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A DESIGN METHODOLOGY FOR ADAPTIVE TYPE-2 FUZZY LOGIC CONTROLLERS

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The main objective of the study is to provide a valid and effective methodology for the design and development of adaptive type-2 fuzzy controllers (AT2FLCs). The methodology is based on an in depth analysis of the process dynamics and the use of an Adaptive Neuro Fuzzy Inference System (ANFIS) technique for the optimization of controllers. The application of the methodology is shown in the design and development of AT2FLCs for two biochemical processes characterized by uncertainty and time varying parameters. The simulation results show that the union of the ANFIS optimization method with the adaptive fuzzy algorithm operating on the output scaling factor, allows to obtain robust AT2FLCs, with fewer rules than traditional type-2 FLCs, that minimize the negative effects of all system parameter changes and achieve in all cases a very high control performance.

1. INTRODUCTION

In the last decades nonlinear control techniques have received considerable attention in the industrial process field, although all traditional approaches present many difficulties connected with the restrictive applicability conditions and the computational complexity. The heuristic approach used in the design of fuzzy logic controllers, built up making use of type-1 fuzzy sets, can be seen as an answer to the great complexity of traditional nonlinear control strategies in terms of robustness and effectiveness. Although over the past years many successful fuzzy logic control applications for a number of complex and nonlinear processes have been reported, some difficulties of type-1 fuzzy logic controllers (FLCs) in minimizing the negative effects of uncertainties in the plant model parameters have come out. More recently a new generation of fuzzy controllers, the type-2 FLCs (Mendel, 2001; Hagras, 2007; Castillo et al., 2008; Martinez et al., 2009; Li et al., 2010; Galluzzo and Cosenza, 2009, 2011), built up making use of type-2 fuzzy sets and characterized by a larger number of parameters and design freedom degrees, have shown to be able to handle uncertainties in a better way than traditional type-1 FLCs. However when processes are characterized by time varying parameters, as chemical industrial processes, simple type-2 FLCs may not be able to assure a lasting effective control. The variations of system parameters with time may deteriorate the control action and only the introduction of an adaptive mechanism able to modify the controller action, according to the actual system parameters, can make the control system more robust to parameter changes and to disturbances acting in the system.
A procedure for designing adaptive type-2 FLCs is presented in this paper. An Adaptive Neuro Fuzzy Inference System (ANFIS) technique (Jang, 1993) is used to reduce the computational load of adaptive type-2 FLCs without losing the efficiency of control (Galluzzo and Cosenza, 2010). In fact the use of an ANFIS technique allows to decrease the number of the FLC rules needed to achieve a good control and reduce the computational load, making the controller more flexible and guaranteeing a high performance. The paper is organized as follows: in section 2 the basics of type-2 fuzzy sets and type-2 fuzzy logic systems are briefly introduced; section 3 describes the different steps of the methodology; in section 4 the two biological processes used for the simulations are

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presented together with their control problems; in section 5 simulation results are discussed and finally some conclusions are drawn in section 6.

2. TYPE-2 FUZZY SETS AND LOGIC

2.1 Type-2 fuzzy sets

A type-2 fuzzy set $\widetilde{A}$ is characterized by a type-2 membership function $\mu_{\widetilde{A}}(x,u) \in [0,1]$ and is defined as follows:

$$\widetilde{A} = \int_{x \in X} \int_{u \in J_x} \mu_{\widetilde{A}}(x,u)/(x,u) \tag{1}$$

where $x \in X$ and $u \in J_x \subseteq [0,1]$.

Properties of type-2 fuzzy sets and operations with them have been introduced as for type-1 fuzzy sets (Mendel, 2001) leading to a complex mathematical tool. The computational load of using type-2 fuzzy sets is very high, therefore interval type-2 fuzzy sets are commonly used.

An interval fuzzy set $\widetilde{A}_I$ (Fig. 1) is defined (Mendel, 2001) as:

$$\widetilde{A}_I = \int_{x \in X} \int_{u \in J_x \subseteq [0,1]} 1/(x,u) \tag{2}$$

The secondary grade of an interval fuzzy set can assume only two values: 0 or 1.

