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Implementation of Neural Control for Continuous Stirred Tank Reactor (CSTR)

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Abstract

In this paper a dynamic behavior and control of a jacketed continuous stirred tank reactor (CSTR) is developed using different control strategies, conventional feedback control (PI and PID), and neural network (NARMA-L2, and NN Predictive) control. The dynamic model for CSTR process is described by a first order lag system with dead time.

The optimum tuning of control parameters are found by two different methods; Frequency Analysis Curve method (Bode diagram) and Process Reaction Curve using the mean of Square Error (MSE) method. It is found that the Process Reaction Curve method is better than the Frequency Analysis Curve method and PID feedback controller is better than PI feedback controller.

The results show that the artificial neural network is the best method to control the CSTR process and it is better than the conventional method because it has smaller value of mean square error (MSE). MATLAB program is used as a tool of solution for all cases used in the present work.

Keywords: *Predictive control, PID control, neural network, nonlinear control, continuous stirred tank reactor.*

1. Introduction

Chemical reactors are the most influential and therefore the important units that a chemical engineer will encounter. To ensure the successful operation of a continuous stirred tank reactor (CSTR), it is necessary to understand their dynamic characteristics. A good understanding will ultimately enable effective control systems design. The aim of these notes is to introduce some basic concepts of chemical reaction systems modeling and develop simulation models for CSTR's. Non-linear and linear systems descriptions are derived [1].

Chemical process control requires intelligent monitoring due to the dynamic nature of the chemical reactions and non- linear functional relationships between the input and output variables are involved. CSTR is one of the major processing units in chemical engineering; such a problem remains too complex to be solved by the known techniques; therefore, neural networks models can provide good optimal solutions for many applications [2].

Control and optimization problems are some of the more difficult applications for ANN [3]. The mapping functions that must be learned are generally very complex in nature and the problem constraints that must be satisfied are often conflicting (Control problems, typically, require nonlinear time dependent mapping of input signals).

Neural Networks based on adaptive resonance theory are equipped with unique computational abilities that are needed to function autonomously in a changing environment [4].

Carpenter et al. implemented a self-organizing and adaptive neural network system in the monitoring and control of the behavior of an industrial / platinum flotation plant (Hydrometallurgical process). Other network formalisms, namely radial basis function (RBF) and adaptive resonance theory-2 (ART2) networks have also been employed for fault detection, diagnosis and process monitoring task [5, 6].

LeonardJ et al., Whitley et al. and Krishnaveni et al. used ANN based systems to control patterns estimation for UPFC in power flow problem [7, 8, 9]. Zhang et al used a locally recurrent Neural Network to model the pH dynamics in a CSTR reactor [10]. Petia et al applied a feed forward network in the modeling and control of a fed-batch crystallization process [11].

1.1. Types of Feedback Controller

The block diagram of feedback controller is shown in Fig (1). The most important types of industrial feedback controllers include [13]:

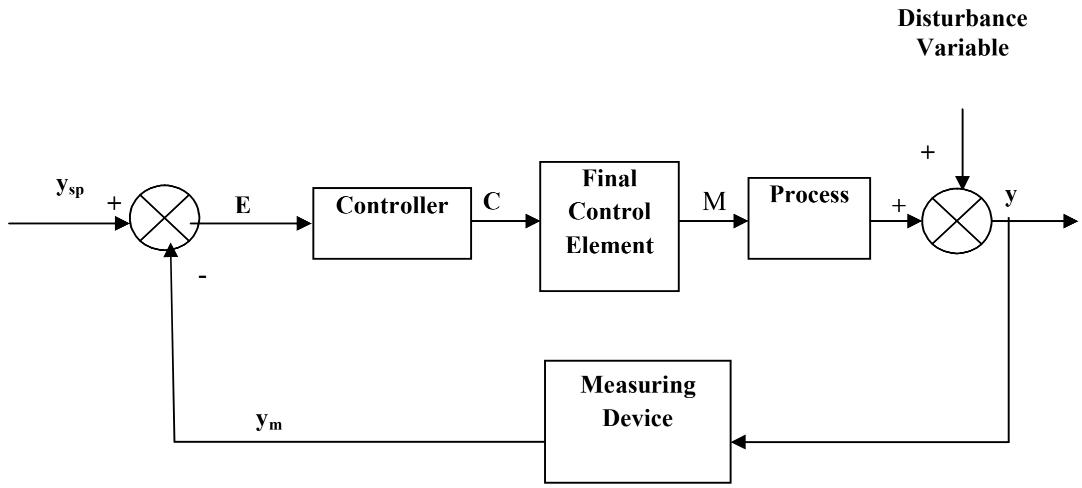

Fig.1. Block Diagram of Feedback Controller.

A) Proportional Control

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

B) Proportional – Integral Controller

Most controller loops use (PI) controller; the advantage of this controller is that it has quick response for large error and does not have set point offset. The measured variable can be returned to the set point without excessive oscillation.

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

C) Proportional – Integral - Derivative Controller (PID)

The adjustment of the input variable is accomplished using all three methods: proportional, integral, and derivative. The advantage of (PID) action is that it gives response. The disadvantage is that you have to tune three parameters.

$$c(t) = K_c E(t) + \frac{K_C}{\tau_I}\int_0^t E(t)\,dt + c_s \qquad \ldots(3)$$

1.2. Description of the Artificial Neural Networks Model

Referring to Figs. (2 and 3), in 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 [14]. There are two types of artificial neural network:

