# Design of a fuzzy controller for pH using genetic algorithm

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*Abstract:* The control of pH is important in the chemical industry, poses a difficult problem because of inherent nonliniarities and frequently changing process dynamics. The work described in this paper aims at exploring a technique for producing adaptive fuzzy logic controller (FLC), in which a genetic (GA) is employed to alter membership functions. GA is an adaptive search technique based on natural selection and genetics rules. An adaptive GA-FLC scheme is presented for control of the pH process, the objective is to drive the pH of the solution to the desired set point in the shortest time by adjusting the valves on the two control input streams.

Key-Words : genetic algorithms, fuzzy logic, process control, nonlinear control, pH.

## **1** Introduction

A fuzzy set is fully defined by its membership functions. For most control applications, the sets that have to be defined are easily identifiable. However, for other applications they have to be determined by knowledge acquisition from an expert or group of experts. Once the fuzzy sets have been established, one must consider their associated membership functions. How best to determine the membership function is the first question that has to be tackled.

The approach adopted for acquiring the shape of any particular membership function often depends on the application. For most fuzzy logic control (FLC) problems, the membership functions are assumed to be linear and usually triangular in shape. So, typically the sets that describe various factors of importance in the application and the issues to be determined are the parameters that define the triangles. These parameters are usually based on the control engineer's experience and/or are generated automatically. However for many other applications, triangular membership functions are not appropriate as they do not represent accurately the linguistic terms being modeled and the shape of the membership functions have to be elicited directly from the expert, by a statistical approach or by automatic generation of the shapes[8].

GA methods, which are basically random search techniques have been applied to many different problems like function optimization, routing problem, scheduling, design of neural networks, system identification, digital signal processing, computer vision, control and machine learning [1,10].

Attaining and maintaining control of pH is a problem that exemplifies the need for an adaptive controller. The problem of effectively manipulating pH is apparent in a number of diverse industries including mineral processing, wastewater treatment, and chemical processing. Also found are the difficulty in controlling the pH-process, arising mainly from its heavy nonlinearity and uncertainly, and the diversity of control approaches applied, ranging from PID control, self tuning adaptive control, non-linear linearization control, and various model-based control to fuzzy control and neural network control[2,6,7].

GA was used first by Karr [11] in determination of member-ship functions. Karr applies GAs to design of fuzzy logic controller (FLC) for the cart pole problem. He presents two examples: a non-adaptive GA designed FLC and a GA designed adaptive FLC where the membership functions are adapted in real time. The membership functions here are Gaussian in nature and the objective is to minimize an objective function (fitness function in GA terminology) that minimizes the squared difference between the cart and centre of the track that the cart is on, whilst at the same time keeping the pole balanced [9].

In this paper, an adaptive GA-FLC scheme is presented for control of the pH process, the objective is to drive the pH of the solution to the desired set point in the shortest time by adjusting the valves on the two control input streams.

# 2 pH process

The theoretical example that we propose is a continuous process Fig.1, it contains both nonlinearities and changing process dynamics and is an extension of the system studied by Niemi and jutila [1]. It is composed of four tanks each one containing a solution. All solutions have same chemical composition, but the concentration of these chemicals varied from tank to tank[3].

The chemical composition, concentration and appropriate dissociation constants are listed in Table 1.

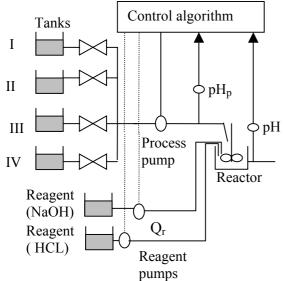


Fig.1: A pH neutralization process

The operation consists to draw up continuously from tank(I) with a flow rate of 11/min which will be beck in the reactor, then provoke disturbance with solutions of other tanks as show in Fig.1. The objective of the control problem is to drive the pH of the solution to the desired set point in the shortest time by adjusting the two pumps regents. In this case the reagent is a strong base (NaOH) and a strong acid (HCL).

Table 1 : Dissociation constants and<br/>concentrations of tanks solutions.

comp	onent	Dissociation							
		Constants (mole/l)							
hydrochloric A	Acid $(C_A)$	×							
4- Nitrophenol	$(C_{a1})$	$K_{a1} = 7.24 * 10^{-8}$							
Pyridine (C <sub>b1</sub> )			$K_{b1} = 1.5 * 10^{-9}$						
Ammonia (C <sub>b2</sub> )			$K_{b2} = 1.78 \times 10^{-5}$						
Concentrations (mole/1)									
Ι	Ī	]	III	IV					
0.0065	0.0015	0.065		0.025					
0.01	0.01	0.01		0.01					
0.002	0.0005	0.0009		0.0005					
0.00035	0.0005	0.0	009	0.0005					

### **3** Chemical model of the process

The composition of the chemicals included in the process is symbolized as follows. The concentration of the strong acid, hydrochloric acid, is denoted by  $C_A$ .  $C_A$ : concentration of the strong acid (HCL).

