Study on Control of CSTR Using Intelligent Strategies

Khalid M. Mousa
Chemical Eng. Dep./Al-NahrianUniversity
drkhalidalzobai@yahoo.com

Zainab Essaim Dawood
Chemical Eng. Dep./Al-NahrianUniversity
zaynab.dawood@yahoo.com

Abstract

A non linearity, interaction and complexity in modeling lead to a great difficulties in CSTR control system, this paper interested in CSTR control using PID, fuzzy logic and intelligent control strategies. Water flow rate and ethyl acetate were selected as manipulated variables while sodium acetate and reactor temperature as controlled variables. Firstly the system identification was conducted and the results show that the multi input multi output system can be represented by the following matrix

$$\begin{matrix} C_D \\ T \end{matrix} = \begin{bmatrix} \dfrac{0.022e^{-0.33s}}{15S+1} & \dfrac{5e^{-0.33s}}{21S+1} \\ \dfrac{0.0056e^{-6s}}{21S+1} & \dfrac{5.9e^{-0.33s}}{21S+1} \end{bmatrix} \begin{matrix} F \\ F_c \end{matrix}$$

The compare among the strategies show preference of fuzzy control.

Keywords: CSTR, Fuzzy control, intelligent control

Introduction

Alkaline hydrolysis of ethyl acetate is essentially an irreversible and second order reaction. Industrial importance of the reaction product (sodium acetate), necessitate for process improvement in terms of maximum conversion and economical usage of raw materials [1]. Hydrolysis of carboxylic ester under alkaline conditions, also known as saponification reaction, produces soap and an alcohol. Sodium acetate, basically a salt produced when ethyl acetate (EtAc) undergoes hydrolysis in alkaline environment is not used specifically for cleanning purposes as soap but has a wide range of industrial applications such as in pharmaceutical, paint and dying industry, as food additive, in electroplating industry, as meat preservative, photography and purification of glucose. whereas ethanol, a by-product, can be used as biofuel [2]. Our work is interested in control of the following reaction:-

Ethyl acetate (A) +Sodium hydroxide (B) →Sodium acetate (D) +Ethanol (E)

The reaction was exceedingly slow at natural PH because both nucleophile (H2O) and the electrophile (the carbonyl of ethyl acetate) are in reactive [3].

Due to importance of saponification process it's worthy to study the control of the system .PID, fuzzy, and neural control were conducted.

Tuning a PID controller is more difficult because three parameters must be adjusted. The error signal ϵ is used to generate the proportional, integral, and derivative actions, with the resulting signals weighted and summed to form the control signal P applied to the plant model. A mathematical description of the PID controller is [4]

$$P = K_c\left[\epsilon(t) + \frac{1}{\tau_i}\int_0^t \epsilon(\tau)dt + \tau_d\frac{d\epsilon}{dt}\right]$$

Fuzzy logic is a multivalued logic that allows intermediate values to be defined between conventional evaluations like true/false, yes/no, high/low, etc. The most sufficient application area of FL has been in control field. It has been made a rough guess that 90% of applications are in control. Fuzzy control includes fans, complex aircraft engines and control surfaces, helicopter control, missile guidance, automatic transmission, wheel slip control, industrial process and so on. Fuzzy system performs better when compared with a conventional PID controller [5].

Neural control is a branch of the general field of intelligent control, which is based on the concept of artificial intelligence (AI). AI can be defined as computer emulation of the human thinking process. The AI techniques are generally classified as expert systems (ES). A artificial neural networks (ANN) are information processing structures which emulate the architecture and operational mode of the biological nervous tissue. Any ANN is a system made up of several basic entities (named neurons) which are interconnected and operate in parallel transmitting signals to one another in order to achieve a certain processing task. One of the most outstanding features of ANNs is their capability to simulate the learning process [6].

