IMPLEMENTATION OF NEURAL CONTROL FOR NEUTRALIZATIONS PROCESS

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ABSTRACT

The dynamic behavior of neutralization process in (CSTR) is studied theoretically and experimentally, the process control is developed using different control strategies, conventional feedback control, and neural network (NARMA-L2, NN Predictive) control for acetic acid/caustic soda system.
A good agreement is obtained between the simulated and experimental responses of the dynamic model for the pH neutralization system in open loop.
The optimum tuning of control parameters are found by two different methods; Frequency curve method (Bode diagram) and Process Reaction Curve using the mean of Square Error (MSE) method. PI and PID controls are implemented as control strategies in this work.
The results show that the artificial neural network is the best method to control on neutralization process and it is better than the conventional method, for all cases the NARMA-L2 controller is the preferable method for control purposes because it has smaller value of mean square error (MSE). MATLAB program is used as a tool of solution for all cases used in this work.

Keywords: Neutralization, CSTR, Artificial Neural Network, (NARMA-L2, NN Predictive) control.

1 INTRODUCTION

1.1 Neutralization Process

The neutralization process has long been taken as a representative problem of nonlinear chemical process control due to its nonlinearity and time-varying nature. The neutralization is a chemical reaction. The control objectives are to drive the system to a different pH conditions (tracking control) or to regulate the effluent pH value despite the disturbance by manipulating the flow rate of titrating stream [1].
Henson and Seborg [2] proposed the dynamic model of the pH neutralization system using conservation equations and equilibrium relations. The 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.
In wastewater treatment, atypical pH control system consists of one or more reactors, mixer, measuring elements, controllers and reagent delivery systems. Control of pH is important to many processes including: wastewater neutralization, chemical and biological reaction, production of pharmaceuticals, fermentation, food production, municipal waste digestion, acid pickling/etching processes, coagulation/precipitation processes, boiler water treatment, and cooling water treatment [3].
Basically, a pH control system measures the pH of the solution and controls the addition of a neutralizing agent (on demand) to maintain the solution at the pH of neutrality, or within certain acceptable limits. These pH control systems are highly varied, and design depends on such factors as flow, acid or base strength or variability of strength, method of adding neutralizing agent, accuracy of control (i.e., limits to which pH must be held), and physical and other requirements [4].

1.2 pH Control Methods

Many methods are used to control pH neutralization process, which may be classified into:

A. Conventional methods (Feedback control)

Feedback control in general is the achievement and maintenance of desired condition by using an actual of the condition and comparing it to a reference value (set point), and using the difference between those to eliminate any difference between them. Most controller use negative feedback in which measured process output (control variable) is the subtracted from a desired value (set point) to generate an error signal (Ei). The controller recognizes the error signal and manipulates a process input (control element) to reduce the error; Fig. 1 represents the block diagram of Feedback Controller. The most important types of industrial feedback controllers [5] include

a) <u>Proportional Control</u>

$$c(t)=K_c E(t)+c_s \quad (1)$$

b) <u>On – off controller</u>

The simple controller would be on-off controller. The manipulated variable is at either maximum or at zero. The on-off controller is a proportional controller with a very high gain.

c) <u>Integral Control</u>

$$c(t)=\frac{K_c}{\tau_I}\int_0^t E(t)\,dt+c_s \quad (2)$$

d) Derivative Control

$$c(t)=K_C\tau_D\frac{dE}{dt}+c_s \quad (3)$$

e) Proportional – integral Controller

$$c(t)=K_C E(t)+\frac{K_C}{\tau_I}\int_0^t E(t)\,dt+c_s \quad (4)$$

f) Proportional-integral-derivative Controller (PID)

$$c(t)=K_C E(t)+\frac{K_C}{\tau_I}\int_0^t E(t)\,dt+K_C\tau_D\frac{dE}{dt}+c_s (5)$$

B. Modern method (Artificial Neural Network control)

Neural computing is one of the fastest growing areas of artificial intelligence. The reason for this growth is that neural nets hold great promise for solving problems that have proven to be extremely difficult for standard digital computers. The typical neural net consists of processing neurons and information flow channels between the neurons, called interconnect. There are three layers of neurons: input, hidden and output [6] of particular relevance in the process control field is the well-established ability of neural networks to learn complex nonlinear functional relationships. This immediately suggests that neural networks may be used for nonlinear process modeling by learning the complex nonlinear relationships between process variables [7]. Neural networks have been used successfully to control non-linear processes, both in simulation [8, 9] and online [10].

