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Type-2 fuzzy control of a fed-batch fermentation reactor

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Abstract

The aim of the paper is to present the application of type-2 fuzzy logic controllers (T2FLCs) to the control of a fed-batch fermentation reactor in which the penicillin production is carried out. The performance of the control system using T2FLCs is compared by simulation with that of a control system using type-1 fuzzy logic controllers (T1FLCs). The non linear model used for the simulation study is an unstructured model characterized by the presence of non linearities, parameter uncertainty and measurement noise. Simulation results confirm the robustness of the T2FLC which shows a better performance than its type-1 counterpart particularly when uncertainties are present in the control system.

Keywords: type-2 fuzzy logic controller, uncertainties, non linear system, fed batch fermentation reactor.

1. Introduction

Many industrial chemical processes are characterized by high nonlinear dynamics and by uncertainties and often the control of these processes that makes use of traditional PID controllers does not give satisfactory results. Fuzzy logic controllers provide a relative simple way to control system which have a considerable non-linear behavior, but when the processes to be controlled are characterized by uncertainties, the choice of traditional fuzzy controllers (*type-1* fuzzy controllers), that are usually implemented using type-1 fuzzy sets, may not be the optimal solution. There exist two typologies of fuzzy controllers: the *type-1* and the *type-2* fuzzy controllers. It has been demonstrated that type-1 fuzzy logic controllers cannot handle the uncertainties present in the control system. The type-2 fuzzy logic systems instead, making use of more complex fuzzy sets (type-2 fuzzy sets) with a larger number of parameters, can handle all kind of uncertainties and therefore minimize their negative effects in the control system.

Type-2 fuzzy logic controllers have been applied in anaesthesia control (Castillo et als. 2005), in level control (Wu and Tan, 2006) and more recently in autonomous mobile robot control (Martinez et als., 2009) and in biochemical reactor control (Galluzzo and Cosenza, 2009). The process that is considered in this work is the production of penicillin in a fed-batch reactor. The process model used for the simulations is an unstructured model (Birol et als., 2002) that provides a detailed description of the process, taking in to account many input variables as pH, temperature, aeration rate, agitation power, substrate feed flow rate and the CO2 evolution term. The task of the control system is to maximize the penicillin production, at same time safeguarding the environment for the growth of the biomass by keeping constant the pH and the temperature of the system at the desired values. The performance of type-1 FLCs was first compared with that of traditional PI controllers, developed by (Birol et als., 2002), and then with that of type-2 fuzzy controllers. The process model was made more realistic by the introduction of measurement noise and dead time.

2. Type-2 Fuzzy Logic

2.1. Type-2 fuzzy sets

The concept of higher order fuzzy sets, as a natural development of type-1 fuzzy sets, was firstly introduced by Zadeh (1975). The effective development of type-2 fuzzy logic takes place only twenty years later (Karnik and Mendel, 1998). An extended presentation and discussion of type-2 fuzzy sets can be found in Mendel (2001).

While membership functions of type-1 fuzzy sets are crisp functions, membership functions of type-2 fuzzy sets are fuzzy numbers in the range 0-1; each fuzzy number represents the uncertainty that is associated with each value of the set.

A type-2 fuzzy set $\tilde{A}$ is mathematically defined (Karnik and Mendel, 2002) as:

$$\tilde{A} = \int_{x \in X} \int_{u \in J_x} \mu_{\tilde{A}}(x,u)/(x,u) \qquad \textit{(Eq. 1)}$$

where $x \in X$, $u \in J_x \subseteq [0,1]$ and $\mu_{\tilde{A}}(x,u) \in [0,1]$ is a type-2 membership function (Fig.1a).

The domain of this secondary membership function (third dimension in Fig. 1a) is the *primary membership function* (FOU = Footprint of Uncertainty) of x (blurred triangular areas of Fig. 1a). At a specific value of *x*, say *x*', there is not a single value for the membership function as for type-1 fuzzy sets; instead, the membership function takes on values (in the third dimension) wherever the vertical line intersects the blur.

For computational reasons only interval type-2 fuzzy sets, a particular case of type-2 fuzzy sets, are used. An interval type-2 fuzzy set $\tilde{A}_I$ (Fig1b) is defined as follows:

$$\tilde{A}_I = \int_{x \in X} \int_{u \in J_x \subseteq [0,1]} 1/(x,u) \qquad \textit{(Eq. 2)}$$

In this case the membership grades of all elements in the FOU are all equal to 1 (Fig. 1b).

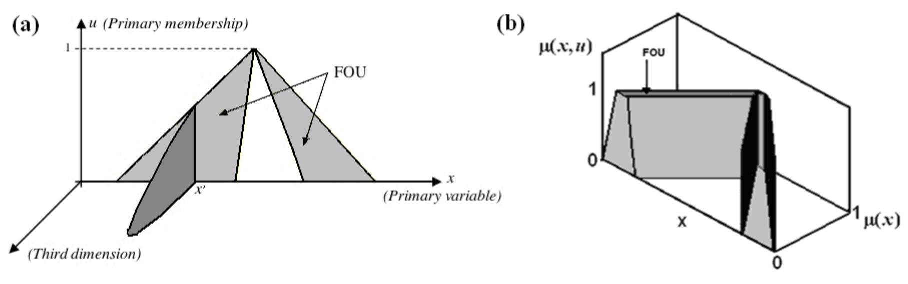

Fig.1. (a) General type-2 fuzzy set and (b) Interval type-2 fuzzy set. FOU (shaded region).

