# FAULT TOLERANT FUZZY IMC CONTROL IN A PH PROCESS


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**Keywords:** IMC non-linear control, ANFIS, Fault tolerant control, fuzzy logic, sulfitation tower.



## Abstract

This paper proposes a new fault tolerant control methodology using Fuzzy Internal Model Control (IMC) for nonlinear systems. The models (direct and inverse plant models) used in the IMC controller are generated by an adaptive neural network called ANFIS, which implements a fuzzy inference system of Takagi-Sugeno type. The inverse model of the IMC controller is reconfigured by exploiting information estimated from a fault diagnosis unit and a qualitative model of the system, in terms of a fuzzy logic system. Simulation examples for a fault tolerant sulfitation control problem are given to demonstrate the effectiveness of the proposed scheme.


## 1 Introduction

The last two decades have been seen continuous improvement in systems and control techniques resulting from the spectacular progress in control theory and computer technologies. Meanwhile, stimulated by the growing demand for improving the reliability and performance of systems, many fault diagnosis and fault tolerant control methods have been developed which have the capability of detecting the occurrence of faults and retaining satisfactory system performance in the presence of faults [3, 11].

Fault tolerance of dynamic systems can be achieved either from systems robustness to fault as well as other uncertainties or from controller reconfiguration (or restructuring) in response to specific faults. The former methodology since no information about faults is utilized by control systems, can be referred as "passive fault-tolerant control systems", [4]. However, the magnitude of faults that can be accommodated by a fixed control structure and parameters is often limited. By utilizing the fault information obtained from fault detection and identification (FDI) scheme, reconfigurable control modifies the control function in response to the faults so that it is referred to as "active fault tolerant control". This can be obtained by control law re-scheduling [1], linear quadratic control [7], pseudo-inverse methods [6], adaptive control methods [13, 5], etc.

As most plants are inherently nonlinear and the faults may often amplify the nonlinearities by driving the plants from a relatively linear operation point into a more nonlinear operation region, the study of fault tolerant control for nonlinear systems is important. In the attempt to solve this problem, methods such as neural networks and fuzzy systems have been used due to their capabilities of forming arbitrarily accurate approximation to any continuous nonlinear functions [16, 5].

In this paper, an active fault tolerant system design methodology using fuzzy IMC controller is proposed, and it has been applied to a highly nonlinear system. The ability of neural networks to represent nonlinear relations leads to the idea of using networks directly in a model-based control strategy. A suitable control strategy within directly incorporates the plant model is provided by Internal Model Control (IMC). In this work, fuzzy neural networks, called ANFIS [9], had been used for the construction of the plant model and its inverse and they are used directly within the IMC control structure. The ANFIS architecture is used because it represents a fuzzy inference system, and as a result of the training of the network some fuzzy rules are obtained, which can be used to interpret the system.

After that, a fault diagnosis algorithm has been used based on the nonlinear model obtained by the ANFIS architecture, and the information provided by this algorithm is used to reconfigure the controller. In this work, the controller is the inverse model of the system, that consist of a set of fuzzy rules of Takagi-Sugeno type, the key idea is to modify these rules when a fault is detected. Specifically, the independent terms of those rules are modified based on knowledge of the system (a qualitative plant model) using a fuzzy logic inference system. This methodology has been applied to a highly nonlinear system: a sulfitation tower.

The paper is organized as follows, in the section 2 the nonlinear internal model control is presented, together with the ANFIS network, and in the section 3 the fault-tolerant scheme is described. In section 4 the application of this methodology to the sulfitation process is presented, with a description of the system, of the fault-tolerant control system design, and the results when parametric faults have occurred in the system. Finally section 5 concludes this paper.