The Footprint of Uncertainty (FOU) is the main characteristic of type-2 fuzzy set (Mendel, 2001): it consists of a shaded region bounded by a lower (LMF) and an upper membership function (UMF) (Fig.1a). The FOU can be considered as a measurement of dispersion of the system input. Its introduction allows to handle the system uncertainties and minimize their negative effects.

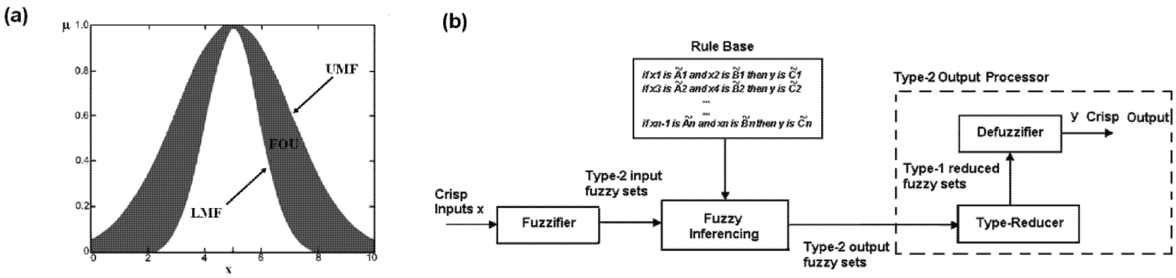

Fig. 1: (a) FOU (shaded region), lower membership function (LMF) and upper membership function (UMF) for a type-2 fuzzy membership function; (b) Structure of a type-2 fuzzy logic system.

2.2 Type-2 fuzzy logic systems

As type-1 fuzzy logic systems (FLSs), type-2 fuzzy logic systems (Mendel and Jang, 1999) also include four components (Fig. 1b): a rule-base, a fuzzifier, an inference-engine and an output-processor. The last component, the output-processor, is the main difference between a type-1 and a type-2 FLS. It maps a type-2 fuzzy set into a type-1 fuzzy set and then, as a normal type-1 defuzzifier, transforms the fuzzy output in a crisp output.

The structure of type-2 fuzzy rules is the same of type-1 fuzzy rules; the only difference consists in the nature of membership functions. Considering in fact a type-2 FLS with p inputs $x_1 \in X_1, \ldots, x_p \in X_p$ and one output $y \in Y$ and assuming that there are only M rules, the lth rule of the rule base has the following form (Mendel, 2001):

R^l: IF x_1 is $\widetilde{F}_1^l$ and …..and x_p is $\widetilde{F}_p^l$, THEN y is $\widetilde{G}^l$ $\quad l = 1, \ldots M$

3. DESIGN METHODOLOGY

The knowledge of the dynamic characteristics of a process is the basis of the design of an effective control system. The first phase of the proposed methodology is therefore a thorough analysis of the process dynamics aimed at obtaining the possible operating regions and their main dynamic features. Adaptive controllers are mainly used when processes to be controlled are non linear and/or with varying parameters. This means that a non linear analysis has to be carried out with the determination of possible equilibrium and bifurcation points and an assessment of the parameter variability. The ultimate goal of the dynamics study is the definition of the control objectives.
The second step of the methodology involves the design of one or more type-1 fuzzy controllers, depending on the control objectives, using one of the design methods available. In the proposed methodology Takagi-Sugeno (1985) controllers are used since the following optimization phase require this type of fuzzy controllers.
The use of a large number of rules in a fuzzy logic controller makes the control system more accurate and precise providing a high performance, but unfortunately increases the computational load of the processor. The reduction of the rule number is possible through the ANFIS optimization technique (Jang, 1993). A Takagi-Sugeno fuzzy system may be presented in the form of a neural network structure called ANFIS. The main advantage of the ANFIS technique is the construction of an input-output mapping based on both human knowledge (in the form of fuzzy *if-then* rules) and stipulated input-output data pairs.
In the proposed optimization method in fact, the inputs and the outputs of a type-1 fuzzy controller with many rules, 49 in the example shown in Fig. 2a, constitute the training data for the adaptive network-based fuzzy inference system. The training paradigm uses a gradient descent and a least squares algorithm to optimize the antecedent and the consequent parameters respectively. This allows obtaining a new fuzzy system (Fig. 2a) with a rule base made up of fewer rules, 3 in the example, but with the same high control performance of the original fuzzy controller. The optimized type-1 fuzzy system, with first order Sugeno inference, represents the new type-1 fuzzy controller and takes the place of the previous type-1 fuzzy controller with more rules.

