Adaptive Type-2 Fuzzy Logic Control of Non-Linear Processes

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The main objective of this study is to provide a valid and effective approach for the design and development of an adaptive type-2 fuzzy controller (AT2FLC), based on the analysis of the nonlinear process dynamics and the use of an ANFIS technique for the optimization of the controller. The performance of the obtained AT2FLC, characterized by a few number of rules, is higher than the performance of a traditional type-2 fuzzy controller with a larger rule base. The proposed controller is particurarly suitable for the control of processes characterized by uncertainty and time varying parameters.

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 successfull 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, type-2 FLCs (Mendel, 2001; Hagras, 2007; Castillo et al., 2008; Galluzzo et al. 2008), built up making use of type-2 fuzzy sets, characterized by a larger number of parameters and design freedom degrees, has shown to be able to handle uncertainties better than traditional type-1 fuzzy systems. 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 has been developed. An ANFIS (Adaptive Neuro Fuzzy Inference System) technique is used to reduce the computational load of adaptive type-2 FLCs without losing the control efficiency. In

fact the use of an ANFIS technique allows to decrease the number of the FLC rules needed to achieve a good control, reducing the computational load, making the controller more flexible and guaranteeing a high performance.

2. Adaptive type-2 fuzzy controllers

2.1 Interval type-2 fuzzy sets

Type-2 fuzzy sets are essentially characterized by type-2 membership functions, in which a secondary grade is introduced to take into account the uncertainty of membership. This is outlined by the Footprint of Uncertainty (FOU), the shaded region bounded by a lower and an upper membership function in Fig.1.

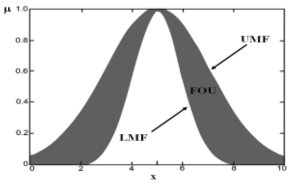

Figure 1: FOU (shaded region), lower membership function (LMF) and upper membership function (UMF) for a type-2 fuzzy membership function.

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. The secondary grade of interval sets can assume only two values, 0 or 1.

2.2 Type-2 fuzzy logic controllers

As for a type-1 fuzzy logic system (FLS), also a type-2 FLS contains four components: rules, fuzzifier, inference-engine and output-processor. The main difference between type-2 and type-1 FLS is the output-processor, that for a type-1 FLS is just a defuzzifier, while, for a type-2 FLS contains two components. The first component, the type-reducer, maps a type-2 fuzzy set into a type-1 fuzzy set, while the second component is just a normal defuzzifier that transforms a fuzzy output into a crisp output.

2.3 ANFIS

A Takagi-Sugeno (1985) fuzzy system may be presented in the form of a neural network structure. This form is called ANFIS (Adaptive Neuro Fuzzy Inference System)(Jang, 1993). 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.**Type-2 fuzzy controller optimization**

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 increases the computational load of the processor. The reduction of the rule number of adaptive type-2 fuzzy controllers is possible through the ANFIS optimization technique that uses as inputs a type-1 fuzzy controller with a large number of rules and the error and the integral of the error. In the proposed optimization method, the inputs and the outputs of a type-1 fuzzy controller with a 49 rule base constitute the training data for the adaptive network-based fuzzy inference system (ANFIS). The training paradigm uses a gradient descent and a least squares algorithm to optimize the antecedent and the consequent parameters respectively. This allows to obtain a new fuzzy system with a rule base made up of only three rules (Fig. 3a) 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 49 rules.

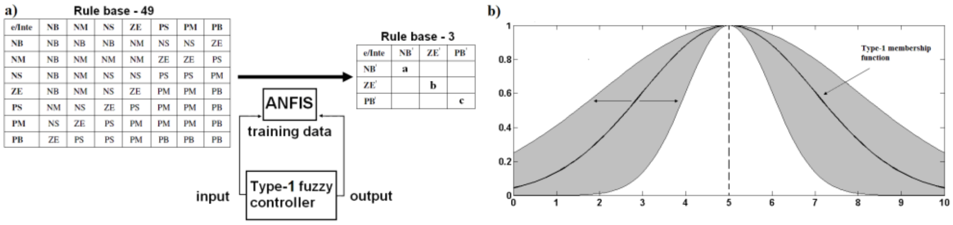

Figure 3: a) Reduction of rule number by ANFIS technique . b) Type-2 membership function obtained blurring a type-1 membership function symmetrically with respect to the centre.

The procedure to tune the type-2 fuzzy controller starts with type-1 fuzzy sets because it is not possible to apply the ANFIS directly to a type-2 fuzzy system (Mendel, 2001). The new optimized type-1 fuzzy system obtained with ANFIS is therefore used to initialize the parameters of the new type-2 fuzzy system.

The center of type-2 Gaussian membership functions is the same of that of type-1 Gaussian 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 Gaussian membership function is the average of the amplitude values of the lower and upper type-2 fuzzy Gaussian membership functions (Fig. 3b). This new optimized type-2 fuzzy system, with first order Sugeno inference, constitutes the new type-2 fuzzy controller with only 3 rules.

2.4 Adaptive type-2 fuzzy logic controller

The adaptive type-2 fuzzy logic controller (AT2FLC) has a structure similar to the controller proposed by Mudi and Pal (2000).

The output scaling factor (SF) of the main fuzzy controller is periodically updated online by the fuzzy rules of a secondary fuzzy controller, according to the current trend of the controlled process. The type-2 adaptive fuzzy logic controller used here, 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..