Control engineering has enjoyed tremendous growth during the years since 1955. Particularly with the advent of analog and digital computers and with the perfection achieved in computer sophisticated control schemes have been devised and implemented. On the technological front fully automated computer control schemes have been introduced for electric utilities and many complex industrial processes with several interacting variable particularly in the chemical and metallurgical processes [7]. In 1977, L.A. Zadeh studied fuzzy sets as a basis for a theory of possibility, the theory of fuzzy sets define the concept of a possibility distribution as a fuzzy restriction which acts as an elastic constraint on the values that may be assigned to a variable [8]. In 1999, S.S. Ge et al. studied the nonlinear adaptive control using neural networks and its application to CSTR systems, adaptive tracking control is considered for a class of general nonlinear systems using multilayer neural networks (MNNs) the effectiveness of the proposed controller is illustrated through an application to composition control in a continuously stirred tank reactor (CSTR) system [9]. In 2002, Mircea Lazar et al. studied a neural predictive controller for non-linear systems; the resulting implementation of the neural predictive controller is able to eliminate the most significant obstacles encountered in non-linear predictive control applications by facilitating the development of non-linear models and providing a rapid, reliable solution to the control algorithm. Results are given for simulation experiments, which demonstrate the effectiveness of the proposed approach [10], Martin T. Hagan et al. studied an introduction to the use of neural networks in control systems; the multilayer perceptron neural network introduced and describes how it can be used for function approximation [11]. In2006, JaroslavaŽilková et al. studied the nonlinear system control using neural networks, [12]. In 2007, Dauda Olurotimi Araromi et al. studied the neural network control of CSTR for reversible reaction using reverence model approach; non-linear control of CSTR for reversible reaction is carried out using Neural Network as design tool. The Model Reverence approach in used to design ANN controller, the comparison shows that ANN controller outperforms PID in the extreme range of non-linearity [13]. In 2009, Suja Malar et al. studied the modelling of continuous stirred tank reactor using artificial intelligence techniques, attempts are made to alleviate the modeling difficulties using “Artificial Intelligence” AI techniques such as neural, fuzzy and neuro-fuzzy. Simulation results demonstrate the effectiveness of Artificial Intelligence modeling techniques [14]. In 2011, Bahman Zare Nezhad et al. studied the application of the neural network based model predictive controllers in nonlinear industrial systems, Neural Network is considered as a prediction model for control purposes to determine an optimal sequence of control moves [15]. In 2012, S.V.A.R.Sastry et al. studied the application of fuzzy logic for the control of CSTR, There has been considerable interest in its state estimation and real time control based on mathematical modeling, the performance comparison of different modeling techniques has been given in terms of root mean square error [16]. S.Kajan studied the neural controllers for nonlinear systems in MATLAB, For the purpose of neural control structures a direct and inverse neural model of a nonlinear dynamic system using three-layer perception network was created.

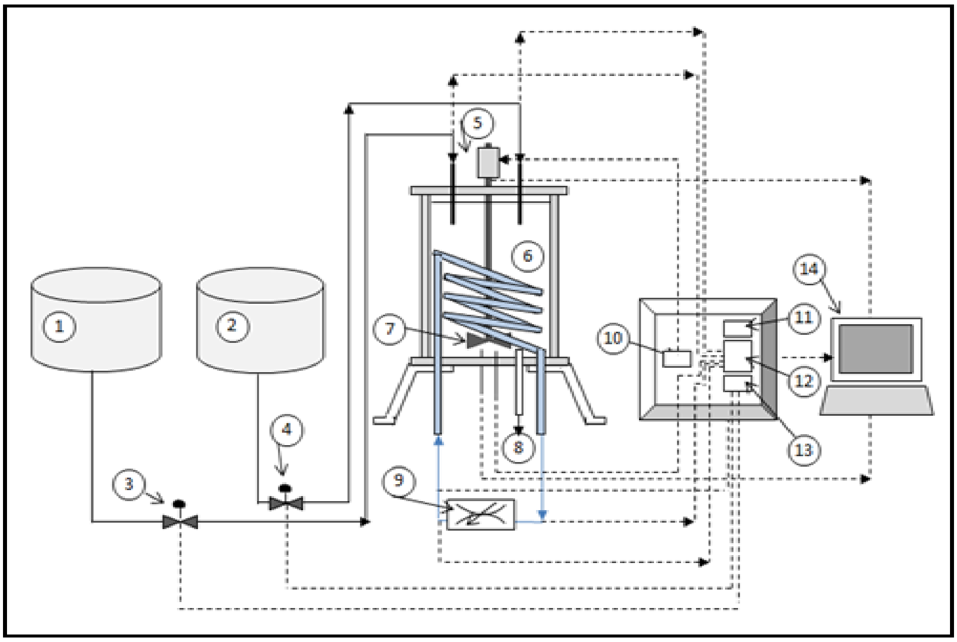
These neural models were used in following control structures: direct inverse control, internal model control and predictive control. The performance tests for particular controllers were realized in the simulation environment MATLAB/Simulink using selected types of nonlinear dynamic processes [17]. In 2013, KhyatiSahu et al. studied the fuzzy logic control of continuous stirred tank reactor, fuzzy PI controller applied to a CSTR to describe the behavior of CSTR, mass and component balance equations have been developed and a non-linear CSTR plant has been modeled with the help of those equations [18]. MahaNazarEsmaeel studied the Fuzzy logic Control of continuous stirred tank reactor, the system is studied by introducing step change in concentration, inlet flow, flow of heating fluid, inlet temperature and heating fluid temperature and measuring the temperature change in the reactor. It has been shown that the proposed fuzzy logic controller has given an excellent tracking and regulation performance compared to that of the PID control system [19].

The aim of this work is to study the control of CSTR using fuzzy and neural strategies using MATLAB simulation and compared the results with a PID control.

Experimental Work

In this work, sodium hydroxide (NaOH) and ethyl acetate (EtAc) was used as reactants. The experimental work was carried out in reaction system as shown in figure 1 .