## 2 The non-linear Internal Model Control

The basic idea of linear Internal Model Control (IMC) is illustrated in the Fig. 1. The key characteristic of this control design approach is the inclusion of a plant model within the control structure. If the model is a perfect representation of the process, the influence of the process output on the feedback signal vanishes. The feedback signal then only carries the influence of disturbances. However, in practice the model and the plant are rarely similar. The feedback signal then combines the model error (model uncertainty) with the disturbances. Based on this structure, perfect control is obtained if the controller $C$ is chosen as the inverse of the internal model $M$. IMC controllers have been extensively studied in the case of linear modelling of the process, and have been shown to have good robustness properties against disturbances and model mismatch [10].

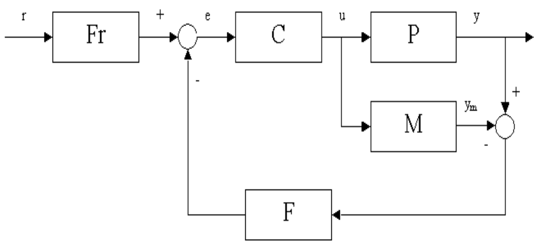


Figure 1: IMC Structure

The IMC structure can also be used in the nonlinear case. The method simply consists in including a nonlinear plant model in place of the linear one. Some possible alternatives exist in order to chose the nonlinear model, such as a fuzzy model from input-output data [2], a model based on first principles, [12] or a model based on neural networks [8, 15].

In this work the nonlinear model proposed for the IMC, is the Adaptive Network Based Fuzzy Inference System (ANFIS), developed by [9], which is a fuzzy inference system implemented in the framework of adaptive networks. An adaptive network (Fig. 2) is a multilayer feedforward network in which each node performs a particular function on incoming signals as well as a set of parameters pertaining to this node. The ANFIS architecture implements a fuzzy inference system, for example in the Fig. 2 it implements a system with two inputs $x$ and $y$, one output and two rules of Takagi and Sugeno's type:

Rule 1: If $x$ is $A_1$ and $y$ is $B_1$ then $f_1 = p_1x + q_1y + r_1$
Rule 2: If $x$ is $A_2$ and $y$ is $B_2$ then $f_2 = p_2x + q_2y + r_2$.

The ANFIS architecture is described here. In layer 1 every node $i$ has the function: $O_i^1 = \mu_{A_i}(x)$, where $x$ is the input to node $i$, and $A_i$ is the linguistic label (small, large, etc.). In other words, $O_i^1$ is the membership function of $A_i$ and it specifies the degree to which the given $x$ satisfies the quantifier $A_i$. Every node in layer 2 multiplies the incoming signals and sends the product out, i.e, each node output is a T-norm that performs the connector AND.

$$w_i = \mu_{A_i}(x) * \mu_{B_i}(y), i = 1, 2 \tag{1}$$

$$\overline{w}_i = \frac{w_i}{w_1 + w_2}, i = 1, 2 \tag{2}$$

$$O_i^4 = \overline{w}_i f_i = \overline{w}_i(p_i x + q_i y + r_i) \tag{3}$$

In the layer 3 each node calculates the ratio of the $ith$ rule's firing strength to the sum of all rules' firing strengths (eq. 2).

