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Development of a Predective Type-2 Neurofuzzy Controller

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A controller that combines the main characteristics and advantages of three different control methodologies is proposed for the control of systems with nonlinearities and uncertainties. A neural network predictive control approach is implemented modifying the output of a controller with a fuzzy logic structure that uses type-2 fuzzy sets. Neural networks are also used to optimize the membership function parameters. The proposed controller is tested by simulation for the control of a bioreactor characterized by bifurcation and parameter uncertainty.

1. Introduction

The control of processes characterized by high non linearity, like some bioreactors, is quite difficult: this is particularly true for systems that present bifurcations. The dynamics of these nonlinear systems can be strongly dependent on one or more parameters and their operative conditions remain stable only if the values of these parameters remain in a limited range. If the system parameters go out of this range, also for small changes, the system may reach new equilibrium points characterized by instability or unacceptable for operative conditions of the plant (Hale and Kocak, 1991). Nonlinear controllers like fuzzy controllers, neural networks controllers or predictive controllers are used to control such systems because they can handle the changes in the system parameters. Despite their popularity, research has shown that all these controllers have difficulties in modelling and minimizing the effects of uncertainties in the plant model. In the last years a new generation of fuzzy controllers has been developed, based on the use of type-2 fuzzy sets (Mendel, 2002) and some control applications reported in the literature (Wu and Tan, 2004; Hagras, 2004; Castillo et al., 2005, Galluzzo et al., 2008) show that their performance is higher than type-1 fuzzy logic controllers (FLCs). The advantage of type-2 fuzzy logic is in fact the ability to handle the uncertainties present in the system. In this paper, three different control techniques (predictive, neural and type-2 fuzzy control) are combined for the control of a bioreactor characterized by bifurcation and uncertainties. The simulation results of the type-2 predictive neuro-fuzzy controller (T2PNFC) are compared with those obtained using a neuro predictive controller and a type-2 FLC with a larger number of rules.

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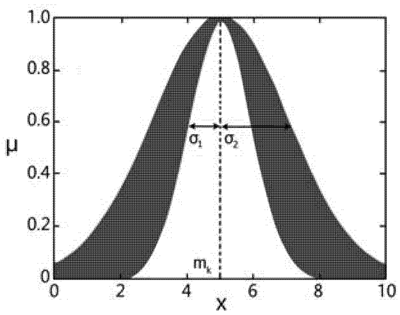

Fig. 1. FOU for a Gaussian primary membership function with uncertain standard deviation

2. Type-2 fuzzy systems

Fig. 1 illustrates a type-2 fuzzy membership function. It is obtained by blurring a type-1 Gaussian membership function with mean m_k and standard deviation σ_k. The shaded areas is called the Footprint of Uncertainty (FOU) and is representative of the uncertainty of the system. For computational reasons, in this paper only interval type-2 fuzzy sets are considered:

An interval type-2 fuzzy set (IT2FS) $\widetilde{A}_I$ is defined as:

$$\widetilde{A}_I = \int_{x \in X} \left[\int_{u \in J_x \subseteq [0,1]} \left(\frac{1}{u} \right) \right] / x \qquad \forall \; x \in \mathbf{X} \tag{1}$$

where $u \in J_x$ is a secondary grade and the domain of a secondary membership function is called the primary membership of x, where $J_x \subseteq [0,1] \quad x \in X$.

Consider the case of a Gaussian primary membership function having a fixed mean, m_k and an uncertain standard deviation that takes on values in $[\sigma_{k1}, \sigma_{k2}]$, i.e:

$$\mu_A(x) = \exp\left[-\frac{1}{2} \left(\frac{x - m_k}{\sigma_k} \right)^2 \right] \qquad \sigma_k \in [\sigma_{k1}, \sigma_{k2}] \tag{2}$$

Corresponding to each value of σ_k we will get a different membership curve. The uniform shading for the FOU again denotes interval sets for the secondary membership functions and represents the entire interval type-2 fuzzy set $\mu_A(x,u)$. The FOU can be described in terms of type-1 upper and lower membership functions (Mendel and Liang, 1999), representing the bounds for the FOU of a type-2 fuzzy set Ã.

