NEURO-FUZZY CONTROL OF A TWO-INPUT TWO-OUTPUT FLUID MIXER

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ABSTRACT: This paper presents the use of a neuro-fuzzy structure in a qualitative control of a fluid mixer, which is a multivariable and intrinsically non-linear plant. The mixer has as inputs two fluids of different colours and, as its output, the colour of the resulting mix. The actual control system consists of two independent fuzzy controllers which are responsible for maintaining the water level at a given height and for adjusting the colour of the fluid in the mixing tank. One of the main difficulties in the design of fuzzy control systems, especially when the plant is a complex one, is the definition of an optimal or near-optimal rule-base. The neuro-fuzzy controller offers the possibility of creating that rule base automatically, through the constant evaluation of the system error during a learning phase. Simulation results show that responses can be improved by the use of neuro-fuzzy controllers.

KEYWORDS: Fuzzy Control, Neural Nets, Neuro-fuzzy systems, Rule-base, NEFCON

INTRODUCTION

Ordinary hybrid systems are defined in many different ways. Putting it simple, hybrid system are those composed by more than one intelligent system. They are are expected to be more powerful since they combine different intelligent techniques in an advantageous manner. Two or more intelligent systems can be combined to create a unique hybrid system. The most common are:

Sequential hybrid system: this model represents the weakest degree of integration and is composed of two intelligent systems connected in series (Figure 1a). One example of this type of system may be a pre-processor Fuzzy System activating a Neural Net.

Auxiliary hybrid system: this model is composed of a sub-system added by another intelligent sub-system. The integration degree is greater than in the previous case (Figure 1b). An example of this kind of system is a Genetic Algorithm used for determining the weights of a Neural Net.

Incorporated hybrid system: these represent the greatest degree of integration. There is no possible differentiation between the intelligent systems. It can be said that the first system contains the second one and vice-versa. An example is a Neuro-Fuzzy system, where a fuzzy inference system is implemented by employing a neural net structure, as shown in Figure 1c. Among the most common hybrid models are the Neuro-Fuzzy, Neuro-Genetic, Neural-Statistics and Fuzzy-Genetic systems.

A Neuro-Fuzzy system combines the learning capabilities of neural networks with the linguistic rule interpretation of fuzzy inference systems. The basic idea of a Neuro-Fuzzy system is the implementation of a Fuzzy Inference System under the distributed parallel architecture of a neural net, thus taking advantage of the learning capabilities of neural networks.

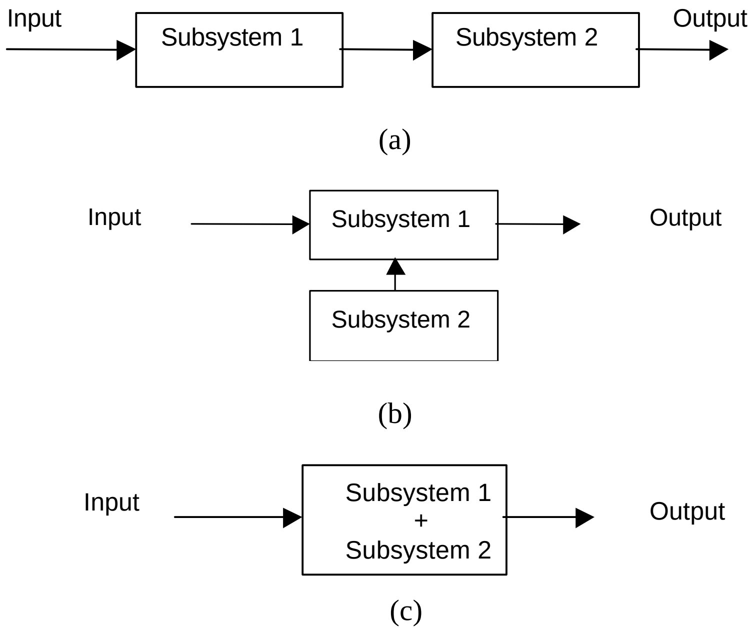


Figure 1: Hybrid systems

In this work a neuro-fuzzy structure is used in the design of a complex task controller; the results are compared to those obtained through the use of a conventional fuzzy controller (Iriarte Lamas et al. (1999)) where the control strategy, i.e. rule-base, has been defined by an expert.