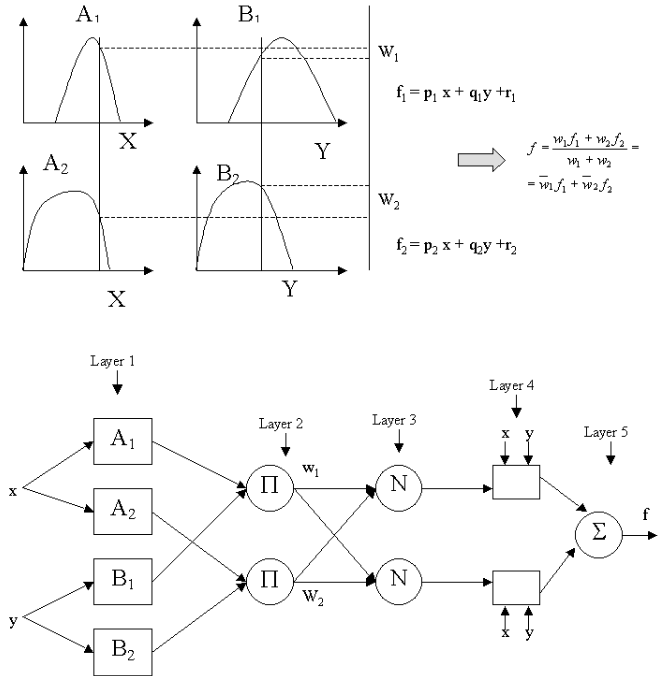


Figure 2: Takagi-Sugeno fuzzy reasoning and the equivalent ANFIS architecture

And each node in layer 4 has the node function represented in eq. 3, where $p_i, q_i, r_i$ is the consequent parameter set. Finally, the single node in the layer 5 calculates the overall output as the summation of all incoming signals, i.e.,

$$O^5 = \sum_i \overline{w}_i f_i = \frac{\sum_i w_i f_i}{\sum_i w_i} \tag{4}$$

Thus, an adaptive network which is functionally equivalent to a Takagi and Sugeno fuzzy inference system has been constructed. The use of this ANFIS architecture within the IMC structure, is implemented in two steps. The first one involves training an ANFIS network to represent the plant response. This network is then used as the plant model operator $M$ in the control structure of Fig. 1. The network is trained in the classical way, i.e., the error signal used to adjust the net weights is the difference between the plant output and the network output. Thus, the net is forced towards copying the plant dynamics.

Following standard IMC practice, the controller is selected as the plant inverse model. The second step in the procedure is then, to train a second ANFIS network to represent the inverse of the plant. To do this the architecture shown in Fig. 3 is used [8]. Here, the plant model (obtained in the first learning step) is used in the inverse learning architecture rather the plant itself. For inverse modelling, the error signal used to adjust the network is defined as the difference between a synthetic signal (the desired network output) and the network output. This tends to force the transfer function between the reference and the output of the model to unity; i.e., the network being trained is forced to represent the inverse model of the plant model. Having obtained the inverse model, this ANFIS network is then used as the controller block $C$ in the control structure of Fig. 1.

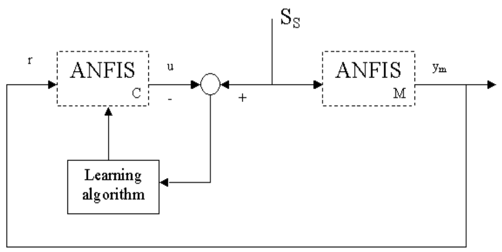


Figure 3: Use of synthetic signal to obtain the inverse model

# 3 Fault tolerant fuzzy IMC controller

## 3.1 Fault detection and Identification scheme

Model-based fault diagnosis is the detection, isolation and characterization of faults in the components of a system [3] or in the system itself, based on a model of the process. The difference between measurements and model outputs are called residues, which are the signals to which a threshold is set, in such a way that when a fault occurs, the residual becomes greater than the threshold. Once a threshold is exceeded, an analysis of the residual leads to the fault isolation. Through, the general structure of model-based fault diagnosis has two main stages: residual generation and decision making.

A fault detection system capable of detecting both additive and multiplicative faults have been developed. The residues are generated as the difference between the model and the system outputs. The model used is the one defined as direct model in the IMC structure, then using the same model that for control purposes the modelling effort is reduced drastically. The residual designed in that way takes non-zero values when a fault occurs or when a reference change is set. This drawback can be overcome if an appropriate decision making method is used.

The decision making system does not perform over the residue but over the absolute value of its derivative. The value obtained in this way is compared with a threshold, which is exceeded when a fault or a reference change occurs. In order to differentiate between both cases, a new residue is introduced. This is calculated as the maximum of the absolute value of the derivative of the windowed reference. A threshold is provided to this new residue. This last residue is calculated in that way because when a reference change is introduced, the residue associated to the system output has a delay in taking a value different from zero. If the reference were not windowed, both residues would not exceed their thresholds at the same time. The window memorizes changes in the reference.

