

## **Adaptive Neuro Fuzzy Sliding Mode Based Genetic Algorithm Control System to Control of a pH Neutralization Process**

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### **ABSTRACT**

In this paper, an adaptive neuro fuzzy sliding mode based genetic algorithm (ANFSGA) control system is proposed for a pH neutralization system. In pH reactors, determination and control of pH is a common problem concerning chemical-based industrial processes due to the non-linearity observed in the titration curve. An ANFSGA control system is designed to overcome the complexity of precise control of pH. In the proposed control system the genetic algorithm is employed to do the crossover and mutation operation in adaptive neuro fuzzy inference system (ANFIS) mechanism. In this way, on-line learning ability is employed to deal with external disturbance by adjusting the control parameters. The control objective is to drive the system state to the original equilibrium point or to track the set point.

**Keywords:** ANFIS; pH neutralization; Sliding mode; Reactor; Genetic algorithm

### **INTRODUCTION**

The pH process is widely used in various areas such as the neutralization of industrial wastewater, biochemical and electrochemical processes, the paper and pulp industry, maintenance of the desired pH level at various chemical reactions, production of pharmaceuticals and biological processes, coagulation and precipitation processes and many other areas.

The control of pH is one of the most difficult challenges in the process industry because it shows a strong nonlinear behavior due to the nonlinear

characteristics resulted from the feed components or total ion concentrations. The main dynamics of such a process are determined by predictable variations due to the effect of the nonlinearities in the control loop and are most often handled by using an adaptive control approach. Various control techniques used in controlling the pH processes are reported in the literature in the last years. Thus, [1] proposed on-line recursive least-squares method to control the pH process. [2] developed model reference adaptive controller base for pH process and a fuzzy

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and neural network controller to improve the system response. [3] presented a linearization technique for using a PID control system for a mixing tank. Model algorithmic control (MAC) strategy has been proposed by [4] for a pH neutralization process. This control system is extended to nonlinear processes using Hammerstein model that consists of a static nonlinear polynomial function followed in series by a linear impulse response dynamic element. [5] developed a fuzzy control and sliding mode control in PH neutralization process. [6] investigated a feedback PID-like fuzzy controller scheme for pH control to deal with instability problems near the equivalence point in neutralization processes. [7] presented a Takagi–Sugeno fuzzy recurrent neural network (T–S FRNN) to model a pH neutralization process. [8] proposed a pH neutralization process and a methylcyclohexane (MCH) distillation column from Aspen Dynamic Module to demonstrate the effectiveness of a fuzzy partial least squares (DFPLS) modeling method and control system.

In control field, variable structure control (VSC) with sliding mode, which is commonly known as sliding mode control (SMC), is a nonlinear control strategy that is well known for its robustness characteristics. Many methods based on sliding mode have been developed to control the dynamic systems, in particular, [9] developed decoupled adaptive neuro-fuzzy (DANF) sliding mode control system methods for the chaos control problem in a system without precise system model information. [10] investigated a double-inductance double-capacitance (LLCC) resonant driving circuit and a sliding-mode fuzzy-neural-network control (SMFNCC) system for the motion control of an LPCM. [11] developed artificial intelligence control system for underwater vehicle. [17]

presented an adaptive and fuzzy neural network sliding-mode controllers for motor-quick-return servomechanism.

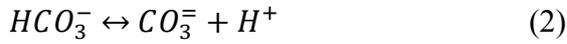
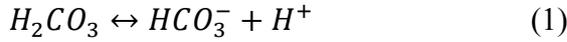
A total sliding-mode-based genetic algorithm control system for a linear piezoelectric ceramic motor driven by a newly designed hybrid resonant inverter discussed by [12].

This paper proposed an ANFSGA control system to control a pH Neutralization Process problem.

## THE REACTION INVARIANT MODEL

In this section a simplified schematic diagram of the UCSB bench-scale pH neutralization system is shown in Fig. 1. This process consists of an acid stream ( $q_1$ ), buffer stream ( $q_2$ ) and base stream ( $q_3$ ) that are mixed in tank 1. Prior to mixing, the acid stream enters tank 2 which introduces additional flow dynamics. The acid and base flow rates are regulated with flow control valves, while the buffer flow rate is controlled manually with a rotameter. The tank level ( $h$ ) and effluent pH are measured variables. Because the pH probe is located downstream from tank 1, a time delay ( $\theta$ ) is introduced in the pH measurement. Dilute acid and base streams are employed for safety and environmental reasons. In present work, the pH is controlled by manipulating the base flow rate and the acid and also the buffer flow rates are considered to be unmeasured disturbances. Using conservation equations and equilibrium relations, the dynamic model of the pH neutralization system is derived and demonstrated in Fig. 1. This model also includes valve and transmitter dynamics as well as hydraulic relationships for the tank outlet flows. Modeling assumptions include perfect mixing, constant density, and complete solubility of the ions involved. The model is presented in the

following and more details can be found in [20]:



The equilibrium constants can be presented as following:

$$K_{a1} = \frac{[HCO_3^-][H^+]}{[H_2CO_3]} \quad (4)$$

$$K_{a2} = \frac{[CO_3^{2-}][H^+]}{[HCO_3^-]} \quad (5)$$

$$K_w = [H^+][OH^-] \quad (6)$$

The chemical equilibrium is modeled by defining two reaction invariants for each inlet stream ( $i \in [1, 4]$ ):

$$W_{ai} = [H^+]_i - [OH^-]_i - [HCO_3^-]_i - 2[CO_3^{2-}]_i \quad (7)$$

$$W_{bi} = [H_2CO_3]_i + [HCO_3^-]_i + [CO_3^{2-}]_i \quad (8)$$

The invariant  $W_a$  is a charge related quantity, while  $W_b$  represent the concentration of the  $CO_3^{2-}$  ion. Unlike pH, these invariants are conserved quantities. The pH can be determined from  $W_a$  and  $W_b$  using the following relations:

$$W_b \frac{\frac{K_{a1} + 2K_{a1}K_{a2}}{[H^+] + \frac{K_{a1}K_{a2}}{[H^+]^2}}}{1 + \frac{K_{a1} + K_{a1}K_{a2}}{[H^+] + \frac{K_{a1}K_{a2}}{[H^+]^2}}} + W_a + \frac{K_w}{[H^+]} - [H^+] = 0 \quad (9)$$

$$pH = -\log([H^+]) \quad (10)$$

The dynamic model of the neutralization is derived as following in which a mass balance on tank 2 yields

$$A_2 \frac{dh_2}{dt} = q_1 - q_{1e} \quad (11)$$

where the parameters  $h_2$  and  $A_2$  are level and cross-sectional area of tank 2, respectively.  $q_{1e}$  is the exit flow rate and can be presented as following:

$$q_{1e} = C_{v1} h_2^{0.5} \quad (12)$$

where  $C_{v1}$  is a constant valve coefficient. An overall mass balance on tank 1 yields:

$$A_1 \frac{dh_1}{dt} = q_{1e} + q_2 + q_3 - q_4 \quad (13)$$

In the above equation  $A_1$  is the cross-sectional area of tank 1. The exit flow rate  $q_4$  is modeled as:

$$q_4 = C_{v4}(h_1 + z)^n \quad (14)$$

where  $C_{v4}$  is a constant valve coefficient,  $n$  is a constant valve exponent, and  $z$  is the vertical distance between the bottom of tank 1 and the outlet for  $q_4$ . By combining mass balances on each of the ionic species in the system, the following differential equations for the effluent reaction invariants ( $W_{a4} + W_{b4}$ ) can be derived:

$$A_1 h_1 \frac{dW_{a4}}{dt} = q_{1e}(W_{a1} - W_{a4}) + q_2(W_{a2} - W_{a4}) + q_3(W_{a3} - W_{a4}) \quad (15)$$

$$A_1 h_1 \frac{dW_{b4}}{dt} = q_{1e}(W_{b1} - W_{b4}) + q_2(W_{b2} - W_{b4}) + q_3(W_{b3} - W_{b4}) \quad (16)$$

The pH and level transmitters are modeled as first order transfer functions with unity gain and time constants  $\tau_{pH}$  and  $\tau_h$ , respectively. The desired flow rates  $q_1$  and  $q_3$  serve as set points for cascade flow control loops with sampling period  $\Delta t_c = 1$  s which are modeled as first-order transfer functions with unity gain and time constant  $\tau_v$ . The sampling period for pH measurement and control is  $\Delta t = 15$  s. Nominal model parameters and operating conditions are given in Table 1.

### Control system

In this section an adaptive neuro fuzzy sliding mode based genetic algorithm (ANFSGA) control system is proposed for a pH neutralization system as a set point tracking problem. To achieve the control

objective, a tracking error  $e(t) = y_{sp} - y$ , can be defined.  $y_{sp}$  and  $y$  are desired pH set point and current pH in tanker 1, respectively. To design the proposed control system a sliding surface can be introduced as

$$S(t) = \left(\frac{d}{dt} + \lambda\right)^2 \int_0^t e(\tau) d\tau \quad (17)$$

where  $\lambda$  is a positive constant. Note that, since the function  $S(t) = 0$  when  $t = 0$ , there is no reaching phase as in the sliding-mode control [15,16].