OVERVIEW

The neuro-fuzzy system is employed in the control of the coloration of the resulting mix of two different fluids, while avoiding overflow in the mixing tank. The introduction of a new variable allows the reasoning process to occur in a decoupled fashion, and, in consequence, two independent fuzzy controllers can be used. A similar strategy has been employed and results have been encouraging.

The aim of the current work is to improve process responses through adjustmentes in the rule-base. In contrast with ordinary fuzzy controllers, neuro-fuzzy ones are able to automatically create an appropriate rule-base through training. The replacement of both fuzzy controllers by two neuro-fuzzy ones is expected to give better responses. The size and structure of the fuzzy sets were maintained as before, so that results obtained with the neuro-fuzzy structure could be compared with the previously employed one.

DESCRIPTION OF THE PLANT

The plant, shown in Figure 2, consists of a mixing and two auxiliary tanks. The first auxiliary tank contains coloured water $\mathbf{c_1}$, while the second one contains clear water $\mathbf{c_2}$. The input flow $\mathbf{q}$ to the mixing tank is controlled by two valves, which regulate the output flows $\mathbf{q_1}$ and $\mathbf{q_2}$ from the auxiliary tanks. The output flow $\mathbf{q_0}$, taken as a disturbance, has the coloration $\mathbf{c}$ of the resulting mix and is a function of the output pipe cross-section $\mathbf{ab}$, of the liquid level $\mathbf{h}$ in the mixing tank, and of a constant $\mathbf{C_d}$ related to the shape and material of the output pipe.

In order to simplify the simulation, it has been assumed that the auxiliary tanks always contain sufficient liquid for the process to keep on running. The mixing tank dimension is 20x10x80 cm and the output cross-section $\mathbf{ab}$ can be set to values between 0 and 0.4 cm^2. The output flow $\mathbf{q_0}$ lies between 0 and 60 cm^3/sec. Colorations $\mathbf{c_1}$ and $\mathbf{c_2}$ are set to 1 and 0, respectively.

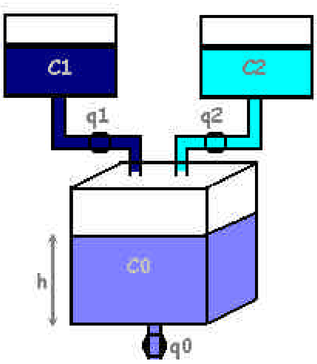


Figure 2: The Fluid Mixer

To derive a practical mathematical model so that simulated experiments can be performed, the time needed to obtain a uniform mixture, time delays related to flows in the pipes, and the dynamics of input and output valves have been neglected (Barreto (1976)). The following equations model the plant dynamics:

$$q - q_0 = \frac{dV}{dt} = S.\frac{dh}{dt} \tag{1}$$

$$q = q_1 + q_2 \tag{2}$$

$$q_0 = Cd.ab.\sqrt{2gh} \tag{3}$$

where g is the gravity acceleration, V is the volume of liquid and S is the area of the liquid surface in the mixing tank.

By using (3) in (1):

$$\frac{dh}{dt} = -\frac{Cd.ab.\sqrt{2gh}}{S} + \frac{q}{S} \tag{4}$$

The mixing process is modelled by:

$$\frac{dh}{dt} = \frac{1}{S}(q_1 + q_2 - q_0) \tag{5}$$

$$c_1.q_1 - c_0.q_0 = \frac{d(c_0.S.h)}{dt} = S(c_0.\frac{dh}{dt} + h.\frac{dc_0}{dt}) \tag{6}$$

By combining (5) and (6):

$$\frac{dc_0}{dt} = \frac{1}{S.h}(c_1.q_1 - c_0(q_1 + q_2)) \tag{7}$$

Equations (4) and (7) describe the system's dynamics; **h** and $\mathbf{c_0}$ are the variables to be manipulated by the controlling system.

