ON-LINE CONTROL OF THE NEUTRALIZATION PROCESS BASED ON FUZZY LOGIC

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The pH process is difficult to control due to the nonlinearities and uncertainties and therefore the use of the conventional PI controller cannot be the adequate method. Thus, the fuzzy control strategy for a pilot plant pH neutralization system is developed and experimentally evaluated. In this paper, a rule-based controller that incorporates fuzzy logic controller has been designed and evaluated. Through simulation study, it has been shown that the estimated parameters are in good agreement with the experimental values. Also the proposed fuzzy logic controller has given an excellent tracking and regulation performance compare to that of the velocity form of PI control and the Shinskey nonlinear adaptive control systems.

Keywords: pH Control, Fuzzy Control, Neutralization Process

1. INTRODUCTION

Control of pH is important to many processes including wastewater neutralization, chemical and biological reaction, fermentation, etc. The control of pH is a difficult task due to the process highly nonlinearity and it is very sensitive to disturbances near the point of neutrality. Thus, the control of pH process may require the application of advanced control techniques to improve control and overcome the nonlinearity. Fuzzy control provides effective solutions for nonlinear and partially unknown processes, mainly because of its ability to combine information from different sources.

The control of pH in stirred tanks has been treated extensively in the literature. A large volume of literature in the field of pH control is dedicated to continuous (as distinct from batch) wastewater neutralization because it presents a challenging control problem, which is of industrial importance. Shinskey [¹] is credited with introducing the first industrially implemented adaptive pH controller. Here, the titration curve was represented by a three section piecewise linear approximation, which was adapted online on the basis of the frequency of oscillation of the measured pH. Other workers have tried to represent the titration curve more accurately. Pajunen [²] used a Wiener model, which represented the titration curve using a piecewise polynomial approximation. Gulaian and Lane [³] used singular value decomposition to form a linear sum of reselected "building block" titration curves. Malhuli et al. [⁴] parameterizes a model of the titration curve, which represents it as a single fictitious acid of variable concentration and dissociation constant. An alternative approach is to try to linearize the problem by controlling some variable other than pH, which is derived from flow rate, pH and other measurements. These transformed variables include the strong acid equivalent [⁵], and reaction invariant [⁶,⁷]. Methods of control employing these transformed variables are usually based on a reduced order theoretical model [⁸]. The model states, which are the transformed variables, are calculated from flow and pH measurements and usually some prior knowledge...
of the system species is assumed (e.g. Wright and Kravaris[5] assume knowledge of the titration curve).

Model predictive control (MPC) has grown into a mature research area since its inception in late 1970s. Researchers have proposed several ways to equip MPC with the capability to deal with nonlinear processes. Linear model-based control methods [9-11] have been successfully applied in industrial applications. The development of nonlinear internal model controllers by operator theory has been proposed [12] but the method is quit complex. Kulkarni et al. [13] developed a simple new method for designing nonlinear internal model control (IMC) controllers for single input single output systems and they applied it to the neutralization of a simulated strong acid-strong base system. They concluded that the controller provides perfect set point compensation and excellent disturbance rejection.

With the progress in the modeling technique for pH processes, many different model-based control methods have been proposed under different problem settings. Among them are inline process model-based control [14], nonlinear inferential control [15]. Patwardhan et al. [16] use methods of implementing an input constrained nonlinear MPC in latent spaces by partial least squares based Hammerstein and Wiener models. The proposed approach is demonstrated on a simulated pH-level control of acid-base neutralization process. Zhu and Seborg [17] use a Hammerstein model to do MPC of a univariate pH control process and Norquay et al. [18] demonstrated the use of a Wiener model based MPC on pH control process.