The impetus for employing artificial neural network ANNs to control nonlinear systems is due to their advantages over other nonlinear modeling paradigms. pH process can have characteristics, including nonlinearity, which render it difficult to control. Consequently, a great deal of research effort has been applied to pH control and numerous different control strategies have been proposed. Several workers have applied model-based control, employing empirical models, to pH control. Nahas *et al.* [11] applied a neural network based internal model controller to a simulated CSTR pH neutralization process. The nonlinear control system includes dead time compensation in terms of a Smith predictor

Referring to Fig.s (2 and 3), the network functions each neuron receives a signal from the neurons in the previous layer, and each of those signals is multiplied by a separate weight value. The weighted inputs are summed, and passed through a limiting function which scales the output to a fixed range of values. The output of the limiter is then broadcast to all of the neurons in the next layer. So, to use the network to solve a problem, we apply the input values to the inputs of the first layer, allow the signals to propagate through the network, and read the output values [12]. There are two types of artificial neural network:

A. NN Predictive Control

Pottmann and Seborg [13, 14] applied a neural network model predictive control algorithm to a pH neutralization process

The model predictive control method is based on the receding horizon technique. The neural network model predicts the plant response over a specified time horizon. The predictions are used by a numerical optimization program to determine the control signal that minimizes the following performance criterion over the specified horizon [5].)

$$\sum_{j=N1}^{N2}(y_p(t+j)- y_m(t+j)^2+\rho\sum_{j=1}^{Nu}(u'(t+j-1)-u'(t+j-2))(6)$$

Where N1, N2, and Nu define the horizons over which the tracking error and the control increments are evaluated. The u variable is the tentative control signal, y_p is the desired response, and ym is the network model response.

B. NARMA-L2 control

Using the NARMA-L2 model, you can obtain the controller [12, 15]

$$u(k+1) = \frac{y_r(k+d)-f[y(k),\ldots,y(k-n+1),u(k),\ldots,u(k-n}{g[y(k),\ldots,y(k-n+1),u(k),\ldots,u(k-n+1)]}$$

Therefore, the aim of the present work is to propose (NARMA-L2 and NN Predictive) network, which is used to model the dynamics of the CSTR problem and a typical problem was solved. Artificial Neural Networks (ANNs) have been shown to be effective as computational processors for various tasks including data compression, classification, combinatorial optimization problem solving, modeling and forecasting, and adaptive control [16].

2 THEORY

2.1 Mathematical model for Weak Acid/Strong Base System

Consider a stirred tank reactor into which a weak acid (acetic acid) of concentration [HAc] flows at a rate F_{at} is neutralized by a strong base (sodium hydroxide) of concentration [NaOH], which flows into the tank at a rate F_b as shown in Fig. 4. The volume of the tank is constant and equal to V. Material balances on hydrogen or the hydrogen ion would be extremely difficult to write down because the dissociation of water and the resultant slight change in water concentration would have to be accounted for. This is especially true if one is interested in almost neutral solutions, as is often the case industrially. By making material balances on acetate and sodium, using the acetic acid and water equilibrium relationships and the fact that the solution must be electrically neutral, we can completely formulate the problem.

$$NaOH + HAc + H_2O \Rightarrow H_2O + Ac^- + Na^+ + H^+ + OH^- \quad (8)$$

The acetate and the sodium ions in the outflow from the tank would be related to the total flows F_a and F_b and to the feed concentrations of weak acid [HAc] and strong base [NaOH] entering the tank.
Hence, the mass balances on these weak acid and strong base components are:
Acetate balance:

$$X_A = [HAc] + [Ac^-] \quad (9)$$

$$V \frac{d[X_A]}{dt} = C_A F_a - (F_a + F_b)[X_A] \quad (10)$$

Sodium balance:

$$V \frac{d[X_B]}{dt} = C_B F_b - (F_a + F_b)[X_B] \quad (11)$$

Acetic acid equilibrium:

$$K_a = \frac{[Ac^-][H^+]}{[HAc]} \quad (12)$$

where K_a is the dissociation constant

Water equilibrium

The electro neutrality equation (the charge balance) is

$$[H^+][OH^-] = K_W \quad (13)$$

$$[X_B] + [H^+] = [X_A][OH^-] \quad (14)$$

$$X_B + 10^{-pH} - \frac{X_A}{1 + \frac{10^{-pH}}{K_A}} - 10^{pH-14} = 0 \quad (15)$$