NEURO-FUZZY SYSTEM NEFCON

The neuro-fuzzy controllers have been implemented through the use of the NEFCON system (Nürnberger (1997)), which is able to learn and to optimize online the rule-base of a Mamdani-like fuzzy controller by a reinforcement learning algorithm that uses a fuzzy error measure. The NEFCON model is based on a backpropagation network, with one hidden layer. An example of a neuro-fuzzy controller structure with 6 rules, 2 inputs and one output is shown in Figure 3.

The hidden nodes represent the rules R_1, R_2, R_3,...R_6; the input layer nodes (ξ_1, ξ_2) represent the input values; and the output node (η) corresponds to the controller output. The weights $\mu_r^{(i)}$ represent the antecedents A_r and the weights $v_r^{(i)}$ represent the consequent B_r. For example, rule 1 (R1) is translated as:

$$R1 \Rightarrow \text{IF } \xi_1 \text{ is } A_1 \text{ and } \xi_2 \text{ is } A_2 \text{ THEN } \eta \text{ is } B_1$$

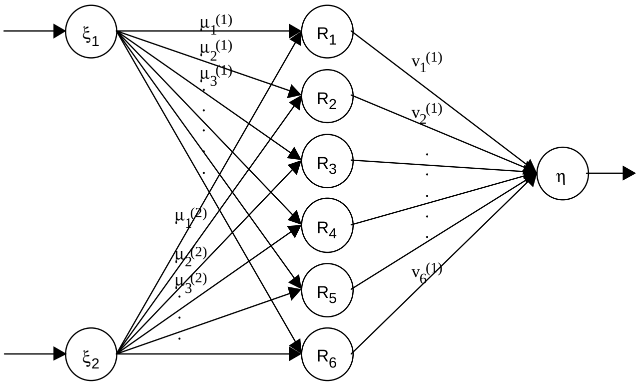


Figure 3: Neuro-Fuzzy System

Rules with the same antecedents (A_r) have the same weights, thus ensuring the integrity of the rule-base.

The learning process of the neuro-fuzzy system is accomplished in two steps, which are (i) weight initialisation and supervised learning process and (ii) rule-base optimisation. Since the learning process is supervised, the generation of a suitable set of rules is highly associated to the linguistic error description supplied to the neuro-fuzzy system during the learning phase. In the plant under consideration the difference between the desired setpoint and the actual process output was used to provide the learning algorithm with a fuzzy error measure.

NEURO-FUZZY CONTROL SYSTEM

The control strategy used is described by a set of linguistic statements, or rules. Consider, for example, the case where each control rule relates two input variables e and ce to the controller output u, and a control algorithm consisting of a set of rules R^1, R^2,..., R^n, of the IF (E is E^j) AND (CE is CE^j) THEN (U is U^j) form, connected by a ELSE connective (Lembessis, Tanscheit (1991)). The combination of those rules can be expressed mathematically (by its membership function) as:

$$\mu_{R^N}(e,ce,u) = f_1[\mu_{R^1}(e,ce,u), ..., \mu_{R^n}(e,ce,u)] \tag{8}$$

where f_1 expresses the ELSE connective. In (8), each control rule j can be expressed as:

$$\mu_{Rj}(e,ce,u) = f_2[f_3(\mu_{Ej}(e), \mu_{CEj}(ce)), \mu_{Uj}(u)] \tag{9}$$

In (9), E = {e}, CE = {ce}, U = {u} are finite universes and E^j, CE^j and U^j are fuzzy subsets of those universes. The operator f_2 stands for implication (Mendel (1995)), and f_3 is the interpretation of the connective AND, which is usually taken as *min* ($\wedge$). The controller decides which action to take through a compositional rule of inference. As is generally the case in control, the controller inputs are real measured values given by singletons, and called here e_s and ce_s. The controller output fuzzy set Us will thus be given by:

$$\mu_{Us}(u) = f_1[f_2(\mu_{E^1}(e_s) \wedge \mu_{CE^1}(ce_s), \mu_{U^1}(u)),...., f_2(\mu_{E^n}(e_s) \wedge \mu_{CE^n}(ce_s), \mu_{U^n}(u))] \tag{10}$$

Since the process requires at its input non-fuzzy values, the controller output fuzzy set must be defuzzified, the result being a value $\mathbf{u}_s$.