The impetus for employing artificial neural network ANNs to control nonlinear systems is due to their advantages over other nonlinear modeling paradigms. Recently, several workers have applied model-based control, employing empirical models, to pH control. Nahas et al. [19] applied a neural network based internal model controller to a simulated CSTR pH neutralization process. Pottmann and Seborg [20] applied a neural network model predictive control algorithm to a pH neutralization process. Draeger et al. [21] who applied ANN based Dynamic Matrix Control to a neutralization reactor. The use of neural networks in the internal model control IMC structure has been proposed and implemented by several workers [22,23] and has been implemented for the control of simulated processes [19,23]. Recently, various forms of MPC have been extended to nonlinear control schemes as surveyed by Doherty [24].

Fuzzy control techniques have recently been applied to various Complex industrial processes such as batch chemical reactors, blast furnaces, cement kilns, distillation columns. Sabharwal and Chen [25] presented a simulation study of fuzzy control of the pH in a chemical stream. They controlled the pH is controlled by addition of two chemicals - Sulfuric acid (to lower the pH) and Caustic (to increase the pH). In their study, a simulation of the control problem has been generated and a menu-driven has been developed which enables the user to simulate different states of the control problem by modifying the tuning parameters. They show that the rules learned by the fuzzy clustering method perform well. These results provide support for the use of fuzzy clustering algorithms in process control.

In this paper, three methods were experimentally applied, first, the use of the computer to replace the conventional analogue PI controller in a typical single input single output pH control loop, secondly the use of Shinskey adaptive controller and thirdly the use of fuzzy control.

2. THEORY

2.1 PI Control

The operation of an ideal PI controller is described by

\[ P = P_0 + K_c (E + \frac{1}{\tau_i} \int Edt) \]  

(1)

In conventional control applications, a controller, whose output approximates the right side of Equation (1), can be built through the use of pneumatic components or operational amplifiers, integrators, and summers. In computer-control applications a discrete equivalent to Equation (1) is employed. In the development of algorithms that are based on Z transforms we specify the nature of the response to be achieved, whereas in the digital equivalent to the PI controller we adjust the constants \( K_c \) and \( \tau_i \) so as to achieve a desired response.

An alternative form for the PI and PID control algorithms is the so-called velocity form. In this form, one does not compute the actual value of the controller output signal at the nth sampling instant, but its change from the preceding period. To obtain the digital equivalent to the PI controller, the integral term of Equation (1) is numerically approximated to give an expression for the output of the algorithm at sampling instant. Thus the Equation (1) becomes:

\[ P(k) = P(k-1) + K_c \left[ E(k) - E(k-1) + \frac{T}{\tau_i} E(k) \right] \]  

(2)

Equation (2) is referred to as the velocity form of the PI algorithm, because it computes the incremental output instead of the actual output of the controller. The velocity form of the algorithm also provides some protection against reset windup, because it does not incorporate sums of error sequences.

2.2 Shinskey Adaptive Control

A nonlinear relation between reagent flow and measured pH distinguishes the pH control. If uniform damping is to be achieved in a highly nonlinear pH control loop, a complementary nonlinear control function must be used. The simplest form of this nonlinear function appears as a combination of three straight lines. Both the widths of the deadband and the
gain within it must be adjustable to match the particular process being encountered. As with the process titration curve, the controller gain is not simply the slope of the nonlinear function at a given point, but rather the slope of a line connecting that point with zero error.

The nonlinear function must be adjusted to fit the particular process being controlled. In the absence of a titration curve, or when the buffering is variable, this becomes a trial and error procedure. With the deadband set at zero, a limit cycle will ordinarily ensure, even with a very wide proportional band. The width of the limit cycle is a guide of the deadband need not be quite as wide to stop the limit cycle.

Adjustment of the proportional band should be made for fast recovery from upsets that drive the measurement outside of the deadband. If the proportional band is too narrow, an excursion outside the deadband on one side will produce enough corrective action to drive the measurement out the other side, thereby creating a limit cycle larger than the deadband, but the natural period.