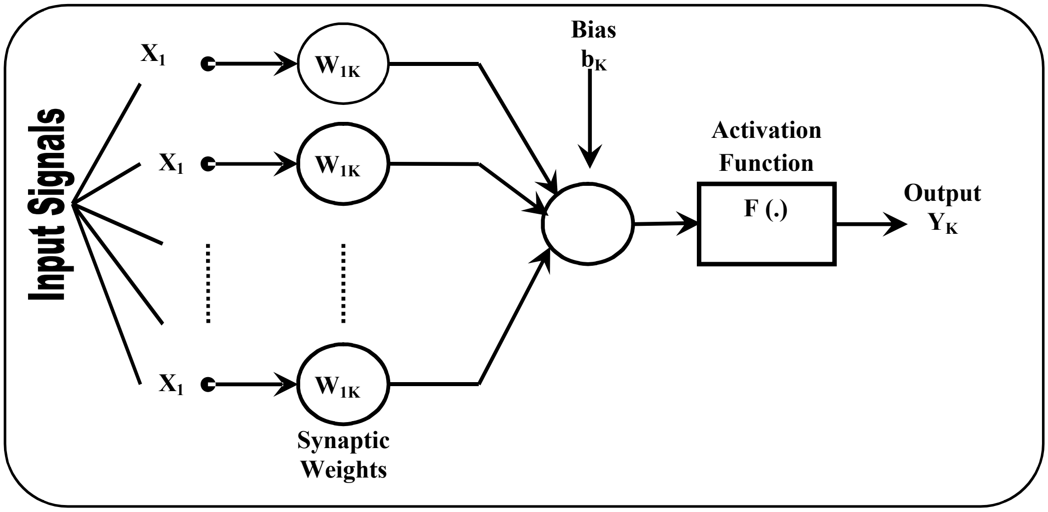

Fig.2. Nonlinear Model of Neuron

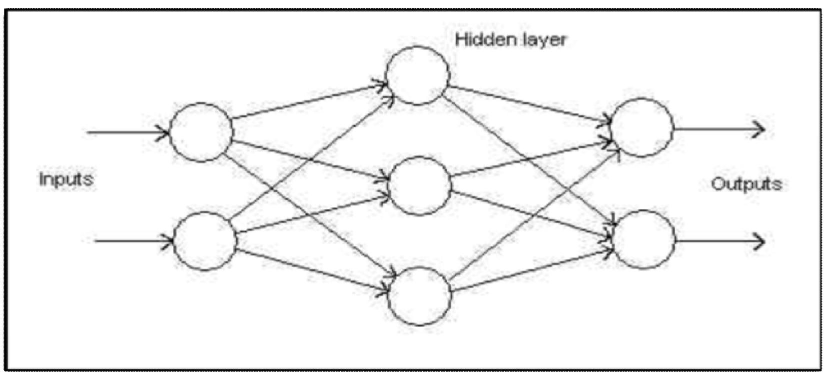

Fig.3. A Generalized Network.

A) NN Predictive Control

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 [3].

$$\sum_{J}^{N2} = N1\begin{pmatrix} y_p(t+j) - y_m(t+j)^2 + \\ p\sum_{j=1}^{Nu}\left(u'(t+j-1) - u'(t+j-2)\right) \end{pmatrix} \quad \ldots(4)$$

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. The p value determines the contribution that the sum of the squares of the control increments has to the performance index.

The block diagram in Figs (4 and 5) illustrates the model predictive control process. The controller consists of the neural network plant model and the optimization block. The optimization block determines the values of u' that minimize J, and then the optimal u is the input to the plant. The controller block is implemented in stimulant; the neural network plant model uses previous inputs and previous plant outputs to predict future values of the plant output [15].

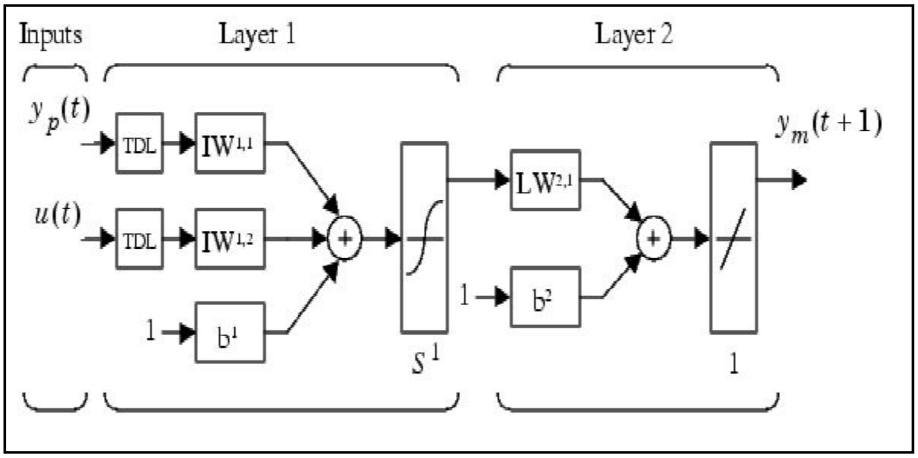

Fig.4. NN Predictive Control.

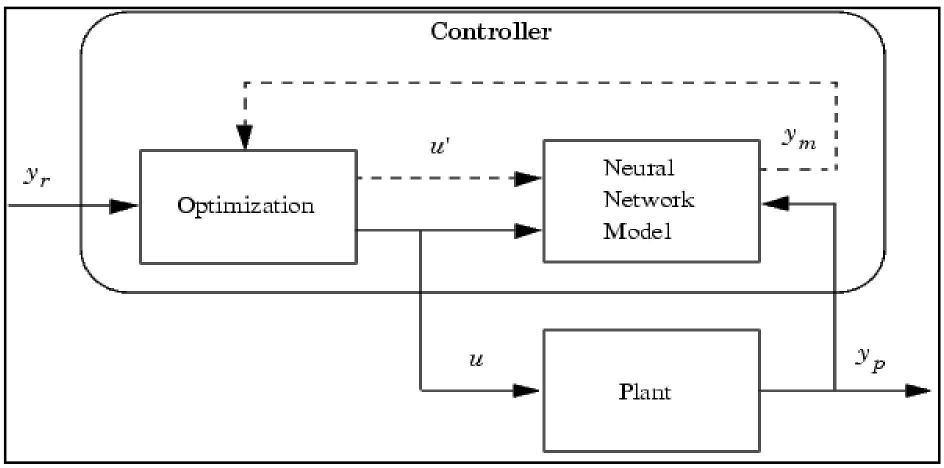

Fig.5. Block Diagram of the NN Predictive Control.

B) Narma-L2 Control

Using the NARMA-L2 model, you can obtain the controller [14]

$$u(k+1) = \frac{y_r(k+d) - f[y(k), \ldots, y(k-n+1), u(k), \ldots, u(k-n+1)]}{g[y(k), \ldots, y(k-n+1), u(k), \ldots, u(k-n+1)]} \quad \ldots(5)$$

Which is realizable for ($d \geq 2$). The following figure is a block diagram of the NARMA-L2 controller.

This controller can be implemented with the previously identified NARMA-L2 plant model, as shown in Figs (6 and 7).

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 that was solved. Neural networks are well known for their ability to imitate the skill of experts by capturing knowledge, generalizing non-linear functional relationship between input- output variable, and they provide a flexible way of handling complex and intelligent information processing. 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.

The neural network predictive controller developed in this paper uses a neural network model of a nonlinear plant to predict future plant performance. The controller calculates the control input that will optimize plant performance over a specified future time horizon. Simulation of the neural network based predictive control of the continuous stirred tank reactor is presented.

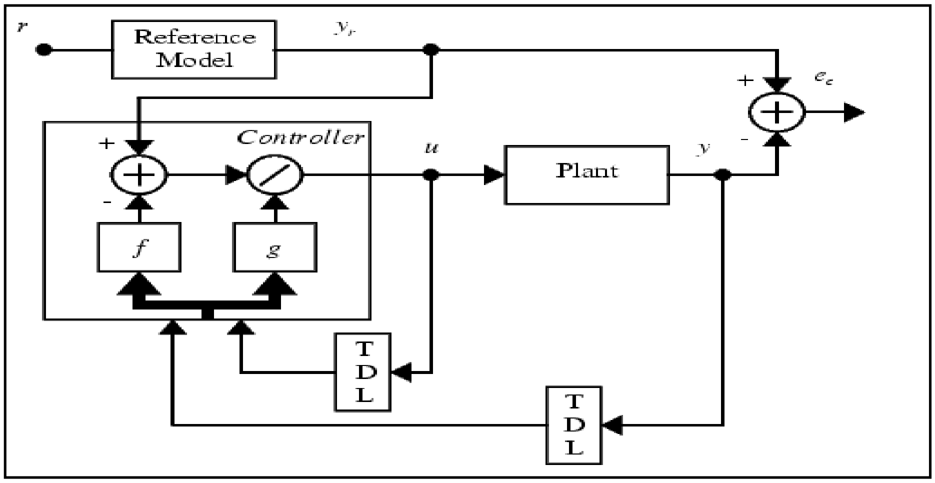

Fig.6. Block Diagram of the NARMA-L2 Control.