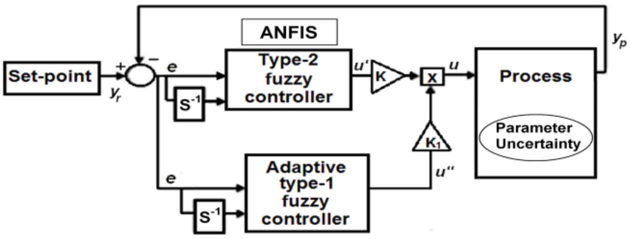

Figure 4: Block diagram of the adaptive type-2 fuzzy logic controller

The control variable generated by the type-2 fuzzy logic controller u'(t) 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(t) is then sent to the plant, characterized by time-variant parameters (Fig. 4). 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).

3. Control of a benchmark process

3.1 Process model

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 a specific process are reported. A detailed analysis of the process model used as benchmark in the simulated control tests, can be found in Lei et al. (2001). The model describes the production of Saccharomyces Cerevisiae. The concentration of glucose, used as carbon and energy source, strongly influences the growth behavior of the same Saccharomyces Cerevisiae. Therefore the control target is the control of the glucose concentration inside the bioreactor using the dilution rate as manipulating variable. Moreover an efficient control of the glucose concentration is required to avoid the Crabtree effect (Postma et al., 1989).

3.2 Control problem

Let us suppose that the process, without control, is operating with a constant value (0.065 gl^{-1}) of the substrate concentration. The corresponding equilibrium value of the dilution rate and biomass concentration are 0.38 h^{-1} and 6.9 gl^{-1} respectively.

Let us also suppose that the initial value of the system kinetic parameter k_7 (1.203) decreases for 50 hours with a ramp change (slope = 0.005). In Fig. 2 a) and b) the new steady state conditions reached by the glucose substrate concentration (15 gl^{-1}) and by the biomass concentration ($\cong 0$ gl^{-1}) are shown. This new operative condition, although stable, is obviously not acceptable. It is important to note that a very small change of a

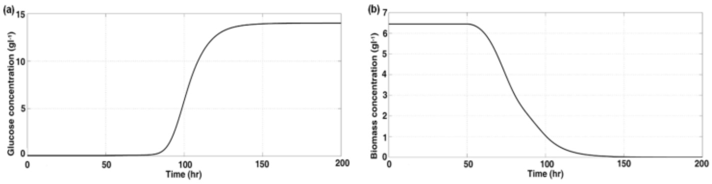

Figure 2: Glucose (a) and biomass (b) steady state conditions reached by the glucose substrate concentration (15 gl^{-1}) and by concentration for a linear change of k_7

particular kinetic parameter of the system may cause a large decrease in the biomass product. When a variation of a system parameter produces so drastic effects in the process, the use of an adaptive mechanism in the main control action of the fuzzy controller is the only right choice.

4. Results

In Fig. 5a the responses of the controlled process, using a T2FLC and an AT2FLC, to a step disturbance in the substrate feed concentration (S_f) are shown. The step disturbance in S_f, from 15 to 14 gl^{-1}, is introduced at t =10 hr keeping constant all system parameters. Both controllers let the glucose concentration value to come back to the set point (0.065 gl^{-1}) removing the effects of the step disturbance in S_f.

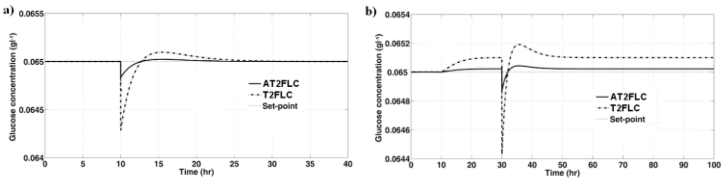

Figure 5: a) Response of the controlled system to a step disturbance in S_f (from 15 to 14 gl^{-1} at t =10 hr. b) Response of the controlled system to a disturbance in k_7 (ramp disturbance starting at t =10 hr) and to a step disturbance in S_f (from 15 to 14 gl^{-1} at t =30 hr).

The AT2FLC performs better than the simple T2FLC in terms of response speed and offset after the disturbance.

Fig. 5b shows instead the simulation results obtained making time-variant the system parameters and in particular imposing a ramp change to the k_7 kinetic parameter value (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). In this case both type-2 fuzzy controller 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 T2FC is more accentuated than that of the AT2FLC.

In Fig. 6 the responses of the controlled system to a combination of variable and parameter disturbances are reported (in particular: a step in S_f from 15 to 14 gl^{-1} at t = 5 hr; a step in k_7 from 1.203 to 1.1 at t =25 hr; a step in the 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).

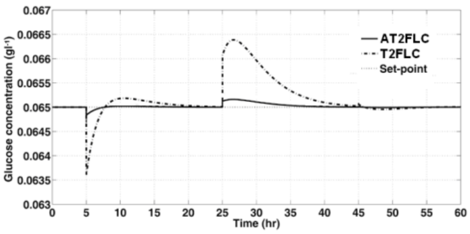

Figure 6: Response of the controlled system to step disturbances in S_f (from 15 to 14 gl^{-1} at t =5 hr), in k_7 (from 1.203 to 1.1at t =25 hr), in k_{il1} (from 0.94 to 1) and in k_3 (from 0.501 to 0.48 at t = 45 hr).

The simulation results shown in Fig. 6 confirm the previous results: the AT2FLC turns out to be a fast and robust controller both for changes in the feed substrate concentration and kinetic parameters, in comparison with the T2FLC. Notice that the change of the two kinetic parameters k_{il1} and k_3 seems to have no effects on the bioreactor controlled by the AT2FLC.

5. Conclusions

Simulation results confirm the superiority of the AT2FLC, over the simple T2FLC, in obtaining a high speed response and a limited offset, thanks to a slender, but equally efficient, rule set obtained with the ANFIS technique. The union of the ANFIS optimization method and the adaptive fuzzy algorithm operating on the output scaling factor, allows to obtain a AT2FLC able to minimize all the negative effects of parameter changes (step or ramp disturbances) achieving a very high control performance with a minimum computational load.

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