Control of the penicillin production using fuzzy neural networks

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ABSTRACT

This paper addresses the control of a penicillin fermentation pilot plant using IMC strategies with modules based on FasArt neuro-fuzzy system. FasArt features fast stable learning and shows good MIMO identification, which makes it suitable for development of the modules in IMC. Experiments have been done training FasArt on real data and applying the controller to the pilot plant, and show that the trend of reference is captured, thus allowing high penicillin production. Other experiments have been aimed towards development of soft sensors of important variables using FasArt. Biomass, viscosity and penicillin production predictors are very accurate, and reveal that FasArt modules could be employed for fault detection, control with constraints or predictive control.

1. INTRODUCTION

Control of biochemical processes is very difficult due to their strong non linear dynamics and time varying parameters. Moreover, many variables are of difficult measurement, and usually involve expensive laboratory analyses. This is why traditionally experts knowledge and heuristics have been used for the control of such processes. However, biochemical products, in particular penicillin, have an important added value, and therefore improvements in production are of great industrial interest. For this reason, during the last decades many researches have been making a careful laboratory study of these processes [18] [22] [2] [16] [20] [21].

A traditional approach for dealing with the control non linear systems with variable parameters has been to seek an equivalent linear system, thus simplifying the problem. However, loss of information may be critical in the penicillin production problem, because large perturbations and non linearities can take the system outside the equilibrium state. For all these reasons, it can be useful to make use of non-linear techniques as fuzzy neural networks.

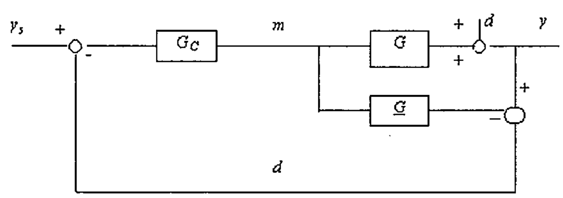

Fig. 1: Basic IMC structure, where G is the plant, $\underline{G}$ is the model, G_c is the controller; d and $\underline{d}$ are the perturbation and its estimation.

To cope with the problems derived from perturbations and sensor uncertainty, Internal Model Control (IMC) strategy has been selected, since it features good robustness to noise. Besides, it permits a rational control design procedure, allowing considering control quality and robustness in design decisions [13]. The basic IMC structure shown in figure 1 includes a plant model, and the inverse model, to control the actual plant. Though any feedback controller can be structured as an IMC, and conversely an IMC can be transformed into feedback form, the design of the controller associated to IMC is easier than the design of that associated to a feedback structure, due to the fact that IMC structure allows including explicitly robustness as a design objective, with the use of perturbation estimation as feedback signal. Therefore IMC has dual stability, perfect control and zero offset properties [13] [12]. Furthermore, it has been proved that IMC can be extended to control of non linear plants [11].

However, the lack of a plant model or the inverse model can be a serious drawback. If valid analytical models are not available, or are not accurate enough, which is often the case for bioprocesses, neuro-fuzzy methods can be considered as useful approaches to build model and control modules by learning direct and inverse dynamics from plant data. Furthermore, neural networks are well suited for non linear plant identification.

FasArt [4] is a neuro-fuzzy system which main features are fast stable learning guided by matching, fuzzy representation of the knowledge which allows the inclusion of expert rules, and good MIMO identification performance which makes it very appropriate for building IMC strategies.

Due to the inherent difficulty of this problem, it has been studied in incremental levels of complexity. First, a simulation was required to test the capabilities of FasArt neuro-fuzzy system. Much research has been devoted to mathematical modeling of penicillin production process, but there is not a model that satisfactorily describes the process, and they usually are very sensible in their parameters. However, there are several simplified models [22] [2] [16] [20] [21] that describe the process under nominal conditions. Among these, Tiller [22] model has been selected because it is a segregated model, and thus permits a better understanding of the underlying dynamics. This model assumes the well-accepted fact that biomass penicillin fermentation presents an initial exponential growing

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stage followed by a production stage, of slow growing. A simulator was developed based on the Tiller model and used to generate data around nominal conditions and test FasArt identification capabilities. Successful identification results have been reported elsewhere [6] [11] [14].