Where

$K_w = 10^{-14}$ $(mol/l)^2$ $K_A = 1.75*10^{-5}$ $pH = -\log_{10}[H^+]$

2.2 Experimental Work

A laboratory pH control system was developed with provision for two separate liquid feeds; the essential part of the neutralization system is a 3.318 L cylindrical mixing vessel of glass with a variable speed motor driven stirrer. The mixing vessel has effluent and reagent feed, sampling outlet (or drain), dip electrode, and an overflow line to maintain the liquid level in the vessel. Dimensions of the vessel are 0.15 m inside diameter and 0.17 m total height with a 0.15 m height of the overflow. The stirrer is fitted with cruciform rotor and has one impellers type turbine made of stainless steel. The stirrer operates with the range of 0-100 rpm. The pH of the solution in the mixing vessel is monitored by a pH meter, which is fitted at the top of vessel [17].
The effluent fed from 20 L glass tank and the reagent fed from 50 liter stainless steel tank using two polypropylene centrifugal pumps of capacity 0.41 L/sec. Two rotameters having the stainless steel float with range of flow (0–1 L /sec) were employed for measuring the flow rate of the effluent and reagent. The neutralization system which was used during the experimental work is Acetic acid - caustic soda system. The physical properties of these chemicals are given in Table 1.
Six runs were carried out for the proposed neutralization system (acetic acid - caustic soda), the acetic acid was the influent and the caustic soda was the reagent. Acid flowrate was fixed at 15 lit. /min. by using a needle valve in rotameter. Base flowrate stepped up from 15 to 30 lit. /min. by using needle valve in rotameter. The transient responses of the neutralization process listed in Table (2) for two types of responses which are: -

A. The response for a step change (+ve) for base flowrate
B. The response for a step change (-ve) for base flowrate

Computer simulation was carried out using MATLAB. MATLAB's Graphical User Interface (GUI) can be used for investigating of the static and dynamic behavior and adaptive control of the nonlinear system represented by continuous stirred tank reactor (CSTR) [18].

3 RESULTS AND DISCUSSION

The first part is to study the dynamic behavior of the system experimentally and plot the step responses where the transfer functions between the controlled variables and manipulated variables are computed from the experimental work. The second part is to study the closed loop system which is the main aim of this work through applying different control strategies, these strategies are: feedback control, NARMA-L2 control and NN Predictive control.

3.1 Dynamic Behavior

The dynamic responses are studied for different step change in the manipulated variable (F_B) in order to study the effect of each change on the controlled variable (pH). These changes are:

(20 % and 30%) step change in the base flow rate (F_B). The experimental runs for dynamic of neutralization process are listed in Table 2. The effect of the base flow rate (F_B) on the pH is illustrates in Figs. (5 and 6). From Fig. 5 it can be seen that the increase in the base flow rate (F_B) is directly proportional to pH for different steps in the base flow rate (F_B) (computer simulation programs), while in Fig. 6 an increase in the base flow rate (F_B) is directly proportional to pH on using different steps in the base flow rate (F_B) (experimental work).

Figs. (7 and 8) show the experimental dynamic of neutralization process for +ve and –ve step changes.

3.2 The closed loop system

Feedback controller is applied using PI and PID controller modes to control the CSTR process; therefore, tuning the control parameters (proportional gain (K_C), time integral (τ_I) and time derivative (τ_D) must be done first. The optimum values of the controller parameters (K_C, τ_I, τ_D) are obtained using computer simulation programs based on mean square error (MSE). The control tuning is found by two different methods which are Process Reaction Curve *(*PRC*)* and Frequency Analysis *(*Bode diagram).

a. Results of control tuning using PI, PID controller

In this section, the step change is taken in the set point of the pH using PI and PID controller modes as follows:-

Fig. 9 shows the Bode diagram of the closed loop of (CSTR) reactor of pH neutralization process.

Fig. 10 shows the transient response of different control tuning methods with PI controller mode while Fig. 11 shows the (time$\times$absolute error) versus time for this case. Fig. 12 shows the transient response of different control tuning methods with PID controller mode while Fig.13 shows the (time$\times$absolute error) versus time. Fig. 14 shows the comparison between the transient response for PI and PID controllers while Fig. 15 shows the comparison between the (time$\times$mean square errors) versus time for this case.

All the control parameters of PI and PID controllers are listed in Tables (3 and 4). It is clear that PID mode is better than PI mode because of the good tuning of adjusted parameters values in PID mode which gives the smaller overshoot and makes the system with smaller oscillation and reaches the new steady state value in shorter time and reaches the new steady state value in shorter time.

