Adaptive IMC using fuzzy neural networks for the control on non linear systems

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Abstract. This paper introduces the use of FasBack neuro-fuzzy system for the identification and control of non linear MIMO plants within IMC scheme. FasBack presents fast stable learning guided by matching and error minimisation, and presents good MIMO identification performance. Emphasis is made on the on-line adaptive capability of FasBack that can be used to develop adaptive IMC strategies, which are of interest in the cases of badly learned dynamics or plant parameters varying with time. Results for the control of a theoretical non linear MIMO plant from the literature reveal satisfactory performance for static model and controller, while performance is improved if adaptation is enabled. In addition, the control of a simulated penicillin plant is studied under several realistic conditions, in which adaptation shows to improve performance.
Keywords: Adaptive IMC, non linear MIMO plants, penicillin simulated plant, FasBack, fuzzy neural networks

1. Introduction

Chemical and biochemical processes are very difficult to control due to their strong non linear dynamics and time varying parameters. Moreover, chemical and biochemical products have a significant added value. For these reasons during the last decades many researches have been making a careful laboratory study of these processes ([14] and [17] are some studies of penicillin production). These studies were aimed to achieve better knowledge of process dynamics develop specialised instrumentation.

Dealing with non linear systems with variable parameters is a most difficult task in the systems control field. Traditional approach has been to search for an equivalent linear system, i.e. most conventional controllers employ techniques where control parameters are adjusted according to a linearization of the system transfer function near its equilibrium state, in such a way that the equilibrium state is an attractor of the state space of the system. Processing of nonlinearities is avoided due to its complex mathematical nature. Thus, well known techniques from linear systems theory may be used. This solution simplifies considerably the problem, although loss of information may be critical in many cases because in the case of large perturbations and non linear discontinuous transfer functions (usual for chemical and biochemical processes), the system may fall far outside the

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equilibrium state, and control based on linearization around equilibrium point usually fails.

IMC structure permits a rational control design procedure, allowing considering control quality and robustness in design decisions [10], and it has been proved that it can be easily extended to control of non linear plants [8]. If analytical models are not available, numerical methods may be used, among which neural networks provide a solution to build model and control modules by learning direct and inverse dynamics, and are well suited for non linear plant identification. FasBack [5] neuro-fuzzy system feature fast stable learning guided by matching and error minimisation, 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. Furthermore, FasBack on-line stable adaptation capabilities permit the design of an adaptive IMC, which is of interest in the case of badly learned dynamics due to the lack of data, or time varying plants.

The rest of this paper is organised as follows: Section 2 briefly describes FasBack neural network features. Section 3 describes IMC strategy pointing out the ways to obtain model and control modules. Also FasBack adaptation capabilities to integrate it into an adaptive IMC strategy are commented. Section 4 presents experimental results on a theoretical MIMO plant proposed in [16]. Section 5 studies identification and control performance of a simulated [17] penicillin plant, showing results for realistic scenarios in which plant output measurements are taken at a lower rate than control action requires, there is noise present in output measurements and plant is time varying. Finally, section 6 presents the conclusions.

2. FasBack: a fuzzy neural network that allows fast stable on-line adaptation

FasBack architecture [5] is a hybrid system based on Adaptive Resonance Theory (ART) [11] family of neural networks combining the advantages of fuzzy sets theory [19]. It is initially based on Fuzzy ARTMAP [7] architecture, which has two unsupervised modules (ART_A and ART_B) which cluster input and output, while another module contains the relations between them. FasArt neural network [2] was proposed to overcome the several ambiguities observed on Fuzzy ARTMAP supervised neural networks, by the introduction of fuzzy logic in a formal way, so that learning is equivalent to generating a base of fuzzy rules, and prediction as the use of a fuzzy inference engine with these rules to relate input to output. Due to the duality between neural network and fuzzy system present in FasArt, the universal approximation principle can be applied, ensuring that there exists a set of rules that allow the system to approximate any function to any given accuracy [18]. 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. Furthermore, in [6] rules partial inversion is used, in which the consequents (outputs) and some of the antecedents (state variables) are used to obtain the rest of the antecedents (control signals).

Besides these improvements, FasBack makes use of backpropagation algorithm [15] to refine learning in order to reduce global error, by locally refining the least or worse learned input/output relations. This is carried out by using the descending gradient method, which vary parameters (weights) in the direction indicated by the index derivative of error with respect to the parameters vector [18]. Furthermore, a penalty method is used to reduce the influence of (maybe temporarily) wrong rules, although these rules are not completely forgotten and can be recalled if they become valid again. Due to the fact that this refining is local, and wrong rules are not forgotten completely, adaptation is stable and can be carried out on line, without the need of storing previously learned patterns, as it would be the case with multilayer perceptrons using backpropagation learning algorithm. In section 3 it will be pointed out how adaptation is made for the two FasBack networks involved in an IMC structure, which is rather different for the control module.