As a first approximation to the control of a simulated plant using these neuro-fuzzy models was to invert the obtained fuzzy rules modeling plant dynamics, which in turn were learned by FasArt neural network, as has been done for other non linear systems [8]. However, in order to make controller more robust to noise, IMC strategy has also been tested using FasArt modules mapping direct and inverse dynamics [14]. In addition, Adaptive IMC strategies were implemented using FasBack, a modification of FasArt that can also learn to minimize output error, with satisfactory results in cases of varying parameters [14] [1].

After having satisfactorily tested FasArt identification capabilities with simulated data, real data was collected at Antibióticos, S.A.U. fermentation pilot plant in León, Spain for training the neural networks. Initially the main objective has been to train models for IMC necessary modules. Correct results were obtained for the identification of biomass direct and inverse dynamics [1]. Here these FasArt modules trained on real data have been used within an IMC controller that has been tested in Antibióticos real plant. Moreover, this paper shows identification results for other important variables, which can be used for other purposes, such as fault detection, control with constraints or optimization.

The rest of this paper is organized as follows: section 2 reviews FasArt architecture and some of its properties; section 3 presents the work carried out on Antibióticos pilot plant, to obtain an IMC controller for biomass, and several soft sensors for important variables in the process. Finally, section 4 presents the conclusions.

2. REVIEW OF FasArt

FasArt architecture

FasArt [4] is a hybrid system based on Adaptive Resonance Theory (ART) [15] family of neural networks, which also combines the advantages of fuzzy sets theory [24]. Its architecture is similar to that of Fuzzy ARTMAP [10], as shown in figure 2. Two unsupervised modules (ART_A and ART_B) cluster input and output respectively, governed by several sintony parameters: vigilance parameters ρ_A and ρ_B determine how fine clustering of input and output should be; fuzzification rates γ_A and γ_B indicate how fuzzy or crisp input and output clusters are; finally β_A, β_B, β_A^C and β_B^C are learning rates. The inter-ART module contains the relations between ART_A and ART_B. FasArt neural network overcomes several ambiguities present in Fuzzy ARTMAP supervised neural networks, by the introduction of fuzzy logic in a formal way, so that learning is equivalent to the generation of a fuzzy rules set. This is achieved by establishing a duality between neuron activation function and fuzzy set membership. Furthermore, prediction consists of the use of a fuzzy inference engine with such rules. Due to the duality between neural network and fuzzy system present in FasArt, the universal approximation principle obtained for fuzzy systems [23] can also be applied to FasArt. Also due to this duality, inversion of the rules is straightforward, i.e. inversion of the model can be made by reverting the knowledge of direct dynamics, as it has been used for the control of other non linear plants, in which the consequents (outputs) and some of the antecedents (state variables) are used to obtain the rest of the antecedents (control signals) [9].

Further improvements of FasArt include learning guided by error minimization in FasBack [7], which can be used to develop adaptive controllers [14] [1]

Use of FasArt modules in IMC

The main modules necessary for implementation of IMC are a model of the plant to be controlled, and the actual control

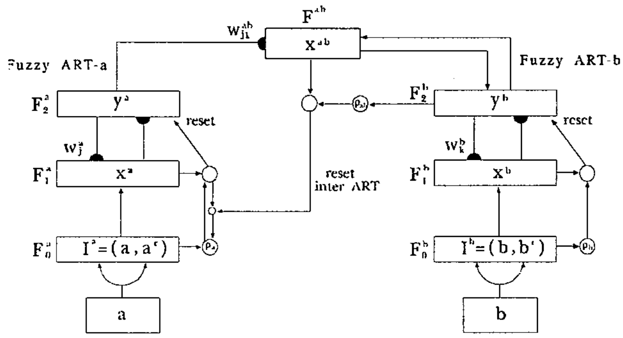

Figure 2. FasArt architecture.

module, which most often is related to as inverse model of the plant. As it has been mentioned, FasArt is specially adapted to build such modules.