 $C_B$ : concentration of the strong base ( $C_B=0$ ).

C<sub>a1</sub>: weak concentration acid (4-nitrophenol).

 $C_{b1}$  and  $C_{b2}$  :weak concentrations bases(pyridine and ammonia).

C<sub>r</sub> : concentration of the reagent used.

The equilibrium condition in dilute water solution is:

$$C_{+} - \frac{K_{w}}{C_{+}} - C_{A} + C_{B} - \frac{K_{a1}}{C_{+} + K_{a1}} C_{a1} + \frac{K_{b1}C_{+}}{K_{b1}C_{+} + K_{w}} C_{b1}$$
$$+ \frac{K_{b2}C_{+}}{K_{b2}C_{+} + K_{w}} C_{b2} - H_{r}C_{r} = 0$$
(1)

 $C^+$ : is the hydrogen ions concentration.

 $K_W = 1.0 \times 10^{-14}$  is the ion-product of water.

 $K_{a1}$ ,  $K_{b1}$ ,  $K_{b2}$ : are the dissociation constants of the acid and the base weak bases.

 $H_r$  takes the value (+1) or (-1) according to the used reagent:

 $H_r = +1$ : reagent is base.

 $H_r = -1$ : reagent is acid.

The pH value is defined by :

$$pH=-log[C^{+}(mole/l)]$$
(2)

The equilibrium condition is valid at every point in the reactor.

To develop an adaptive FLC using GA's, a computer model of the pH process is required, this is due to the way in which the adaptive FLC designed. While the FLC is actually manipulating the laboratory pH system, a GA search for improved membership functions by performing simulation of the pH system using computer model. Fig.2 shows a schematic of the basic design where a GA searches for high performances membership while the FLC manipulates the pH system[4,5].

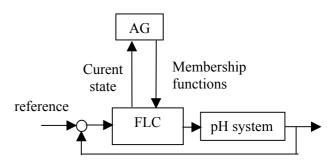


Fig.2: A functional block of control system.

Before the details of the adaptive GA FLC are presented, some of the special characteristics of GA's are discussed.

### **4** Genetic algorithms

The GA is searching process based on the laws of natural selections and genetics. Generally, a simple GA contains three basic operations: selection, genetic operations and replacement. A typical GA cycle is shown in Fig.3.

If Fig.3 is examined, it will be seen that the first step needed to start the GA process is construction of initial population. Initial population is the potential solutions set that is generalized randomly or heuristically. The general method used at this stage is a random construction of population individuals heuristically via parameter values that are known to be close to the solution [11].

The next step of pre-evolution phase is to evaluate the initial individuals and it is needed to determine the next generations that will constitute the subpopulation.

Initial population may possibly include the solution. After this stage, the evolution phase loops until a solution is found or the generation number reaches the pre-determined maximum generation number or there has been no mutation combination left to try and any increase in the average success of population could not be achieved [1,9].

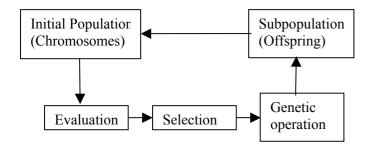


Fig.3 A typical GA cycle.

# 5 Computation of membership functions using genetic algorithms

At this point, most of the groundwork has been laid for the development of an adaptive pH GA FLC. The mechanics of a GA have been introduced, and the basic coding scheme that will be used has been described. The FLC used rules of the form:

#### IF (condition ) THEN (action)

where the condition portion of the rules was composed of the current difference between the set point and the actual pH value (e), and the current time rate of change of difference ( $\Delta e$ ), the action portion of the rules was composed of the change in the volumetric flow rates of the regent input acid and base ( $\Delta Qr$ ).

Thus, the FLC composed of 49 rules, which allowed for the inclusion of all possible combinations of the

Table.2 : Fuzzy rules basis.

Δe	NL	NM	NS	ZE	PS	PM	PL
e							
NL	NM	PL	NM	PS	PM	NS	PL
NM	NS	NM	NL	PS	NS	ZE	NS
NS	ZE	PM	NL	NL	NL	PS	ZE
ZE	NS	PM	PS	ZE	PS	PL	PS
PS	PM	NM	PS	ZE	NS	PL	ZE
PM	PM	PM	NS	PS	NL	PL	NM
PL	NM	NM	PL	PL	NL	PM	PS

conditions variables as described by chosen linguistic variables. The complete rules set is included in Table 2. A standard center of area method was used for defuzzification.