2.2. Uncertainty

Fuzzy logic based on type-2 fuzzy sets shows all its potential if applied to systems characterized by uncertainties. It is well known that uncertainty is an inherent part of real control systems. The measurement noise, the coarse estimation of process parameters, the system parameters changes, even the ambiguity in the meaning of words used in the rules are all source of uncertainties (Klir and Wierman, 1998). The FOU, the main characteristic of type-2 fuzzy sets that corresponds to the shaded region in Fig.1, is used to capture the uncertainties present in the system, therefore minimizing their negative effects.

3. Process control

3.1. Control strategy

The model of the process for the penicillin production is that described by (Birol et als., 2002). The main aim of the fed-batch fermentation control is to maximize the penicillin production, minimizing the presence of not desired compounds. This condition must be compatible with the safeguard of the biomass or the process will not give any good result. The cellular consumption of glucose produces acid substances which decrease the pH in the system, consequently the controller that manipulates the basic stream has a fundamental role in keeping a suitable environment for the penicillin production. The controller that manipulates the acid stream operates only for excessive actions of the first controller.

The set point of the pH control loop is set at a value of 5.0. It is also necessary to control the temperature of the system in order to have a good running of the process, since with the growth of the biomass the reaction heat, produced by the cellular metabolism, increases the temperature of the system, risking to wipe out all cellular population.

The set point of the temperature control of the culture medium is set at 298 K. Two fuzzy controllers were designed to control the temperature of the culture by manipulating the heating/cooling water flow rates.

In conclusion the performances of three control systems (PID, type-1 FLC and type-2 FLC) were analyzed and compared by simulation. Each control system is composed by 4 controllers of the same kind: traditional PID, traditional type-1 FLCs and the new type-2 FLCs respectively.

3.2. Fuzzy controllers

Each fuzzy controller was designed using two input variables: the error (e) and the integral of the error (inte) and one output (control variable). For each variable of type-1 FLCs, Gaussian membership functions were chosen and Sugeno inference method (with constant output) was used. Also Type-2 FLCs use the Sugeno inference method (with constant output): the type-2 Gaussian internal and external membership functions,. the gain, the integral actions, the operative range, the shape of membership functions and the values of constant outputs of type-1 FLCs were chosen minimizing the ISE (Integral-Square-Error) index. The structure of type-2 FLCs is the same of type-1 FLC (same operative range, rules, membership functions layout, Sugeno outputs, gain and integral actions); the only difference regards the Gaussian membership functions amplitude. Each type-1 fuzzy Gaussian membership functions is in fact characterized by an amplitude value that is the average of type-2 fuzzy internal and external Gaussian membership functions amplitude values.

The rules of a type-2 FLS just represent a type-2 relation between the input space and the output space. Their structure is the same of type-1 rules, the only difference consists in the membership functions nature. The lth-rule of a type-2 FLS with p inputs and l outputs is given by:

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

4. **Results and discussions**

4.1. Type-1 FLC vs PID

Birol et al. (2002) developed a software, available at the web site (http://www.chee.iit.edu/_/control/software.html), for the simulation of the temperature and pH control of the penicillin process, that makes use of four traditional PID controllers.

In Fig. 2 the performances of traditional controllers of the simulator software were compared with that of type-1 fuzzy logic controllers for the control of pH and temperature respectively. The type-1 FLC leads the system from a disturbed point to the desired value of pH faster than PID controller, attenuating the acidity change which occurs at 45 hours after the start. Moreover with type-1 FLC the system keeps stable at the set-point value without oscillations, that are present with the PID control.

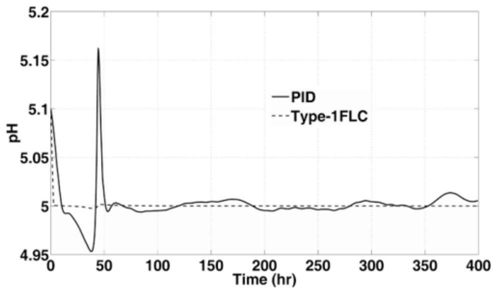

Fig. 2. Control of pH by PID control and type-1 starting from a disturbed point with pH set point equal to5 - System without uncertainties.

Also for the temperature control the performance of PID controller is inferior to that of type-1 FLC.

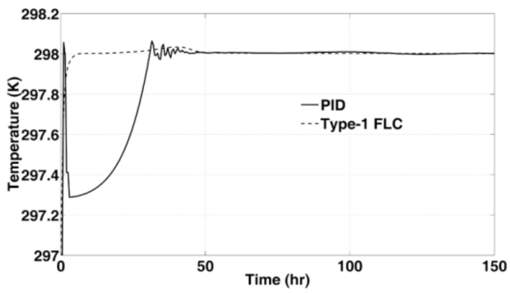

Fig. 3. Temperature control by a traditional PID controller and a type-1 FLC, starting from a disturbed with temperature set-point equal to298 K.