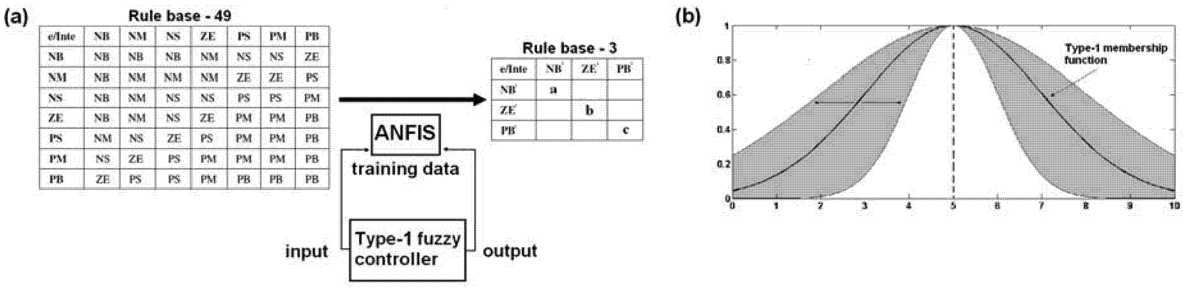

Fig. 2: a) *Reduction of rule number by ANFIS technique; b) Type-2 membership function obtained blurring a type-1 membership function symmetrically with respect to the centre .*

The following step consists in obtaining a type-2 fuzzy controller (Mendel, 2001) starting from the optimized type-1 fuzzy controller obtained with ANFIS. It is necessary to use first a type-1 FLC since it is not possible to apply the ANFIS technique directly to type-2 FLC.
The rule base of the type-2 fuzzy controller is the same of the optimized type-1 fuzzy controller while type-2 membership functions substitute type-1 membership functions.
The center of type-2 membership functions is the same of that of type-1 membership functions, while the amplitude values for the external (upper) and internal (lower) membership functions of type-2 fuzzy sets are instead chosen minimizing the integral of absolute error (IAE). In addition each amplitude value of a type-1 fuzzy membership function is the average of the amplitude values of the lower and upper type-2 fuzzy membership functions, as shown in Fig. 2b for a Gaussian membership function. This type-2 fuzzy logic controller (T2FLC), with first order Sugeno inference, constitutes an optimized type-2 fuzzy controller.

The adaptive type-2 fuzzy logic controller (AT2FLC) is designed around the T2FLC obtained in previous step following the structure proposed by Mudi and Pal (2000).
In this particular adaptive mechanism, the output scale factor (SF) of the main fuzzy controller is online updated periodically by the fuzzy rules of a secondary fuzzy controller, according to the current trend of the controlled process. The adaptive type-2 fuzzy controller here used, is characterized by a normal type-2 fuzzy controller with 3 rules and by an adaptive mechanism, constituted by a type-1 fuzzy controller with 2 rules.

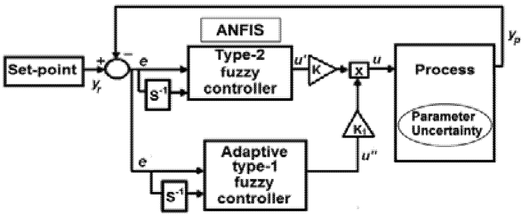

Fig. 3: Block diagram of the adaptive type-2 fuzzy controller

The control variable generated by the type-2 fuzzy logic controller u', multiplied by the scaling factor K, is updated, with the product operator, by the signal that comes from the adaptive type-1 fuzzy controller K_1u''. The resulting signal u is then sent to the plant, characterized by time-variant parameters (Fig. 3). The error (*e*) and the integral of the error (*int e*) are, also in this case, the inputs of the two fuzzy controllers (the main and the adaptive).

4. CASE STUDIES

The design procedure has been tested successfully through the design of several adaptive controllers for various processes. Here only the results obtained by simulation for two specific processes are reported.