With these residues, the decision making is based on a simple rule: If both residues exceed their respective thresholds, a reference changed has occurred; if only the residue associated to the system output violates its threshold, a fault has occurred. The only problem is that this system is unable of detecting a fault that occurs at the same time that a reference change.

## 3.2 Fault Tolerant Control with a priori Knowledge

In Fuzzy-IMC, the role of the controller is carried out by an inverse model of the plant. This inverse model is implemented by an ANFIS network, which main characteristic is the set of rules that conform it. The ANFIS, at least in the way employed here, is a Takagy and Sugeno fuzzy inference system. This means, that the consequent part of the rules are first grade functions of the inputs, so, the consequent of each rule has an independent term (the $r_i$ parameters shown in eq. 3 and in Fig. 2). In this work they are called Consequent Independent Terms (CIT). The fault-tolerant strategy is based on inducing changes on the CIT set. The controller is reconfigured in this way every time that a fault is detected and isolated. Due to the non-linear nature of the system, the amount of change in the CIT set depends on the operation point. In order to calculate the size of the change a qualitative model is used. The qualitative model expresses the relationship between the input and the output in such a way that it is a reliable model even when a fault has occurred. This model can be expressed as the following rule, where $y$ is the output system and $u$ is the control action:

Let be $error = reference - y$,
If $error > 0 \Leftrightarrow reference > y \Rightarrow \Delta u < 0$
If $error < 0 \Leftrightarrow reference < y \Rightarrow \Delta u > 0$

This rule can be expressed mathematically as eq. 5, where $\omega_0(k)$ is the CIT set at period $k$ and $e(k)$ is the error. The role of parameter $L_r$ is to adapt the qualitative model to the operation point in which the fault has occurred, so the adapted qualitative model can be used to change the CIT set in a way that the fault is accommodated.

$$\omega_0(k+1) = \omega_0(k) - L_r \cdot e(k) \tag{5}$$

In order to calculate the values of $L_r$, a fuzzy inference system was designed. The input of this fuzzy system is the reference, that is, the value that is desired the plant reaches under fault. The output of the fuzzy system is the $L_r$ parameter value that accommodates the fault, and the rules are obtained with prior knowledge of the plant.

# 4 Application to a non-linear process

## 4.1 Plant description

The sulfitation is a chemical process used in the sugar refining industry in order to decrease the pH of a solution of lime milk, $Ca(OH)_2$ by means of a flow of sulfur dioxide, $SO_2$. The process takes place usually in a closed vessel with a reaction tank inside that receives a continuous flow $F$ of the product through the ceiling, and a flow $F_g$ of $SO_2$ through the bottom (Fig. 4). The sulfur dioxide bubbles react with the water to give a sulfur acid that neutralizes the $(OH)^-$ from the base. The liquid inside the tank overflows it and leaves through the bottom at a lower pH. A valve is used to manipulate the $SO_2$ flowrate and therefore, the pH of the output product. The reactions that take place inside the reactor are:

$$
\begin{aligned}
&H_2O + SO_2 \longrightarrow SO_3H_2\\
&SO_3H_2 \Longleftrightarrow SO_3H^- + H^+\\
&SO_3H^- + CaOH^- \longrightarrow SO_3Ca
\end{aligned}
$$

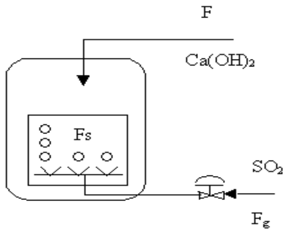


Figure 4: Structure of the plant

A mathematical model of the process derived from first principles [14] can be summarized in the set of equations :

$$
\begin{aligned}
&b\frac{dF_s}{dt} = -F_s + kF_g\\
&\frac{V}{F}\frac{dX}{dt} = -X + [CaOH^-]_i - \frac{\alpha}{F}F_s\\
&\frac{dC}{dt} = \frac{F_s}{V} - \frac{V}{F}\frac{FC}{V}\\
&\text{pH} = -\log{[H^+]}\\
&[\text{H}^+] = \text{X } [-1 + \text{sign(X)}\sqrt{1+\frac{4K_w}{X^2}}]/2
\end{aligned} \tag{6}
$$