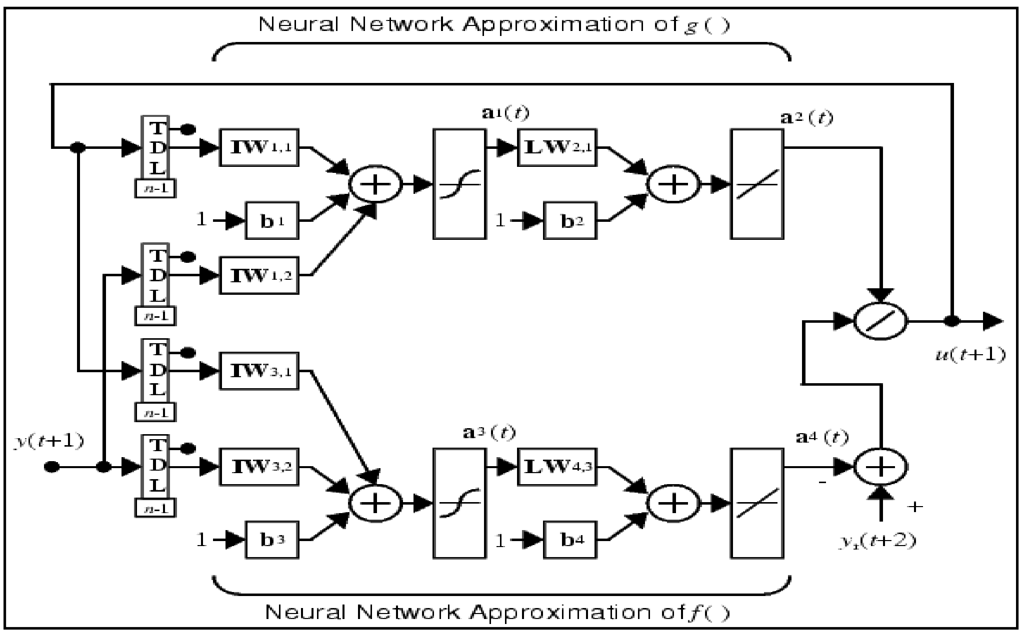

Fig.7. Narma L2 Control Structure.

2. Theory

2.1. Modeling Process Scheme

A jacketed continuous stirred tank reactor of Butru [16] is taken as an example process in the present work which has been used to carry out the exothermic chemical reaction of acetic anhydride with water. A dynamic model for first order CSTR is developed to predict the transient responses to normal and abnormal (upsets) conditions using servo technique. The mathematical model obtained using mass and energy balances is used to develop a model for controlling, feed rate, the jacket rate and both feed rate and jacket rate using several control strategies, feedback and neural network (NARMA-L2, and NN Predictive) control for two different scheme. The chemical reaction is:

$$(CH_3CO)_2O + H_2O \longrightarrow 2CH_3\,COOH \quad \ldots(6)$$

Figure (8) shows the schematic diagram of jacketed reactor. The anhydride (feed) enters the reactor through control valve (CV1) with flow rate (F1) and temperature (T1). The concentration of anhydride in feed stream and reactor are (CNo and CN) respectively; while the concentration of the product (acetic acid) is (CA) and the acidity of solution is (pH). The temperature and volume of reactants in the reactor are (T and V) respectively . The reactor is cooled by water-jacket through control valve (CV2) with hold up of Vj. The inlet temperature, outlet temperature and flow rate of cooled water are (Tj, Tjo and Fj) respectively. The inner and surface areas of the reactor are (Ai and Ao) respectively.

The experimental results of this work are taken from the same reference [16]. The properties of the feed solutions and parameters of the reactor are presented in Tables (1 and 2) and the approximate correlation of the above reaction is given by:

Ca = 198.182 EXP (-1.849 pH)

Total Mass Balance

$$F_1 + F_2 - F = \frac{dV}{dt} = 0 \quad \ldots(7)$$

$$F = F_1 + F_2 \quad \ldots(8)$$

Mass Balance on component (A)

$$F_1 C_{Ao} - FC_A - VK_o C_A e^{-\frac{E}{RT}} = V\frac{dC_A}{dt} \quad \ldots(9)$$

Heat Balance on component (A)

$$F_1\rho C_P T_1 + F_2\rho C_P T_2 - F\rho C_P T - \Delta H_r V K_o C_A e^{-\frac{E}{RT}} + UA_H(T_j - T) = V\rho C_P\frac{dT}{dt} \quad \ldots(10)$$

Heat Balance on the jacket

$$F_j\rho_j C_{Pj}(T_{jo} - T_j) - UA_H(T_j - T) = V_j\rho_j C_{Pj}\frac{dT_j}{dt} \quad \ldots(11)$$

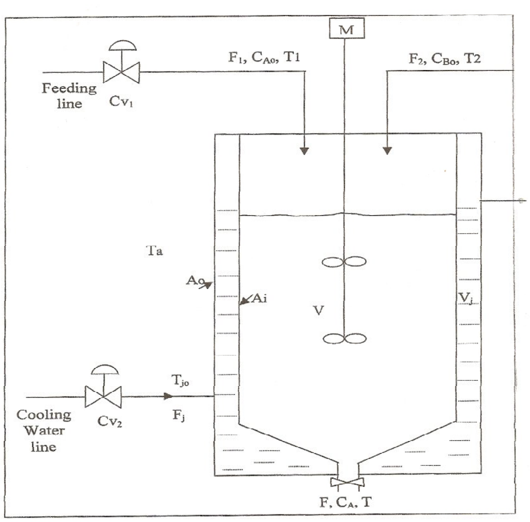

Fig.8. Schematic Diagram of Jacketed CSTR Process.

Table 1,
Properties of the Feed Solutions at the 25^{0}C.

Material	Density Kg/m^3	Concen-tration mole/L	Ionization constant	Molecular weight
Acetic acid	1528	19.1	Completel y ionized	40
Distillate water	1050	14	1.75*10^{-5}	60.05

Table 2,
Parameters of the Reactor of Butrus [16].