The nonlinear function described is symmetrical, and is therefore only useful for control in the neutral region. If control is desired at some other point, for example, pH 3, nonlinear compensation is desirable but it must be asymmetric. For a simple titration curve, it is possible to remove the high gain region from one side of the set point and adjust the deadband width so that its edge coincides with the knee of the curve.

2.3 Fuzzy Control

\[ \mu_A(u) = \frac{1 - \mu_A(u)} {2} \]

A fuzzy control system was developed based on fuzzy mathematics, which is a branch of applied mathematics. The fuzzy mathematics has broad applications in many fields including statistics and numerical analysis, systems and control engineering, pattern recognition, signal and image processing, and biomedical engineering alike [26]. Fuzzy control provides effective solutions for nonlinear and partially unknown processes, mainly because of its ability to combine information from different sources, such as available mathematical models, experience of operators, process measurements, etc. Like other control mechanisms, fuzzy logic control is essentially a feedback control system.

2.3.1 Fuzzy set basic operation

The theory of sets and the concept of a set itself constitute a foundation of modern mathematics. As far as one considers mathematical and simulation models of application problems, is on deals with mathematics and the set theory at the base of mathematics. The space which fuzzy sets are working in is called the universal set. Then a fuzzy subset (A) of universal set (U) is characterized by a membership function (\( \mu_A(u) \)) which is assigns to each element (U \( \not\in \) u). This function determines if the element of the universal set does or does not belong to this subset A. Hence the function may have two values: TRUE or FALSE or in numbers, 1 or 0.

\[ \mu_A(u) = \begin{cases} 1 & \text{if and only if } u \in A \\ 0 & \text{if and only if } u \not\in A \end{cases} \]

The main operations used are defined as follow:

1. The intersection of the fuzzy subsets (A) and (B) of the universal set (X) is denoted by: (A \( \cap \) B) with characteristic function define by: \( \mu_{A\cap B}(u) = \min(\mu_A(u), \mu_B(u)) \) This corresponds to the logical “AND” operation.

2. The union of the fuzzy subsets (A) and (B) of the universe set (U) is denoted by: (A \( \cup \) B) with characteristic function define by: \( \mu_{A\cup B}(u) = \max(\mu_A(u), \mu_B(u)) \) This corresponds to the logical “OR” operation.

3. The complement of a fuzzy subset (A) of the universe set (U) is denoted by: \( A^c \) This corresponds to the logical “NOT” operation. In fuzzy set theory the characteristic function is usually called the membership function.

2.3.2 Design of fuzzy logic controller

The decision-making activities of a process operator in a regulation control task are shown in the dotted block in Figure (1); for the purposes of this work this activity is expressed as a fuzzy relationship or algorithm, relating significant observed variables to the control actions. The form of the decision rules employed depends on the process under control and the heuristics employed. In the case of single input-single output regulation tasks which are the subject of this study, the process operator is assumed to respond to the system error (E) and its rate of change (CE), the result of a control decision being a change in the control valve setting (CU). The resulting control system has a measurement and control action basis similar to the versatile proportional + integral control system used extensively in the process industry [27]. The first step in fuzzy logic is to convert the measured signal x (which might be the error signal in a control system) into a set of fuzzy variables. This is called fuzzy classification or fuzzification. It is done by giving values (these will be our fuzzy variables) to each of a set of membership functions. The values for each membership function are labeled \( \mu(x) \), and are determined by the original measured signal x and the shapes of the membership functions. A common fuzzy classifier splits the signal x into five fuzzy levels as follows:

1. LP: x is large positive
2. MP: x is medium positive
3. S: x is small
4. MN: x is medium negative
5. LN: x is large negative
A five level defuzzifier block will have inputs corresponding to the following five actions:
1. LP: Output signal large (positive)
2. MP: Output medium (positive)
3. S: Output signal small
4. MN: Output signal medium (negative)
5. LN: Output signal large (negative)

