Hybrid GA Fuzzy Controller for pH Process

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Abstract

Control of a pH process is great difficulty due to time varying and nonlinear characteristics. Fuzzy Logic has been successfully applied to many applications in control with uncertainties. An important consideration in designing any fuzzy control system is the formation of the fuzzy rules and the membership functions. Generally the rules and the membership functions are formed from the experience of the human experts. With an increasing number of variables, the possible number of rules for the system increases exponentially, which makes it difficult for experts to define a complete rule set for good system performance. Also the system performance can be improved by tuning the membership functions. In a fuzzy system the membership functions and rule set are codependent, they are encoded into the chromosome and evolved simultaneously using Genetic Algorithm. The performance of the proposed approach is demonstrated through development of fuzzy controller for a bench mark pH process. In both set point tracking and disturbance rejection, simulation results show the better performance when compared to fuzzy logic controller.

Keywords—Genetic Algorithm, Fuzzy Logic Control, Internal Model Control, pH process

1. Introduction.

The regulation and control of pH process is a typical problem found in a variety of industries including pharmaceuticals, biotechnology and chemical processing. The high performance and robust pH control is often difficult to achieve due to its nonlinear characteristics. For many years PID controllers have been used for the control of pH process. Tuning of PID controllers is needed to obtain the satisfactory performance. There are many methods for tuning PID gains namely Ziegler-Nichols (ZN), Cohen and Coon (CC), Internal Model Control (IMC) and Performance criteria optimization. Ziegler-Nichols tuning [1] is one of the most widely used method to tune the PID controllers. Tuning the controller by Ziegler-Nichols method does not provide optimum system response since they are dependent on the exact mathematical model of a process. Cohen and Coon method [2] requires limited process knowledge but it offers low damping and high sensitivity to the system. Internal model control [3] is easy to shape sensitivity function but for unstable plants it can not be applied. The adaptive learning algorithm of Universal Learning Network (ULN) represents the modeling and control of nonlinear black box systems with large time delay [4]. The main difficulty in control is due to the disturbances and parameter uncertainties. The fuzzy set theory is particularly useful for application in control with uncertainties [5]. In recent years, there have been several applications of Genetic Algorithm to control of dynamical systems. Genetic Algorithm (GA) [6] is a parallel, global search technique.
based on the concept of natural selection. This technique has the capability to solve nonlinear and complex optimization problems.

The main issue in the evolutionary design of fuzzy systems using GA is their genotype representation. The rules are encoded into the chromosome while fixing the membership function [7]. Each membership function is represented by several critical points and GA is used to evolve the membership function using all the possible rules [8, 9]. Since in a fuzzy system the membership function and rule set are co-dependent, they should be designed or evolved at the same time. Homaifar [10] proposed that GA is used to tune the membership function and evolve the rule set at the same time.

There are some drawbacks in doing so: first, the computational efficiency associated with fuzzy logic is lost using a high number of rules [11, 12] and second, the robustness decreases with the increasing number of rules. In most applications, not all the possible rules need to be used; only a portion of the rules are needed. In this paper, a method for optimal design of a fuzzy logic controller using genetic algorithm is proposed that can evolve the rule set and the membership function simultaneously. The effectiveness of the proposed approach is examined through offline simulation of a pH process.

2. System Description and Model Development.

The pH is the measurement of the acidity or alkalinity of a solution. The pH process consists of neutralization of two monophonic reagents of a weak acid (acetic acid) and a strong base (sodium hydroxide). The method implement mass balances on components called reaction invariants of the Continuous Stirred Tank Reactor (CSTR) solution. The model of the pH neutralization process used in this work follows that proposed by McAvoy et al. [13] and is shown in Fig.1. Assumption of perfect mixing is general in the modeling of pH processes. Material balances in the reactor can be given by

\[
\frac{dX_a}{dt} = F_a C_a - \left( F_a + F_b \right) X_a
\]  

\[
\frac{dX_b}{dt} = F_b C_b - \left( F_a + F_b \right) X_b
\]

Figure 1. pH process

Invoking the electro neutrality condition, the sum of the ionic charges in the solution must be zero.

