Lednický P (1995) Bioprocess Engineering 12, 1–9.

Mészáros A, Rusnák A, Najim K (1997) Chem. Biochem. Eng. Q. 11 (2): 81-88.

Morari M, Zafiriou E (1989) Robust Process Control. Prentice Hall, Englewood Cliffs,NJ, USA.

Omidvar O, Elliott DL (1997) Neural Systems for Control. Academic Press, San Diego,USA.

Ramasamy S, Desphande PB, Tambe SS, Kulnakarni BD (1995) Proc. R. Soc. Lond. A 449: 655-667.

Thibault J, van Breusegem V, Cheruy A. (1990) Biotechnol. Bioengng. 36: 1041-1048.