Martial	Property
Area for heat exchange	5.33x10^{-2} (m^3)
Ideal gas constant	8.314 (kJ/kmol K)
Heat of reaction	- 45000 (kJ/ kmol)
Activation energy	36700 (kJ/kmol)
Overall heat transfer coefficient	1480 (w/ m^2 K)
Heat capacity for jacket	4.186 (kJ/kg K)
Density of acetic acid	1.05 (kg/m^3)
Density of acetic anhydride	1.08 (kg/m^3)
Density for jacket	997 (kg/m^3)
Feed flow rate	1.83x10^{-2} (m^3/min)
Distillate water flow rate	1.714x10^{-5} (m^3/min)
Jacket feed flow rate	0.0235 (m^3/min)
Jacket output flow rate	0.0235 (m^3/min)
Inlet temperature of reactant	298 (K)
Jacket feed temperature	298 (K)
Jacket outlet temperature	299 (K)
Reaction rate constant	9.36 (min^{-1})
Concentration inlet	0.999 (kmol/m^3)
Volume of reactor	2x10^{-3} (m^3)
Volume of jacket	2x10^{-3} (m^3)
Height of reactor	0.5 (m)

2.2. Control Schemes

2.2.1 Scheme A/ Control of the Reactant Concentration

The acetic acid concentration C_A was controlled by manipulating the reactant flow rate (F_1) as shown in Fig.(9). The holdup of reactor was adjusted by using a level controller; hence, the reactant flow rate is kept constant. The transfer function for Scheme A is:

$$G1(s) = \frac{129e - 0.15}{15.4s + 1} \qquad \ldots (12)$$

The approximate correlation of this relation was established by least squares method which gives the experimental form.

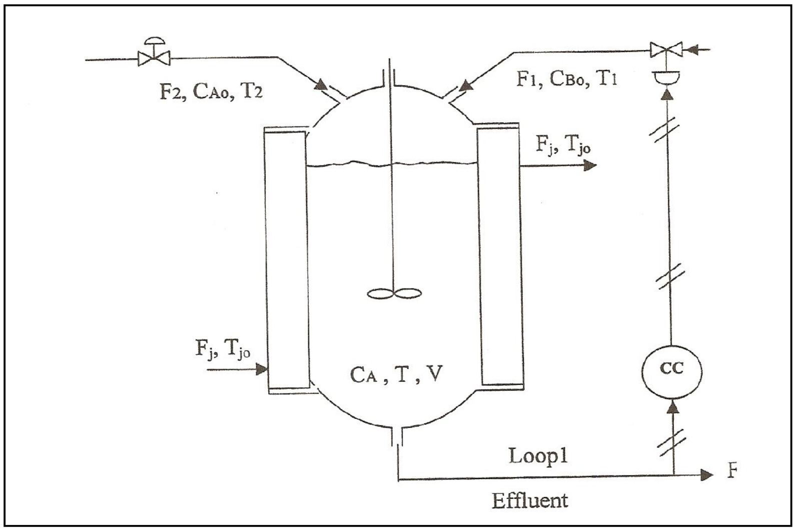

Fig.9. Scheme A of Control of Reactant Concentration.

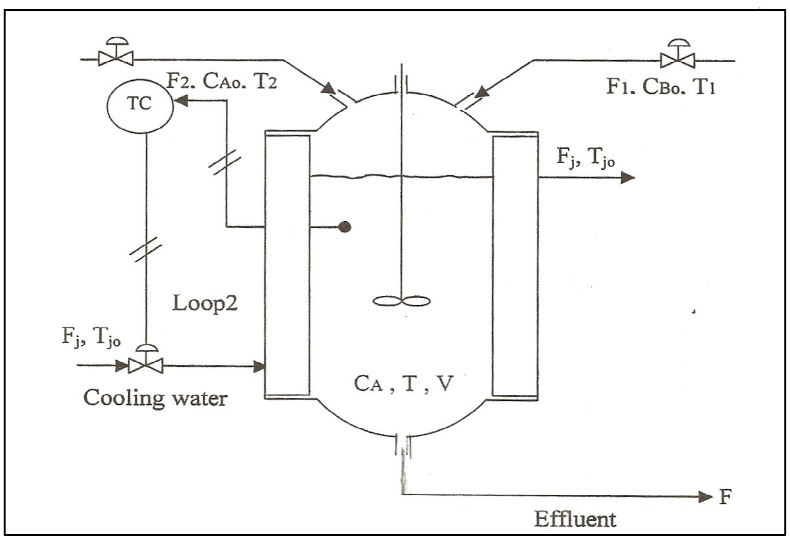

Fig.10. Scheme B of Control of Reactor Temperature.

2.2.2 (Scheme B)/ Control of the Reactor Temperature.

In this scheme, the reactor temperature T is controlled by manipulating the cooling water flow rate (F_1) as shown in Fig.(10).

The transfer function for Scheme B is:

$$G2(s) = \frac{173e - 0.15}{17.6s + 1} \qquad \ldots (13)$$

2.3. Simulation Program

Computer simulation was carried out using MATLAB. It starts with the creation of a mathematical model and the obtained equations are solved by using an appropriate calculation method.

MATLAB's Graphical User Interface (GUI) can be used for investigating the static and dynamic behavior and adaptive control of the nonlinear system represented by continuous stirred tank reactor (CSTR). There are many types of models; the main categories are real models and computer models. Based on this division, also simulation can be done for a real model investigation of its behavior as a result of input stimulation [17]. The importance of computer simulation will grow in the future when computers are faster [18].

3. Results and Discussion

The first part is to study the dynamic behavior of the system theoretically and plot the step responses where the transfer functions between the controlled variables and manipulated variables are computed from the experimental work of Butrus [16]. 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

In this section, the dynamic responses are studied for a different step change in the manipulated variable which is the reactant flow rate F_1 in order to study the effect of this change on the controlled variable of the acetic acid concentration C_A(in terms of pH (scheme A) and the temperature of reactor T (scheme B)). These changes are: (-50 % and -100%) step change in the feed flow rate F_1. The responses are shown in Figs (11 and 12). These results are obtained by using computer simulation programs. From these Figures, it can be seen that the concentration increases and the temperature decreases with the decreasing of the feed flow rate for different step changes.

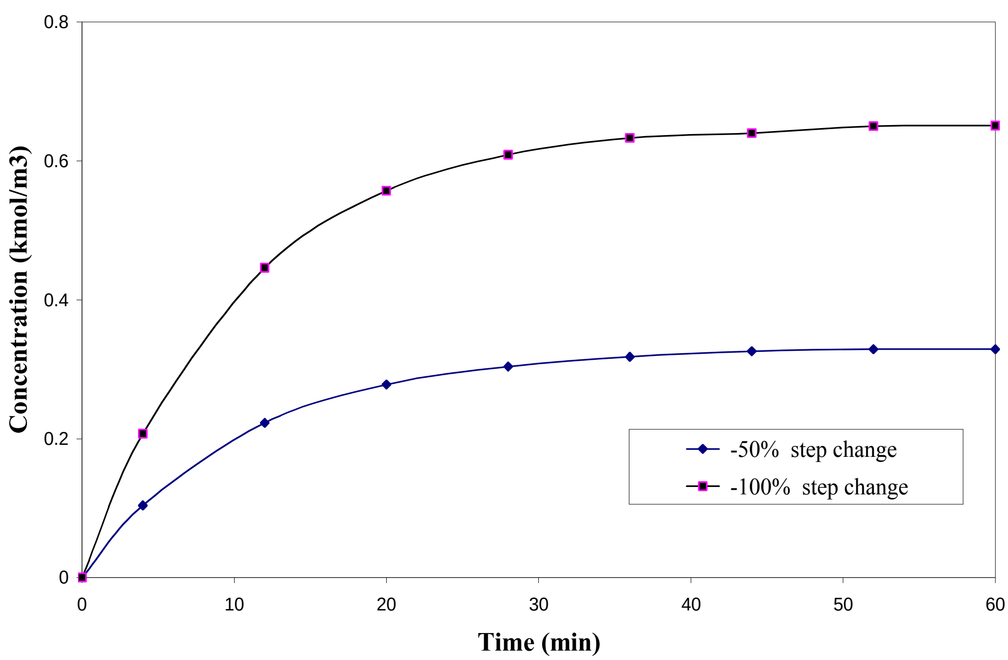

Fig.11. Transient Response of Concentration for Step Change in Feed Flowrate.