To simplifying, the dynamics of tank 2 are neglected. Therefore, a nonlinear state-space model of the process can be obtained by defining the state variables, disturbance, input and output as:

$$x \triangleq [W_{a4} \quad W_{b4} \quad h_1]^T, d \triangleq q_2, u_a \triangleq q_3, y \triangleq pH \quad (18)$$

where  $u_a$  is the actual value of the base flow rate which differs from the base flow rate calculated by the controller  $u_c$  due to the valve dynamics. Using these definitions, the process model has the form:

$$\dot{x} = f(x) + g(x)u_a + p(x)d \quad (19)$$

$$c(x, y) = 0 \quad (20)$$

where

$$f(x) = \left[ \frac{q_1}{A_1 x_3} (W_{a1} - x_1) \quad \frac{q_1}{A_1 x_3} (W_{b1} - x_2) \quad \frac{1}{A_1} (q_1 - C_{v4} (h_1 + z)^n) \right]^T$$

$$g(x) = \left[ \frac{1}{A_1 x_3} (W_{a3} - x_1) \quad \frac{1}{A_1 x_3} (W_{b3} - x_2) \quad \frac{1}{A_1} \right]^T \quad (22)$$

$$p(x) = \left[ \frac{1}{A_1 x_3} (W_{a2} - x_1) \quad \frac{1}{A_1 x_3} (W_{b2} - x_2) \quad \frac{1}{A_1} \right]^T \quad (23)$$

$$c(x, y) = x_1 + 10^{y-14} - 10^{-y} + x_2 \frac{1+2 \times 10^{y-pK_2}}{1+10^{pK_1-y}+10^{y-pK_2}} \quad (24)$$

The valve dynamics are modeled by a first-order differential equation with unity gain and time constant  $\tau_v$ :

$$\dot{u}_a = -\frac{1}{\tau_v} u_a + \frac{1}{\tau_v} u_c \quad (25)$$

The nonlinear controller design is based on a modified in-put-output linearization approach which accounts for the implicit output equation in (24). Taking the time

derivative of (24) using (19) and rearranging yields:

$$\dot{y} = -c_y^{-1}(x, y) c_x(y) [f(x) + g(x)u_a + p(x)d] \quad (26)$$

where

$$c_x(y) = \left[ 1 \quad \frac{1+2 \times 10^{y-pK_2}}{1+10^{pK_1-y}+10^{y-pK_2}} \quad 0 \right]^T \quad (27)$$

$$c_y(x, y) = (\ln 10) \left[ 10^{y-14} + 10^{-y} + x_2 \frac{10^{pK_1-y}+10^{y-pK_2}+4\{10^{pK_1-y}\}\{10^{y-pK_2}\}}{\{1+10^{pK_1-y}+10^{y-pK_2}\}^2} \right] \quad (28)$$

Because  $c_y^{-1}(x, y) c_x(y) g(x) \neq 0$  for all  $x$  and  $y$  of interest, the model has relative degree  $r = 1$  and standard input-output linearization techniques can be applied to (26).

### Adaptive Neuro-Fuzzy Sliding Mode

The architecture diagram of neuro - fuzzy inference mechanism is depicted in Fig. 2. The adaptive neuro-fuzzy sliding mode controller is composed of a neuro-fuzzy network with on-line learning algorithm. Let **input** =  $[S(t), \dot{S}(t)]$  and **output** =  $u_a$  be the input and output variables to the adaptive neuro-fuzzy sliding mode system, respectively.

### Description of Adaptive Neuro-Fuzzy

In the proposed controller, the four layers NN is used (Fig. 2). Layers I-IV represents the inputs to the network, the membership functions, the fuzzy rule base and the outputs of the network, respectively.

#### Layer I: input layer

Inputs and outputs of nodes in this layer are represented as

$$net_1^1 = S(t), y_1^1 = f_1^1(net_1^1) = net_1^1 = S(t), \quad (29)$$

$net_2^1 = \dot{S}(t), y_2^1 = f_2^1(net_2^1) = net_2^1 = \dot{S}(t),$  (30) where  $y_1^1$  and  $y_2^1$  are outputs of the input layer. In this layer, the weights are unity and fixed.

*Layer II: membership layer*

In this layer, each node performs a fuzzy set and the Gaussian function is adopted as a membership function

$$net_{1,j}^{II} = -\frac{(x_{1,j}^{II} - m_{1,j}^{II})^2}{(\sigma_{1,j}^{II})^2}, \quad y_{1,j}^{II} = f_{1,j}^{II}(net_{1,j}^{II}) = \exp(net_{1,j}^{II}) \quad (31)$$

$$net_{2,k}^{II} = -\frac{(x_{2,k}^{II} - m_{2,k}^{II})^2}{(\sigma_{2,k}^{II})^2}, \quad y_{2,k}^{II} = f_{2,k}^{II}(net_{2,k}^{II}) = \exp(net_{2,k}^{II}) \quad (32)$$

where  $m_{1,j}^{II}$ ,  $m_{2,k}^{II}$  and  $\sigma_{1,j}^{II}$ ,  $\sigma_{2,k}^{II}$  are the mean and the standard deviation of the Gaussian function, respectively. The variables  $x_{1,j}^{II}$  and  $x_{2,k}^{II}$  are the outputs of layer I.