FasBack is characterised by several sintony parameters, which have clear physical meaning. Among them the most important are vigilance parameters $\rho_{A,B}$ which show how fine clustering of output and output, and $\gamma_{A,B}$ which is a fuzzification rate indicating how fuzzy or crisp input and output sets generated should be.

3. Internal Model Control (IMC)

IMC structure permits a rational control design procedure, allowing considering control quality and robustness in design decisions [10]. This has made IMC structure attractive for many industrial applications.

3.1. Description

IMC can be considered as a derivation from feedback control simply by subtracting and adding the effect of the control signal *m* on the measurement signal yielding an entirely equivalent setup [10]. If we consider a new controller G_c representing a controller *C* with model feedback (equation 1), the basic IMC structure is obtained, as shown in figure 1.

$$G_C = \frac{C}{1 + C\underline{G}} \tag{1}$$

Therefore, any conventional feedback controller *C* can be structured in the way an IMC is built. Conversely, any IMC can be converted into feedback form, by selecting a feedback controller *C* of the form:

$$C = \frac{G_C}{1 - G_C\underline{G}} \tag{2}$$

Although both structures can be interchanged, the design of a controller G_c, associated to IMC structure is easier than the design of the controller *C* associated to a feedback structure. Furthermore, IMC structure allows including explicitly robustness as a design objective, due to the special kind of feedback signal $\underline{d}$, given by equation 3.

$$\underline{d} = \frac{d}{1 + (G - \underline{G})G_C} \tag{3}$$

which in the case of perfect model ($G = \underline{G}$) corresponds to the disturbance *d*, while in the case of a feedback controller, feedback signal $\underline{d}$, is the perturbed output of the system *y*. It therefore can be shown [10] that IMCs have the following properties:

Dual Stability: If the model is perfect ($G = \underline{G}$), the IMC closed-loop is stable if the controller G_c and the plant *G*, are stable.

Perfect Control: If the controller is equal to the inverse model ($G_c = \underline{G}^{-1}$), and the IMC closed-loop is stable, then $y(t) = y_s(t)$ for all $t > 0$ and all disturbances $d(t)$.

Zero Offset: If the steady-state gain of the controller is equal to the inverse of the model gain ($G_c(0) = \underline{G}^{-1}(0)$) and the IMC closed-loop is stable, then for asymptotically constant set points and disturbances, there will be no offset ($\lim_{t \to \infty} y(t) = y_s$)

3.2. Generalisation to non linear MIMO systems

To make IMC useful for industrial applications, we should extend it to non linear systems control. In [8] it has been shown that IMC can be applied to non linear plants with the restrictions that with non linear systems, operations from linear blocks algebra are not generally valid, and the effect of disturbances (which for linear systems can be considered as an addition *d* to output *y* due to superimposition principle) cannot be considered as additive, an therefore not measured disturbances will lead to differences between the model and the plant.

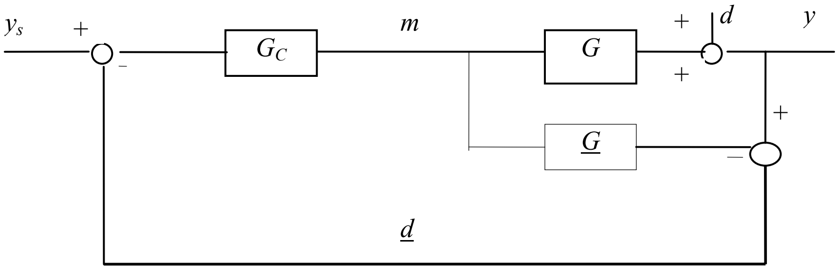


Figure 1: Basic IMC structure [10].

In addition, considering that many industrial processes are multivariate, it becomes necessary to generalise IMC strategy to such processes. In [9] this kind of application is proposed by the so-called Multiloop Design Procedure. This consists in partitioning MIMO system into input/output pairs, and employing a series of SISO controllers to control each pair. The multiloop IMC structure is postulated by selecting the controller G_c and the process model G to be diagonal transfer matrices. However, in section 4 we will show that pure MIMO IMC can be applied to multivariate non linear processes with satisfactory results.

3.3. IMC implementation using FasBack neuro-fuzzy system

The main modules necessary for implementation of IMC are a model of the plant to be controlled, and the actual controller, which most often is related to an inverse model of the plant. As shown in the following sections, FasBack is specially adapted to build such modules. Although in many practical applications it will be necessary to use additional blocks, such as filters and reference generators, here these will be left off.

Model: The model must capture direct 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. If there are not analytic models available, numerical techniques for system identification can be used. If the plant is linear (or approximately linear), autoregressive statistical techniques can be used, such as ARX and ARMAX models, Box-Jenkins techniques, etc. Neural networks can be considered as a particular case of non linear numerical methods, consisting of learning associations of plant input/output pairs. In addition, fuzzy logic can be helpful to integrate experts knowledge into a plant model, either by numerical techniques or, more usually, by neural techniques. In this case, hybrid neuro-fuzzy models are obtained, as for example using FasArt [2] [4] and FasBack [5] architectures.