3. Bioreactor control

3.1 Bioreactor Model

The bioreactor used for the study has only two components: the biomass and the

Table 1 – Model equations, variables and parameter values of the bioreactor

Model equations	Symbol	Variable or parameter	Value	Units
	X	Biomass concentration		$[Kg/m^3]$
$\frac{dx}{dt} = \mu(S)X - \frac{XF}{V}$	S	Substrate concentration		$[Kg/m^3]$
	F	Feed flow rate		$[m^3/hr]$
	V	Volume	0.004	$[m^3]$
$\frac{dS}{dt} = \frac{\mu(S)X}{Y} - \frac{(S_F - S)F}{V}$	S_F	Substrate-feed concentration	4	$[Kg/m^3]$
	Y	Yield coefficient	0.4	
$\mu(S) = \mu_{\max} \frac{S}{K_2 S^2 + S + K_1}$	μ	Growth rate		$[h^{-1}]$
	μ_{max}	Maximal growth rate	0.53	$[h^{-1}]$
	K_1	Saturation parameter	0.12	$[Kg/m^3]$
	K_2	Inhibition parameter	0.4545	$[Kg/m^3]$

substrate. The model equations, variables and parameter values (Bequette, 1998) are reported in Table 1.
A biomass growth rate with substrate inhibition kinetics is considered.
The substrate and biomass balances are coupled by the nonlinear growth rate function μ(S)X which is the main source of nonlinearity and uncertainty in this simple model.

3.2 Control strategy

The control of nonlinear systems exhibiting a behavior characterized by bifurcation can be very difficult to realize. Let us consider or instance the effects on the system of a change of another system parameter. The bifurcation parameter of the considered case is the dilution rate. The line with pronounced stroke in Fig. 1 is the equilibrium curve corresponding to the initial stable condition of the reactor. Let the bioreactor be (without control) in the low branch of the continuity diagram (high conversion) with a constant value of the substrate concentration = 0.1748 kg/m^3 , the corresponding equilibrium value of the dilution rate is = 0.30 h^{-1} (point A). If the maximal growth rate in the feed μ_{max} changes from 0.53 to 0.43 h^{-1}, a new continuity diagram (thin curve), with new limit points, has to be considered. The value of the abscissa of the new lower limit point is lower than the previous one, therefore the new value of the substrate can be read in the upper branch of the new continuity diagram obtained for μ_{max} = 0.43 h^{-1} (thin curve). The new value is = 4 h^{-1} (point B) because the presence of a branch point (BP). This new operative condition, although stable, is characterized by a very low concentration of the biomass, therefore it is not a desirable point. The target of the control system would be to keep constant the value of S = 0.1748 kg/m^3 although disturbances in μ_{max}, by manipulating the control variable D and forcing the system to stay in the lower branch of the new continuity diagram. The same has to be obtained for disturbances or uncertainty on other parameters.

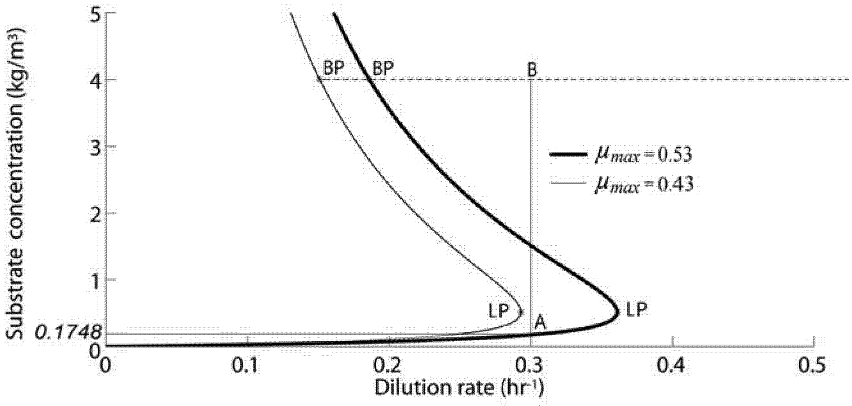

Fig. 2. Bifurcation diagrams, for $\mu_{\max}$ *= 0.53 and for* $\mu_{\max}$ *= 0.43.*