The first one gives the time evolution of $F_s$, the flow of sulfur dioxide transferred to the liquid, with $k$ the solution coefficient and $b$ the characteristic time to the solution. The magnitude $X$ is defined as $X = [OH^-] - [H^+]$, $V$ is the volume of the reaction tank, $\alpha$ a dissociation constant, $k_w$ is the water ionic product, $[Ca(OH)^-]_i$ the input concentration of these ions and the variable $C$ is defined as $C = [SO_3H_2] + [SO_3H^-]$. Finally the constants $\alpha$ and $k_W$ are calculated as:

$$
\begin{aligned}
&\alpha = \frac{-K_{eq} + \sqrt{K_{eq}^2 + 4K_{eq}C}}{2C}\\
&K_{eq} = Z_s \exp\frac{-Es}{RT}\\
&k_w = Z_a \exp\frac{-Ea}{RT}
\end{aligned} \tag{7}
$$

with $K_{eq}$ the equilibrium coefficient of the reaction, $Es$ and $Ea$ are the activation energies, and $Za$ and $Zs$ are constants.

The control aim is to maintain the $pH$ at the output at a specified value despite the disturbances acting on the system. The control variable is the $SO_2$ flowrate and the main disturbances is the $pH$ ($pHa$) of the incoming flowrate $F$ which is related to the concentration $[Ca(OH)^-]_i$.

### 4.2 Control system design

The first step to apply the fuzzy IMC controller is to obtain a suitable representation of the system. The strong nonlinearity present in the system can be modelled by means of an ANFIS network, where the gas flowrate ($F_g$) is the input to the system and the $pH$ is the output, in the following series-parallel model:

$$pH(t) = f(F_g(t), F_g(t-1), pH(t-1), pH(t-2)) \tag{8}$$

Here the ANFIS net has three membership functions of gaussian type for each input, this gives a total number of $3^4$=81 fuzzy rules. For training the network, suitable data is needed, to get this, a step train in the manipulated input $F_g$ is generated with different amplitudes and frequencies, using a sampling time of 30 seconds. After training, the desired and predicted values for both training data and checking data are essentially the same in Fig. 5. The fuzzy rules generated by the ANFIS architecture are of the form:

If $F_g(t)$ is $A_1$ and $F_g(t-1)$ is $B_1$ and $pH(t-1)$ is $C_1$ and $pH(t-2)$ is $D_1$ then $pH(t)$= $a_1 * F_g(t)$ + $b_1 * F_g(t-1)$ + $c_1 * pH(t-1)$ + $d_1 * pH(t-2)$ + $w_0$

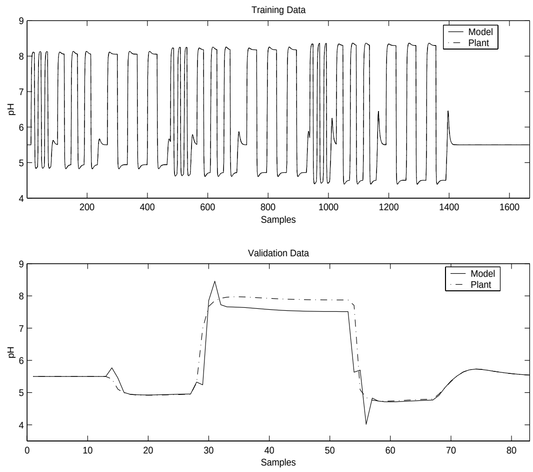


Figure 5: System output and ANFIS output for training data and for validation data

The second step to apply the fuzzy IMC controller to the sulfitation tower is to obtain an inverse model of the plant, training another ANFIS network. Due to the highly non-linear behaviour of the system, the synthetic signal (Fig. 3) has to be such that, it generates so much data in the critical non-linear regions of operation. The ANFIS architecture used to generate the inverse model is:

$$F_{gs}(t) = g(pH_m(t-1), pH_m(t-2), pH_m(t-3)) \tag{9}$$

where $F_{gs}$ is the synthetic signal and $pH_m$ is the output of the model trained in the first step. Here, three membership functions has been used for each input, and $3^3 = 27$ fuzzy rules are generated for the inverse model. After training the final result is shown in Fig. 6 which shows the output of the net and the non-linear simulation model, for both training and validation data. Perfect matching is not possible since noise and disturbances are included in the simulation.