*Layer III: rule layer*

This layer includes the rule base used in the fuzzy logic control. Each node in this layer multiplies the input signals and outputs the result of product

$$net_{jk}^{III} = (x_{1,j}^{III} \times x_{2,k}^{III}), \quad y_{jk}^{III} = f_{jk}^{III}(net_{jk}^{III}) = net_{jk}^{III} \quad (33)$$

here  $x_{1,j}^{III}$  and  $x_{2,k}^{III}$  are the outputs of layer II. The values of link weights between the membership layer and rule base layer are unity.

*Layer IV: output layer*

This layer represents the inference and defuzzification which are used in the fuzzy logic system. For defuzzification, the center of area method is used, Therefore, the following form can be obtained:

$$a_i = \sum_j \sum_k W_{jk}^{IV} y_{jk}^{III}, \quad b_i = \sum_j \sum_k y_{jk}^{III}, \quad net_{0,i}^{IV} = \frac{a_i}{b_i}, \quad y_{0,i}^{IV} = f_{0,i}^{IV}(net_{0,i}^{IV}) = \frac{a_i}{b_i} \quad (34)$$

where  $y_{jk}^{III}$  is the output of the rule layer,  $a_i$  and  $b_i$  are the numerator and the denominator of the function used in the center of area method according to the

each degrees and  $W_{jk}^{IV}$  is the center of the output membership functions used in the fuzzy logic system, respectively. The aim of the learning algorithm is to adjust the weights of  $W_{jk}^{IV}$ ,  $m_{1,j}^{II}$ ,  $m_{2,k}^{II}$  and  $\sigma_{1,j}^{II}$ ,  $\sigma_{2,k}^{II}$ . finally,  $y_{0,i}^{IV}$  is the output of proposed inference system.

The on-line learning algorithm is a gradient descent search algorithm in the space of network parameters. The Lyapunov function is chosen as  $\frac{1}{2} S^2(t)$ . The aim is to minimize the derivative of Lyapunov function respect to time or  $S(t)\dot{S}(t)$ .

*On-line learning algorithm*

The error expression for the input of Layer IV can be expressed as follow:

$$\delta_{0,i}^{IV} = -\frac{\partial S(t)\dot{S}(t)}{\partial y_{0,i}^{IV}} \frac{\partial y_{0,i}^{IV}}{\partial net_{0,i}^{IV}} = \zeta_1 S(t), \quad (35)$$

where  $\zeta_1$  is the learning rate for  $W_{jk}^{IV}$ . Therefore, the changing of  $W_{jk}^{IV}$  is written as

$$W_{jk}^{IV} = -\frac{\partial S(t)\dot{S}(t)}{\partial net_{0,i}^{IV}} \frac{\partial net_{0,i}^{IV}}{\partial a_i} \frac{\partial a_i}{\partial W_{jk}^{IV}} = \frac{1}{b_i} \delta_{0,i}^{IV} y_{jk}^{III} \quad (36)$$

Since the weights in the rule layer are unified, only the approximated error term needs to be calculated and propagated by the following equation:

$$\delta_{jk,i}^{III} = -\frac{\partial S(t)\dot{S}(t)}{\partial net_{0,i}^{IV}} \frac{\partial net_{0,i}^{IV}}{\partial y_{1,j}^{III}} \frac{\partial y_{1,j}^{III}}{\partial net_{jk,i}^{III}} = \frac{1}{b_i} \delta_{0,i}^{IV} (W_{jk}^{IV} - \partial y_{0,i}^{IV}) \quad (37)$$

The error received from Layer III is computed as

$$\delta_{1,j,i}^{II} = \sum_k \left[ \left( -\frac{\partial S(t)\dot{S}(t)}{\partial net_{jk,i}^{III}} \right) \frac{\partial net_{jk,i}^{III}}{\partial y_{1,j}^{II}} \frac{\partial y_{1,j}^{II}}{\partial net_{1,j,i}^{II}} \right] = \sum_k \delta_{jk,i}^{III} y_{jk,i}^{III} \quad (38)$$

$$\delta_{2,k_i}^{II} = \frac{\sum_j \left[ \left( -\frac{\partial S(t)\dot{S}(t)}{\partial net_{jk_i}^{III}} \right) \frac{\partial net_{jk_i}^{III}}{\partial y_{2,k_i}^{II}} \frac{\partial y_{2,k_i}^{II}}{\partial net_{2,k_i}^{II}} \right]}{\sum_j \delta_{jk_i}^{III} y_{jk_i}^{III}} = \quad (39)$$

