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Adaptive Process Control Using Fuzzy Logic and Genetic Algorithms

By

C. L. Karr
U.S. Bureau of Mines, Tuscaloosa Research Center
Tuscaloosa, AL 35486-9777

ABSTRACT

Researchers at the U.S. Bureau of Mines have developed adaptive process control systems in which genetic algorithms (GAs) are used to augment fuzzy logic controllers (FLCs). GAs are search algorithms that rapidly locate near-optimum solutions to a wide spectrum of problems by modeling the search procedures of natural genetics. FLCs are rule based systems that efficiently manipulate a problem environment by modeling the "rule-of-thumb" strategy used in human decision making. Together, GAs and FLCs possess the capabilities necessary to produce powerful, efficient, and robust adaptive control systems. To perform efficiently, such control systems require a *control element* to manipulate the problem environment, an *analysis element* to recognize changes in the problem environment, and a *learning element* to adjust to the changes in the problem environment. Details of an overall adaptive control system are discussed. A specific laboratory acid-base pH system is used to demonstrate the ideas presented.

INTRODUCTION

The need for efficient process control has never been more important than it is today because of economic stresses forced on industry by processes of increased complexity and by intense competition in a world market. No industry is immune to the cost savings necessary to remain competitive; even traditional industries such as mineral processing (Kelly and Spottiswood, 1982), chemical engineering (Fogler, 1986), and wastewater treatment (Gottinger, 1991) have been forced to implement cost-cutting measures. Cost-cutting generally requires the implementation of emerging techniques that are often more complex than established procedures. The new processes that result are often characterized by rapidly changing process dynamics. Such systems prove difficult to control with conventional strategies, because these strategies lack an effective means of adapting to change. Furthermore, the mathematical tools employed for process control can be unduly complex even for simple systems.

In order to accommodate changing process dynamics yet avoid sluggish response times, adaptive control systems must alter their control strategies according to the current state of the process. Modern technology in the form of high-speed computers and artificial intelligence (AI) has opened the door for the development of control systems that adopt the approach to adaptive control used by humans, and perform more efficiently and with more flexibility than conventional control systems. Two powerful tools for adaptive control that have emerged from the field of AI are fuzzy logic (Zadeh, 1973) and genetic algorithms (GAs) (Goldberg, 1989).

The U.S. Bureau of Mines has developed an approach to the design of adaptive control systems, based on GAs and FLCs, that is effective in problem environments with rapidly changing dynamics. Additionally, the resulting controllers include a mechanism for handling inadequate feedback about the state or condition of the problem environment. Such controllers are more suitable than past control systems for recognizing, quantifying, and adapting to changes in the problem environment.

The adaptive control systems developed at the Bureau of Mines consist of a *control element* to manipulate the problem environment, an *analysis element* to recognize changes in the problem environment, and a *learning element* to adjust to the changes in the problem environment. Each component employs a GA, a FLC, or both, and each is described in this paper. A particular problem environment, a laboratory acid-base pH system,

serves as a forum for presenting the details of a Bureau-developed, adaptive controller. Preliminary results are presented to demonstrate the effectiveness of a GA-based FLC for each of the three individual elements. Details of the system will appear in a report by Karr and Gentry (1992).

PROBLEM ENVIRONMENT

In this section, a pH system is introduced to serve as a forum for presenting the details of a stand-alone, comprehensive, adaptive controller developed at the U.S. Bureau of Mines; emphasis is on the method not the application. The goal of the control system is to drive the pH to a setpoint. This is a non-trivial task since the pH system contains both nonlinearities and changing process dynamics. The nonlinearities occur because the output of pH sensors is proportional to the logarithm of hydrogen ion concentration. The source of the changing process dynamics will be described shortly.

A schematic of the pH system under consideration is shown in Fig. 1. The system consists of a beaker and five, valved input streams. The beaker initially contains a given volume of a solution having some known pH. The five, valved input streams into the beaker are divided into the two *control input streams* and the three *external input streams*. Only the valves associated with the two control input streams can be adjusted by the controller. Additionally, as a constraint on the problem, these valves can only be adjusted a limited amount (0.5 mL/s/s, which is 20 pct of the maximum flow rate of 2.5 mL/s) to restrict pressure transients in the associated pumping systems.