\([Na^+]+[H^+]=[AC^-]+[OH^-]\)

(3)

The \([X]\) denotes the concentration of the \(X\) ion. The equilibrium relations also hold for the water and the acetic acid,

\[K_a = \frac{[AC^-][H^+]}{[HAC]}\]

(4)

Defining, \(X_a = [HAC]+[AC^-]\), \(X_b = [Na^+]\) and use of Equations (3) and (4)
Let $pH = -\log_{10} [H^+]$ and $pK_a = -\log_{10} K_a$. The titration curve is given by

$$X_a + 10^{-pH} - 10^{-pH+14} \frac{X_a}{1+10^{pKa-pH}} = 0$$

(6)

Where $K_a$ and $K_w$ are dissociation constant of acetic acid.


When designing a Fuzzy Logic Controller using Genetic Algorithms [14], the following issues are to be addressed

- Representation
- Fitness function formation

3.1 Representation

The representation strategy is how to encode the variables into the chromosome. The representation of rules used in this paper has three sections: rule selection, representation for the input variables and the representation for the output variables. The rule selection bit may be zero or one. one represent the selection of the rule. Depending on the ranges of the input variables and output variable, number of bits has been chosen for representing each rule of the rule set. The input variables of the pH process are error and the rate of change of error and output variable is base flow rate are consider for fuzzy variables. Five membership functions are allotted for each input and output variables. The input variables are represented by IP1 and IP2 and the output variable is represented by OP.

![Figure 2. Fuzzy Space.](image)

Triangular membership function is used in this paper. Each membership function is represented by five membership points with overlap between each membership function as shown in figure 2. A total of 13 membership points (P1 to P13) are required for representing each input variable as a fuzzy set. In those thirteen points, first and last points (P1 and P13) are fixed. The remaining eleven membership points are evolved between the dynamic ranges such that P2 has [P3, P13], P3 has [P1, P13], P4 has [P2, P3], P5 has [P6, P10], P6 has [P4, P7], P7 has [P5, P13], P8 has [P9, P13], P9 has [P5, P10], P10 has [P7, P13], P11 has [P12, P13] and P12 has [P8, P13]. With the above representation a typical chromosome will look like the following:

<table>
<thead>
<tr>
<th>IP1</th>
<th>IP2</th>
<th>OP</th>
</tr>
</thead>
<tbody>
<tr>
<td>110</td>
<td>010</td>
<td>011</td>
</tr>
<tr>
<td>P1</td>
<td>P2</td>
<td>P3</td>
</tr>
<tr>
<td>MF1</td>
<td>MF2</td>
<td>MF3</td>
</tr>
</tbody>
</table>

![Diagram](image)
3.2 Fitness Function

The next important consideration is the choice of fitness function. Evaluation of the individual is accomplished by calculating the objective function value for the problem using the parameter set. The result of the objective function calculation is used to calculate the fitness function of the individuals. The Integral Square Error, settling time and overshoot are taken as performance indices and the objective function is given by minimize

\[ f = f_{\text{ISE}} + f_{\text{os}} + f_{\text{st}}. \]  

(7)

The minimization objective function given by (12) is transformed to fitness function as

\[ \text{Fitness} = \frac{k}{1 + f}. \]  

(8)

Where \( k \) is a constant. In the denominator a value of 1 is added with \( f \) in order to avoid division by zero.

4. Results and Discussion.

The GA-based algorithm is applied to find the optimal parameters of the Fuzzy controller. The objective function in this pH process is minimization of error. The optimization variables are represented as binary numbers in GA population. The initial population is randomly generated between the variables lower and upper limits. Tournament selection is applied to select the members of the new population. The performance of GA for various values of cross-over and mutation probabilities in the ranges 0.6-1.0 and 0.001-0.1, was evaluated. The Descriptions of the pH process variables with corresponding symbols and its values are given in Table.1. The best results of the proposed GA are obtained with the following control parameters. Number of generations = 30, Population size = 20, Crossover probability = 0.8, Mutation probability = 0.08.