The reaction system consists of 2L Borosilicate glass reactor supplied with stainless steel water heating coil, stainless steel mechanical stirrer of two blades, two transparent tanks A and B for feed and two peristaltic pumps. A detail of device of reaction system is shown in table 1. First of all a steady stat reaction was conducted. The reactor filled with 0.5 L of 0.1M ethyl acetate and0.5 L of 0.1M sodium hydroxide (1 L operation volume), the feed flow rates from each tank to the CSTR are adjusted to be 20 ml/min using peristaltic pumps supply by Panreac company. The conductivity and temperature of the reaction medium in the CSTR were measured every 2 minutes until reach to steady state. The flow rates of inlet and outlet liquids, conductivity and PH for the liquids in the reactor were recorder using data logger. After reach a steady state, a 50% step change on the flow rate of ethyl acetate (A) was introduced, the conductivity and temperature were measure every two minutes till reach to a new steady state. The same procedure was done using 50% step change on the hot water. The conductivity obtained throughout the experiment is converted into concentration data using calibration curve.



No.	device
1	Tank A
2	Tank B
3	peristaltic pump of Tank A
4	peristaltic pump of Tank b
5	Electrical motor
6	Reactor
7	Two Blades
8	Outlet Flow
9	Heater
10	The digital regulator of the mixer
11	Power Switch
12	Temperature controller system
13	Flow rate controller system
14	Computer

Figure 1: Schematic diagram of laboratory CSTR reactor system

Results and discussion

A dynamic identification of CSTR was conducted experimentally by introduced a step change in manipulated variables (ethyl acetate and hot water) and record the response of controlled variables (reaction temperature and ethyl acetate concentration). Cohen-coon method was used to study the dynamic of the system and the results show that the system can be represented by the following matrix:-

$$\begin{matrix} C_D \\ T \end{matrix} = \begin{bmatrix} \dfrac{0.022e^{-0.33s}}{15S+1} & \dfrac{5e^{-0.33s}}{21S+1} \\ \dfrac{0.0056e^{-6s}}{21S+1} & \dfrac{5.9e^{-0.33s}}{21S+1} \end{bmatrix} \begin{matrix} F \\ F_c \end{matrix}$$

The set points of controlled variables were 30 ˚C reactor temperature and 0.078 mol/l of sodium acetate concentration. The steady state values of manipulated variables were 20 ml/min of ethyl acetate flow rate and 175 mL/min water flow rate in coil. Figure (2) represented the block diagram of PID control system strategy.

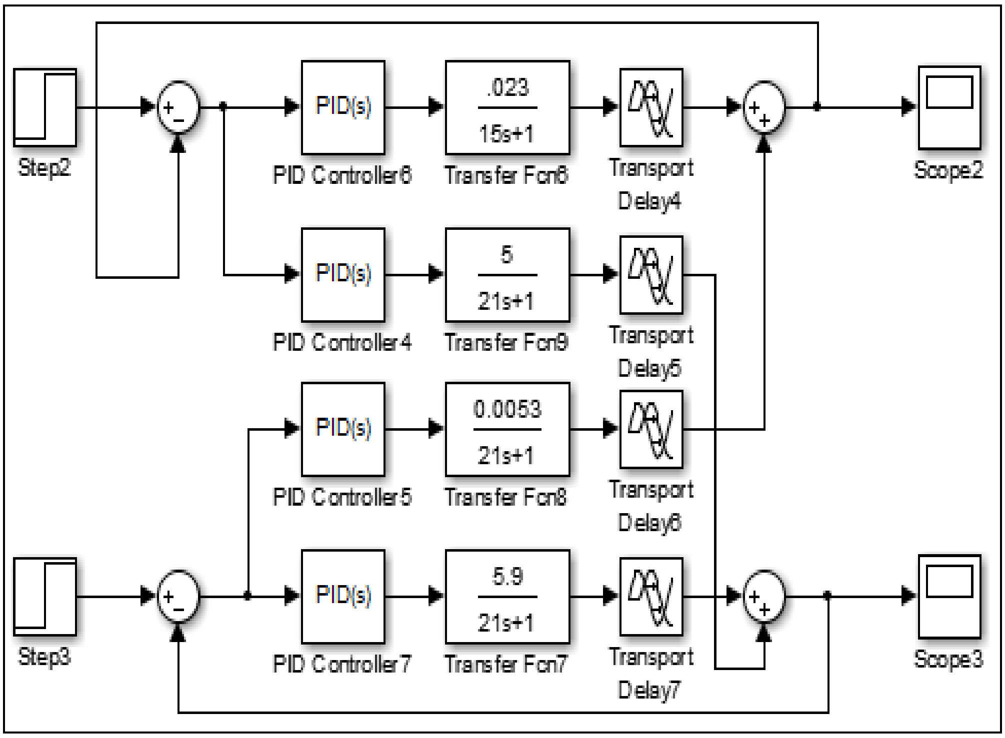


Figure 2: Block diagram of MIMO system using PID system.