Model inversion: Before building the inverse model it must be considered that it is not always possible, due to the fact that either the inverse does not exist, or even if it exists its implementation is not physically possible. Some reasons for this are: the model is a non minimum phase model, a model with time delays, or using the inverse of the model will require high gain loops.

If the model $\underline{G}$ is linear and can it be inverted, then the calculation of its inverse $\underline{G}^{-1}$ by analytic means is immediate. Furthermore, even if the model is not linear there exist analytic methods to obtain the inverse, such as Hirshorn method [12], although it is sensitive to noise and numerical errors and therefore not recommended [8]. A serious inconvenience of these methods is the actual knowledge of an analytic model, which is seldom feasible in practice. On the other hand, if the model $\underline{G}$ is linear but presents inversion difficulties (it is non minimum phase, has time delays or requires high gain loops) an approximate inverse can be obtained. Some techniques for this are proposed in [10].

However, in most practical cases an analytical model is not available. Here neural networks can be used to learn inverse dynamics, using as input to the neural network the output of the system, and as supervision the inputs of the system, either in the expected operational range of the plant [13], or in the whole operating space. FasBack neuro-fuzzy systems can be used within both strategies, by using incremental learning to locally refine the general inverse model. Furthermore, fuzzy rules inversion can be applied to rules extracted from FasBack weights, as shown in [3]. In the present paper, FasBack neural network is introduced into IMC structure to construct an adaptive strategy. Adaptation of the model is carried out by learning input/output pair at each cycle. Adaptation of the controller follows a law similar to that proposed in [13], which in a general form is:

$$\overline{p}(k+1) = \overline{p}(k) + \alpha \cdot \overline{e} \cdot J \tag{4}$$

where $\overline{p}(k)$ is the parameter (weights) vector, e is the tracking error, $J = \{j_{mn}\} = \frac{\partial y_m}{\partial u_n}$ is the Jacobian matrix of the plant, calculated numerically using the model, and α is an adaptation rate, which is 0.4 in all simulations.

4. Identification and control of a theoretical non linear MIMO plant

To study the performance of the proposed IMC strategy using FasBack adaptive neuro-fuzzy system, the identification and control of the following non linear MIMO plant proposed in [16], and also used in [18], is studied:

$$\begin{bmatrix} y_{p1}(k+1) \\ y_{p2}(k+1) \end{bmatrix} = \begin{bmatrix} \dfrac{y_{p1}(k)}{1+y_{p2}^2(k)} \\ \dfrac{y_{p1}(k)y_{p2}(k)}{1+y_{p2}^2(k)} \end{bmatrix} + \begin{bmatrix} u_1(k) \\ u_2(k) \end{bmatrix}$$

Although it is possible identify and control this system like two SISO systems and assuming it is known the additive effect of control signals, like in [16], we shall illustrate capabilities of neuro fuzzy systems in a more general manner: Applying a MIMO strategy without suppositions on system structure, the more general non linear MIMO system $\vec{y}_p(k+1) = \vec{f}(\vec{y}_p(k), \vec{u}(k))$ is obtained. To apply IMC strategy model and control modules must be trained. For building model module, plant is excited with random control signals u_1 and u_2 normally distributed [-1, 1] to obtain 5000 samples of the form:

$$\begin{aligned} Input_A &= \left[y_{p1}(k), y_{p2}(k), u_1(k), u_2(k)\right] \\ Input_B &= \left[y_{p1}(k+1), y_{p2}(k+1)\right] \end{aligned}$$

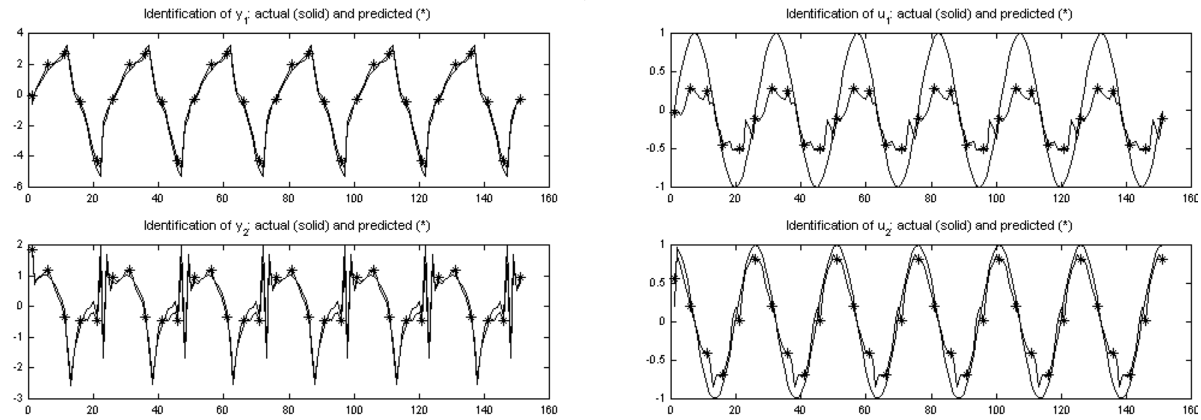
A FasBack network (with parameters ρ_A=0.3, ρ_B=0.4, γ_A=5 and γ_B=10) was trained over 10 cycles for these 5000 samples to learn direct dynamic of the plant $\hat{\vec{y}}_p(k+1) = \hat{\vec{f}}(\vec{y}_p(k), \vec{u}(k))$, using 103 nodes in ART_A, and 13 in ART_B. To test identification performance the plant is excited with an input vector $\left[sin(2\pi k/25), \cos(2\pi k/25)\right]^T$ (like in [16]), obtaining results show in figure 2(a), which are similar to those achieved in [16], but using only 5000 samples instead on 100000, and no *a priori* knowledge of the plant structure.