The defuzzifier combines the information in the fuzzy inputs to obtain a single crisp (non-fuzzy) output variable. There are a number of ways of doing. This is the simplest and most widely used method and is called the center of Gravity Method. It works as like this: If the fuzzy levels LP...LN have membership values that are labeled $\mu_1...\mu_5$, then the crisp output signal $u$ is defined as:

$$
\frac{\sum_{i=1}^{5} \mu_i \cdot u}{\sum_{i=1}^{5} \mu_i}
$$

The complete procedures of the fuzzy controller design can be described as follow [27-29]:

1. Choose a suitable scaled universe of set (U) of; where L and –L represent the positive and negative ends respectively of this universe which is quantified into equally spaced levels in between those two ends. $E_i$ and $CE_i$ represent the error and its rate of change for the same instant (i).
2. The calculation of the error and its rate of change, from the fuzzy logic control point of view the calculations of error (E) and its rate of change (CE) are as follow: $E_i = (\text{Measured value})_i - \text{Set value}$, $CE_i = \text{Instant error} - \text{Previous error}$.
3. Both $E_i$ and $CE_i$ are multiplied by the same scale factor of the universe of set to ensure mapping their values into suitable intervals that belong to each one, also this scale factor helps to simplify handling the numerical values of all variable.
4. Choose a membership function, such as number of classes to describe all the values of the linguistic variable on the universe, the position of different membership functions on the universe of discourse, the width of the membership functions and the shape of a particular membership function.
5. Calculate the applicability degree. At this the degree to which the whole condition part (all the inputs) satisfies the rule is calculated. This degree is called the degree of applicability of the condition part. It is denoted as $\beta; \beta = \min (\mu_A(u), \mu_C(u))$

6. The fuzzy decision rules are developed linguistically to do a particular control task and are implemented as a set of fuzzy conditional statements of the form: “IF E is PB AND CE is NB THEN PM Action “. This form can be translated with the help of fuzzy set definition into a new statement; “IF PEB AND NCB THEN PUM”

7. The derivation of the fuzzy rules can be obtained directly from the phase-plane of error and its rate of change. Table 1 shows the fuzzy rules conclusions. The seven fuzzy sets definition generates (49) rules fuzzy controller. $-L \leq (E_i, CE_i) \leq L$

8. Choice of the defuzzification procedure. The defuzzification goal in Mamdani type fuzzy controllers is to produce a crisp output taking the fuzzy output obtained after rules processing. The center of gravity (COG) method is used.

9. Fuzzy Controller program: The fuzzy controller can be programmed in C, FORTRAN, Basic, Matlab, or virtually any other programming language. Suppose that we let the computer variable $x_1$ denote $E(t)$, which we call the first input, and $x_2$ denote $CE(t)$, which we will call the second input. Using these definitions, consider the program for a fuzzy controller that is used to compute the fuzzy controller output given its two inputs:

1. Obtain $x_1$ and $x_2$ values. (Get inputs to fuzzy controller).
2. Compute $\mu_1(i)$ and $\mu_2(j)$ for all i, j. (Find the values of all membership functions given the values for $x_1$ and $x_2$ and linguistic-numeric value i, j).
3. Compute $\beta(i, j)= \min (\mu_1(i), \mu_2(j))$ for all i, j. (Find the values for the premise membership functions for a given $x_1$ and $x_2$ using the minimum operation).
4. Compute $U_A(i,j) = \text{area (Rule (i,j), } \beta(i,j))$ for all i, j. (Find the area under the membership functions for all possible implied fuzzy sets, where area $= w(h-(h^2/2))$ [30]).
5. Let num.=$0$, den.=$0$. (Initialize the center of gravity numerator and denominator values).
6. For i=0 to 7
7. For j=0 to 7 (cycle through all areas to determine COG). num.=$\text{num.}+U_A(i,j)$ (center of rule(i,j)) (Compute numerator for COG)
den.=$\text{den.}+U_A(i,j)$ (Compute denominator for COG)
8. Next j

Figure 1. Fuzzy control system.
Table 1. Fuzzy Controller Rules of the pH System.