In Fig. 1 there are two filters $F$ and $Fr$, the first one is to reduce the noise and disturbances before to feedback the signal in order to avoid stability problems, and the latter is a filter to smooth the reference signal. In this work the filters used are:

| Parameter | Value |
|---|---|
| Plant output residue | 0.01 |
| Reference residue | 0.0 |
| Window size | 40 |

Table 1: Threshold and window values

$$
\begin{aligned}
F_r &= 1 \\
F &= \frac{10^{-6}}{z+10^{-6}}
\end{aligned}
\qquad (10)
$$

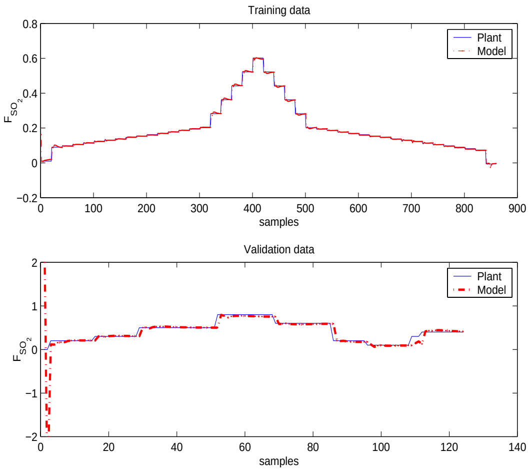


Figure 6: System output and ANFIS inverse model output for training data and for validation data sets

Finally, the response to reference changes and disturbances for this fuzzy IMC structure apply to the sulfitation plant is shown in Fig. 7. It is possible to see that the controller response is not the same in all the operation points, specially for the change from $pH = 8$ to $pH = 7$, that is slower and with a large overshoot, but by the way the results are quite adequate.

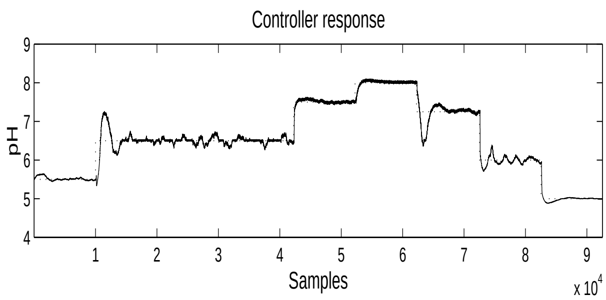


Figure 7: Fuzzy IMC controller response to changes in the reference and disturbances in $pHa$

### 4.3 Fault tolerant control experiments

In order to implement the FDI scheme explained in section 3.1, to the sulfitation plant the thresholds and the window were set to the values showed in table 1.

The experiments have shown that the delay in fault detection is seven sample times. The fault detection system is able to detect faults in sensors, actuators and in the system itself, that is, additive and multiplicative faults, but until now no diagnostic scheme has been implemented. Figure 8 shows the system behaviour, residues and alarm evolution under fault and reference change conditions. At time $1000$ there is a reference change and at $2000$ there is a multiplicative fault, simulated as a step in the temperature shown in eq 7. It can be seen how both the reference and system residues become greater than zero at time $1000$. Otherwise, when a fault occurs, only the system output residue is greater than zero. In the case of a reference change, the memory effect provided by the windowed reference avoid a false alarm.