To implement the IMC controller it is also necessary to develop a controller module, which is achieved through a FasBack network with the same parameters, by learning inverse dynamic with patterns of the general form:

$$\begin{aligned} Input_A &= \left[y_{p1}(k), y_{p2}(k), y_{p1}(k+1), y_{p2}(k+1)\right] \\ Input_B &= \left[u_1(k), u_2(k)\right] \end{aligned}$$

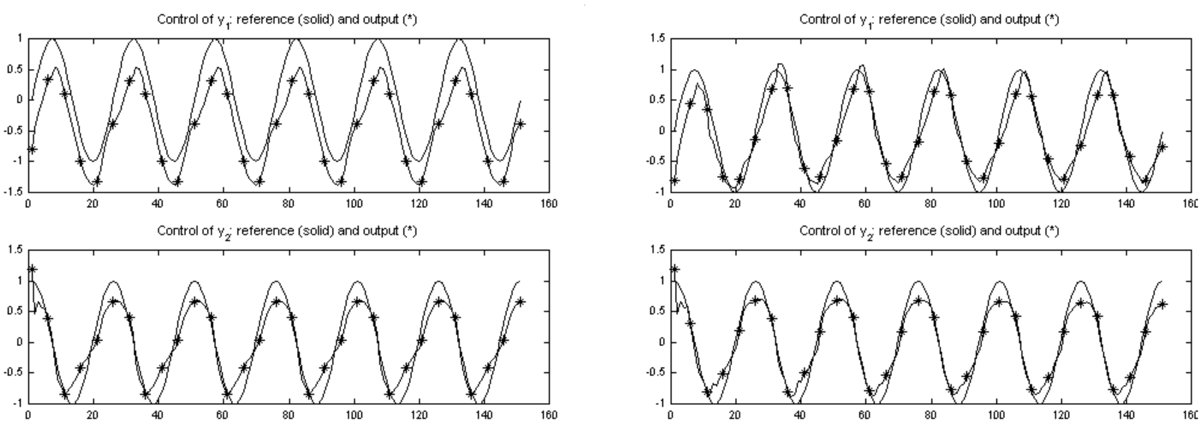
Identification performance is tested estimating the control signal that would produce the actual output of the previous test, i.e. ideal output of controller module would be the aforementioned control law $\left[sin(2\pi k/25), \cos(2\pi k/25)\right]^T$. Results are shown in figure 2(b), where it can be easily appreciated that identification of inverse dynamics is worse than that of direct dynamic. This is due to the fact that samples in training set for inverse dynamics learning do not cover thoroughly the output variation space, and also to the compromise problem between different possible control actions needed to achieve a given plant output.

Worse identification of inverse dynamics will result in a poor control result, which can be solved enabling adaptive capabilities of neural networks involved in IMC strategy. In figure 3(a) control results are shown for the non adaptive IMC strategy with the model and controller model previously built, to track trigonometric references $\left[sin(2\pi k/25), \cos(2\pi k/25)\right]^T$ as in [16]. It can be seen that performance is not very satisfactory, especially for variable y_{p2}, due to the bad inverse dynamics learning achieved. To improve the learning of the control operation space we enabled adaptive capabilities of the neural networks involved in the IMC, resulting into progressively improved control performance, as shown in figure 3(b).



(a) (b)

Figure 2: Identification of (a) direct dynamics (y_{pi} and $\hat{y}_{pi}$), using 242 nodes in ART_A and 25 in ART_B. (b) inverse dynamics (u_{pi} and u_{pi}) using 242 nodes in ART_A and 25 in ART_B.



(a) (b)

Figure 3: Control of MIMO plant for references $[sin(2\pi k/25), \cos(2\pi k/25)]^T$ when (a) adaptation is not enabled (b) adaptation is enabled, and control performance improves with time. In this case, used nodes did not increase.