The GA took 20s to complete the 30 generations. After 30 generations, it is found that all the individuals have reached almost the same fitness value. This shows that GA has reached the optimal solution. Fig.3 shows the convergence of proposed GA algorithm. It is observed that the variation of the fitness during the GA run for the best case and shows the generation of optimal variables. It can be seen that the fitness value increases rapidly in the first 5 generations of the GA. Then the value increases slowly, and settles down near the optimum value with most of the individuals in the population reaching that point. The optimal membership functions of error, rate of change of error and the feed flow rate are shown in Fig.4 to Fig.6 respectively.

Next for comparison IMC, FLC and proposed GA-FLC are tuned the PI controller for pH process with disturbances in acid flow rate. Fig.7 shows the tracking performance of proposed GA-FLC, FLC and IMC tuned PI controller for set point level in between 7 to 9. The proposed GA-FLC has minimum settling time and minimum peak overshoot compared to the other tuning methods. FLC method shows the satisfactory response but it has more rise time at the set point 7. IMC tuning of PI shows more peak overshoot at the set point 7. Fig.8 shows the controller action of proposed GA-FLC, FLC and IMC tuned PI controller for set point level in between 7 to 9. From the figure it can be observed that the base flow rate of proposed algorithm does not exceed the limit of 0.8 l/min. Fig.9 shows the pH response of proposed GA-FLC, FLC and IMC tuned PI controller for set point level in between 9 to 11. FLC method shows the satisfactory response but it has more rise time at the set point 10 and set point 9. IMC tuning of PI shows more peak overshoot at the set point 11. Fig.10 shows the controller action of proposed GA-FLC, FLC and IMC tuned PI controller for set point level in between 9 to 11. From the figure it can be observed that the base flow rate of proposed algorithm does not exceed the limit of 0.8 l/min and overall performance of the proposed algorithm is better than FLC and IMC methods. The optimized rule surface is shown in Fig.11.
Figure 3. Convergence of proposed GA

Figure 4. Optimal design of error

Figure 5. Optimal design of change of error

Figure 6. Optimal design of base flow rate

Figure 7. Setpoint tracking between 7-9 using IMC, Fuzzy and GA-Fuzzy

Figure 8. Controller action between 7-9 using IMC, Fuzzy and GA-Fuzzy

Figure 9. Setpoint tracking between 9-11 using IMC, Fuzzy and GA-Fuzzy

Figure 10. Controller action between 9 to 11 using IMC, Fuzzy and GA-Fuzzy
Table 1: Description of the pH process

<table>
<thead>
<tr>
<th>Symbols</th>
<th>Description</th>
<th>Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>V</td>
<td>Volume of the Continuous Stirred Tank Reactor</td>
<td>7.4 l lit</td>
</tr>
<tr>
<td>F_a</td>
<td>Flow rate of the influent stream</td>
<td>0.24 l min⁻¹</td>
</tr>
<tr>
<td>F_b</td>
<td>Flow rate of the titrating stream</td>
<td>0-0.8 l min⁻¹</td>
</tr>
<tr>
<td>C_a</td>
<td>Concentration of the influent stream</td>
<td>0.2 g mol l⁻¹</td>
</tr>
<tr>
<td>C_b</td>
<td>Concentration of the titrating stream</td>
<td>0.1 g mol l⁻¹</td>
</tr>
</tbody>
</table>

7. Conclusion.

In this paper, we have proposed a Genetic Algorithm for obtaining the optimal design of the Fuzzy controller. In the proposed approach, the development of rule base and the formation of the membership function are evolved simultaneously. The performance of the algorithm in obtaining the optimal values of Fuzzy controller parameters has been analyzed in pH process through computer simulation. The simulation result shows the proposed GA is able to optimize the Fuzzy controller satisfactorily and show the better performance compared to fuzzy logic control and Internal Model Control.

References