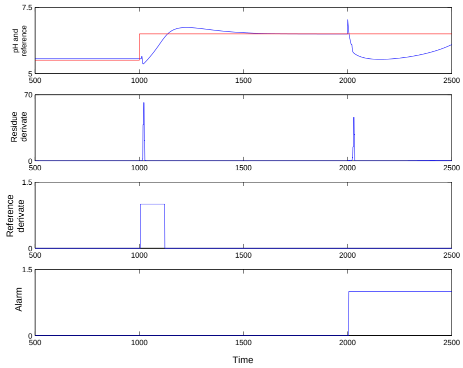


Figure 8: Residues evolution during reference change and fault

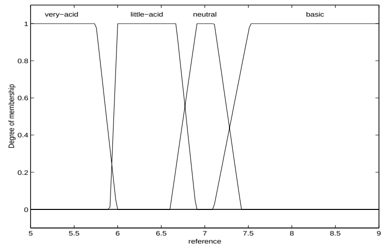


Figure 9: Membership functions of the input to the fuzzy inference system used to reconfigure the IMC controller

The qualitative model used in this application is the eq. 5, where the input to the system is the gas flowrate $F_g$ and the output is the $pH$. In order to calculate the parameter $L_r$, a Takagi-Sugeno type fuzzy inference system has been designed. The input to this inference system is the pH reference, and it has 4 membership functions defined in Fig. 9, the output is the $L_r$ parameter and it is a linear combination of the inputs and the rules are:

If $pHreference$ is $very - acid$ then $L_r = 1$
If $pHreference$ is $little - acid$ then $L_r = 6 * input - 34$
If $pHreference$ is $neutral$ then $L_r = 2$
If $pHreference$ is $basic$ then $L_r = 6 * input - 34$

Some experiments have been carried out to prove the fault tolerant control system designed. Figure 10 shows the plant output behaviour when the reference is set to $6.5$. Fault time is

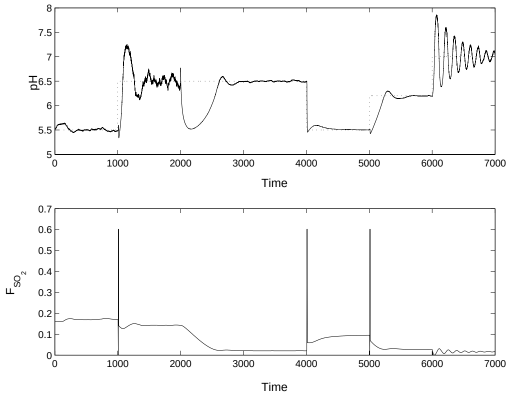


Figure 10: Fault at $t = 2000$ and $pH_{ref} = 6.5$

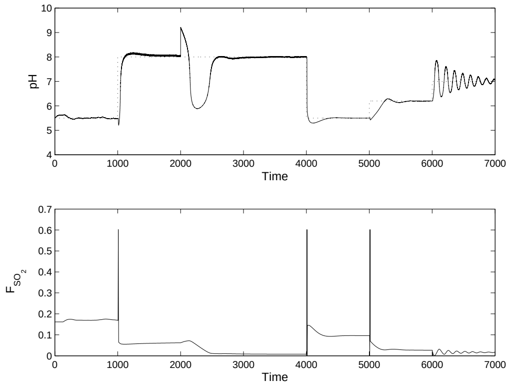


Figure 11: Fault at $t = 2000$ and $pH_{ref} = 8.0$

2000 s. Immediately after the fault detection, the accommodation begins. At time 3300 the output has reached again the reference. Once a time the system is accommodated, the action of the rule expressed in eq. 5 is canceled. Since this equation changes the controller rules, the controller is unable of reproducing accurately the system dynamic, unless eq. 5 will be applied indefinitely, each time an error occurred in the system. In figure 11 results for a fault at reference $8.0$ are shown. In this case accommodation is reached at time $2800$. The control degradation is very severe, but the fuzzy inference system reconfigures the IMC controller to reach again the reference. By the way, it is possible to see that the controller is not very good when the system reach the value of $pH = 7$, the response is very oscillatory. This shows that the problem is not yet solved and more studies are necessary to improve this response.