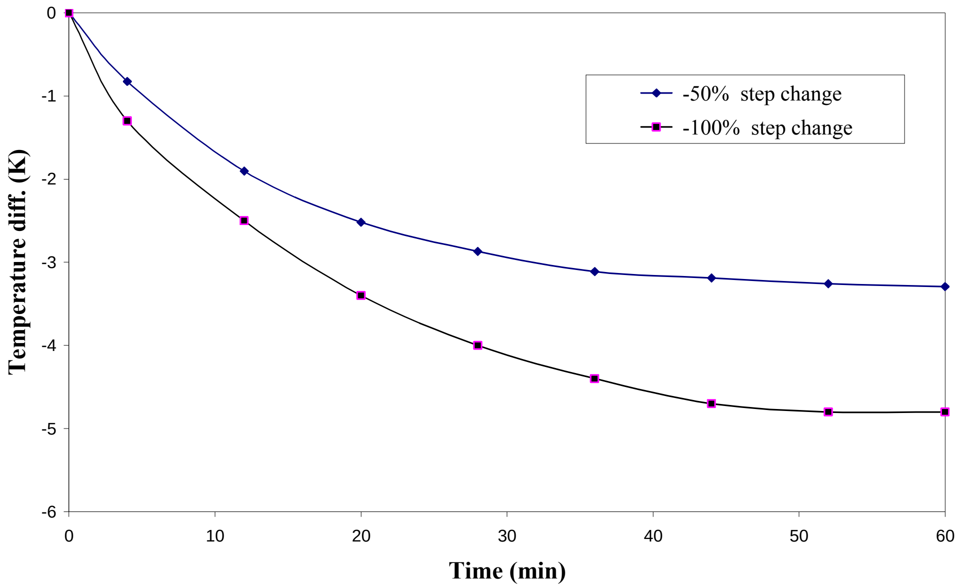

Fig.12. Transient Response of Reactor Temperature for Step Change in Feed Flowrate.

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, PI and PID controller is used to control CSTR reactor for the two transfer functions (Eq. 13 and 14) as follows:

Figs (13 and 14) show the Bode diagram of the closed loop system for the first and second transfer functions respectively to determine the value of ultimate gain (Ku) and ultimate period of sustained cycling (Pu) in order to tune the adjusted parameters values for the CSTR reactor as shown in Tables (3 and 4).

On the other hand, Figs (15 and 16) show the transient response of different control tuning methods with PI controller mode; while Figs (17 and 18) show the (Time $\times$ absolute square error) versus time for the first and second transfer functions respectively.

The results in Figs (19 and 20) show the transient response of different control tuning methods with PID controller mode; while Figs (21 and 22) show the (Time $\times$ absolute square error) versus time for the first and second transfer functions respectively.

The control parameters of PI and PID for first transfer function are listed in Tables (3 and 4) while the same parameters for the second transfer function are listed in Tables (5 and 6).

From the Comparison of the Process Reaction Curve method with Frequency Analysis Curve method, it is concluded that the tuning by using Frequency Analysis Curve method is worse 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 also the proportional gains are larger for the Process Reaction Curve method.

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. 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. The results agree with the work of Derar [19].

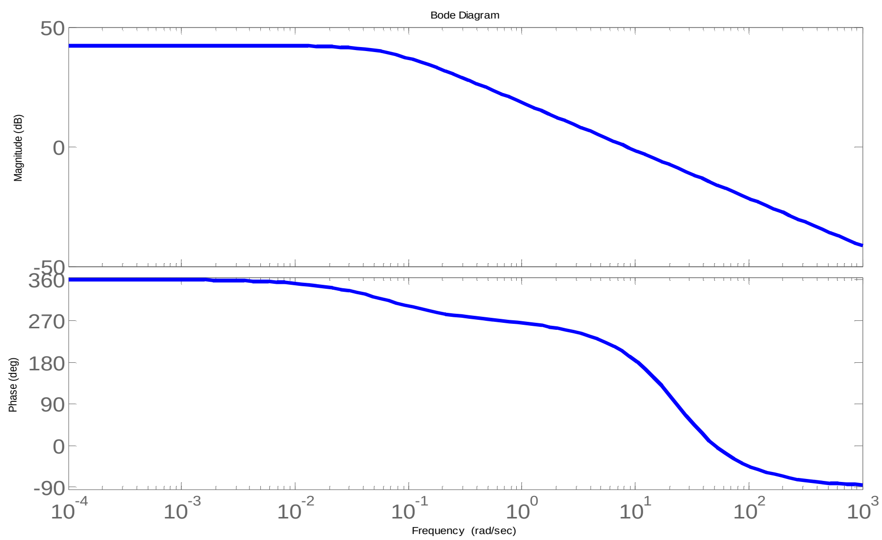

Fig.13. Bode Diagram of the CSTR Process.

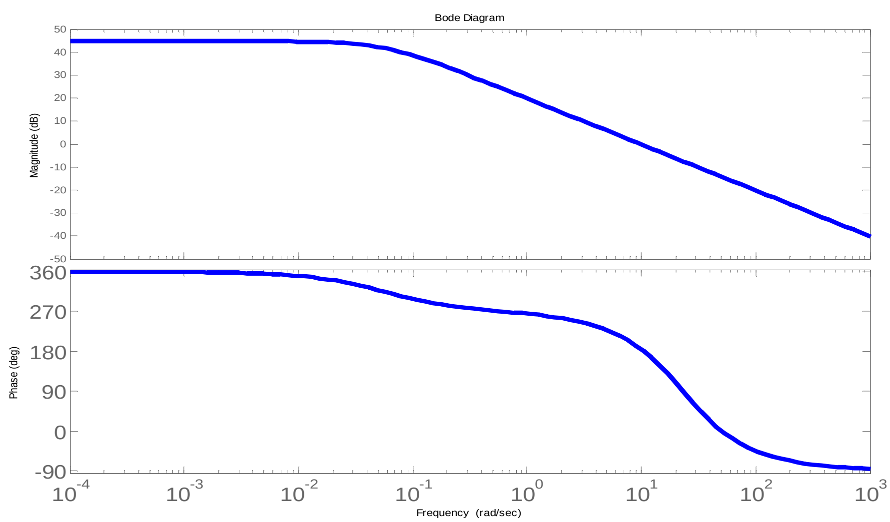

Fig.14. Bode Diagram of the CSTR Process.