The tuning methods were used in PID are Ziegler, ChienHronesReswick, and Cohen-Coon. Table (1) shows the results of these methods.

Table 1: list the results of three methods for PID tuning.

Method		Kp	Ki	Kd
Ziegler Nichols	g_{11}	1519.372	0.66	0.165
	g_{21}	55.02646	12	3
	g_{22}	2.683663	0.66	0.165
	g_{12}	5.194805	0.66	0.165
Chien Hrones Reswick	g_{11}	1202.836	0.462	0.1551
	g_{21}	43.56261	8.4	2.82
	g_{22}	2.124567	0.462	0.1551
	g_{12}	4.112554	0.462	0.1551
Cohen Coon	g_{11}	1367.469	1.991022	0.154771
	g_{21}	50.70357	30.98267	2.744111
	g_{22}	2.380487	2.228852	0.1572
	g_{12}	4.67544	1.991022	0.154771

Figure (3) and (4) indicated that Ziegler–Nichols method is the best one because its reach to set point faster than other methods. In figure 3 the Ziegler–Nichols Method reach to the set point at 15 min while in figure 4 reach to the set point at 25 min.

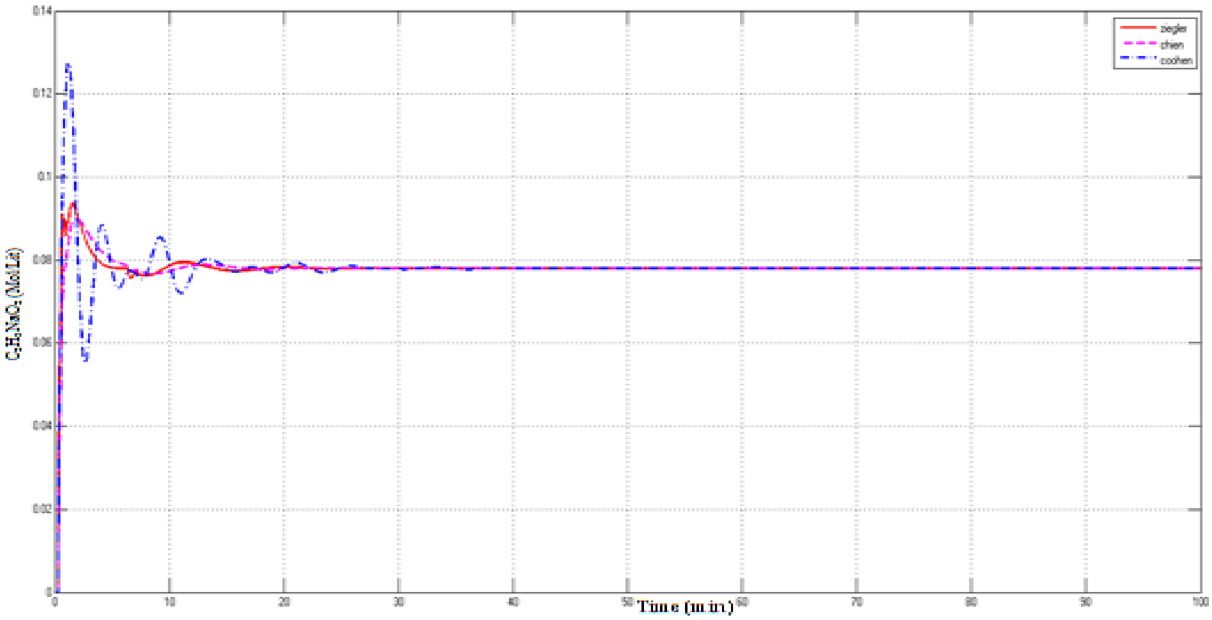


Figure 3: Comparison between Concentrations (Mol. /Lit) of sodium acetate for three Methods at 50% step change on ethyl acetate flow rate