The PID controller leads the system to set-point slowly and with an oscillatory behavior at the begin of the simulation. The fuzzy controller dynamics is much faster than and also in this case the set-point value is reached without abrupt changes.

4.2 Type-1 FLC vs Type-2 FLC

In a real context control must take into account the inaccuracies and the dynamics of measurement instruments. Dead times and uncertainties may destabilize a system making it difficult to be controlled. The measurement of pH is more difficult and more subjected to the risks of uncertainties and in these simulations only in the feedback control ring of the pH were introduced the uncertainties. represented by measurement noise.The dynamics of the pH measurement instrument was considered by adding a dead time (18 seconds) and a noise. Type-1 and type-2 FLCs performances were compared in this situation. In the last figures (Fig.4-6) only the performances of type-1 and type-2 FLCs for the pH control are shown. For the temperature control where uncertainties are not introduced into the control system, the performances of type-1 and type-2 FLCs are very similar.

From Fig. 4 it is easy to note that without the presence of the noise, the behaviour of pH in the systems controlled by type-1 and type-2 FLCs is very similar. Each fuzzy controller leads the system to the set-point value highly reducing the oscillation amplitude that occurs around 40 hr after the start.

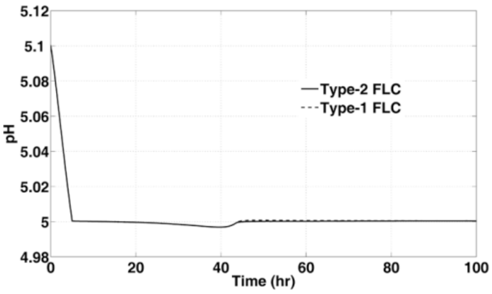

Fig. 4. pH control by type-1 FLC and type-2 FLC, with set-point = 5, starting from an initial offset. - System without uncertainties.

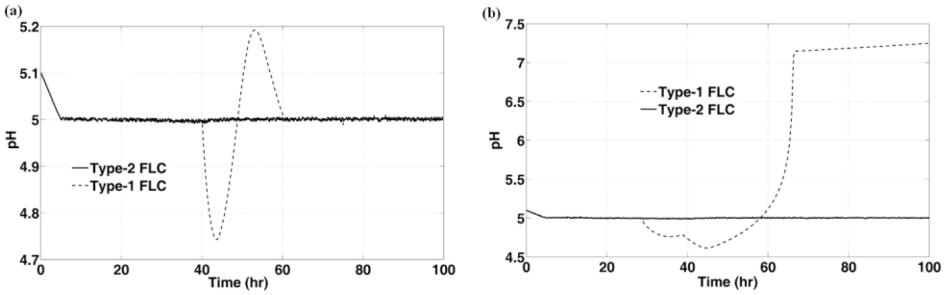

Fig. 5. pH control by type-1 FLC and type-2 FLC, with set-point = 5, starting from an initial offset. – (a) Noise in the control variable measurement with low amplitude value. (b) Noise with high amplitude in the control variable measurement.

Fig. 5a shows the performance of type-1 and type-2 FLCs with the introduction of noise in the measurement of the controlled variable. The system controlled by type-1 FLCs shows a large oscillation amplitude around 40 hours, at this time in fact there is a passage to the fed-batch operation. Large variations of pH from the desired value (= 5) erase the favorable environment for penicillin production. The maximum and minimum peaks of pH value reached by the system controlled by type-1 FLCs are around 5.19

and 4.75 respectively. After 60 hours the behavior of the system becomes regular and similar to that controlled by type-2 FLC. If the amplitude noise is further increased (Fig. 5b), the type-1 FLC cannot control the system and the value of pH increases enormously at t = 60 h reaching the value of 7.25 at t=100 h. The increase of the noise amplitude does not affect instead the performance of the Type-2 FLC that is able to assure the desired constant value of pH, and to reduce the oscillations.

5. Conclusions

In this paper a feedback control configuration with traditional PID controllers, type-1 FLCs and type-2FLCs were considered for the pH and temperature control of a fed-batch reactor for the production of penicillin and their performances were compared.
The results of simulations show that PID controllers cannot compare with type-1 FLCs. The non-linearities present in the system can be better handled using fuzzy control.
By use of type-2 fuzzy sets is possible to increase the performance of fuzzy controllers, in fact the simulation results for the pH control show that type-1 FLCs performance is outclassed by its type-2 counterpart when the system is characterized by uncertainties. Only in this environment characterized by uncertainty the type-2 FLC can show all its potential. Increasing the uncertainty degree of the control system, the difference between the performances of type-1 and type-2 FLC becomes even more evident. In an environment characterized by noise, as in the real world it occurs, the type-2 fuzzy logic control shows all its robustness and effectiveness.

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