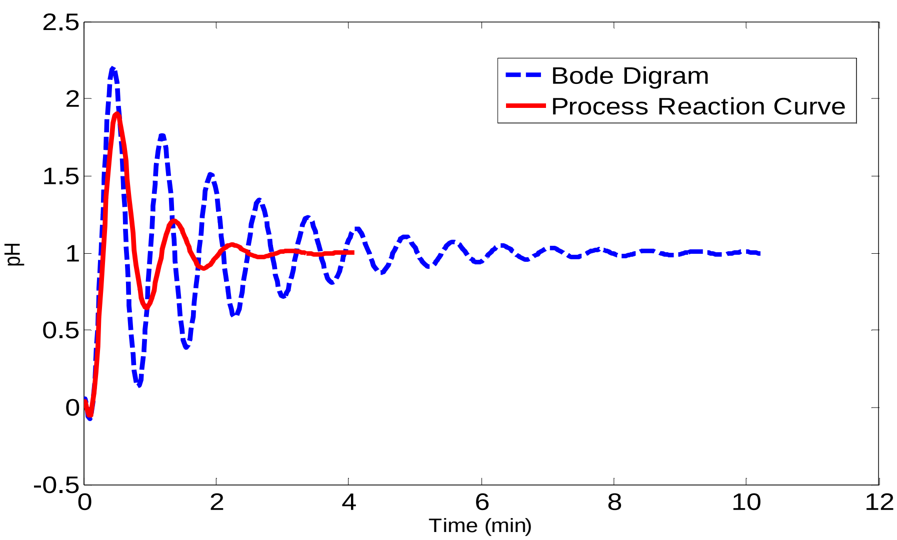

Fig.15. Transient Response of the CSTR Process with PI Feedback Controller.

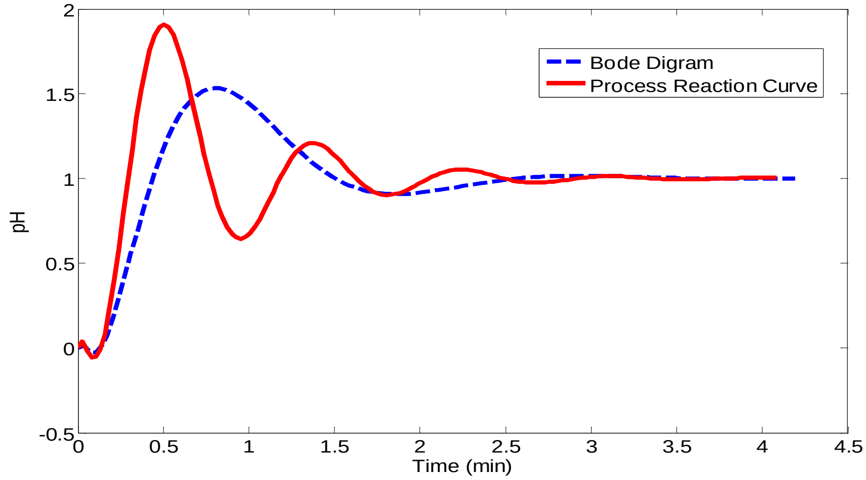

Fig.16. Transient Response of the CSTR Process with PI Feedback Controller.

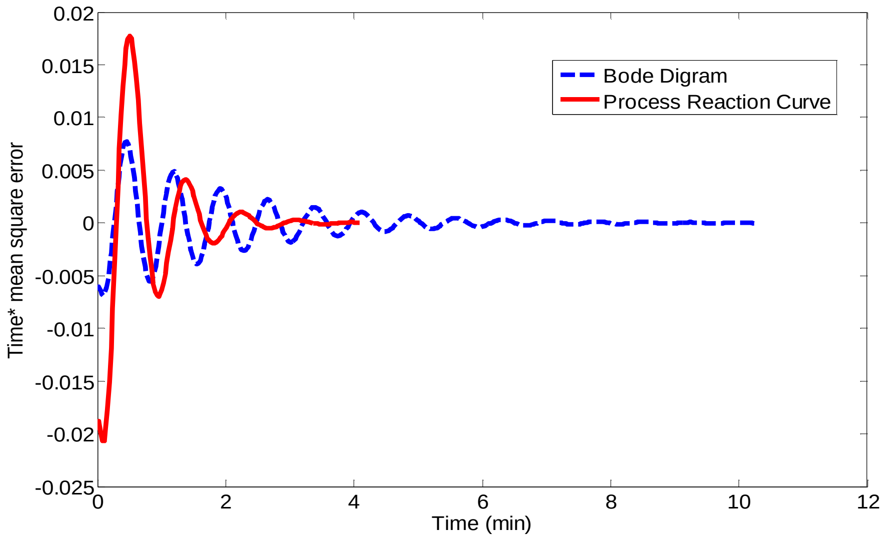

Fig.17. The Relationship between the)Time × mean Square Error) and Time with PI Feedback Controller.

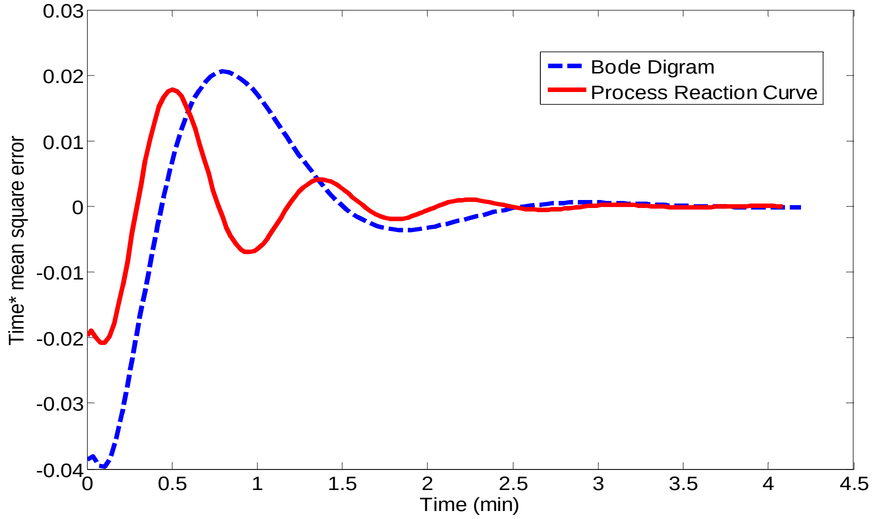

Fig.18. Time × mean Square Error versus Time with PI Feedback Controller.