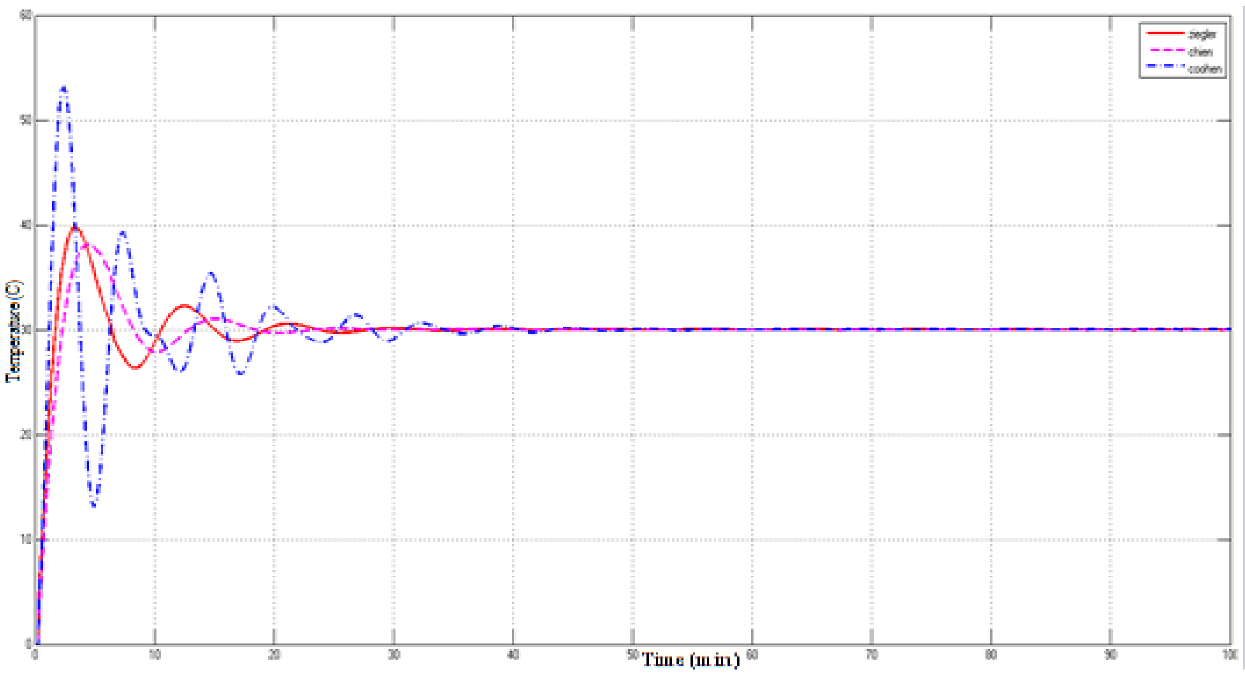


Figure 4: Comparison among Temperatures (˚C) of CSTR for three Methods at 50% step change on water flow rate in coil vs. time (min)

Fuzzy logic controller depends on operator Experian's; the optimal values were found by using computer simulation program (MATLAB). 25 rules were used as shown in table (2) [20]. figure (5) shows block diagram represented the fuzzy control strategy while figure (6) shows the response of sodium acetate under the effects of 50% step change in ethyl acetate flow rate. The results indicate that the response reach faster than PID controller. Fuzzy need 20 min to reaches to the set point (0.078 mol/L), while PID reach at 28min. The overshoot passes through 0.078 mol/L at the same time at 1 min. It's clear from figure (7) a superable of fuzzy control compared with PID due to eliminate the over shoot from the system. Using 50% step change in coil water flow rate, fuzzy controller reachs to the set point at 10 min faster than the PID but the overshoot passes through 30˚C at 3 min of PID while fuzzy controller passes at 5 min. Table 2 shows the rule used in this work.

Table 2: Rule fuzzy Logic Controller [20]

	NB	NS	Z	PS	PB
NEB	PUB	PUB	PUB	PUS	ZU
NES	PUB	PUS	PUS	ZU	NUS
ZE	PUB	PUS	ZU	NUS	NUB
PES	PUS	ZU	NUS	NUS	NUB
PEB	ZU	NUS	NUB	NUB	NUB

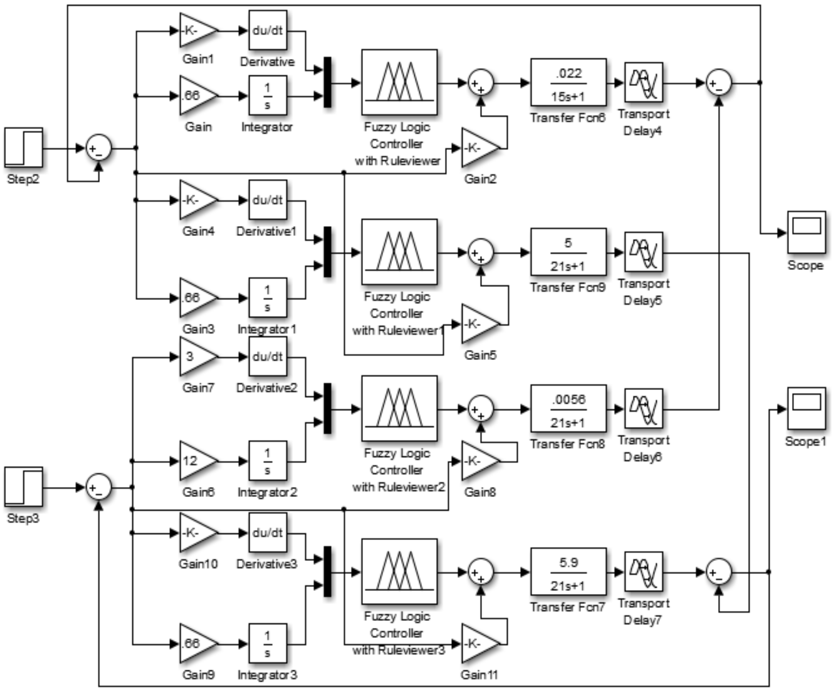


Figure 5: Block diagram of fuzzy logic system.