In the fluid mixer under consideration, the control system has to be designed to keep both the output coloration $\mathbf{c_0}$ and the liquid height **h** in the mixing tank at desired setpoints. The quantitative information needed by the control system in order to attain these goals is given by the coloration error $\mathbf{e_c}$ and change in coloration error $\Delta\mathbf{e_c}$, the height error $\mathbf{e_h}$, and the output flow $\mathbf{q_0}$. Since the chosen strategy makes use of two independents fuzzy controllers, one for height control and another for coloration control, it is more convenient to choose as output variables the total flow **q** (eq. 2) and the proportion $\mathbf{q_r}$ of coloured water in the total flow, defined as:

$$q_r = \frac{q_1}{q_1 + q_2} \qquad (11)$$

The height controller has two quantitative inputs, $\mathbf{e_h}$ and $\mathbf{q_0}$, and one output, **q**. The coloration controller has as quantitative inputs $\mathbf{e_c}$ and $\Delta\mathbf{e_c}$, and $\Delta\mathbf{q_r}$ as its output. There is a slight difference between the height and coloration controllers. While in the former, precision is not a fundamental factor, in the latter the goal is to have a fine control, with null steady-state error if possible; thus the use of a structure with PI characteristics.

HEIGHT CONTROL

In the design of the height controller, fuzzy sets NB, NM, Z, M, B, PB are assigned to $E_h=\{e_h\}$, and fuzzy sets Z, S,M, B, VB to Q = {q} and $Q_0 = \{q_0\}$, as specified by their membership functions shown in Figures 4 and 5. The universes of discourse for each variable are shown in these figures. The non-fuzzy actual values of the measured input variables are mapped to the chosen universes of discourse through scaling factors $\mathbf{GE_h}$ and $\mathbf{GQ_0}$, which are part of blocks S_0 and S_1 in the simulation diagram of Figure 8. The resulting values are called $\mathbf{e_{hs}}$ and $\mathbf{q_{0s}}$. The defuzzified controller output $\mathbf{q_s}$ is mapped to the process input actual values through a scaling factor **GQ**, so that $q = q_s \times GQ$. In this controller, f_1 is implemented by *max* and f_2 by *min* (Driankov et al. (1993)); Mean of Maxima (MOM) is used for defuzzification.

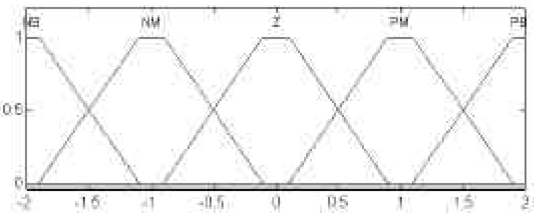


Figure 4: Membership functions for E_h

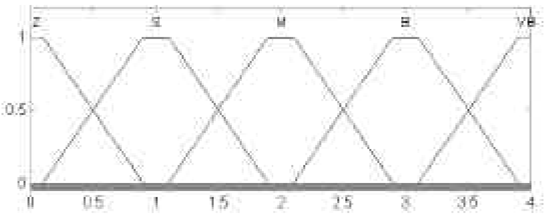


Figure 5: Membership functions for Q and Q_0

The rule-base for height control for the ordinary fuzzy controller (in italics) and the resulting rule-base for the neuro-fuzzy controller (after learning) are shown in table 1. The entries correspond to the values of the total flow **Q**.