The update laws of  $m_{1,j}^{II}$ ,  $m_{2,k}^{II}$  and  $\sigma_{1,j}^{II}$ ,  $\sigma_{2,k}^{II}$  also can be obtained by the gradient decent search algorithm, it means:

$$\dot{m}_{1,j_i}^{II} = -\frac{\partial S(t)\dot{S}(t)}{\partial net_{1,j_i}^{II}} \frac{\partial net_{1,j_i}^{II}}{\partial m_{1,j_i}^{II}} = \zeta_2 \delta_{1,j_i}^{II} \frac{2(x_{1,j}^{II} - m_{1,j_i}^{II})}{(\sigma_{1,j_i}^{II})^2} \quad (40)$$

$$\dot{m}_{2,k_i}^{II} = -\frac{\partial S(t)\dot{S}(t)}{\partial net_{2,k_i}^{II}} \frac{\partial net_{2,k_i}^{II}}{\partial m_{2,k_i}^{II}} = \zeta_3 \delta_{2,k_i}^{II} \frac{2(x_{2,k}^{II} - m_{2,k_i}^{II})}{(\sigma_{2,k_i}^{II})^2} \quad (41)$$

$$\dot{\sigma}_{1,j_i}^{II} = -\frac{\partial S(t)\dot{S}(t)}{\partial net_{1,j_i}^{II}} \frac{\partial net_{1,j_i}^{II}}{\partial \sigma_{1,j_i}^{II}} = \zeta_4 \delta_{1,j_i}^{II} \frac{2(x_{1,j}^{II} - m_{1,j_i}^{II})^2}{(\sigma_{1,j_i}^{II})^3} \quad (42)$$

$$\dot{\sigma}_{2,k_i}^{II} = -\frac{\partial S(t)\dot{S}(t)}{\partial net_{2,k_i}^{II}} \frac{\partial net_{2,k_i}^{II}}{\partial \sigma_{2,k_i}^{II}} = \zeta_5 \delta_{2,k_i}^{II} \frac{2(x_{2,k}^{II} - m_{2,k_i}^{II})^2}{(\sigma_{2,k_i}^{II})^3} \quad (43)$$

where  $\zeta_2$ ,  $\zeta_3$ ,  $\zeta_4$ , and  $\zeta_5$  are the learning-rate parameters of the mean and the standard deviation of the Gaussian functions.

#### **Adaptive neuro fuzzy sliding mode genetic algorithm (ANFSGA) control system**

In this section a control law based genetic algorithm is proposed for a pH neutralization system. The proposed control system is included the sliding mode control concept and the neuro fuzzy sliding-mode-based evolutionary procedure. In order to achieve the control object, the evolutionary spirit of GA is embedded. The neuro fuzzy approach is used to further ensure the correct

evolutionary direction and decide the appropriate evolutionary step. In this section, the control law is made as the chromosome in GA with floating point coding. This process, which is a real one, is to be replaced by the adaptive neuro fuzzy sliding mode crossover method. An adaptive neuro fuzzy sliding mode mutation is employed just after selecting the chromosomes. The first step after creating a generation is to calculate the fitness function of each member in the population. If the evolutionary direction is correct, the fittest control action can be obtained. In order to achieve the correct evolutionary direction and to ensure the stable system dynamic, the concept of the sliding mode control system is embedded in the genetic operators to form the direction-based operators with the adaptive neuro fuzzy sliding mode evolutionary procedure.

Now, a fitness function is defined as an exponentially term by the following form [12]:

$$FIT(S) = \exp[-\zeta \times (S(t)^2 + \dot{S}(t)^2)] \in [0,1] \quad (44)$$

where  $\zeta$  is a positive constant,  $S$  is the sliding surface and  $\dot{S}$  is the first derivative of  $S$  which is defined as Eq. (17). The next step after evaluation is creating a new population from the current generation. The selection operation determines which chromosome is participated to producing offspring for the next generation. Initially the population selected randomly, which is mean that several control actions are randomly selected from operational region  $[u_{a_{min}}, u_{a_{max}}]$ . After comparing the fitness values of all the individuals, the best one is regarded to as the elite. If the fitness value of the new control action is higher than the all previous ones, it will become the new elite.

Crossover operation is used to reshape in GA system, which can produce offspring by charging the features of parent. In this study, sliding surface is combined with crossover operation by the following form:

$$u_{aGA,new} = u_{aGA,old} + \mu_1 \times S + \mu_2 \times \dot{S}, \quad (45)$$

where  $u_{aGA,new}$  is the generated offspring,  $u_{aGA,old}$  is the selected elitist chromosome of the last generation,  $\mu_1$  and  $\mu_2$  are the positive tuning parameters of  $S$  and  $\dot{S}$ , respectively. Here, the important problem is selecting the tuning parameters. The small tuning step may be not satisfied the stability conditions, therefore an adaptive neuro fuzzy sliding mode system is used to produce the tuning coefficients.

In this section the adaptive neuro fuzzy sliding mode mechanism of previous section is considered to produce  $\mu_1$  and  $\mu_2$ . Let  $input = FIT(S)$  for both adaptive neuro fuzzy sliding mode mechanisms and  $output_1 = \mu_1$  and  $output_2 = \mu_2$ . For two systems different mean and the standard deviation of the Gaussian function is used. To avoid the problem of local optimization an adaptive neuro fuzzy sliding mode mechanism is used to mutation operation. Traditional mutation methods are not useful to produce better offspring in an on-line learning ability view point. Therefore, the stability of system may be destroyed. If the control action cannot let the system dynamic stay on the sliding surface after fuzzy sliding mode crossover, the mutation operation will further compel the system dynamic to close the sliding surface by using the fuzzy sliding mode inference mechanism.