The parameter set in this study, which consist of an entire set of fuzzy membership functions Fig.4.

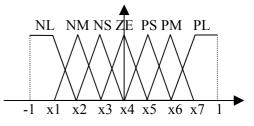


Fig.4: Parameters of membership functions

All these parameters are coded in a chromosome (integer chain) of 58 lengths whose genes are  $\{1, 2, ..., 7\}$ . For 777 controller, we have:

- Seven fuzzy partitions for the discourse universe of error.
- Seven fuzzy partitions for the discourse universe of the error variation.
- Seven fuzzy partitions for the discourse universe of the flow rate

Thus we have a 49 fuzzy rules which constitute the 49 first alleles of the chromosomes.

The used membership functions are triangular, symmetric defined over a discourse universe normalized in the interval [-1,1], as show in Fig.4.

 $x_1,x_2,...,x_7$  represent the peaks of each membership functions (NL,NM,...,PL), and because the form of use functions is triangular symmetric, we can only define the parameters  $x_5,x_6, x_7$  as follows:  $x_1=-x_7$ ;  $x_2=-x_6$ ;  $x_3=-x_5$ ;  $x_4=0$ . The peak of ZE is always zero.

Thus for each variable, we define three parameters (the peak of PL, the peak of PM, and the peak of PS). the parameters to optimize for the three variables are:

epiPS the PS peak, epiPM the PM peak, and epiPL the PL peak (for(e)).

vpiPS, viPM, and vpiPL (for( $\Delta e$ )).

upiPS, upiPM, and upiPL (for( $\Delta Qr$ )).

The chromosomes will have the structure of Fig.5.

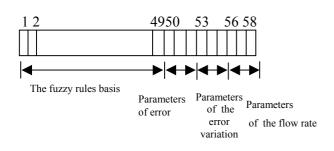


Fig.5: The Chromosomes Structure

The parameters of the genetic algorithm are : The population size is fixed to 50. The mutation probability equals to 0.03 The crossing probability equals to 0.8 The maximal number of generations is 50

As was pointed out earlier, there are basically two decisions to be made when using a GA in a search problem . the issue of coding has been addressed. Thus, consider the second decision: how to evaluate the merit of each string (each membership function set). This task of defining a fitness function is always application specific; it always comes down to accurately describing the goal of the controller. In this case, the objective of the controller is to drive the pH to the desired set point and to maintain the system pH at the desired setpoint.

Each of the experiments used different GA objective functions or performance indices. The performance index(J) is related to fitness (F) using the following relationships:

$$F = \frac{1}{1+J} \tag{3}$$

$$J = \sum_{k=1}^{150} e^2(k) \tag{4}$$

### 6 Simulation results

The operation consists to draw up continuously from tank(I) with a flow rate, then provoke disturbance with solutions of other tanks.

Fig.6 compares the performance of the adaptive GA FLC with a nonadaptive FLC that does not employ a GA. The adaptive controller is able to achieve the objective ( $pH_{ref}=7$ ) much more efficiently than the nonadaptive FLC because the adaptive controller accounts for the fact that dynamics of the problem have changed.

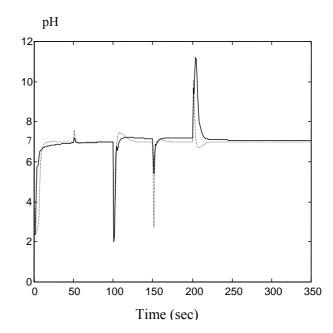


Fig.6 : Comparative representation responses (solid: FLC with AG; dashed :FLC without AG

### 7 Experimental results

In this section , the adaptive GA FLC are used the control response is presented in Fig.7

The observed peaks are due to the momentary representing then disturbances that are immediately followed by the appropriate regulator action aiming to approach the measured pH to that fixed by the reference.

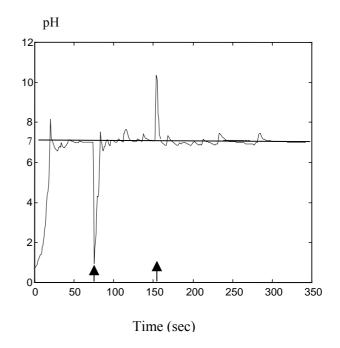


Fig.7: Response of the regulator FLC with AG

### 8 Conclusion

The results presented in this section demonstrate much of the power of adaptive FLC's. they are able to maintain a high degree of control over the laboratory pH system despite drastic changes in the system characteristics. Perhaps the most intriguing aspect of this application is the fact that the system parameters that were alerted. All changes in FLC performance are due to alterations in the membership functions. Based on the results presented demonstrate the effectiveness of alerting the membership functions for a number of situations that are difficult to control. The adaptive pH GA FLC is an effective system that deserves more consideration.

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