The goal of the control problem is to drive the system pH to the desired setpoint in the shortest time possible by adjusting the valves on the two control input streams. Achieving this goal is made considerably more difficult by incorporating the potential for changing the process dynamics. These changing process dynamics come from three random changes that can be made to the pH system. First, the concentrations of the acid and base of the two control input streams can be changed randomly to be either 0.1 M HCl or 0.05 M HCl and 0.1 M NaOH or 0.05 M NaOH. Second, the valves on the external input streams can be randomly altered. This allows for the external addition of acid (0.05 M HCl), base (0.05 M CH₃COONa), and buffer (a combination of 0.1 M CH₃COOH and 0.1 M CH₃COONa) to the pH system. Note that the addition of a buffer is analogous to adding inertia to a mechanical system. Third, random changes are made to the setpoint to which the system pH is to be driven. These three random alterations in the system parameters dramatically alter the way in which the problem environment reacts to adjustments made by the controller to the valves on the control input streams. Furthermore, the controller receives no feedback concerning these random changes.
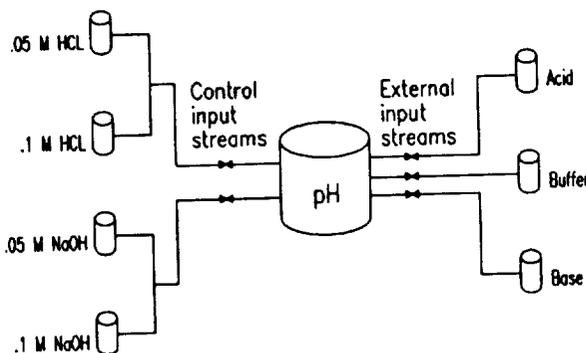

Fig. 1. Basic structure of the pH system.

The pH system was designed on a small scale so that experiments could be performed in limited laboratory space. Titrations were performed in a 1,000-mL beaker using a magnetic bar to stir the solution. Peristaltic pumps were used for the five input streams. An industrial pH electrode and transmitter sent signals through an analog-to-digital board to a 33-MHz 386 personal computer which implemented the control system.

STRUCTURE OF THE ADAPTIVE CONTROLLER

Figure 2 shows a schematic of the Bureau's adaptive control system. The heart of this control system is the loop consisting of the control element and the problem environment. The control element receives information from sensors in the problem environment concerning the status of the *condition variables*, i.e., pH and ΔpH. It then computes a desirable state for a set of *action variables*, i.e., flow rate of acid (Q_{ACID}) and flow rate of base (Q_{BASE}). These changes in the action variables force the problem environment toward the setpoint. This is the basic approach adopted for the design of virtually any closed loop control system, and in and of itself includes no mechanism for adaptive control.

The adaptive capabilities of the system shown in Fig. 2 are due to the analysis and learning elements. In general, the analysis element must recognize when a change in the problem environment has occurred. A "change," as it is used here, consists of any of the three random alterations to a parameter possible in the problem environment. (Of importance is the fact that all of these changes affect the response of the problem environment, otherwise it has no effect on the way in which the control element must act to efficiently manipulate the problem environment.) The analysis element uses information concerning the condition and action variables over some finite time period to recognize changes in the environment and to compute the new performance characteristics associated with these changes.

The new environment (the problem environment with the altered parameters) can pose many difficulties for the control element, because the control element is no longer manipulating the environment for which it was designed. Therefore, the algorithm that drives the control element must be altered. As shown in the schematic of Fig. 2, this task is accomplished by the learning element. The most efficient approach for the learning element to use to alter the control element is to utilize information concerning the past performance of the control system. The strategy used by the control, analysis, and learning elements of the stand-alone, comprehensive adaptive controller being developed by the U.S. Bureau of Mines is provided in the following sections.
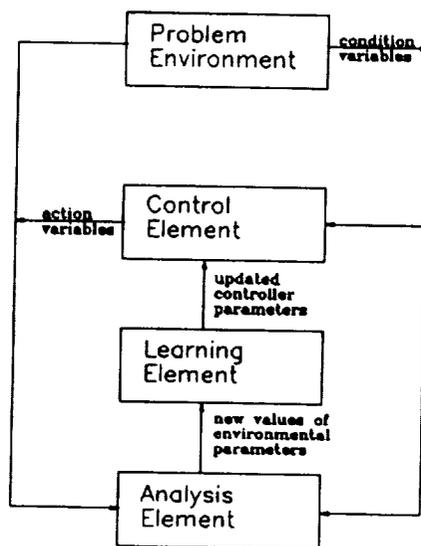

Fig. 2. Structure of the adaptive control system.