Results after time of adaptation are similar to those shown in [16], but with the more general strategy that does not make assumptions about the plant structure. Although in this particular case of a theoretical plant this fact is not very important, in industrial cases this is a major concern. For example in [1] a biochemical (*sacharomyces cerevisae* fermentation) problem is presented, where in the unrealistic case of a totally known plant, a PID controller performs better that advanced control strategies, but when less suppositions about plant dynamics are made, the less structured controllers give better results. In the following section, this philosophy will be illustrated with another biochemical problem.

All simulations were run under MATLAB 5.1 on a Pentium 166 MHz computer, and off-line leaning time was around 1 minute. Each test experiment took around 15 seconds in non adaptive cases and 30 in adaptive cases.

5. Identification and control of a simulated penicillin plant

Traditionally the application of complicated mathematical models to control and track the fermentation has been used. Generally, the biological systems are so complex that results have not been too brilliant. The non linearity, variation of the parameters with time, difficulty and impossibility of measuring many of the variables involved make it very difficult to fit a model within the traditional control systems. To test FasBack based IMC system, to work on a penicillin problem it has been initially decided to work on simulated data. Among the several models existing in the literature Tiller model [17] has been selected, because in opinion of Antibióticos, S.A. (León, Spain) industrial experts it is a good approximation to real cases. It is a segregated model with parameters varying along time. The proposed system is not only able to learn parameters variation off-line during learning phase, but has also proved able to learn the effect of the time variation of some parameters in real time, as shown further in this section.

To identify direct and inverse dynamics, we generated 30 fermentations each of them during 240 hours, in which feeding law was selected randomly within bound suggested by experience, as shown in figure 4(a), and the rest of the input laws were kept fixed among fermentations. Gaussian noise was added to the output of 0.1% amplitude to gas measurements, and 5% to laboratory analysis. Furthermore, although simulator provides measurements of any variable every hour, laboratory variables were down-sampled to realistic rates, and then interpolated, to have a more accurate approach to results that would be obtained when training with real data.

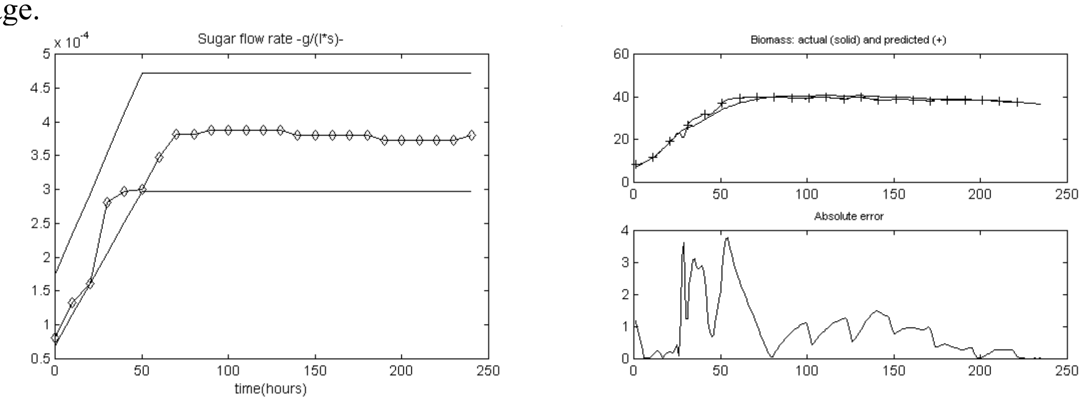
Direct and inverse dynamics were learned using two FasBack neural networks with 10 training cycles (each of 30 fermentations of 240 points). For direct dynamics $F(t)$, $CPR(t)$, $CPR(t-1)$, and $CPR(t-2)$ were used to predict $X(t+1)$, and for inverse dynamics $X(t+1)$, $CPR(t)$, $CPR(t-1)$, and $CPR(t-2)$ were used to estimate $F(t+1)$, where X is the biomass concentration g/l, CPR is the carbon dioxide production rate in $g/(l \cdot s)$, and F is the sugar flow rate, measured in litters of water per second, assuming that a constant concentration of sugar is present in the flow. In results presented in this section also the penicillin concentration P is also shown, measured in g/l.

After training, the controller and model modules were generated using 50 nodes in ART_A and 39 in ART_B for the controller, and 47 nodes in ART_A and 34 in ART_B for the model. Satisfactory identification results, as shown in figure 4(b), permit us to build an IMC strategy using these two modules.