From the Comparison of the Process Reaction Curve method with Frequency Analysis Curve method, it was concluded that; the tuning by using Frequency Analysis Curve method is worst than Process Reaction Curve method because Frequency Analysis Curve method depends on closed loop system, while, Process Reaction Curve method depends on open loop system and the proportional gains are larger for the Process Reaction Curve method. Also the area under the curve of the Process Reaction Curve method is lower than the area under the curve of the Frequency Analysis Curve method and values of the MSE in the first method are less than those in the second method.

b. Results of control tuning using NARMA-L2 and NN Predictive controller

NARMA-L2 algorithm and NN Predictive control are implemented using back-propagation networks in this work, which depend on

* changing the number of neurons in the hidden layer can be represented the degree of complexity of the system.
* The ability of input layer to store information was used to represent the dynamic behavior of system by using the tapping delay lines for input/output signals.

Figs. (16 and 17) shows the transient response of NARMA-L2 and NN Predictive control respectively. Comparing NARMA-L2 with NN Predictive control, it can be seen that; the NARMA-L2 control is better than NN Predictive control because the values of the MSE in the first method are less than those in the second method. The comparison between NARMA-L2 and NN Predictive controls is listed in Table 5 while the comparisons among feedback control, NARMA-L2 and NN Predictive controls is listed in Table 6.

CONCLUSIONS

The Process Reaction Curve method *(Cohen –Coon tuning)* is better than the Frequency Analysis Curve method *(Ziegler-Nichols tuning)*. PID feedback controller is better than PI feedback controller. Implementation of artificial neural network is the best method to control the continuous stirred tank reactor (CSTR). The NARMA-L2 control is better than NN Predictive control.