Control Element

The control element receives feedback from the pH system, and based on the current state of pH and ΔpH, must prescribe appropriate values of Q_{ACID} and Q_{BASE}. Any of a number of closed-loop controllers could be used for

this element. However, because of the flexibility needed in the control system as a whole, a FLC is employed. Like conventional rule-based systems (expert systems), FLCs use a set of production rules which are of the form:

$$\text{IF } \{condition\} \text{ THEN } \{action\}$$

to arrive at appropriate control actions. The left-hand-side of the rules (the *condition* side) consists of combinations of the controlled variables (pH and ΔpH); the right-hand-side of the rules (the *action* side) consists of combinations of the manipulated variables (Q_{ACID} and Q_{BASE}). Unlike conventional expert systems, FLCs use rules that utilize fuzzy terms like those appearing in human rules-of-thumb. For example, a valid rule for a FLC used to manipulate the pH system is:

IF {ph is **VERY ACIDIC** and ΔpH is **SMALL**} THEN {Q_{BASE} is **LARGE** and Q_{ACID} is **ZERO**}.

This rule says that if the solution is very acidic and is not changing rapidly, the flow rate of the base should be made to be large and the flow rate of the acid should be made to be zero.

The fuzzy terms are subjective; they mean different things to different "experts," and can mean different things in varying situations. Fuzzy terms are assigned concrete meaning via fuzzy membership functions (Zadeh, 1973). The membership functions used in the control element to describe pH appear in Fig. 3. (As will be seen shortly, the learning element is capable of changing these membership functions in response to changes in the problem environment.) These membership functions are used in conjunction with the rule set to prescribe single, crisp values of the action variables (Q_{ACID} and Q_{BASE}). Unlike conventional expert systems, FLCs allow for the enactment of more than one rule at any given time. The single crisp action is computed using a weighted averaging technique that incorporates both a *min-max* operator and the *center-of-area* method (Karr, 1991). The following fuzzy terms were used, and therefore "defined" with membership functions, to describe the significant variables in the pH system:

pH	Very Acidic (**VA**), Acidic (**A**), Mildly Acidic (**MA**), Neutral (**N**), Mildly Basic (**MB**), Basic (**B**), and Very Basic (**VB**);
ΔpH	Small (**S**) and Large (**L**);
Q_{ACID}	Zero (**Z**), Very Small (**VS**),
Q_{BASE}	Small (**S**), Medium (**M**), and Large (**L**).

Although the pH system is quite complex, it is basically a titration system. An effective FLC for performing titrations can be written that contains only 14 rules. The 14 rules are necessary because there are seven fuzzy terms describing pH and two fuzzy terms describing ΔpH (7*2=14 rules to describe all possible combinations that could exist in the pH system as described by the fuzzy terms represented by the membership functions selected). Now, the rules selected for the control element are certainly inadequate to control the full-scale pH system; the one that includes the changing process dynamics. However, the performance of a FLC can be dramatically altered by changing the membership functions. This is equivalent to changing the definition of the terms used to describe the variables being considered by the controller. As will be seen shortly, GAs are powerful tools capable of rapidly locating efficient fuzzy membership functions that allow the controller to accommodate changes in the dynamics of the pH system.
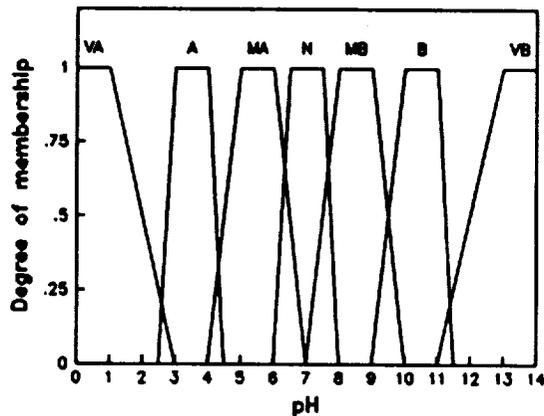
Fig. 3. pH membership functions.