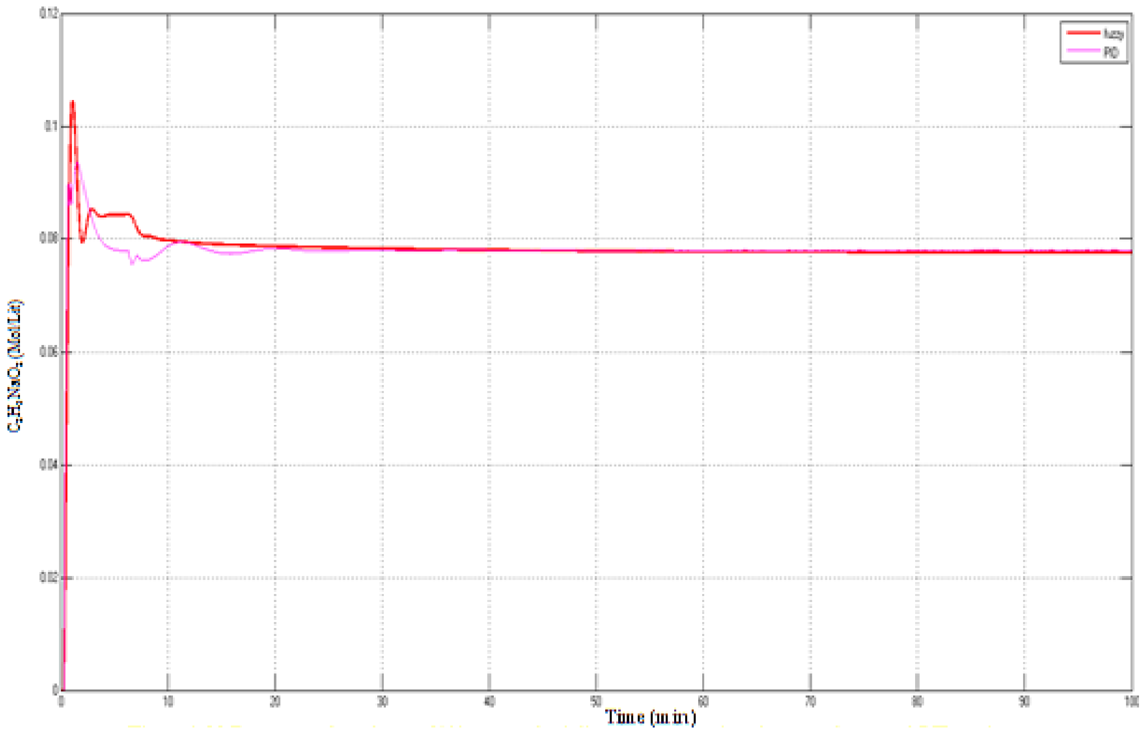


Figure 6: Response of product at 50% step on feed flow.

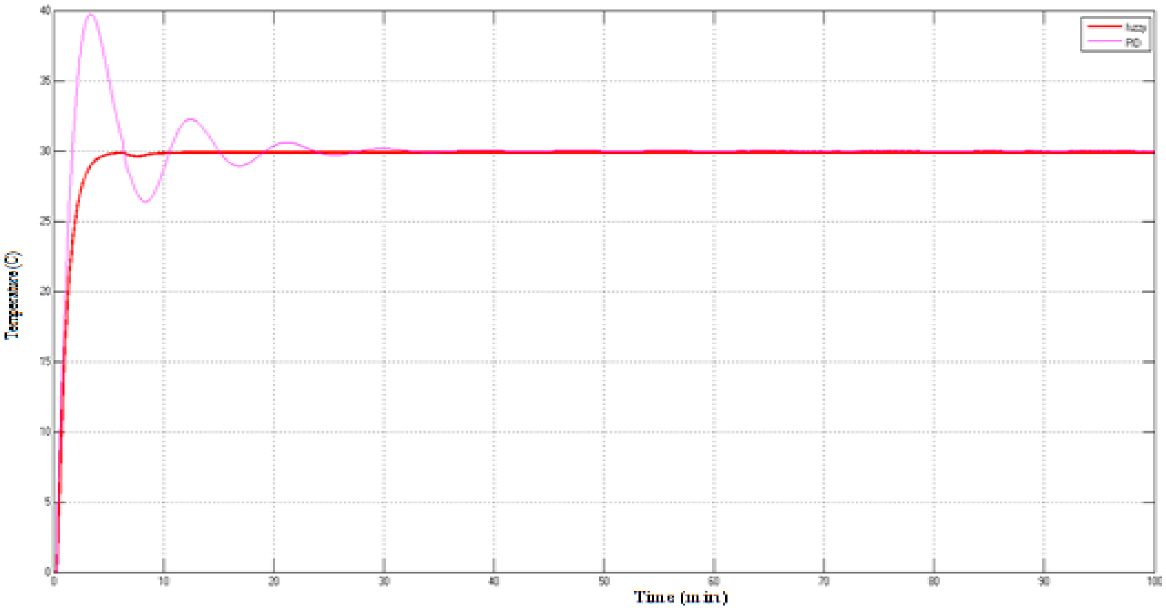


Figure 7: Response of product at 50% step on hot water flow rate.