Q	**Z**	**S**	**M**	**B**	**VB**
PB	*M*	*B*	*VB*	*VB*	*VB*
	M	VB	VB	VB	VB
PM	*S*	*M*	*B*	*VB*	*VB*
	M	M	M	M	VB
Z	*Z*	*S*	*M*	*B*	*VB*
	Z	M	M	M	VB
NM	*Z*	*Z*	*S*	*M*	*B*
	M	Z	Z	M	M
NB	*Z*	*Z*	*Z*	*M*	*B*
	M	M	Z	Z	Z

eh

q0

1. Fuzzy (italics) and Neuro-Fuzzy rule-bases for height control

COLORATION CONTROL

In the coloration controller, fuzzy sets NB, NB, Z, PM and PB are used for $E_c=\{e_c\}$ and $\Delta E_c=\{\Delta e_c\}$, while fuzzy sets NVB, NB, NM, NS, Z, PS, PM, PB and PVB are used for the controller output $\Delta Q_r=\{\Delta q_r\}$, as specified by their membership functions shown in Figures 6 and Fig. 7. The universes of discourse are as shown in these figures. The actual measured values of the controller inputs are mapped to the universes of discourse through scaling factors $\mathbf{GE_c}$ and $\mathbf{G\Delta E_c}$ (contained in blocks S_2 and S_3 in the simulation diagram of Fig. 8), the result being variables $\mathbf{e_{cs}}$ and $\mathbf{\Delta e_{cs}}$. The defuzzified controller output $\mathbf{\Delta q_{rs}}$ is mapped to the process input actual values through a scaling factor $\mathbf{G\Delta Q_r}$. The actual input flows $\mathbf{q_1}$ and $\mathbf{q_2}$ to the fluid mixer are given by $q_1=q_r \times q$ and $q_2=q_r - q_1$. In this controller, f_1 is implemented by *max*, and f_2 by *product* [6]; defuzzification is performed through Center of Gravity (COG), which in general provides smoother and more precise responses than MOM.

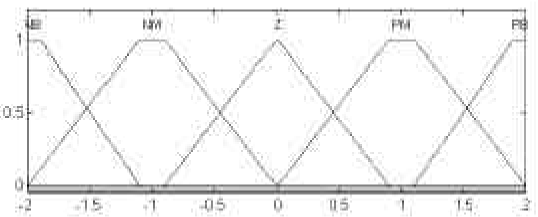


Figure 6: Membership functions for E_c and ΔE_c

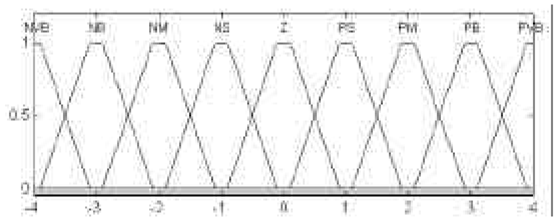


Figure7: Membership functions for ΔQ_r

The larger number of fuzzy sets used for the controller output in coloration control, as compared to height control, is due to the requirement of higher accuracy in the coloration of the resulting mix than that for the level of liquid in the mixing tank. In fact, the reason for keeping **h** at a desired setpoint is mainly to prevent an undesirable overflow in that tank.

The rule-base for height control for the ordinary fuzzy controller (in italics) and the resulting rule-base for the neuro-fuzzy controller (after learning) are shown in table 2. The entries correspond to the values of $\mathbf{\Delta Q_r}$.

ΔQr	**NB**	**NM**	**Z**	**PM**	**PB**
PB	*NVB*	*NB*	*NM*	*NS*	*Z*
	NVB	NVB	NVB	NVB	NVB
PM	*NB*	*NM*	*NS*	*Z*	*PS*
	NVB	NVB	Z	Z	NVB
Z	*NM*	*NS*	*Z*	*PS*	*PM*
	NVB	Z	Z	Z	NVB
NM	*NS*	*Z*	*PS*	*PM*	*PB*
	PVB	Z	Z	Z	Z
NB	*Z*	*PS*	*PM*	*PB*	*PVB*
	PVB	PVB	PVB	PVB	PVB

ec

Δec

2. Fuzzy (italics) and Neuro-Fuzzy rule-bases for coloration control

SIMULATED EXPERIMENTS

The process response will depend on the scaling factors, which can be empirically set beforehand and then tuned in order to improve the controller performance. For example, in the case of the fluid mixer, the range established for **q** and $\mathbf{q_0}$ was from 0 to 60 cm^3. Since the corresponding universes of discourse are [0,4], **GQ** and $\mathbf{GQ_0}$ were initially set at 15. In the case of the conventional fuzzy controller, this value resulted in satisfactory responses and did not need to be tuned. The maximum possible height error $\mathbf{e_h}$ was assumed to be ± 7 cm, which, considering the corresponding universe as [-2,2], gives $\mathbf{GE_h}$=0.3.