3.3 Development of the controller

A hybrid (predictive-neural network-type-2 fuzzy) control structure (T2PNFC) was developed to control the system. The model predictive control method is based on the receding horizon technique and the prediction of the plant response over a specified time horizon is obtained on a model base provided by a neural network after a training stage.

The predictions are carried out by an optimization program that determines the control signal that minimizes a performance criterion over a specified horizon. The second role of the neural networks is to optimize the parameters of the membership functions of a type-2 fuzzy controller with 3 rules, with first order Sugeno inference and a feedback structure. The feedback type-2 fuzzy controller has two inputs: the error between the measured substrate concentration and the set-point value and the integral of the same error. The controller is defined by 6 membership functions only.

The control signal of the feedback type-2 fuzzy controller is modified, through a weighting factor, by the control signal of the predictive-neural network controller and sent to the system. The input signal of the predictive-neural network controller is the measured substrate concentration.

The performance of the proposed controller was compared by simulation with the performance of two other controllers: a neural network predictive controller (NNPC) and a type-2 fuzzy controller (T2FC) with two inputs (the same of the previous type-2 fuzzy controller) and 49 rules (with 7 Gaussian membership functions for the first input and 7 for the second input) with zero order Sugeno inference.

4. Simulation results

A few simulation results are shown in the following. The response of the system substrate to a set-point step (0.1748-0.1758 *kg/m³*) at t = 1hr is shown in Fig. 3. Both fuzzy controllers have a better response than the NNPC.

In Fig. 4 the behavior of the system when a random variation of $\mu_{\max}$ (representative of parameter uncertainty) is introduced is reported. The objective of the bioreactor control is to keep the system in the equilibrium point chosen initially (point A in Fig. 3) even in the presence of random variations of system parameters. The performances of the T2FC and T2PNFC are very similar as far as the controlled variable, i.e. the substrate concentration, is concerned. Each fuzzy controller is able to keep the substrate concentration close to the set-point without large overshoot. The superiority of the T2PNFC is however evident if we consider the manipulative variable (Fig. 4b). The T2FC in fact needs larger variations of the manipulative variable in comparison with the limited variations needed by the T2PNFC.