4.1 Process model 1

The first system considered in this paper is a continuous stirred tank bioreactor (CSTBR) with cell recycle where a pure culture of Pseudomonas Putida in a media containing phenol and glucose is carried out. The model was proposed by Ajbar (2001). Balance equations (Eqs. 3-5) together with the reaction rate expressions (Eqs. 6-7) constitute the bioreactor mathematical model.

$$\overline{D_R}(\overline{S_{f1}} - \overline{S_1}) - \overline{r_1}\,\overline{X} = \frac{\overline{dS_1}}{\overline{dt}} \tag{3}$$

$$\overline{D_R}(\overline{S_{f2}} - \overline{S_1}) - \gamma\eta\overline{r_2}\,\overline{X} = \frac{\overline{dS_2}}{\overline{dt}} \tag{4}$$

$$\overline{D_R}(\overline{X_f} - W\overline{X}) + (\overline{r_1} + \eta\overline{r_2})\overline{X} = \frac{\overline{dX}}{\overline{dt}} \tag{5}$$

$$\overline{r_1} = \frac{\overline{S_1}}{1 + \overline{S_1} + \alpha\overline{S_1^2} + \lambda_1\overline{S_1}\,\overline{S_2}} \tag{6}$$

$$\overline{r_2} = \frac{\overline{S_2}}{1 + \overline{S_2} + \lambda_2\overline{S_1}\,\overline{S_2}} \tag{7}$$

A detailed analysis of the system model, with all parameter values can be found in Ajbar (2001). In Table 1 the dimensionless variables and parameters for the system model are reported.

Table 1: Dimensionless variables and parameters

symbol	Variable/parameter	symbol	Variable/parameter
$\overline{D_R}$	Dilution rate time	α	Self-substrate inhibition constant
$\overline{S_1}$	First substrate concentration	η	Constant
$\overline{S_2}$	Second substrate concentration	γ	Constant
$\overline{X}$	Biomass concentration	t	Time
$\overline{S_{f1}}$	Feed first substrate concentration	λ_1	First cross-substrate ihibition constant
$\overline{S_{f2}}$	Feed second substrate concentration	λ_2	Second cross-bstrate inhibition constant

It is well known that a CSTBR with or without cell recycle can exhibit a number of non linear phenomena. Fig. 4 shows the effects that small parameter variations can have on the system without control. A little change in one or more of these system parameters can increase the steady state value of substrate concentration S_1 (Fig. 4 a), decreasing drastically the biomass concentration value (Fig. 4 b).
In this case the new equilibrium point reached by the system, although stable is not compatible with the operative conditions of the bioprocess. The control target is therefore to control the first substrate concentration using the dilution rate as manipulation variable, assuring low values of the controlled variable $\overline{S_1}$ and high values of the biomass concentration $\overline{X}$ in spite of disturbances and time varying parameters.

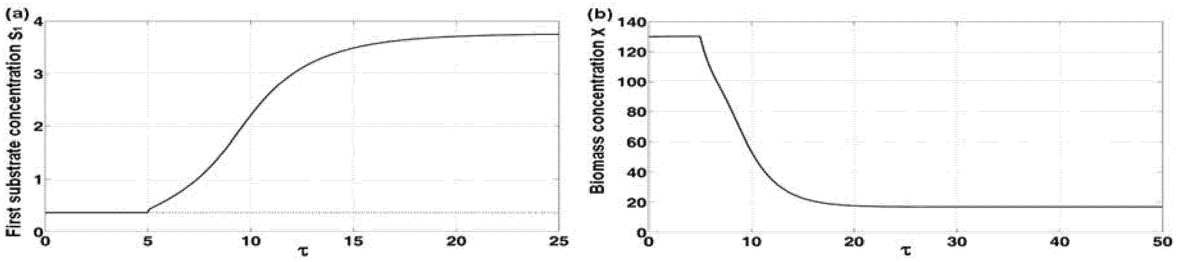

Fig. 4: Response of $\overline{S_1}$ substrate concentration (a) and $\overline{X}$ biomass concentration (b) to step changes in λ_1 from 1.1936 to 1.5, in λ_2 from 0.244 to 0.3, in α from 0.0599 to 0.7 and in W from 0.1 to 0.13 at τ =5, without control.