The offspring after mutation operation can be expressed as

$$u^{\Delta}_{aGA,new} = u_{aGA,new} + \mu_m, \quad (46)$$

where  $\mu_m$  is the adjustment of mutation operation.  $u^{\Delta}_{aGA,new}$  is the offspring after mutation operation which is produced by the adaptive neuro fuzzy sliding mode inference mechanism. In this situation the input to adaptive neuro fuzzy sliding mode system is sliding surface or  $input = S(t)$ . If the fitness value is lower than a specified value ( $FIT_B$ ), the mutation occurs. On the other hand, if the fitness value is higher than the specified value, the mutation idles. The main process of proposed GA-based controller is represented by the following pseudo code:

*Step 1: Select the size of population [N] and the fitness function [FIT(S)].*

*Step 2: Generate the initial population.*

*Step 3: Evaluate the fitness value via (44) and sort the sequence to choose the elite  $u_{aGA,old}$ .*

*Step 4: Adaptive neuro fuzzy sliding mode crossover operation to generate  $u_{aGA,new}$  via (45).*

*Step 5: Comparing the fitness value with the specified value ( $FIT_B$ ), if it is not lower, then go to step 7, else follow the chart.*

*Step 6: Adaptive neuro fuzzy sliding mode mutation operation to generate the  $u^{\Delta}_{aGA,new}$  via (46).*

*Step 7: Output control action.*

*Step 8: Program complete? If yes then the end, if no go to step 3.*

It is noted that in the proposed controller, for the crossover and mutation operations equations 29-34 is used. The adaptive laws and the on-line learning algorithm are used of equations 35- 43. The chattering phenomenon is a particular problem in the control algorithms. The chattering problem can result in degenerate control accuracy and destroy the stability of system. To find the smooth control action and reduce chattering phenomena,

the following soft limit switching function  $f_{SL}$  is presented as

$$f_{SL}(S) = \frac{S(t)^2}{1+S(t)^2} \tanh(S(t)). \quad (47)$$

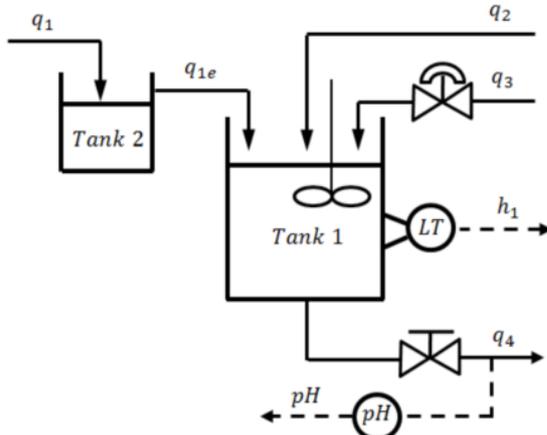


Fig. 1. The UCSB pH neutralization system.

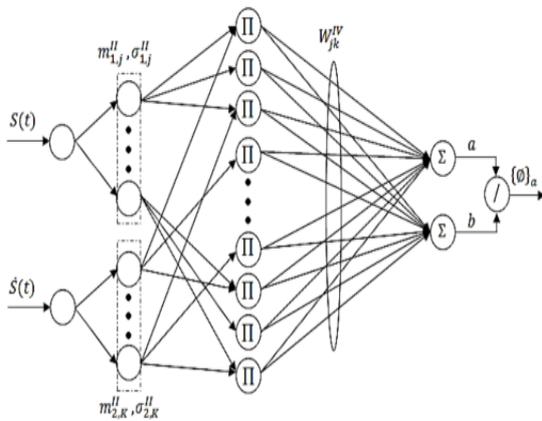


Fig. 2. Schematic diagram of the neuro-fuzzy network.

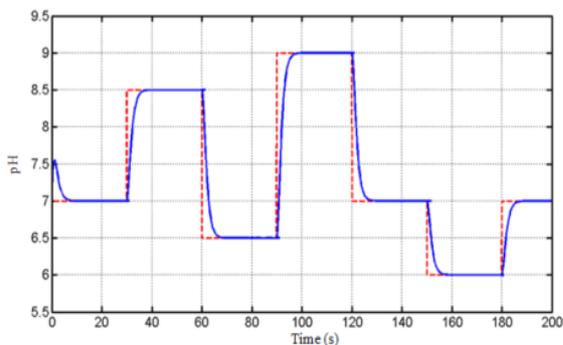


Fig. 3. Simulated ANFSGA control system for set point changes in pH neutralization process.