## 5 Conclusions

A fault tolerant fuzzy IMC controller is presented in this paper. The method consists of three parts. The first one is to calculate a direct model and an inverse model of the process using a neural network (ANFIS), which implements a fuzzy inference system. These models are used directly in the IMC structure. The second part is essentially a fault detection and identification (FDI) algorithm, based on the direct model to identify the faults in the system. Finally the third part is the modification of the consequent parameters of the fuzzy rules that conform the inverse plant model in terms of a qualitative plant model and information received from the FDI unit. This methodology is applied to a sulfitation process with good results, except for some values of the reference as pH = 7. But the drawback of this method is that knowledge of the process with faults in necessary. This information is not so easy to get in the industrial plant, so the method need to be improved.

## Acknowledgements

This work has been supported by the research national agency of Spain (CICYT) throughout project DPI2000-0691-C02-02.

## References

[1] C. Aubrun, H. Noura, and D. Sauter. Online reconfiguration strategy of control law for degraded systems. In *Proc. IFAC SAFEPROCESS*, pages 104–107, Espoo, Finland, 1994.

[2] R. Boukezzoula, S. Galichet, and L. Foulloy. Fuzzy nonlinear adaptive internal model control (FNAIMC). In *European Control Conference, Karlsruhe (Germany)*, 1999.

[3] J. Chen and R. J. Patton. *Robust Model-Based Diagnosis for Dynamics Systems*. . Kluber. Academic Publisher, 1999.

[4] Z. Chen, R. Patton, and J. Chen. Robust fault tolerant system synthesis via LMI. In *Proc. IFAC SAFEPROCESS*, pages 337–342, Hull, U.K., 1997.

[5] Y. Diao and K. Passino. Stable fault tolerant adaptive fuzzy/neural control for a turbine engine. *IEEE Trans. on Control System Technology*, 9(3):494–509, 2001.

[6] Z. Gao and P. J. Antsaklis. Stability of the pseudo-inverse method for reconfigurable control systems. *Inter. Journal of Control*, 53:717–729., 1991.

[7] C. Y. Huang and R. Stengel. Restructurable control using proportional-integral implicit model-following. *Journal of Guidance, Control and Dynamics*, 13 (2):303–309, 1990.

[8] K. Hunt and D. Sbarbaro. Neural networks for nonlinear internal model control. *IEE Proceedings-D*, 138 (5):431–438, 1991.

[9] J. Jang. ANFIS: Adaptative-network-based fuzzy inference system. *IEEE Trans. on Systems, Man and Cybernetics*, 23:665–685, 1993.

[10] M. Morari and E. Zafiriou. *Robust Process Control*. Prentice-Hall, 1989.

[11] R. J. Patton. Fault tolerant control: The 1997 situation. In *Proc. IFAC SAFEPROCESS*, pages 1029–1051, Hull, U.K., 1997.

[12] P. Pisabarro and I. Amores. Control de pH utilizando un controlador IMC no-lineal. Technical report, Dpto. Ingeniería de Sistemas y Automática. Universidad de Valladolid, 2000.

[13] M. M. Polycarpou. Fault accommodation of a class of nonlinear dynamical systems using a learning approach. In *IEEE Inter. Symp. On Intelligent Control/Intelligent Systems and Semitic*, pages 185–190, Cambridge, USA, 1999.

[14] C. Prada, P. Vega, and L. Alonso. Modelling and simulation of a sulfitation tower for adaptive control. In *11th IASTED Conference Applied Modelling and Simulation*, 1984.

[15] I. Rivals and L. Personnaz. Nonlinear internal model control using neural networks: Application to process with delay and design issues. *IEEE Trans. on Neural Networks*, 11:80–90, 2000.

[16] S. Saludes and M. Fuente. Neural networks-based fault detection and accommodation in a chemical reactor. In *14th IFAC World Congress*, pages 169–174, Beijin, China, 1999.