4.2 Process model II
The second process used in the simulation study is a bioreactor for the production of Saccharomyces Cerevisiae. A detailed analysis of the process model can be found in Lei et al. (2001). Eqs. (9-16) constitute the bioreactor mathematical model together with the reaction rate expressions Eqs. (17-27).

$$\frac{ds_{glu}}{dt} = -(r_1 + r_7)x + (S_f - s_{glu})D \quad (9)$$

$$\frac{ds_{pyr}}{dt} = (0.978r_1 - r_2 - r_3)x - s_{pyr}D \quad (10)$$

$$\frac{ds_{acetald}}{dt} = (0.5r_3 - r_4 - r_6)x - s_{acetald}D \quad (11)$$

$$\frac{ds_{acetate}}{dt} = (1.363r_4 - r_5 - r_8)x - s_{acetate}D \quad (12)$$

$$\frac{ds_{EtOH}}{dt} = 1.045r_6 x - s_{EtOH}D \quad (13)$$

$$\frac{dx}{dt} = (0.732r_7 + 0.619r_8 - D)x \quad (14)$$

$$\frac{dX_a}{dt} = 0.732r_7 + 0.619r_8 - r_9 - r_{10} - (0.732r_7 + 0.619r_8)X_a \quad (15)$$

$$\frac{dX_{Acdh}}{dt} = r_9 - r_{11} - (0.732r_7 + 0.619r_8)X_{Acdh} \quad (16)$$

$$r_1 = k_{1l}\frac{s_{glu}}{s_{glu} + K_{1l}}X_a + k_{1h}\frac{s_{glu}}{s_{glu} + K_{1h}}X_a + k_{1e}\frac{s_{glu}}{s_{glu}(K_{1t}s_{acetald} + 1) + K_{1e}}s_{acetald}X_a \quad (17)$$

$$r_2 = k_2\frac{s_{pyr}}{s_{pyr} + K_2}\frac{1}{s_{glu}K_{1t} + 1}X_a$$

(18)

$$r_3 = k_3\frac{s_{pyr}^{\ \ 4}}{s_{pyr}^{\ \ 4} + K_3}X_a \quad (19)$$

$$r_4 = k_4\frac{s_{acetald}}{s_{acetald} + K_4}X_a X_{Acdh} \quad (20)$$

$$r_5 = \left(k_5\frac{s_{acetate}}{s_{acetate} + K_5} + k_{5e}\frac{s_{acetate}}{s_{acetate} + K_{5e}}\frac{1}{s_{glu}K_{5t} + 1}\right)X_a \quad (21)$$

$$r_6 = k_6\frac{s_{acetald} - k_{6r}s_{EtOH}}{s_{acetald} + K_6 + K_{6e}s_{EtOH}}X_a \quad (22)$$

$$r_7 = k_7\frac{s_{glu}}{s_{glu} + K_7}X_a \quad (23)$$

$$r_8 = k_8\frac{s_{acetate}}{s_{acetate} + K_{5e}}\frac{1}{s_{glu}K_{5t} + 1}X_a \quad (24)$$

$$r_9 = \left(k_9 \frac{s_{glu}}{s_{glu} + K_9} + k_{9e} \frac{s_{EtOH}}{s_{EtOH} + K_{9e}} \right) \frac{1}{s_{glu} K_{9t} + 1} X_a + k_{9c} \frac{s_{glu}}{s_{glu} + K_9} X_a \tag{25}$$

$$r_{10} = \left(k_{10} \frac{s_{glu}}{s_{glu} + K_{10}} + k_{10e} \frac{s_{EtOH}}{s_{EtOH} + K_{10e}} \right) X_a \tag{26}$$

$$r_{11} = k_{11} X_{Acdh} \tag{27}$$

The variables and parameters of the model are reported in Table 2.