To test controller performance it must be considered that not any reference can be tracked by a biochemical plant. Here we use a reference inspired in [14], which guarantees high growing rate at exponential growing stage (μ_{gr}), low growing rate at production stage (μ_{pr}), and soft transition between those to rates. Mathematically:

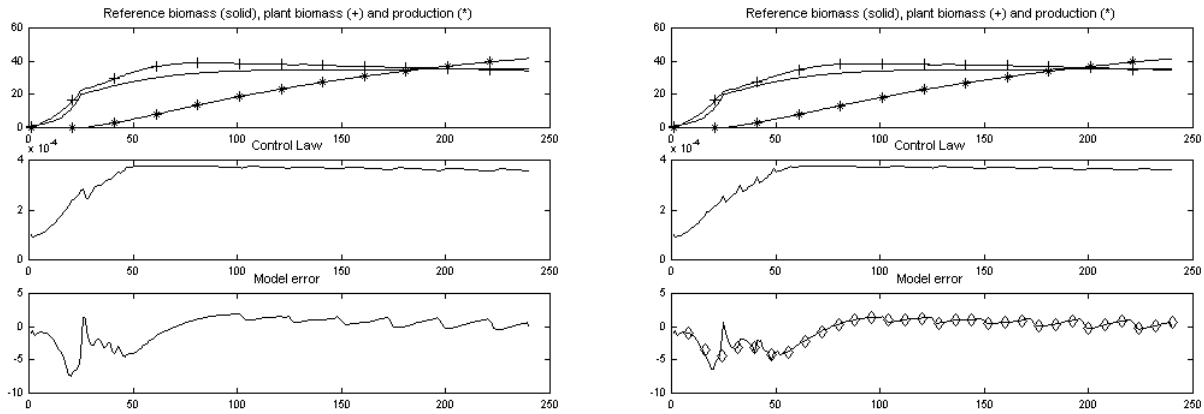
$$X^{ref} = \begin{cases} e^{\mu_{gr} t} & t \le t_1 \\ e^{\mu_{gr} t_1} + \Delta X_{pr} \dfrac{1 - e^{-\mu_{pr}(t-t_1)}}{1 + e^{-\mu_{pr}(t-t_1)}} & t > t_1 \end{cases} \tag{5}$$

where $\mu_{gr} = 0.12h^{-1}$, $\mu_{pr} = 0.045h^{-1}$, $\Delta X_{pr} = 15\,g/l$ is the total growing expected in the production stage, and $t_1 = 25h$ is the time of change from the growing to the production stage.



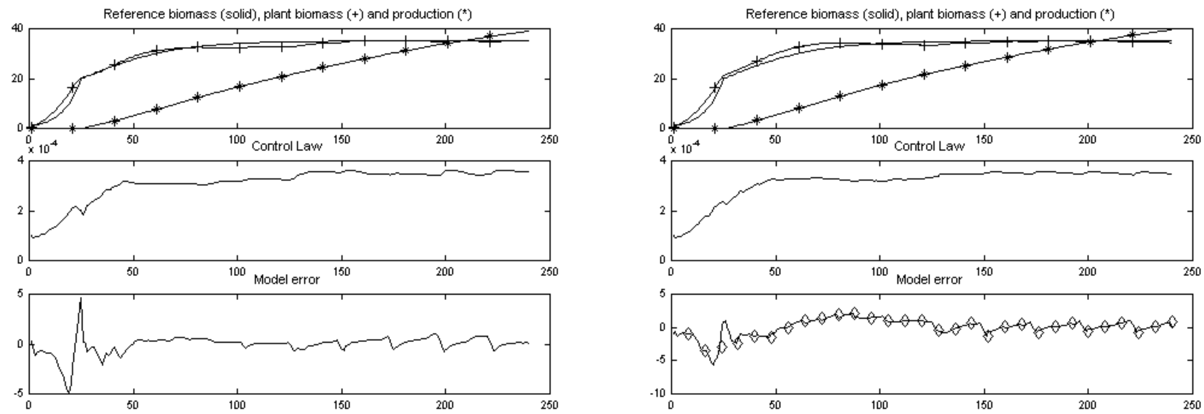
(a) (b)

Figure 4. (a) Example of random feeding law use to simulate fermentations using the Tiller model, and bounds for randomly generated feeding laws. (b) Identification of a fermentation using a FasBack neural network which has learnt direct dynamics.



(a) (b)

Figure 5. Control of the nominal plant when (a) biomass is measured every hour, (b) biomass is measured every eight hours. In this case, marks on the model error plot show error values that are fedback to the controller.



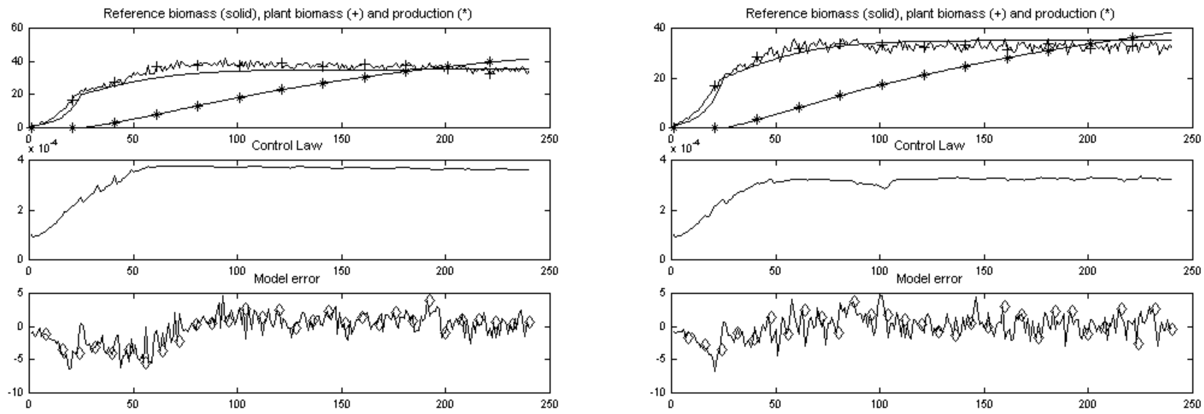
(a) (b)