Block diagram 8 shows the constructed of neural network while figures 9 and 10 show the response of controlled variables(product concentration and temperature) due to a 50% step change on ethyl acetate and water flow rate. The set points of controlled variables were 30 ˚C of temperature and 0.078 mol/l. The steady state values of manipulated variables were 20 ml/min of ethyl acetate flow rate and 175 ml/min. water flow rate in coil.

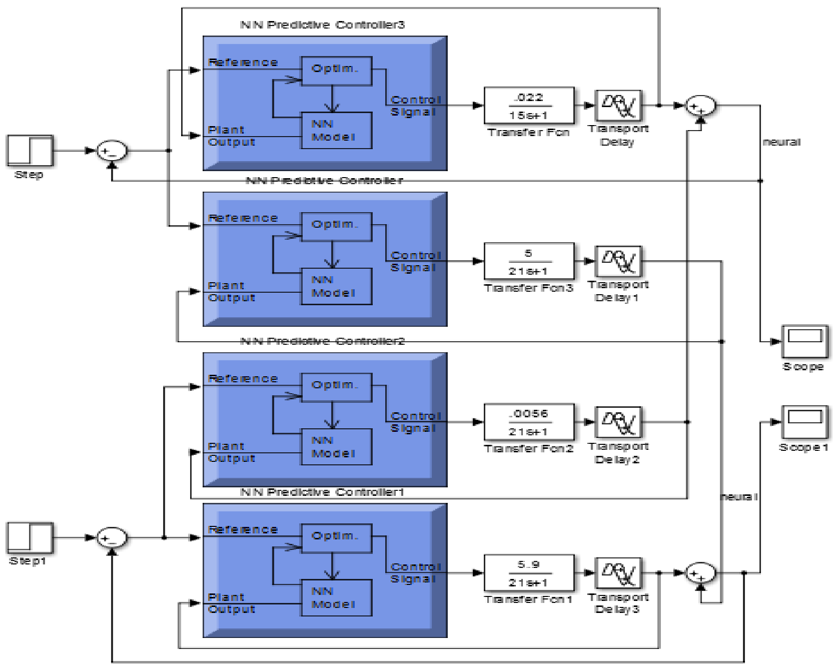


Figure 8: Block diagram of neural network system connect with PID tuning.

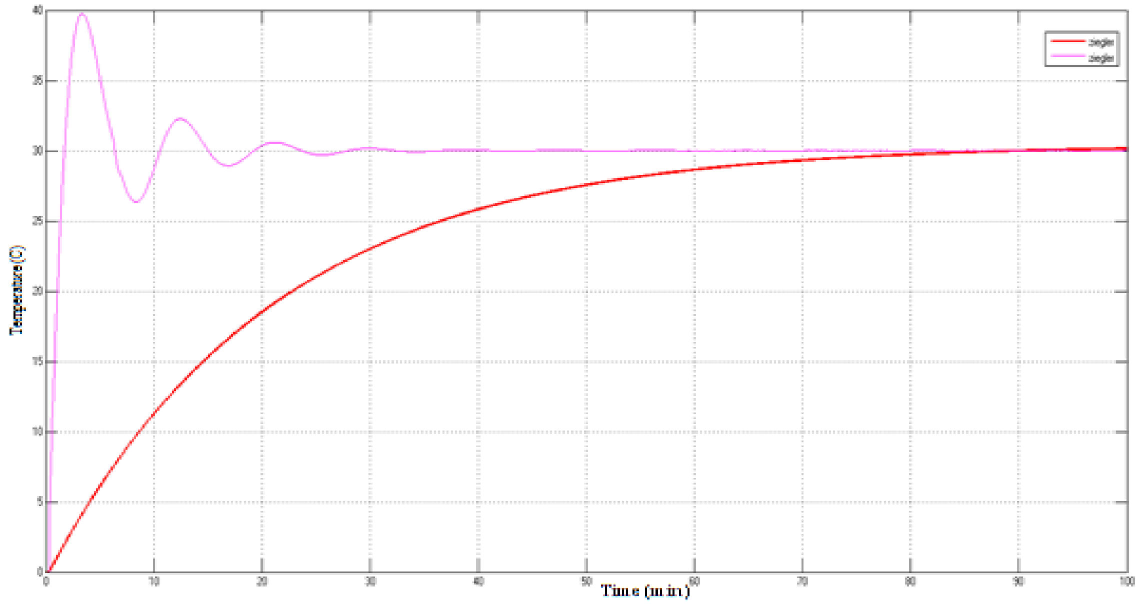


Figure 9: Response of temperature at 50% step on feed flow rate.