Analysis Element

The analysis element recognizes changes in parameters associated with the problem environment not taken into account by the rules used in the control element. In the pH system, these parameters include: (1) the concentrations of the acid and base of the input control streams, (2) the flow rates of the acid, the base, and the buffer that are randomly altered, and (3) the system setpoint. Changes to any of these parameters can dramatically alter the way in which the system pH responds to additions of acid or base, thus forming a new problem environment requiring an altered control strategy. Recall that the FLC used for the control element presented includes none of these parameters in its 14 rules. Therefore, some mechanism for altering the prescribed actions must be included in the control system. But before the control element can be altered, the control system must recognize that the problem environment has changed, and compute the nature and magnitude of the changes.

The analysis element recognizes changes in the system parameters by comparing the response of the physical system to the response of a model of the pH system. In general, recognizing changes in the parameters associated with the problem environment requires the control system to store information concerning the past performance of the problem environment. This information is most effectively acquired through either a data base or a computer model. Storing such an extensive data base can be cumbersome and requires extensive computer memory. Fortunately, the dynamics of the pH system are well understood for buffered reactions, and can be modeled using a single cubic equation that can be solved for $[H_3O^+]$ ion concentrations, to directly yield the pH of the solution. In the approach adopted here, a computer model predicts the response of the laboratory pH system. This predicted response is compared to the response of the physical system. When the two responses differ by a threshold amount over a finite period of time, the physical pH system is considered to have been altered.

When the above approach is adopted, the problem of computing the new system parameters becomes a curve fitting problem (Karr, Stanley, and Scheiner, 1991). The parameters associated with the computer model produce a particular response to changes in the action variables. The parameters must be selected so that the response of the model matches the response of the actual problem environment.

An analysis element has been forged in which a GA is used to compute the values of the parameters associated with the pH system. When employing a GA in a search problem, there are basically two decisions that must be made: (1) how to code the parameters as bit strings and (2) how to evaluate the merit of each string (the fitness function must be defined). The GA used in the analysis element employs concatenated, mapped, unsigned binary coding (Karr and Gentry, 1992). The bit-strings produced by this coding strategy were of length 200:

the first 40 bits of the strings were used to represent the concentration of the acid on the control input stream, the second 40 bits were used to represent the concentration of the base on the control input stream, the third 40 bits were used to represent the flow rate of the acid of the external streams, and the final 80 bits were used to represent the flow rates of the buffer and the base of the external streams, respectively. The 40 bits associated with each individual parameter were read as a binary number, converted to decimal numbers (000 = 0, 001 = 1, 010 = 2, 011 = 3, etc.,), and mapped between minimum and maximum values according to the following:

$$C = C_{min} + \frac{b}{(2^m - 1)} (C_{max} - C_{min}) \tag{1}$$

where C is the value of the parameter in question, b is the binary value, m is the number of bits used to represent the particular parameter (40), and C_{min} and C_{max} are minimum and maximum values associated with each parameter that is being coded.

A fitness function has been employed that represents the quality of each bit-string; it provides a quantitative evaluation of how accurately the response of a model using the new model parameters matches the response of the actual physical system. The fitness function used in this application is:

$$f = \sum_{i=0s}^{i=100s} (pH_{model} - pH_{actual})^2. \tag{2}$$

With this definition of the fitness function, the problem becomes a minimization problem: the GA must minimize f, which as it has been defined, represents the difference between the response predicted by the model and the response of the laboratory system.

Figure 4 compares the response of the physical pH system to the response of the simulated pH system that uses the parameters determined by a GA. This figure shows that the responses of the computer model and the physical system are virtually identical, thereby demonstrating the effectiveness of a GA in this application. The GA was able to locate the correct parameters after only 500 function evaluations, where a function evaluation consisted of simulating the pH system for 100 seconds. Locating the correct parameters took approximately 20 seconds on a 386 personal computer. Industrial systems may mandate that a control action be taken in less than 20 seconds. In such cases, the time the GA is allotted to update the model parameters can be restricted. Once new parameters (and thus the new response characteristics of the problem environment) have been determined, the adaptive element must alter the control element.
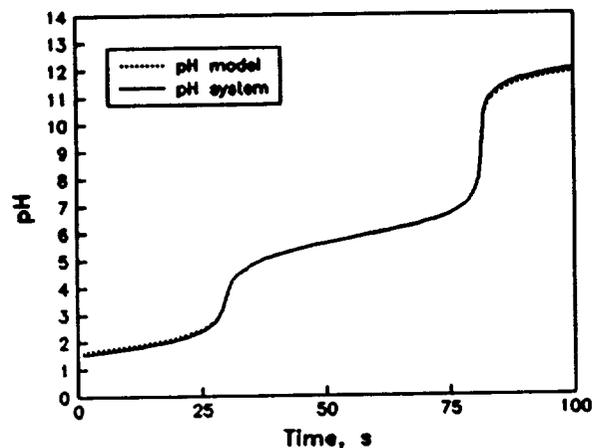

Fig. 4. Performance of an analysis element.