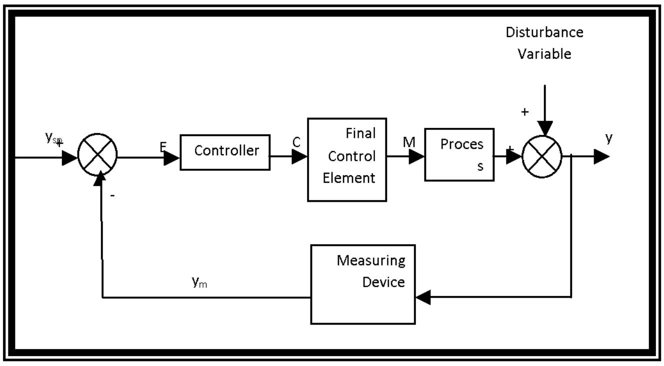

Fig.1. Block diagram of Feedback Controller

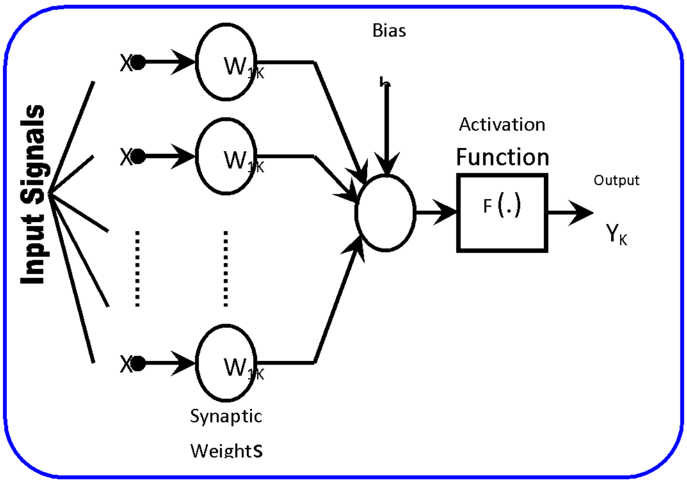

Fig.2. Nonlinear model of neuron

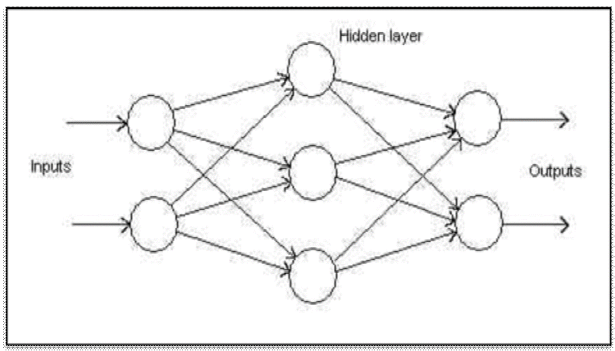

Fig.3. A Generalized network

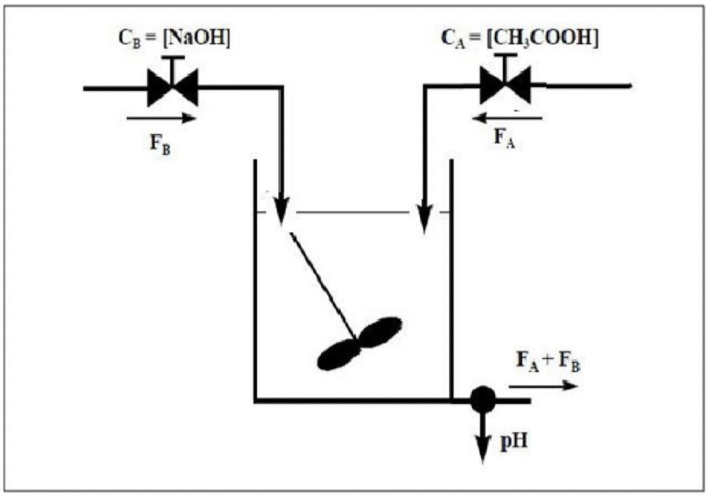

Fig.4. pH Neutralization Process

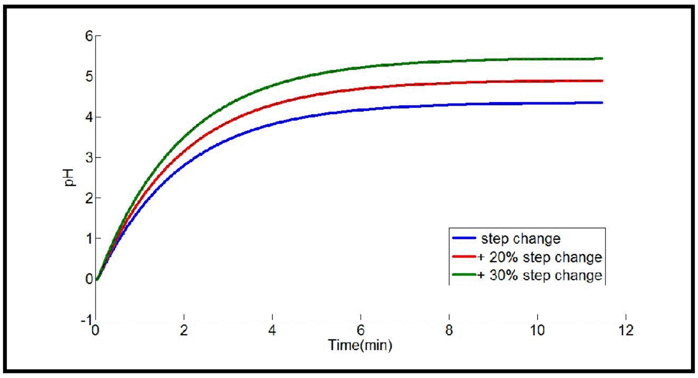

Fig.5. pH versus time at different base flow rates (F_B) from simulation (Process Reaction Curve)

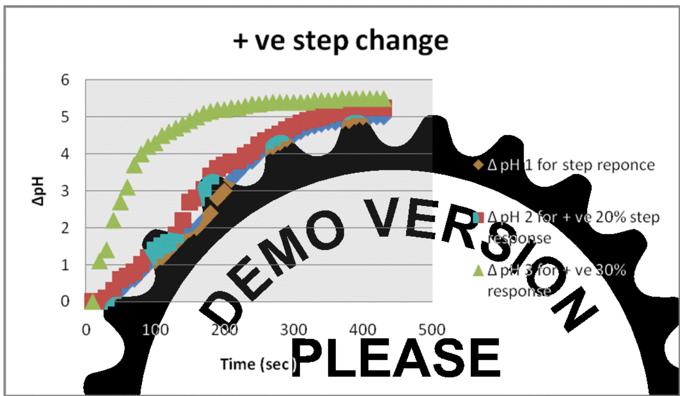

Fig.6. pH versus time at different base flow rates (F_B) from (Experimental work)