<table>
<thead>
<tr>
<th>E</th>
<th>PCB</th>
<th>PCM</th>
<th>PCS</th>
<th>ZC</th>
<th>NCS</th>
<th>NCM</th>
<th>NCB</th>
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</thead>
<tbody>
<tr>
<td>PEB</td>
<td>PUB</td>
<td>PUB</td>
<td>PUB</td>
<td>PUB</td>
<td>PUM</td>
<td>PUM</td>
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</tr>
<tr>
<td>PEM</td>
<td>PUB</td>
<td>PUB</td>
<td>PUB</td>
<td>PUB</td>
<td>PUS</td>
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<tr>
<td>PES</td>
<td>PUM</td>
<td>PUM</td>
<td>PUM</td>
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<td>ZE</td>
<td>PUM</td>
<td>PUS</td>
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<td>NES</td>
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<tr>
<td>NEM</td>
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<tr>
<td>NEB</td>
<td>ZU</td>
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</table>

9. Next i
10. Output \( u_{\text{crisp}} = \frac{\text{num.}}{\text{den.}} \) (Output the value computed by the fuzzy controller)
11. Go to step 1.

3. EXPERIMENTAL WORK

3.1 Description of the Experimental Equipment

A simplified schematic diagram of the pH neutralization system is shown in Figure (2). The process consists of an (base or acid) solution that prepared in a 100 liter feed tank in the base of the equipment, from which it is pumped via a variable area flow meter, and a hand-operated valve, into a stirred mixing vessel of approximately 3.318 liters capacity. The reagent (acid or base) is held in a 50 liter feed tank in the base of the equipment, the whole being constructed in PVC. The reagent is pumped into the mixing vessel via a variable area flow meter, a hand valve, and a pneumatically operated control valve.

A dip electrode and a pH transmitter/indicator monitor the pH of the solution in the mixing vessel; the transmitter output is a current in the range 4-20 mA. This current is fed to a converter unit where converts it to 0-10 volts and then sends to the computer control system. A control signal output from the computer in the range 0-10 volts is fed to a converter unit where converts it to 4-20 mA. The signal is then supplied to a (I/P) converter that in turn supplies an air pressure signal in the range 3-15 psig to operate the control valve.

3.2 Description of the Computer Control System

The computer control system requires a personal computer and an interface unit that consists of an analog to digital converter (ADC) and a digital to analog converter (DAC). This work has involved the use of IBM PC/386 personal computer that is used for process monitoring and control. The interface unit receives an analog signal from the converter unit and converts it to a digital signal through an ADC then sends it to the computer. The output signal from the computer is loaded to the DAC that converts it to an analog signal. Then this signal is fed to a converter where converts it to 4-20 mA.

3.3 Experimental Arrangement

The application of the pH control was tested for three sets of effluent and reagent, these are:
1. Caustic soda (effluent) – Hydrochloric acid (reagent).
2. Ammonia (effluent) – Hydrochloric acid (reagent).
3. Acetic acid (effluent) – Caustic soda (reagent).

The runs of the experiment were carried out at various conditions (feed concentration, feed flow rate, set point change). The disturbances were made throughout the practical work and under all the control methods.

1. Influent flow stepped down from 0.5 to 0.3 lit./min.
2. pH set point stepped down from the neutral point to 5, and then later stepped back to 7.
3. pH set point stepped up from the 8.72 to 10, and then after 7 minutes stepped back to 8.72.

4. RESULTS AND DISCUSSION

In this section, the fuzzy controller presented is applied to the pH neutralization system. In order to ascertain the advantages offered by the fuzzy control strategy, experimental results are also presented for a PI controller and the Shinskey adaptive nonlinear controller. The controllers are evaluated for set point changes and disturbances in effluent flow rate. A simulation study was carried out to establish the effectiveness of the proposed methods in controlling the pH system and to predict the process behavior before doing any practical work. The controller settings obtained from the simulation were used for the application of this control on the real rig.
The simulated system responses and the actual process responses to disturbances under different conditions are plotted in the Figures (4 to 9). These responses show the improvement in controlling the pH process by shortening the required time to reach the pH set point and eliminating the oscillation in the responses. The Figures (4 to 9) show the actual process responses showed an agreement with the simulated responses.