The plant model must capture its dynamics of the plant. In the case of well known dynamics, a mathematical model of the plant can be developed, although this can be costly and inaccurate in many industrial plants, as is the case in the penicillin production plants. In this case, neural networks are a good approach, as shown in [5], where identification of a penicillin plant using simulated and real data is carried out.

To build the control module (inverse model) the direct plant model should be inverted. However, this is not always possible, due to the fact that either the inverse may not exist, or its implementation is not physically feasible. Some reasons for this are: the model is a non minimum phase model, has time delays, or using its inverse will require high gain loops. Furthermore, in most practical cases analytical models are not available, and therefore neural networks can be used to learn inverse dynamics, taking as input signal the outputs of the plant, and as supervision signal the inputs to the plant, either in the expected operational range of the plant [17], or in the whole operating space. FasArt neuro-fuzzy system offers these two possibilities to obtain the control module:

a) by inverting direct dynamics fuzzy rules. In this case, fuzzy rules inversion can be applied to rules extracted from FasArt plant model weights, as shown in [14]. To build such a control module requires one model learning (direct), and the availability of an inversion method.

b) by learning inverse dynamics. In this case, a control module can be built with single model learning (inverse).

Here the second approach has been adopted. Therefore, FasArt is used to learn direct dynamics to build the plant model, and inverse dynamics to build the control module.

3. EXPERIMENTAL RESULTS

Objectives
Provided that the FasArt biomass identifiers trained on real data were satisfactory [1], IMC strategy has been tested in Antibióticos pilot plant for the control of biomass. Although, the final objective of the fermentation is the production of penicillin, the control of penicillin is necessarily related to the control of biomass [18]. Moreover, since penicillin is a secondary metabolite, it is more convenient to control biomass, and therefore more sensible to the manipulated variables. However, it is not necessary to achieve very accurate tracking, since maintaining a desired trend the expected penicillin production can be obtained, as far as process constraints are not violated. In this sense, a biomass reference has been proposed that averages the biomass achieved in several successful fermentations that were controlled by experts. This reference is consistent with the known fact that biomass presents an initial exponential growing stage followed by a production stage, of slow growing, and therefore satisfactory control should achieve the production stage at the desired time and with desired level of biomass.

In addition, working with fermentation experts reveals that reliable software sensors for some variables is a very useful tool for process supervision. Although hardware sensors technology has considerably improved, there are still many variables that are monitored through laboratory analyses. These are often expensive, and involve considerable delays, and thus became useful for *a posteriori* analysis of the process, but hardly for its on line supervision.

Control
To test the validity of this study experiments have been carried out in a fermentation pilot plant of Antibióticos at León, Spain. Plant model and inverse model for identifying and controlling biomass were obtained training FasArt on real data collected from this pilot plant.

Training data consisted of a total of 28 fermentations, including *standard* (normal behavior under nominal conditions), and *non standard* (normal behavior under not nominal conditions). At this stage, anomalous fermentations have not been used in order not to disturb the knowledge acquired in the fuzzy rules. For the plant model, six input were used, including information of nutrients additions, agitation and past measurements of some outlet gases. For the inverse plant, model inputs were desired biomass and past measurements of outlet gases, while outputs were additions to the tank and agitation. It can be seen that some of the variables correspond to plant outputs that are obtained through laboratory measurements, and therefore are sampled at low rates. For training purposes, since all this variables are supervision signals (i.e. they are presented at ART_B module), they were linearly interpolated. This can be done because in the test stage (on line control) their values are not necessary. Due to confidentiality reasons more specific details on the variables involved cannot be given. Also all figures are scaled to [0,1]. FasArt training parameters are those shown in table 1.

Table 1. FasArt parameters in experiments.

	β	ρ	γ	β^C
ART_A	1.0	0.5	10.0	0.1
ART_B	1.0	0.95	100.0	0.1

A sample result obtained in the pilot plant is shown in figure 3. Although tracking of biomass reference is not very accurate, the general trend is captured. Moreover, considering that laboratory measurements involve a high uncertainty and sampling rate is low, laboratory profile is considered by Antibióticos experts only as a trend. As mentioned above this can be considered satisfactory since the objective is not to control biomass but to indirectly control penicillin production. In fact, the production achieved was high. The plant model in IMC produced an output shown in the figure, which is affected by noise in the values of gases measurements, which introduces high frequency components, although the trend is consistent with measured values. This also proves that IMC is robust to small perturbations in plant measurements.