Learning Element

The learning element alters the control element in response to changes in the problem environment. It does so by altering the membership functions employed by the FLC of the control element. Since none of the randomly altered parameters appear in the FLC rule set, the only way to account for these conditions (outside of completely revamping the system) is to alter the membership functions employed by the FLC. These alterations consist of changing both the position and location of the trapezoids used to define the fuzzy terms.

Altering the membership functions (the definition of the fuzzy terms in the rule set) is consistent with the way humans control systems. Quite often, the rules-of-thumb humans use to manipulate a problem environment remain the same despite even dramatic changes to that environment; only the conditions under which the rules are applied are altered. This is basically the approach that is being taken when the fuzzy membership functions are altered.

The U.S. Bureau of Mines uses a GA to alter the membership functions associated with FLCs, and this technique has been well documented (Karr, 1991). A learning element that utilizes a GA to locate high-efficiency membership functions for the dynamic pH laboratory system has been designed and implemented.

The performance of a control system that uses a GA to alter the membership functions of its control element is demonstrated for two different situations. First, Fig. 5 compares the performance of the adaptive control system (one that changes its membership functions in response to changes in the system parameters) to a non-adaptive control system (one that ignores the changes in the system parameters). In this figure, the pH system has been perturbed by the addition of an acid (at 75 seconds), a base (at 125 seconds), and a buffer (at 175 seconds). In this case, the process dynamics are dramatically altered due to the addition of the buffer, and the adaptive controller is better.

Second, the concentrations of the acid and base the FLC uses to control pH are changed (those from the control input streams), which causes the system to respond differently. For example, if the 0.1 MHCl is the control input, the pH falls a certain amount when this acid is added. However, all other factors being the same, the pH will not fall as much when the same volume of the 0.05 M HCl is added. The results of this situation are summarized in Fig. 6. In this simulation, the concentration of the titrants is changed at 50 seconds. As above, the adaptive control system is more efficient.
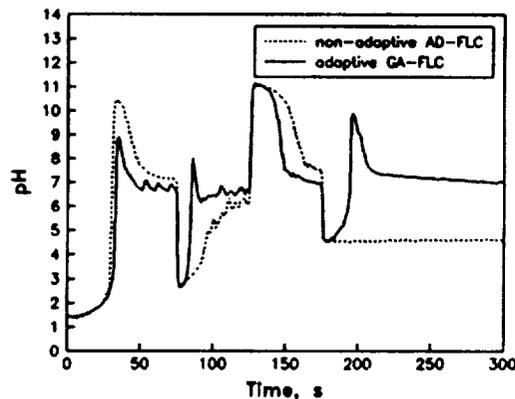

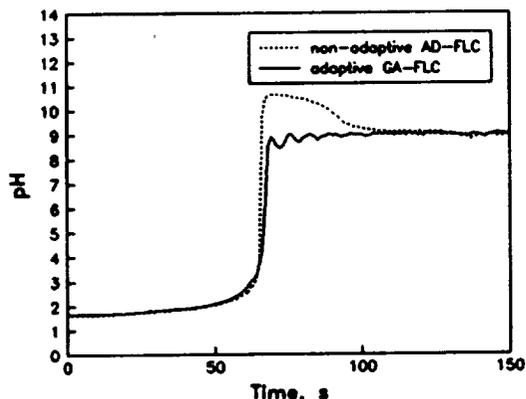Fig. 5. External reagent additions.

Fig. 6. Alteration of titrant concentrations.

SUMMARY

Scientists at the U.S. Bureau of Mines have developed an AI-based strategy for adaptive process control. This strategy uses GAs to fashion three components necessary for a robust, comprehensive adaptive process control system: (1) a control element to manipulate the problem environment, (2) an analysis element to recognize changes in the problem environment, and (3) a learning element to adjust to changes in the problem environment. The application of this strategy to a laboratory pH system has been described.

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