From above, the fuzzy method can be chosen as the best method for controlling the neutralization process and to which other control methods are compared.

To establish a basis for comparison, all the process responses were plotted together between control methods (PI and adaptive control) under the same disturbances as shown in Figures (10 to 13). From the application of both simulation and experimental work using the three methods (velocity form of PI, nonlinear adaptive control and fuzzy control) in controlling the pH of the present system, it appears that the fuzzy control method shows superiority over the other two methods and gives the best performance amongst the three controllers. The pH response to load disturbances was excellent under the fuzzy control for a wide range of conditions. Also it can be seen from the Figures (10 to 14) that the fuzzy control method is superior to other methods in several points, these are:

1. The algorithm is rather simple to operate because few parameters must be selected beforehand, and it can then adapt to changes in process conditions. Furthermore the fuzzy algorithm dose not requires detailed knowledge of process dynamics.
2. The size of pH deviation to disturbances is smaller compared with that of other methods. The fuzzy controller rejects the disturbance quickly without allowing large pH deviations.
3. The pH value reaches after a very short time the new set point, which the time required to return to the set point for disturbances, is shorter than that by the other two methods.
4. The size of pH oscillation around the neutral point is reduced to a low level. Moreover, there was no continuous oscillation in the reagent flow rate by the fuzzy control (unlike the velocity form of PI control).
5. Nonlinear adaptive control method showed an improvement in control of the neutralization process over the velocity form of PI control method. However, nonlinear adaptive method requires the tuning of the additional parameters to the parameters of the PI.
Figure 6. Comparison between the simulated and experimental pH responses for pH set point stepped up and then stepped back under fuzzy control, HAc-NaOH.

Figure 7. Comparison between the simulated and experimental pH responses for step in base flow rate reduced under fuzzy control, NH3-HCl.

Figure 8. Comparison between the simulated and experimental pH responses for pH set point stepped down and then stepped back under fuzzy control, NH3-HCl.

Figure 9. Process responses under velocity form of PI control and fuzzy control for step in base flowrate at pH set point=7, NaOH-HCl.

Figure 10. Process responses under velocity form of PI control and fuzzy control for pH set point stepped up from 5 to 7, NaOH-HCl.

Figure 11. Process responses under velocity form method and fuzzy pH control for pH set point stepped up from 5 to 7, NH3/HCl.
Figure 12. Process responses under Shinskey nonlinear adaptive control and fuzzy pH control for step in base feed reduced at pH set point=7, NaOH/HCl.

Figure 13. Process responses under Shinskey nonlinear adaptive control and fuzzy pH control for pH setpoint stepped down from 7 to 5, NaOH/HCl.

5. CONCLUSIONS

From the present study, the following conclusions can be drawn regarding the control of neutralization process:

1. The digital computer control can give substantially improved control of pH because of the ease with which it can process information and exploit it by implementing many different control methods.

2. The results for fuzzy control of pH of the pilot plant are promising. The fuzzy controller has been successful used to stabilize the controlled system and to achieve a good control performance for time varying set point and changes of feed flow rate. The fuzzy control has both satisfactory static and dynamic properties even though the pH neutralization process, which is considered as a nonlinear and very sensitive near the point of neutrality.

3. The performances of the velocity form method and nonlinear adaptive control were oscillatory, while the performance of the fuzzy controller could dampen the oscillations fairly well. In these tests, when the criterion was the controller’s ability to dampen the oscillations and to react quickly to the changes in the process liquid flow, the fuzzy controller was the best controller.

REFERENCES