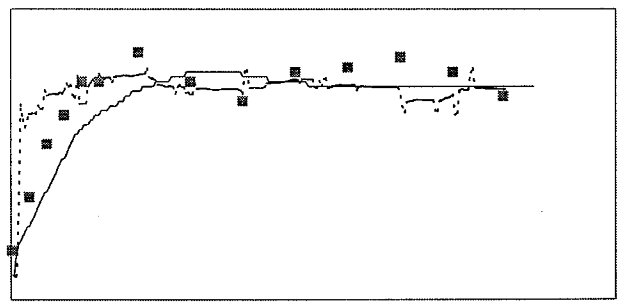

Figure 3. Pilot plant control experiment. Solid plot is reference biomass, dashed is predicted and squares are laboratory measurements.

Monitoring
As mentioned above, software sensors are an important tool for fermentation experts to supervise the process. Therefore, besides the implantation of an IMC controller in Antibióticos pilot plant, some FasArt models were developed for monitoring important variables, such as biomass, penicillin production and viscosity. These models were trained on the same real data, with similar input variables to the plant model described above.

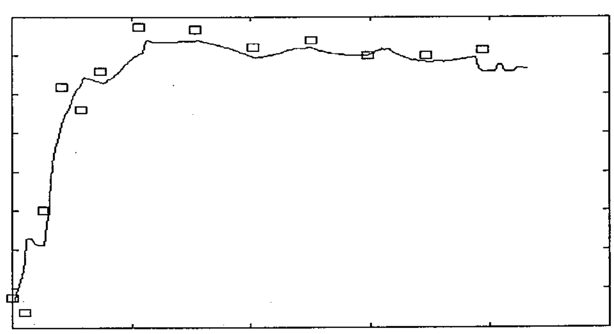

Figure 4. Biomass prediction of FasArt on real input data, where laboratory measurements are shown by squares.

A biomass software sensor was developed using past values of laboratory measurements of biomass as additional input variable. This input was not considered for IMC plant model since it should rely on the availability of such measurements, cannot be guaranteed for on line performance. However, since the main utility of the software sensor is to serve the fermentation expert as a supervision tool, this constraint is not as severe here. Results are shown in figure 4, where it can be appreciated that prediction is accurate.

This predictor can be more accurate that the plant model if past laboratory measurements are recent, while otherwise its prediction should be worse. In the future, a model switching strategy could be used dependent on the time elapsed since last measurement.

For an aerobic bioprocess such as the penicillin production fermentation, it is necessary to maintain dissolved oxygen in the tank over certain threshold. This is achieved by an adequate oxygen transfer in the fermentor. Usually this capability is estimated by means of the oxygen transfer coefficient at mid point of fermentor (K_La). Though this value can be estimated from exhaust gas measurements obtained through mass spectrometry, in general these methods are not valid in the case of viscous mycelial fermentations [3], as is the case of penicillin production. This is due to the fact that high viscosity considerably reduces such transfer capability and affects K_La estimation. However, viscosity itself can be used as good oxygen transfer estimator. Furthermore, a nominal profile of viscosity can be a good indicator of correct process evolution, and thus it can be used for fault detection during the fermentation. However its measurements are difficult, expensive and have an important delay and then a predictor viscosity becomes very useful for the fermentation expert. It could also be used for the implementation of a predictive controller that has to consider constraints in dissolved oxygen.

Here a neuro-fuzzy software sensor of viscosity was developed by training FasArt on the same real data used for IMC modules above. Parameters used are also those shown in table 1. Again, feedings and gas measurements were used as inputs. In addition, the viscosity value obtained in the last laboratory measurements is used as input to the predictor. Results for one unseen fermentation are shown in figure 5, where it can be seen that prediction is very accurate.