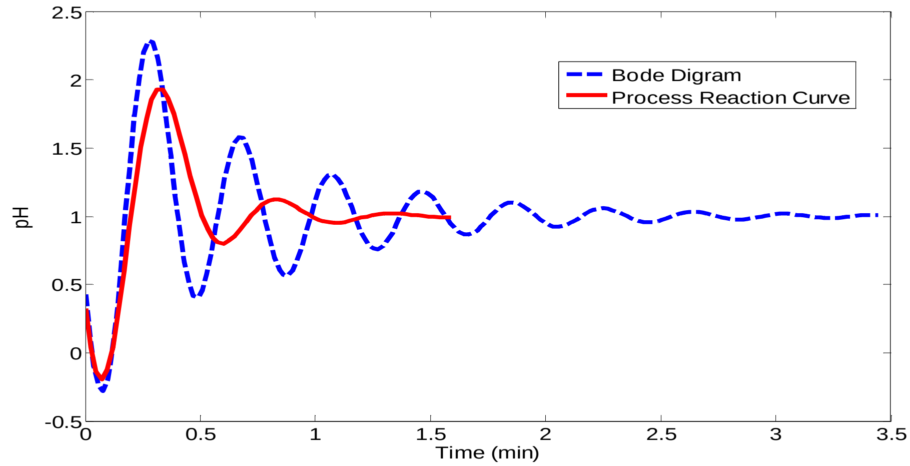

Fig.19. Transient Response of the CSTR Process with PID Feedback Controller.

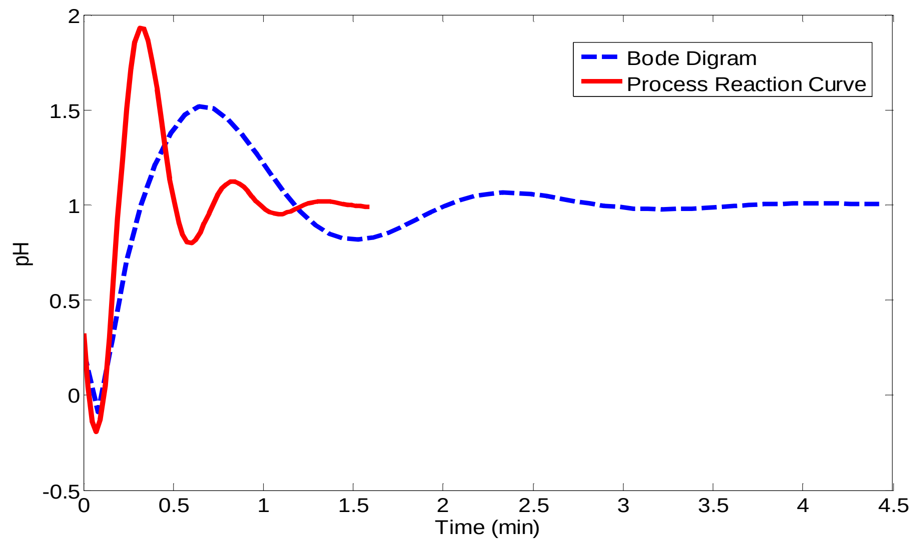

Fig.20. Transient Response of the CSTR Process with PID Feedback Controller.

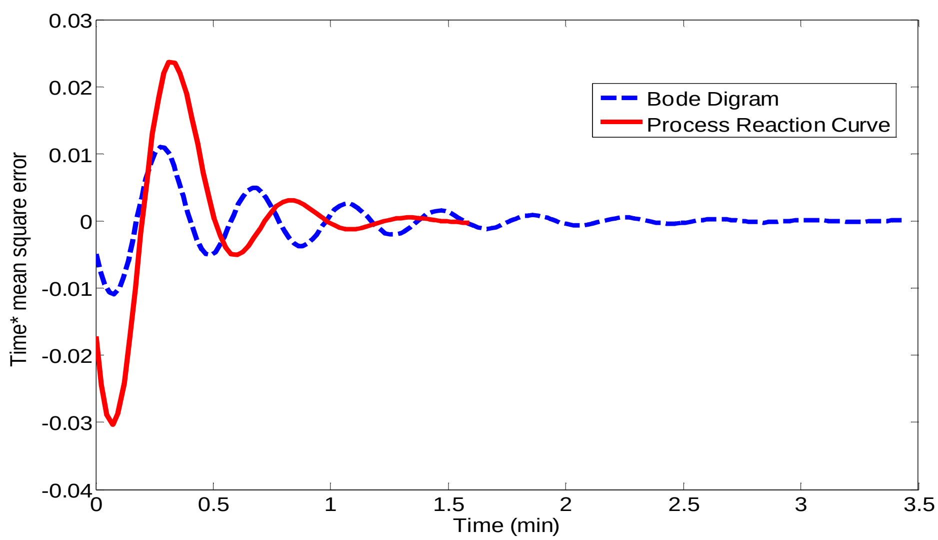

Fig.21. The Relationship between the (Time × mean Square Error) and Time with PID Feedback Controller .

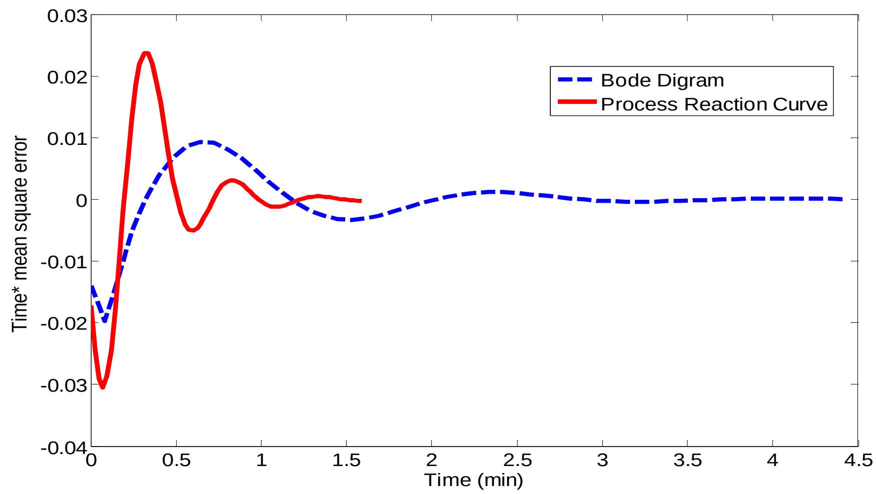

Fig.22. Time × mean Square Error versus Time with PID Feedback Controller.

Table 3,
Control Parameters of PI Controller for First Transfer Function.

Control Tuning Methods	Controller Parameters			MSE
	K_c	τ_I	τ_D	
Frequency Analysis Curve	0.9396	0.4943	-	2.5353*10 ^-4
Process Reaction Curve	0.9971	0.4899	-	1.0721*10 ^-4

Table 4,
Control Parameters of PID Controller for First Transfer Function.

Control Tuning Methods	Controller Parameters			MSE
	K_c	τ_I	τ_D	
Frequency Analysis Curve	1.2159	0.2966	0.0741	1.1071*10 ^-5
Process Reaction Curve	1.7665	0.3677	0.0544	0.3295 *10 ^-5

Table 5,
Control Parameters of PI Controller for 2nd Transfer Function.

Control Tuning Methods	Controller Parameters			MSE
	K_c	τ_I	τ_D	
Frequency Analysis Curve	0.3045	0.4945	-	3.6336*10 ^-4
Process Reaction Curve	0.6126	0.4911	-	1.7094*10 ^-4

Table 6,
Control Parameters of PID Controller for 2nd Transfer Function.