Figure 6. Control of the nominal plant with adaptation of the model and the controller when (a) biomass is measured every hour (model nodes increased to 50 in ART_A and 35 in ART_B (b) biomass is measured every eight hours (model nodes increased to 48 in ART_A). In this case, marks on the model error plot show errors fedback to the controller.

Control performance is shown in figure 5(a) in the unrealistic case of measuring biomass every hour, which is the control action rate. In a more realistic case biomass is measured every eight hours. In figure 5(b) it can be appreciated that this restriction does not affect performance, which is satisfactory. However, the fact that the model reflects a general behaviour of the plant, rather than being accurately describing the actual plant, influences negatively control performance. This can be corrected by enabling adaptation, as shown in figure 6.

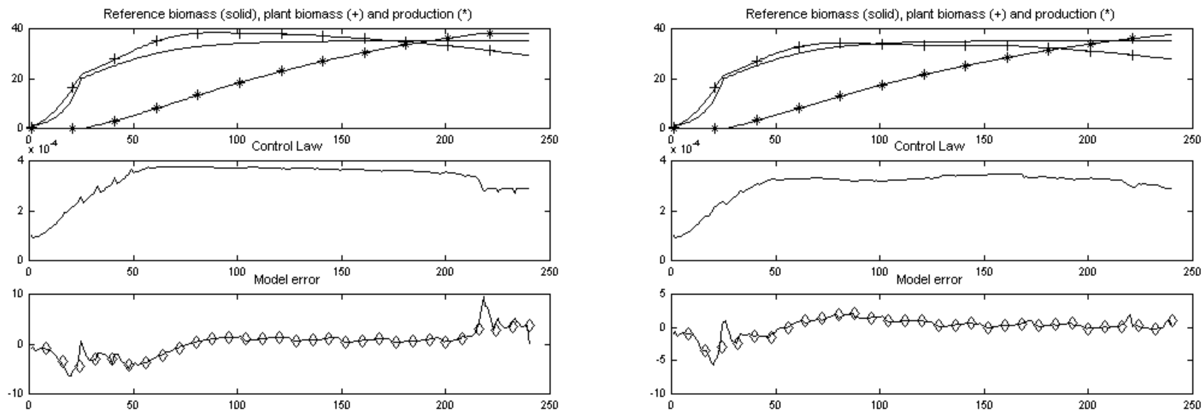
A more realistic approach can be made in the case of presence of noise in plant output. To test this the same experiments were run adding 5% gaussian noise to biomass *laboratory measurements*, and 0.1% gaussian noise to *CPR* measurement provided in reality by a gas spectrometer. Control results in figure 7 show IMC capabilities to compensate noise in the output, for the same reference shown in equation 5.

To simulate the influence of cell damage by lysis and shear forces [17] and test on-line adaptation capability of the proposed system, it has been roughly assumed that these effects influence mainly biomass yield on sugar (Y_{XS} in [17]), supposing that it decreases from 0.5 g/g at time 100 hours to 0.1 g/g at the end of the fermentation. Results (figure 8) show a better tracking of reference in adaptive case to obtain a similar penicillin production, whilst control law is smaller and smoother.



(a) (b)

Figure 7. Control of the nominal plant when there is 5% noise in the measurement of biomass and 0.1% noise in the measurement of CPR and (a) adaptation is not used and (b) adaptation of the model and the controller is applied. In both cases biomass is only measured every eight hours



(a) (b)

Figure 8. Control of a time varying plant where Y_{XS} decreases from 0.5 g/g at time 100 hours to 0.1 g/g at the end of the fermentation. (a) Without adaptation, (b) with adaptation. In both cases biomass is only measured every eight hours

6. Conclusions

In this paper, FasBack neuro-fuzzy system has been introduced into IMC strategy. While IMC is an efficient, stable control strategy that can be easily extended to non linear MIMO problems, FasBack is a solution for the difficult task of building model and control modules, due to its fast stable learning from examples and good performance in MIMO plants identification. This have been seen as applied to a MIMO plant from the literature, where MIMO identification performed similarly to two MISO backpropagation models, with much less training samples and computational effort. Another feature of FasBack, as a fuzzy system, is the possibility of inclusion of experts linguistic rules together with knowledge extracted from examples, and the interpretability of learned knowledge in terms of fuzzy rules. This has not been exploited in this paper but is of interest for future research.