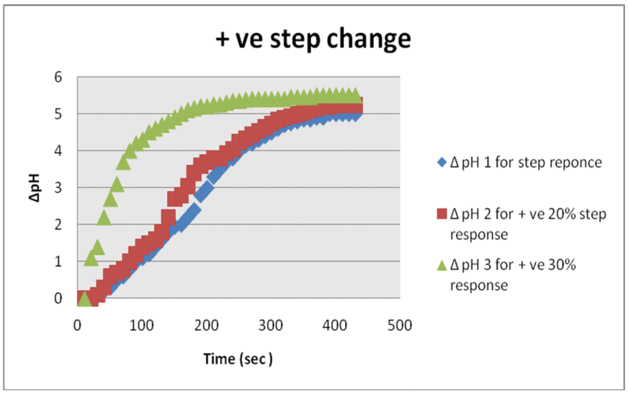

Fig.7. Step change +ve for dynamic of neutralization process in expermantal work

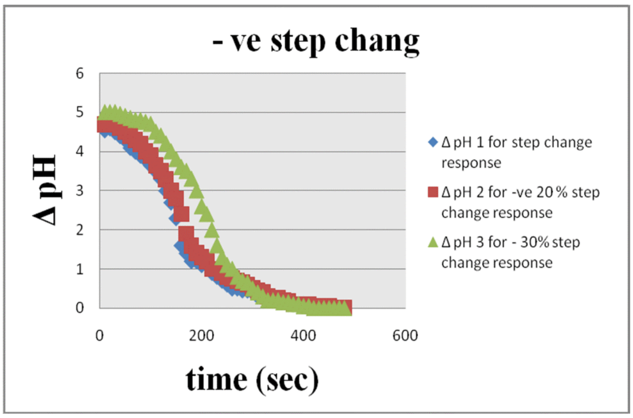

Fig.8. Step change -ve for dynamic of neutralization process in expermantal work

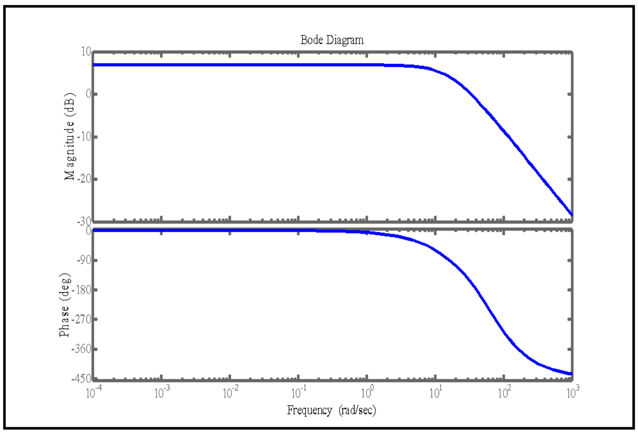

Fig.9. Bode diagram of the pH neutralization process

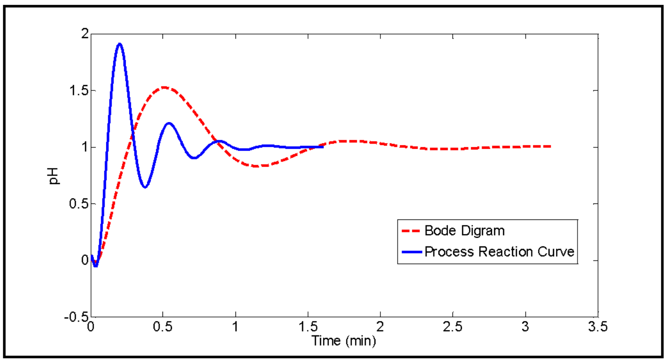

Fig.10. Transient response of the pH process with PI feedback controller mode

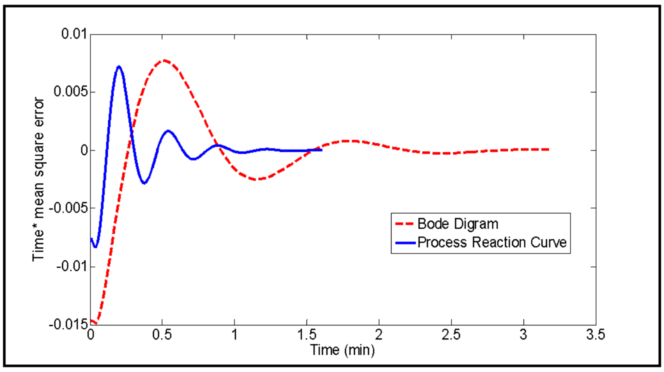

Fig.11. Time × mean square error versus time

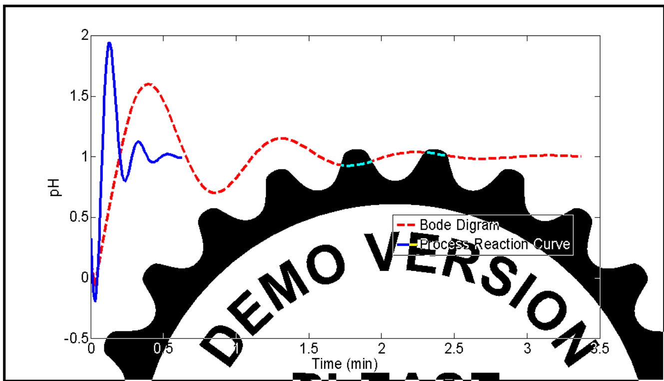

Fig.12. Transient response of the pH process with PID feedback controller mode

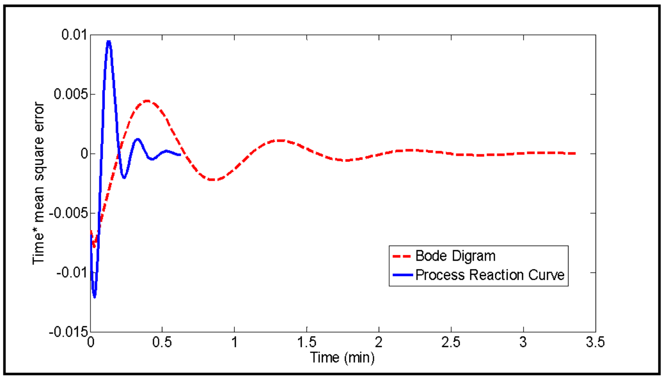

Fig.13. Time × mean square error versus time

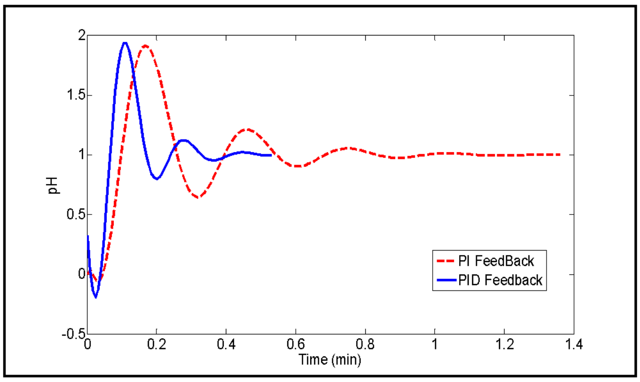

Fig.14.The comparison between the transient response for PI and PID controllers

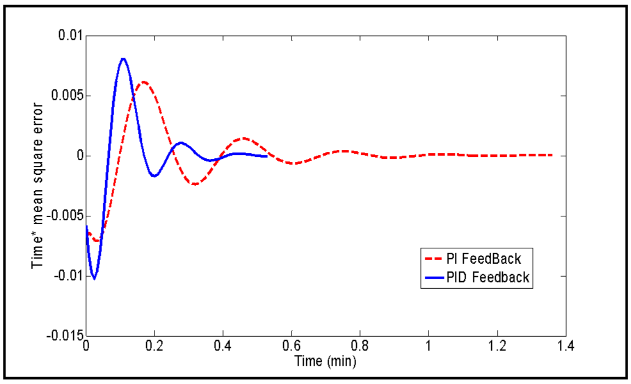

Fig.15. Time× mean error versus time