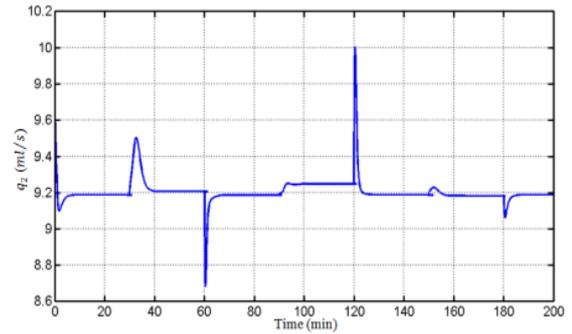


Fig. 4. Simulated for set point changes in pH neutralization process.

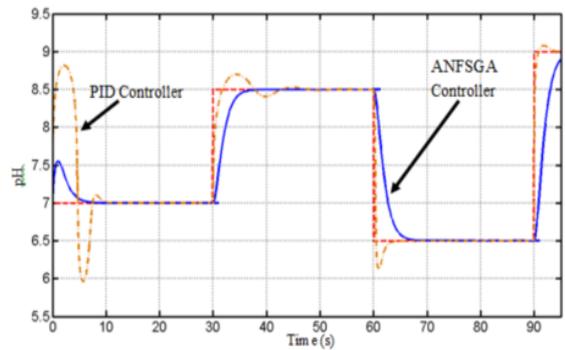


Fig. 5. Simulated results for set point changes in pH neutralization process.

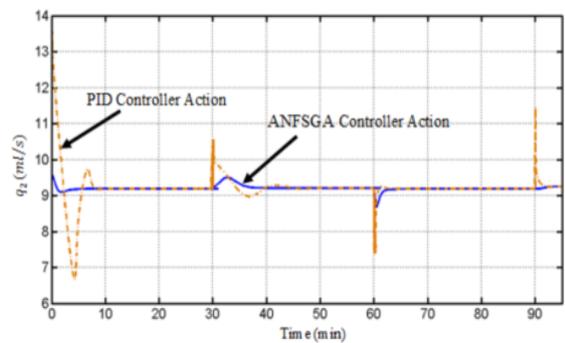


Fig. 6. Simulated for set point changes in pH neutralization process.

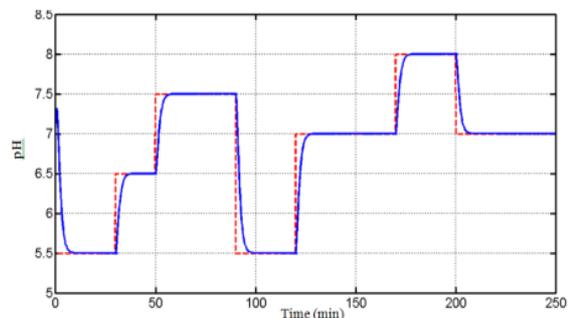


Fig. 7. Simulated ANFSGA control system for set point changes in pH neutralization process.

### Simulation results

The simulation results are demonstrated in Figs (3- 8). Three cases are considered in this section as the following:

Case 1: The nominal buffer flow rate  $d = 0.55 \text{ ml/s}$ .

Case 2: The periodic buffer flow rate with a high amplitude  $d = 2.5 \sin(0.1 t) \text{ ml/s}$ .

Case 3: The periodic buffer flow rate with a high frequency  $d = 0.5 \sin(1 t) \text{ ml/s}$ .

The controller is initialized with the values of the reaction invariants shown in Table 1.

The effectiveness of the proposed control system are depicted in Figs 3 and 4 for the pH set point tracking problem in case 1. In the proposed control system, the control parameters in crossover operation to produce  $\mu_1$  are  $\zeta_1 = 0.0001$ ,  $\zeta_2 = \zeta_3 = \zeta_4 = \zeta_5 = 0.0001$  and to produce  $\mu_2$  are  $\zeta_1 = 0.00005$ ,  $\zeta_2 = \zeta_3 = \zeta_4 = \zeta_5 = 0.0001$ . In the mutation operation the control parameters of ANFSGA control system are  $\zeta_1 = 0.0003$ ,  $\zeta_2 = \zeta_3 = \zeta_4 = \zeta_5 = 0.0002$ . The sliding surface parameter is selected as  $\lambda = 1.2$ . The threshold value to active the mutation operation is applied as  $FIT_B = 0.1$  and the parameter fitness value  $\zeta = -16.3$  is used. It can be regarded that the associated fuzzy sets with Gaussian function for each input signal are divided into NE (negative), ZE (zero) and PO (positive). Moreover, the means of the Gaussian functions are set at -0.5, 0, 0.5 and the standard deviations of the Gaussian functions are set at 0.3 for the NE, ZE and PO neurons.

The reasonable region only make the system to use  $u_a$  of interval  $[u_{a_{min}} = -10, u_{a_{max}} = 20]$  and then by crossover and mutation algorithm, the values near to 20 and -10 are produced, moreover stability of the system is kept in this

operation. Therefore, the reasonable region can be set by designer to have a desired response in this method without tuning the control parameters.