Table 2: Variables and parameters

symbol	Variable/parameter	symbol	Variable/parameter
D	Dilution rate	*Xa*	Active cell material (g g l^{-1})
sglu	Extracellular glucose concentration (g l^{-1})	*XAcdh*	Acetaldehyde dehydrogenase (g g l^{-1})
spyr	Extracellular pyruvate concentration (g l^{-1})	*ki*	Rate constant for reaction i (g g-1 h^{-1})
sacetald	Extracellular acetaldehyde concentration (g l^{-1})	*Ki*	Affinity constant for reaction i (g l^{-1})
sacetate	Extracellular acetate concentration (g l^{-1})	*Kji*	Inhibition constant for reaction j (l g^{-1})
sEtOH	Extracellular ethanol concentration (g l^{-1})	*Sf*	Inlet concentration of glucose (g l^{-1})
x	Biomass concentration (dry weight) (g l^{-1})		

The concentration of glucose used as carbon and energy source strongly influences the behavior of the Saccharomyces Cerevisiae growth.

Suppose working, without control, with a constant value of the substrate glucose concentration of 0.065 gl^{-1}. The corresponding equilibrium value of the dilution rate and biomass concentration are 0.38 h^{-1} and 6.9 gl^{-1} respectively. Suppose that the initial value of the system kinetic parameter k_7 = 1.203 decreases with a ramp change (slope = 0.005) for 50 hours. In Fig. 5 the new steady state conditions reached by the glucose substrate

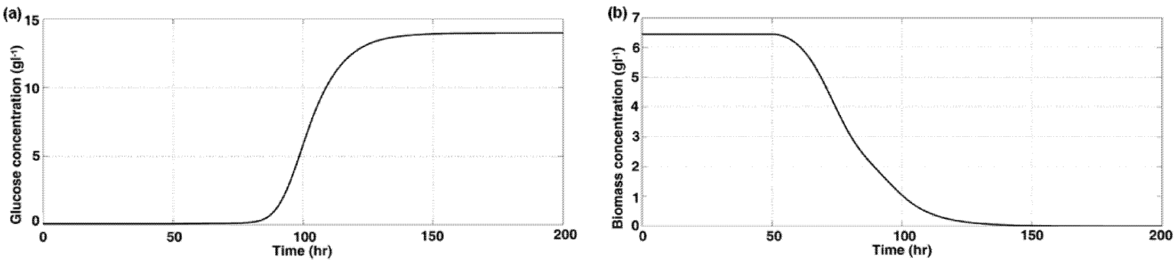

Fig 5: Glucose concentration (a) and biomass concentration (b) for a linear change of k_7 from the initial value of 1.203 to change of S_f from an initial value of 15 to 14 (gl^{-1}) at t = 50 hr.

concentration (15 gl^{-1} in Fig. 5a) and by the biomass concentration (0 gl^{-1} in Fig. 5b) are shown. Also in this case two conclusions can be drawn: the first is that the new operative condition reached by the system, although stable, is not acceptable; the second is that a very small change of a particular kinetic parameter of the system can cause a large decrease of the biomass product. As well as in the previous study case the control target is the control of the glucose concentration inside the bioreactor using the dilution rate as manipulation variable.

Moreover an efficient control of the glucose concentration is required to avoid the Crabtree effect (Postma, 1989). When the effects of a system parameter change on the process production are so drastic, the use of an adaptive mechanism in the controller is almost a forced choice.

5 SIMULATION RESULTS

5.1 System I

In Fig. 6 the performances of two simple fuzzy controllers (without adaptive algorithm): a type-1 and a type-2 FLCs (T1FLC, T2FLC) for a change in the feed substrate concentration $\overline{S}_{f1}$ from 4 to 5 at τ=4 are shown. The simulation results confirm that only when uncertainties (noise in the controlled variable measurement and dead time) are present in the control system the type-2 FLC shows all its potential over its type-1 counterpart (Fig. 6b). However in spite of the good performance, it is easy to note that also the system controlled by T2FLC shows some oscillations characterized by a low amplitude value if compared with those of the T1FLC. To eliminate this problem and to increase the performance of the type-2 FLC, an adaptive type-2 FLC was designed and its performance compared with that of a simple type-2 but with a larger rule set (49 rules).