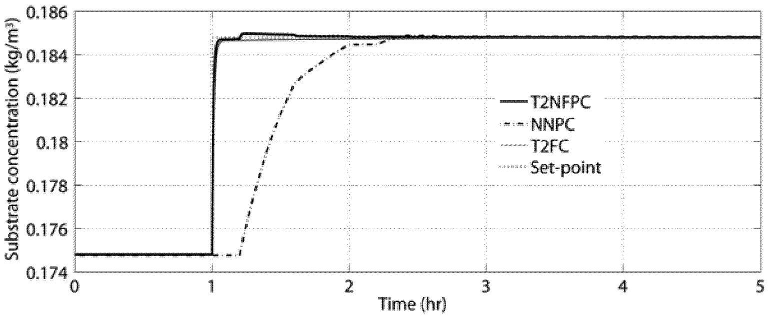

Fig. 3. Response of the controlled system to a step in the set-point

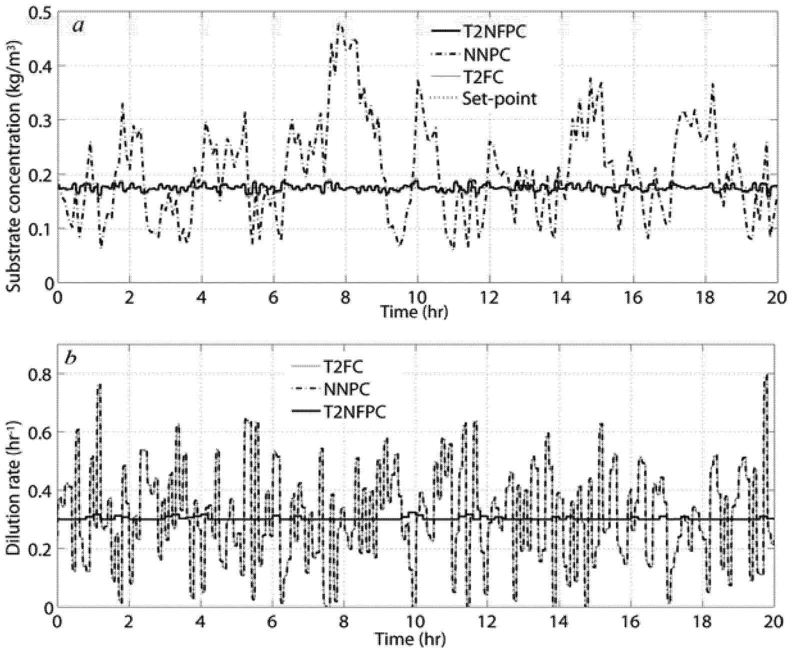

Fig. 4. Response of the controlled (a) and manipulative (b) variables following a random variation of $\mu_{\max}$.

5. Conclusions

A mixed structure controller is proposed for the control of non linear systems presenting bifurcation and uncertainty. The T2NFPC has been implemented by simulation for the control of a fermentation reactor. The performance of the proposed controller, with only 3 rules and Sugeno first order inference, was compared with the performance of a neural network predictive controller and of a type-2 FLC with 49 rules. The simulation results confirm the effectiveness and the robustness of T2NFPC in achieving a very high control performance. The synergic fusion of the three control techniques in fact allows the T2NFPC not only to minimize the negative effects of parameter uncertainty, but also to have a faster and more precise control of the process, both for set point and disturbance changes.

6. References

Bequette B.W., 1998, Process dynamics: modeling, analysis and simulation, Prentice Hall, New Jersey, 530-534.

Castillo O., Huesca G. and Valdez F., 2005, Evolutionary Computing for Optimizing type-2 Fuzzy Systems, Intelligent Control of Non-Linear Dynamic Plants, in: Proc. North American Fuzzy Info. Processing Society (NAFIPS), Ann Arbor, MI, 6, 247-251.

Galluzzo M., Cosenza B. and Matharu A., 2008, Control of a non linear continuous bioreactor with bifurcation by a type-2 fuzzy logic controller, Comuters and Chemical Engineering, 32, 2986-2993.

Hagras H., 2004, A Type-2 Fuzzy Logic Controller For Autonomous Mobile Robots. Proceedings of the IEEE International Conference on Fuzzy Systems, Budapest, Hungary.

Hale J. and Kocak, H. ,1991, Dynamics and Bifurcations. Springer-Verlag, New York, 122-126.

Mendel J.M. and Liang Q., 1999, Pictorial Comparisons of Type-1 and Type-2 Fuzzy Logic Systems, Intelligent Systems and Control, 280-285.

Mendel, J. M., 2002, Uncertainty, Type-2 fuzzy Sets, and Footprints of Uncertainty. Proc.9th Int’l. Conf. on Information Processing and Management of Uncertainty in Knowledge Based Systems, Annecy, France, 325-331.

Wu D. and Tan W.W., 2004, A Type-2 Fuzzy Logic Controller for the liquid level process, Proceedings of IEEE International Conf. on Fuzzy Systems, Budapest, Hungary, 953-958.