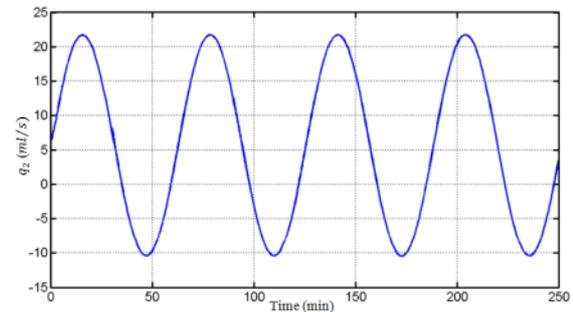


Fig. 8. Simulated for set point changes in pH neutralization process.

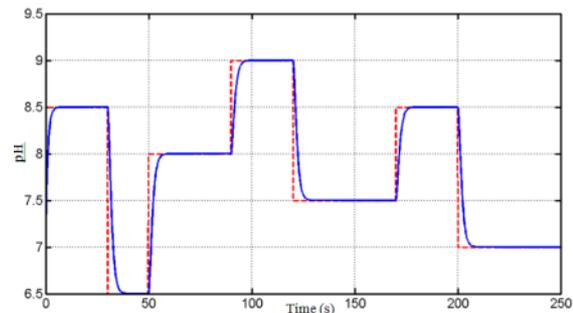


Fig. 9. Simulated ANFSGA control system for set point changes in pH neutralization process.

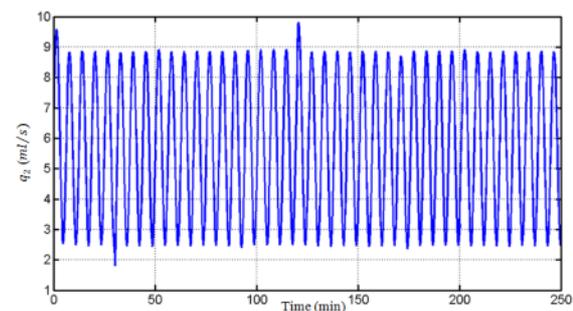


Fig. 10. Simulated for set point changes in pH neutralization process.

To show the performance of the proposed control system a PID controller is employed as a comparison. the smooth control action and fast converging in Figs 5 and 6 show that the response of the proposed control system is much superior than the PID controller. Simulation results for the pH neutralization process for set

point changes are demonstrated in Figs 7-8 and 9-10 for cases 2 and 3, respectively. Simulation shows that the proposed control

system is stable to control the pH in the set point tracking problem under the different.

**Table 1.** Operating Conditions for the pH System

Nominal Condition	
$ q_1  = 0.003 \text{ M HNO}_3$	$h_2 = 3.0 \text{ cm}$
$ q_2  = 0.03 \text{ M NaHCO}_3$	$W_{a1} = 3.00 \times 10^{-3} \text{ M}$
$ q_3  = 0.003 \text{ M NaOH, } 0.0005 \text{ M NaHCO}_3$	$W_{a2} = -0.03 \text{ M}$
$A_1 = 207 \text{ cm}^2$	$W_{a3} = -3.05 \times 10^{-3} \text{ M}$
$A_2 = 42 \text{ cm}^2$	$W_{a4} = 4.32 \times 10^{-4} \text{ M}$
$n = 0.607$	$W_{b1} = 0 \text{ M}$
$z = 11.5 \text{ cm}$	$W_{b2} = 0.03 \text{ M}$
$K_{a1} = 4.47 \times 10^{-7}$	$W_{b3} = 5.00 \times 10^{-5} \text{ M}$
$K_{a2} = 5.62 \times 10^{-11}$	$W_{b4} = 5.28 \times 10^{-4} \text{ M}$
$K_w = 1.00 \times 10^{-14}$	$\tau_{pH} = 15 \text{ s}$
$q_1 = 16.6 \text{ ml/s}$	$\tau_h = 15 \text{ s}$
$q_{1e} = 16.6 \text{ ml/s}$	$\Delta t_c = 1 \text{ s}$
$q_2 = 0.55 \text{ ml/s}$	$\tau_v = 6.0 \text{ s}$
$q_3 = 015.6 \text{ ml/s}$	$\Delta t = 15 \text{ s}$
$q_4 = 32.8 \text{ ml/s}$	$\text{pH} = 7.0$
$h_1 = 14.0 \text{ cm}$	

## CONCLUSION

Buffer tanks are primarily installed to smoothen disturbances that cannot be handled easily by the control system. The nonlinear behavior exhibited by the pH process was controlled using the proposed nonlinear intelligent control system. In this paper a ANFSGA control system as the intelligent control methods have been successfully designed and effectively employed for a pH neutralization process. No constrained conditions and prior knowledge of the controlled system is used in the design process for the proposed controller and the ANFSGA control system is not need to any information of the neutralization process

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