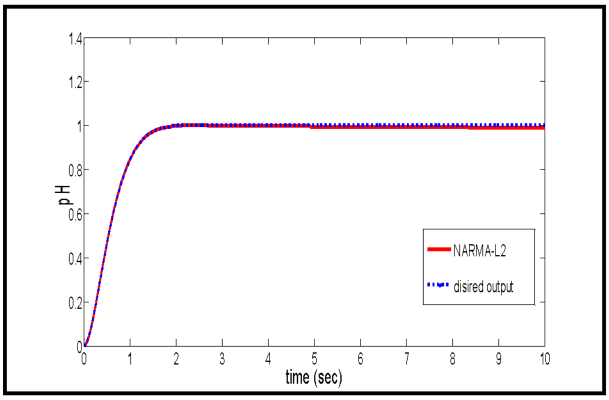

Fig.16.The transient response for NARMA-L2 control

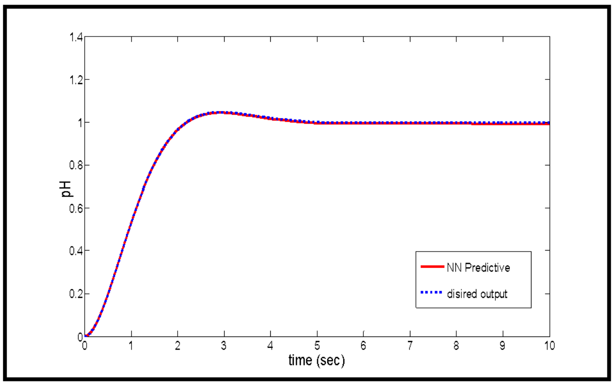

Fig.17. The transient response for NN predictive control

Table1. Properties of The feed Solutions at 25°C

Material	**Density Kg/m^3**	**Concentration mole/L**	**Ionization constant**	**Molecular weight**
NaOH 50%	1528	19.1	Completely ionized	40
HAc 80%	1050	14	1.75*10^{-5}	60.05

Table2. Experimental Runs for Dynamic of Neutralization

Run No.	Influent	Reagent	Type of Change	Conditions
1	HAc	NaOH	Step	Step in base flowrate from 30 to 40 lit. /min. +ve
2	HAc	NaOH	Step	Step in base flowrate from 30 to 45 lit. /min. +ve
3	HAc	NaOH	Step	Step in base flowrate from 30 to 50 lit. /min. +ve
4	HAc	NaOH	Step	Step in base flowrate from 40 to 30 lit. /min. –ve
5	HAc	NaOH	Step	Step in base flowrate from 45 to 30 lit. /min. –ve
6	HAc	NaOH	Step	Step in base flowrate from 50 to 30 lit. /min. –ve