In order to achieve good accuracy in coloration, and considering that the universe of discourse is [-2,2] for that variable, the scaling factor $\mathbf{GE_c}$ was set at 200; and $\mathbf{G\Delta E_c}$ was set at 1500. Finally, $\mathbf{G\Delta Q_r}$ was made equal to 1/15.

For simulation, MATLAB$^{©}$ has been used; its associated tool SIMULINK and the FuzzyToolbox have also been used. The simulation diagram is shown in Figure 8. The experiments are described below.

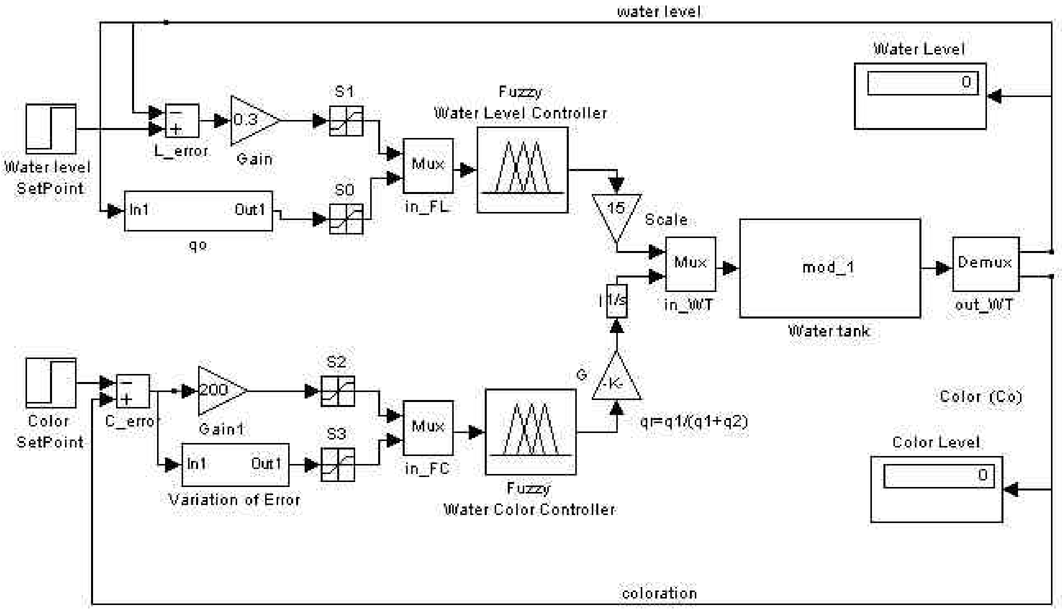


Figure 8: Simulation Diagram

Experiment 1: The resulting mix coloration behaviour is shown in Figure 9. When a step from 0.0 to 0.3 is applied to the reference input, the level of liquid in the mixing tank should be kept constant at 30 cm. It can be seen that the response obtained with the neuro-fuzzy controller (NF) reaches the reference input faster than that obtained with the ordinary fuzzy controller (F).

Experiment 2: The level (height) of liquid in the mixing tank is shown in Figure 10 when a step from 0 to 40 cm is applied to the height reference input. The final coloration should be kept unchanged at 0.5. It can be observed that in both cases the reference input is reached, but the process response obtained with the the neuro-fuzzy controller (NF) is once again faster than that obtained with the simple fuzzy controller (F).