Control Tuning Methods	Controller Parameters			MSE
	K_c	τ_I	τ_D	
Frequency Analysis Curve	0.3941	0.2967	0.0742	5.0057*10 ^-5
Process Reaction Curve	0.9083	0.3679	0.0545	3.4917*10 ^-5

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 depends on:

- Changing the number of neurons in the hidden layer can represent the degree of the 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. (23 and 24) show the transient response of NARMA-L2 and NN Predictive control respectively for the first transfer function only.

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. This comparison is listed in Table (7).

Finally the comparisons among feedback control, NARMA-L2 and NN Predictive control for 1st transfer function is listed in Table (8). Many authors have reported the same results [12, 19].

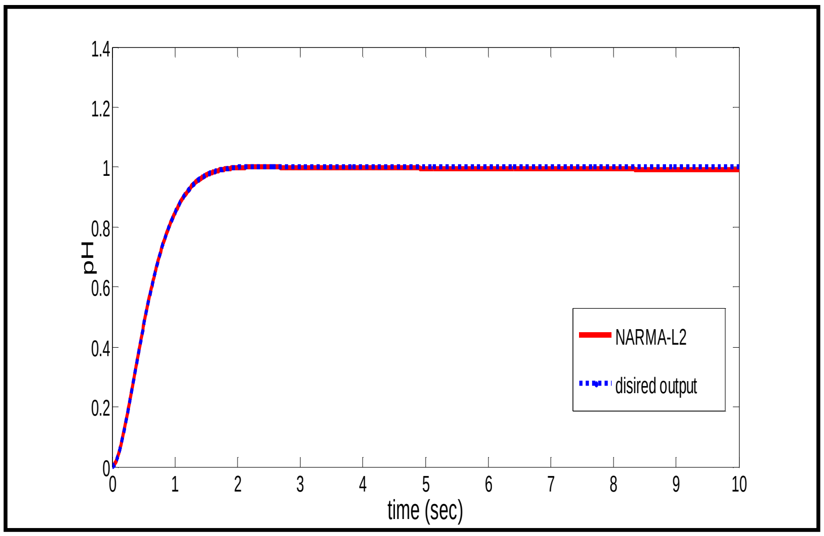

Fig.23. The Transient Response of NARMA-L2 Control.

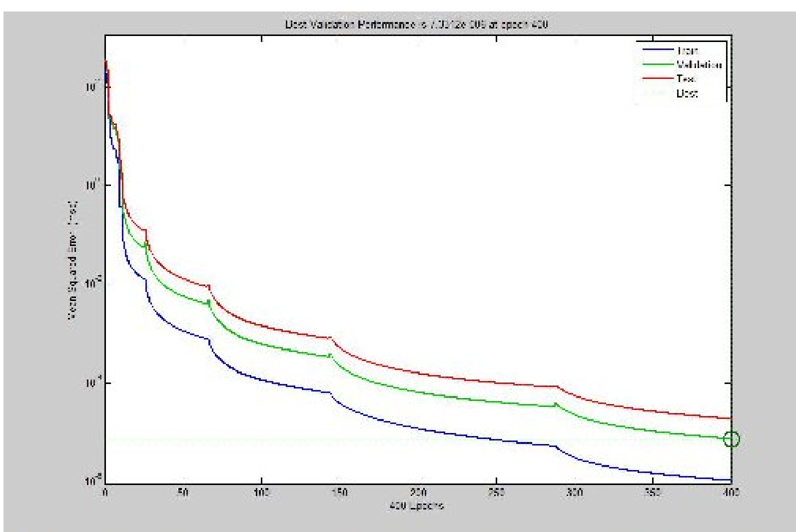

Fig.24. The Performance of NN Predictive Control.

Table 7,
Comparisons between NARMA-L2 and NN Predictive Control Transfer Function.

Criteria	NARMA-L2	NN Predictive
MSE	3.4429*10^-6	4.2112*10^-6
Training	6.43*10^-3	6.99*10^-3
Validation	7.21*10^-4	6.91*10^-3
Test	8.45*10^-4	9.87*10^-4

Table 8,
Comparisons among Feedback Control, NARMA-L2 and NN Predictive Control for 1st Transfer Function.

Controllers	MSE
PID	0.3295 *10 ^-5
PI	1.0721*10 ^-4
NARMA-L2	3.4429*10^-6
NN Predictive	4.2112*10^-6

4. Conclusion

1. The Process Reaction Curve method is better than the Frequency Analysis Curve method.
2. PID feedback controller is better than PI feedback controller.
3. Implementation of artificial neural network is the best method to control the continuous stirred tank reactor (CSTR).
4. The NARMA-L2 control is better than NN Predictive control
5. Finally the network is successfully used to model and solve the CSTR problem keeping the system at its optimum.

Notation

A	Magnitude of change
$\mathbf{A_H}$	Area of heat transfer
C_{A0}	Inlet concentration of acetic anhydride
C_A	Outlet concentration of acetic anhydride
d	Modeling error($y_p - y_m$)
F	Volumetric flow rate of distillate water
F_2	Volumetric flow rate of acetic anhydride
$G_c(s)$	Transfer function of controller
$G_d(s)$	Transfer function of disturbance
H	Nonlinear activation function
L	Linear activation function
m	Number of previous input
M	Model
n	Number of the previous output
Neto	The weighted sum of the inputs
P	Plant
k	Discrete time instant
K	Proportional gain
K	The integral decreasing factor
K_p	Gain of the process
Q	Number of patterns in training set
y_p	Reactor output
y_m	Neural model output
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
V	Volume of tank
sgn	Sigmund function
s	Laplacian variable
t	time
Tcl(s)	Transfer function of close loop
T	Temperature of reactor
T_1	Inlet temperature of reactant
T_2	Outlet temperature of reactant
T_{j0}	Inlet temperature of coolant
T_{jj}	Outlet temperature of coolant
t_d	Time delay

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استخدام نظام السيطره بالشبكه العصبيه للسيطره على مفاعل ذو الخلط المستمر

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الخلاصة

إن الهدف من هذا البحث هو دراسة السلوك الديناميكي وطرق السيطرة لمفاعل كيمياوي مستمر جيد الخلط (CSTR) وذلك باستخدام أنواع مختلفة من المسيطرات مثل المسيطر التقليدي (PI و PID) ومسيطر الشبكة العصبية بنوعين (نارما) و(التنبؤي). تم تمثيل الموديل الرياضي للخزان ذو الخلط المستمر بدالة تحويل من الدرجة الأولى مع تأخير.

تم توصيف متغيرات المسيطر بطريقتين مختلفتين هما Frequency Analysis Curve method و Process Reaction Curve method لإيجاد أفضل قيم للمعاملات K_C τ_D , τ_I ,., و تم استخدام معيار متوسط التربيع للخطأ (MSE) كأساس للمقارنة بين الطريقتين أعلاه.

الشبكة العصبية الصناعية هي أفضل طريقة للسيطرة على ال CSTR وهي أفضل من الطرق التقليدية و ذلك لان معيار متوسط التربيع للخطأ أقل. تم استخدام برنامج MATLAB في هذا البحث كأداة للحل في جميع الحالات.