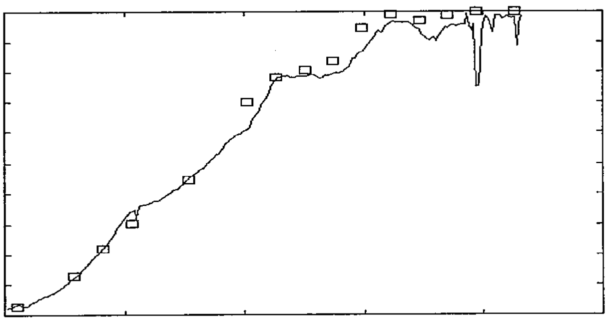

Figure 5. Viscosity prediction of FasArt on real input data, where laboratory measurements are shown by squares.

In addition to viscosity, a software sensor for penicillin production has been developed. It should be understood that the final objective of the fermentation process is penicillin production, and therefore after identification and control, research should be aimed to optimization of the process. In this sense, measurements of penicillin produced should be taken frequently during the fermentation. However, as similar to viscosity and biomass, penicillin laboratory measurements have an important delay and cost. Furthermore, in the particular case of this variable this is especially critical and therefore measurements are taken at very low rates, as can be seen in figure 6.

The penicillin production software sensor was built training FasArt on the same training data as above. Here again training parameters were those shown in table 1. Inputs to the predictor were feedings, gases measurements and previous laboratory measurement of penicillin production. As shown in figure 6, results are very accurate.

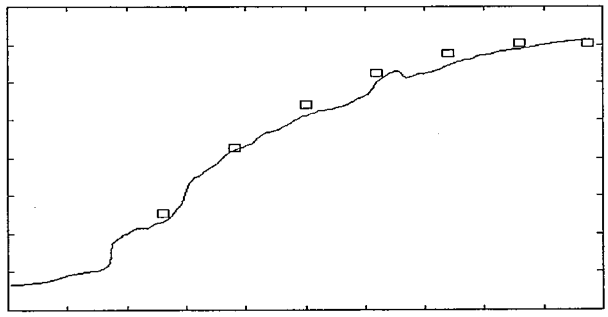

Figure 6. Penicillin prediction of FasArt on real input data, where laboratory measurements are shown by squares.

4. CONCLUSIONS

In this paper, FasArt neuro-fuzzy system has been applied within an IMC strategy for the difficult task of biomass control in the penicillin production process. This problem is highly non linear, has time varying parameters, presents high levels of noise in the measurements, and suffers from a lack of good mathematical models considering the variability of the process. To treat this problem IMC strategy is a reasonable approach, since it presents noise rejection, several desirable properties have been proved for the control of linear systems, and can be easily extended to non linear problems with the use of neural networks of fuzzy systems.

In addition, FasArt neural network provides a solution for the task of building model and control modules in IMC structure, due to its fast stable learning from examples and good performance in plant identification. In this sense, after having satisfactory experience in the use of FasArt for identification and control of a simulated penicillin process, real data from a fermentation pilot plant has been collected to develop neuro-fuzzy models of biomass production. The resulting IMC control has been applied to Antibióticos pilot plant to track biomass reference selected to guarantee profitable penicillin production. The proposed controller is capable to maintain the general trend of biomass reference, and thus allow a high production.

Furthermore, software sensors have been developed for three important variables that are only measured at very low rates. Biomass, viscosity and penicillin production have been monitored with very accurate predictions. These results can be used by fermentation experts for their own diagnostics, or in new tools for fault detection, control with constraints or predictive control.

Ongoing research is devoted to the development of MIMO controllers to simultaneously track references of biomass, viscosity or other important variables in order to optimize penicillin production. In addition, FasArt capabilities to include expert knowledge expressed in terms of fuzzy rules should be exploited to achieve more reliable identifiers, and to provide with fuzzy explanations of the decisions taken during the control stage.

5. ACKNOLEDGEMENTS

This work has been supported by ESPRIT project no.22416 "MONNET" with Cedetel. Authors would like to thank E. Méndez Pérez at Antibióticos S.A.U. in León for her collaboration in the pilot plant experiments.

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