Coloration Height

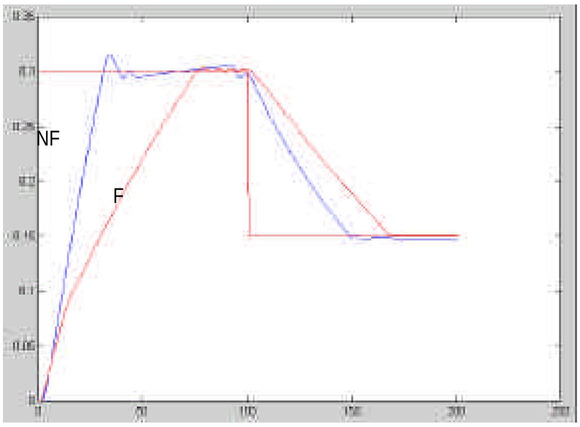


Figure 9: Experiment 1

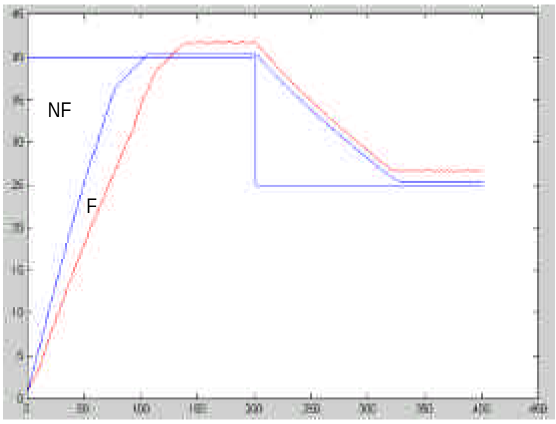
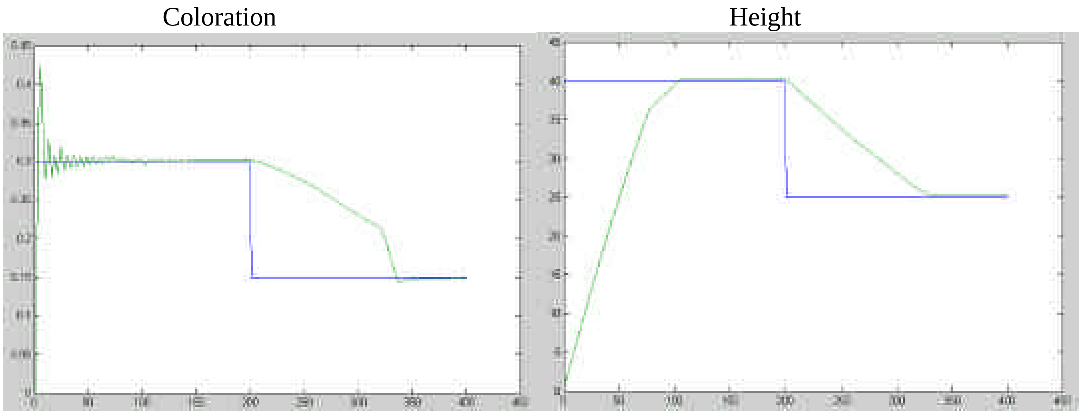


Figure 10: Experiment 2

Experiment 3: Coloration and height variations are shown in Figure 11 when steps of 0.0 to 0.3 and 0.3 to 0.15 are applied to the coloration reference input and steps of 0 to 40 and 40 to 25 cm. are simultaneously applied to the height reference input. As can be observed, the response provided by the neuro-fuzzy controller for coloration is faster than in experiment 1. This is caused by a large input flow; the height controller is trying to reach the setpoint and the input flow is at its maximum at the same time


Coloration

Height

Figure 11: Experiment 3

CONCLUSIONS

The simulated experiments have shown that the approach of using two independent neuro-fuzzy controllers in the control of a MIMO system can give good results. The rule-base generated through the learning process, although different from that defined by an expert, works perfectly well and the main objective of reaching a specified coloration for the liquid in the mixing tank was achieved with good precision - error of less than 0.001. The neuro-fuzzy system is able to create an appropriate set of rules, thus overcoming the difficulty of defining the rule-base. The neuro-fuzzy and fuzzy rule-bases are similar in some cases, and in general they do not conflict, being different only in terms of intensity of the fuzzy variables (ex. NVB ⇔ NM).

The main difficulty was the definition of the linguistic error description to be supplied to the neuro-fuzzy system during the learning process. The neuro-fuzzy system is highly sensitive to this information, which plays a crucial part in the effectiveness of the learning process.

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