Furthermore, on-line adaptive capability of FasBack has been used to add this feature to IMC strategy, obtaining good results both in the case of the direct or inverse model are not accurate, and in the case of plant parameters varying with time. Application of FasBack based IMC to a simulated penicillin plant has been very satisfactory, in the realistic cases of laboratory measurements are not available as often as control signal is required, there is presence of noise in plant output, and plant parameters vary with time. These results suggest a simple efficient control strategy that can be of industrial interest if results can be extrapolated to a real plant instead of a simulated one.

References

[1] Boskovic J.D. and Narendra K.S., “Comparison of linear, Nonlinear and Neural-network-based Adaptive Controllers for a Class of Fed-batch Fermentation Processes”, Automatica, vol. 31, no. 6, pp. 817-840, 1995.

[2] Cano J.M., Dimitriadis Y.A., Araúzo M.J. and López J., “FasArt: A New Neuro-Fuzzy Architecture for Incremental Learning in System Identification”, 13th World Congress of IFAC International Federation of Automatic Control, vol. F, pp. 133-138. San Francisco, CA, USA. June 30 - July 5, 1996.

[3] Cano J. M., Dimitriadis Y. A., Araúzo M. J., Abajo F. and López J. “A Neuro-fuzzy Architecture for Automatic Development of Fuzzy Controllers”, CESA/96, Lille, France, vol 2, pp. 1187-1192, April 1996.

[4] Cano J. M., Dimitriadis Y. A., Araúzo M. J., Abajo F. and López J. “Fuzzy Adaptive System ART-based: Theory and Application to Identification of Biochemical Systems”, CESA/96, Lille, France, vol 2, pp. 918-923, April 1996.

[5] Cano J.M. Dimitriadis Y.A and López J. “FasBack: Matching-error based learning for automatic generation of fuzzy logic systems”, FUZZ-IEEE, Barcelona, Spain, 1997.

[6] Cano J.M., Araúzo M.J., Y.A. Dimitriadis y López J., “Non linear processes adaptive control using fuzzy neural systems”, EUFIC'97 5th European Congress on Intelligent Techniques and Soft Computing, Aachen, Germany. September 8-12, 1997.

[7] Carpenter G., Grossberg S., Markuzon and N., Reynolds J. "Fuzzy ARTMAP: A Neural network architecture for incremental supervised learning of analog multidimensional maps" IEEE Transactions on Neural Networks, vol. 3, pp 698-713, 1992.

[8] Economou C. G., Morari M. and Piasson B. O., “Internal Model Control. 5. Extension to Nonlinear Systems”, Industrial Engineering Chemical Process Design and Development, no. 25, pp. 404-411, American Chemical Society, 1986.

[9] Economou C. G. and Morari M., “Internal Model Control. 6. Multiloop Design”, Industrial Engineering Chemical Process Design and Development, no. 25, pp. 411-419, American Chemical Society, 1986.

[10] Garcia C. E. and Morari M., “Internal Model Control. 1. A Unifying Review and Some New Results”, Industrial Engineering Chemical Process Design and Development, no. 21, pp. 308-323, American Chemical Society, 1982.

[11] Grossberg, S. “Adaptive pattern classification and universal recoding. II: Feedback expectation, olfaction and illusions”. Biological Cybernetics, no. 23, pp. 187-202, 1976

[12] Hirschorn R. M., IEEE Transactions on Automatic Control, vol. 24, no. 6, 1979.

[13] Hunt K. J. and Sbarbaro D., “Neural Networks for nonlinerar internal model control”, IEE proceedings, vol. 138, no. 5, pp. 431-438, September 1991

[14] Mou D. G., "Toward an Optimum Penicillin Fermentation by Monitoring and Controlling Growth trough Computer-aided Mass Balancing", Ph.D. Thesis, MIT, Cambridge, MA, USA, 1979

[15] McClelland J. and Rumelhart, D. “Explorations in Parallel Distributed Processing”. vols 1 and 2. MIT Press, Cambridge, MA, USA, 1986

[16] Narendra K.S. and Parthasarathy K., “Identification and Control of Dynamical Systems Using Neural Networks”, IEEE Transactions on Neural Networks, vol. 1, no. 1, pp. 4-27, March 1990.

[17] Tiller V., Meyerhoff J., Sziele D., Schügerl, Bellgardt, K-H. "Segregated mathematical model for the fed-batch cultivation of a high-producing strain of *Penicillium chrysogenum*". Journal of Biotechnology, no 34, pp. 119-131, 1994.

[18] Wang L. “Adaptive Fuzzy Systems and Control”, PTR Prentice Hall, 1994.

[19] Zadeh L. “Fuzzy Sets”. Information and Control, vol. 8, 1965