Table3. Control parameters of PI controller

Control Tuning Methods	*Controller Parameters*			*MSE*
	K_c	τ_I	τ_D	
Ziegler-Nichols tuning (Bode diagram)	19.0659	0.1949	-	5.0616*10^-5
Cohen –Coon tuning (PRC)	71.0536	0.1950	-	7.4097*10^-6

Table4. Control parameters of PID controller

Control Tuning Methods	*Controller Parameters*			*MSE*
	K_c	τ_I	τ_D	
Ziegler-Nichols tuning (Bode diagram)	24.6736	0.1169	0.0292	4.8345*10 ^-6
Cohen –Coon tuning (PRC)	105.3041	0.1450	0.0214	4.7340*10 ^-7

Table5. Comparisons between NARMA-L2 and NN Predictive control

Criteria	NARMA-L2	NN Predictive
MSE	1.1016*10^-7	1.1675*10^-7
Training	1.34*10^-3	1.87*10^-3
Validation	1.27*10^-4	1.82*10^-3
Test	1.437*10^-4	1.97*10^-4

NOMENCLATURES

Symbol	***Definition***	***Units***
A	Magnitude of change in Process Reaction Curve method	[–]
A_H	Area of heat transfer	m^2
C_A	Concentration of acid	$(kmol/m^3)$
C_B	Concentration of base	$(kmol/m^3)$
D	Modeling error($y_p - y_m$)*	[–]
F_1	Volumetric flow rate of acid	(m^3/min)
F_2	Volumetric flow rate of base	(m^3/min)
f [.],*g* [.], *N2[.]*	Neural input-output mapping functions.	[–]
$G_c(s)$	Transfer function of controller	[–]
$G_d(s)$	Transfer function of disturbance	[–]
$G_p1(s)$	Transfer functions between pH and $F_B(s)$	[–]
$G_{ovl}(s)$	Transfer function of overall	[–]
H	Nonlinear activation function	[–]
L	Linear activation function	[–]

M	Number of previous input	[–]
N	Number of the previous output	[–]
$neth_j$	The weighted sum of the input of node j in the hidden layer	[–]
neto	The weighted sum of the inputs of the output node.	[–]
Nh	Number of nodes in the hidden layer	[–]
Ni	Number of nodes in the input layer	[–]
K	Discrete time instant	[–]
K_c	Proportional gain	[m^3/min]
K_I	The integral decreasing factor	[pH/min]
K_p	Gain of the process	[pH $\times$ min/m^3]
Q	Number of patterns in training set	[–]
y_{des}	Desired output of the plant	[–]
y_{sp}	Set point	[–]
y_1	The output of network N1 [.]	[–]
y_2	The output of network N2 [.]	[–]
Y	Output variable	[–]
Sgn	Sigmund function	[–]
S	Laplacian variable	[–]
s	Slope of the tangent of the PRC method	[–]
Tcl(s)	Transfer function of close loop	[–]
T	Time	[min]
t_d	Time delay	[min]
V	Volume of tank	[m^3]

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الخلاصــــة

إن الهدف من هذا البحث هو دراسة السلوك الديناميكي لنظام المعادلة الكيمياوية في مفاعل كيمياوي مستمر جيد الخلط ودراسة طرق السيطرة المختلفة النظرية والعملية وذلك باستخدام انواع مختلفة من المسيطرات وهي المسيطر التقليدي ومسيطر الشبكة العصبية بنوعين (نارما)و (التنبئي) لنظام (هيدروكسيد الصوديوم و حامض الخليك).

تم توصيف متغيرات المسيطر بطرقتين مختلفتين هما **Frequency curve method** و **Process Reaction Curve** لايجاد افضل قيم للمعاملات K_c و τ_I و τ_D . و تم استخدام معيار متوسط التربيع للخطاء **(MSE)** كاساس للمقارنة بين الطريقتين اعلاها

ان طريقة الشبكة العصبية الصناعية للسيطره هي الطريقة الاقضل من الطرق التقليدية و ذلك لان معيار متوسط التربيع للخطاء اقل و كذلك استخدمنا طريقتين للسيطرة بواسطة الشبكة العصبية الصناعية و هي نارما و التنبئي وتبين ان نارما هي افضل من التنيئي.