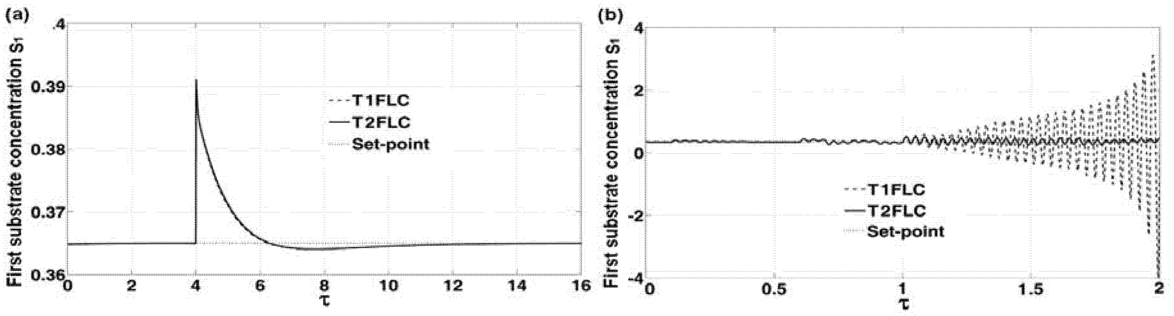

Fig. 6: a) Substrate $\overline{S}_1$ for a step change of $\overline{S}_{f1}$ from an initial value of 4 to 5 at τ =4. b) Substrate $\overline{S}_1$ for a step change of $\overline{S}_{f1}$ from an initial value of 4 to 5 at τ =4, with a dead time and noise in the controlled variable measurement.

Fig. 7a shows that the system controlled by the adaptive type-2 FLC (AT2FLC) has the best performance. The

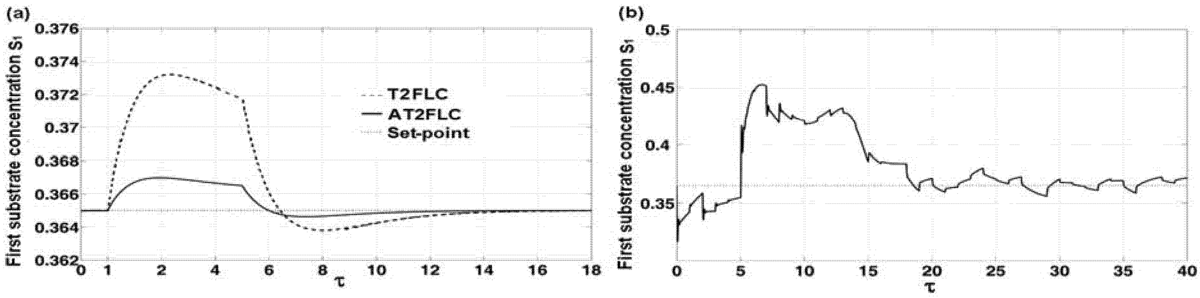

Fig. 7: a) Response of the substrate $\overline{S}_1$ to a ramp disturbance (slope = 0.2) of $\overline{S}_{f1}$ starting at t =1 hr and finishing at t = 6 hr. b) Response of $\overline{S}_1$ substrate to step changes in λ_1 (from 1.1936 to 1.5 at τ =5), in λ_2 (from 0.244 to 0.3 at τ =5), in α (from 0.0599 to 0.7 at τ =5) and in W (from 0.1 to 0.13 at τ =5), with dead time and noise in the controlled variable measurement.

AT2FLC allows the system to reach the set point value faster than ther type-2 fuzzy logic controller and without overshoots. Fig. 7b shows the performance of the only AT2FLC for a control system full of uncertainties and in particular characterized by time varying parameters, dead time and noise in the controlled variable measurement. The performance of the T2FLC is not shown in Fig. 7b, because is characterized by an oscillatory behaviour not comparable with that of the AT2FLC.

5.2 System II

The first simulation (Fig. 8a) shows the control system behavior for a simple step disturbance in the substrate feed concentration (S_f), keeping constant all system parameters. The simulation result of Fig. 8a is obtained introducing at t =10 hr a disturbance in the system with a negative step in S_f, from 15 to 14 gl^{-1}. In each case the control system reaches the set-point value imposed (0.065 gl^{-1}), removing the effects of the step disturbance in S_f. The AT2FLC performs better than the simple T2FLC showing a faster control action and a lower deviation amplitude after the disturbance.

Fig. 8b shows instead the simulation results obtained making time-variant the system parameters and in particular imposing a ramp change to the value of the k_7 kinetic parameter (starting at time 10 hr and lasting until the end of the simulation time) and a step change to S_f value (step from 15 to 14 gl^{-1} at t = 30 hr).

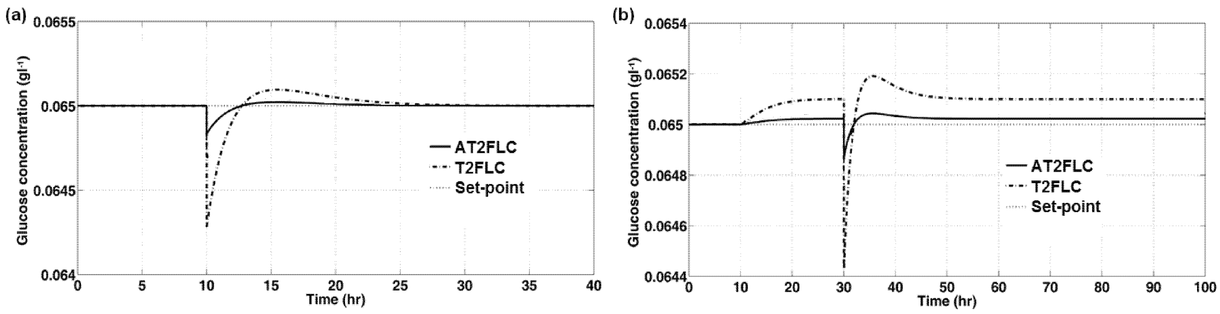

Fig. 8: a) Response of the controlled system to a step disturbance in S_f (from 15 to 14 gl^{-1} at t =10 hr). b) Response of the controlled system to a disturbance in k_7 (ramp disturbance starting at t =10 hr) and to a step disturbance in S_f (from 15 to 14 gl^{-1} at t =30 hr).

In this case both type-2 fuzzy controllers are not able to remove the negative effects of the parameter drift (k_7), but it is evident that the off-set of the system controlled by the T2FLC is more pronounced than that controlled by the AT2FLC.

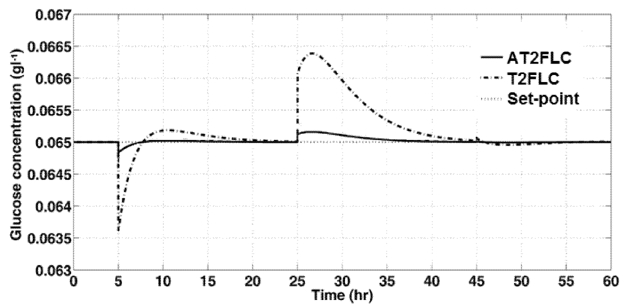

Fig. 9: Response of the controlled system to a step disturbance in S_f (from 15 to 14 gl^{-1} at t =5 hr), in k_7 (from 1.203 to 1.1at t =25 hr), in k_{il1} (from 0.94 to 1 at t = 45 hr) and in k_3 (from 0.501 to 0.48 at t = 45 hr).

The last simulation result shown in Fig.9 is obtained by a combination of variable and parameter disturbances and in particular imposing a first step to S_f from 15 to 14 gl^{-1} at t = 5 hr; a second step to k_7 from 1.203 to 1.1 at t

=25 hr; and a third step to kinetic parameters k_{il1} from 0.94 to 1 and k_3 from 0.501 to 0.48 at the same time t =45 hr. All previous results are confirmed: the AT2FLC results to be a very fast and robust controller for changes in feed substrate concentration and kinetic parameters, in comparison with the T2FLC. In particular the changes in the kinetic parameters k_{il1} and k_3 seem to have not effects on the bioreactor controlled by the AT2STFC.

6. Conclusions

The design methodology presented in this paper allows the development of adaptive type-2 fuzzy logic controllers particularly suitable for the control of nonlinear systems characterized by time-varying parameters. The use of the ANFIS optimization method and an adaptive fuzzy algorithm operating on the output scaling factor produce AT2FLCs able to minimize all the negative effects of process parameter changes (steps or ramp disturbances) and to achieve a very high control performance with a minimum computational load. The results of the simulations carried out using the models of two different biochemical processes confirm that with the AT2FLCs it is possible to obtain a more rapid and effective control than with the simple T2FLCs.

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