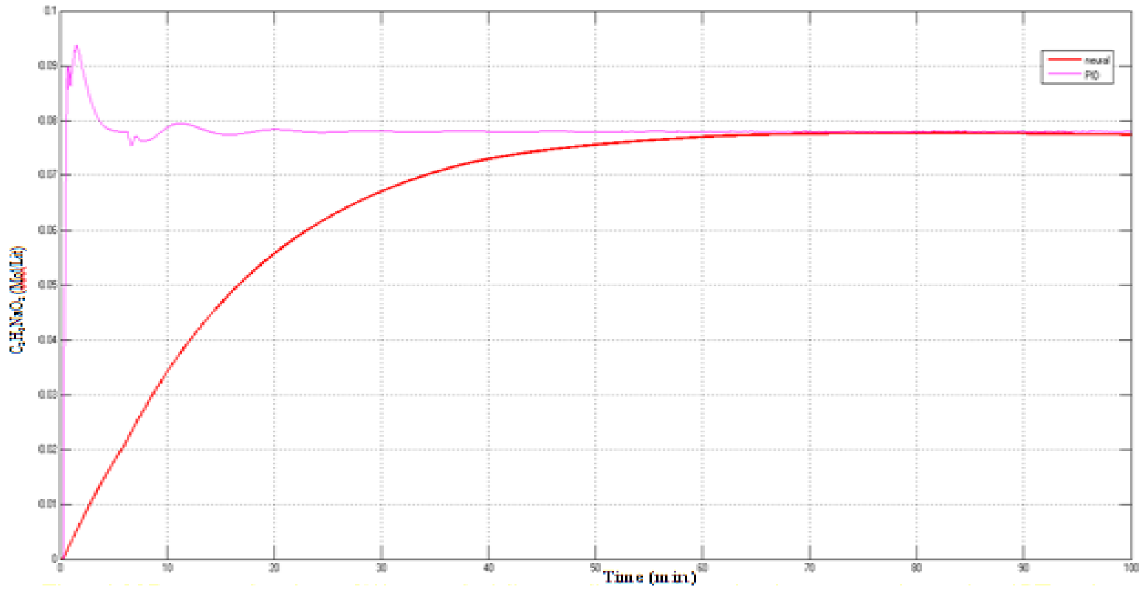


Figure 10: Response of product at 50% step on water flow rate in coil.

All the results of process characteristic were listed in tables (3) and (4).

Table 3: Characteristic of concentration response of 50% step change ethyl acetate flow rate.

Method	Overshoot (Mol/lit)	Rise time (min)	Settling time(min)
Ziegler-Nichols	**0.094**	**0.8**	**15**
ChienHronesReswick	0.09	1.5	17
Cohen-coon	0.129	1	25
Fuzzy logic	0.103	1	10
Neural network	None	None	67

Table 4: Characteristic temperature response at 50% step change water flow rate.

Method	Overshoot (Mol/lit)	Rise time (min)	Settling time(min)
Ziegler-Nichols	40	2	25
ChienHronesReswick	37.5	3	20
Cohen-coon	53	2	40
Fuzzy logic	None	5	10
Neural network	None	None	83

Conclusion

A comparison has been made among the response of a system using fuzzy logic, neural network and PID controller. Fuzzy logic control shows better results according to lower variance which is an important factor to judge the performance of controllers.

Abbreviations:

Kp Proportional gain
Ki Integral gain
Kd Derivative gain
tr Rise time (min)
ts settling time (min)
FL Fuzzy logic
ANN Artificial neural networks
CSTR Continuous Stirred Tank Reactor
MNN Multilayer Neural network
MIMO Multi input Multi output
PID Proportional integral derivative
FOPDT First-order plus dead time
PWM Pulse Width Modulation
ES Expert systems
NB Negative big
NS Negative small
Z Zero
PS Positive small
PB Positive big
NEB Negative error big
NES Negative error small
ZE Zero error
PES Positive error small
PEB Positive error big

References

[1] Charles G. Hill, Jr., "An Introduction to Chemical Engineering Kinetics & Reactor Design", 1977, P (248).

[2] Bursali N., Ertunc S., Akay B., Process Improvement Approach to the Saponification Reaction by Using Statistical Experimental Design, Chem. Eng. Process, p(980) , 2006.

[3] Richard B. Silverman, Mark W. "The Organic Chemistry of Drug Design and Drug Action ", Academic Press, 2014, P (171).

[4] William L. Luyben and, Michael L. Luyben," Essential of Process Control', Department of Chemical Engineering Lehigh University, 1997, P (82,446, 372).

[5] Chennakesava R. Alavala, "Fuzzy Logic and Neural Networks: Basic Concepts and Applications", P (8-84), 2008.

[6] Cirstea M.N., A. Dinu, J.G. Khor and M. McCormick, "Neural and Fuzzy Logic Control of Drives and Power Systems ", P (56-70), 2002.

[7] Antonelli R. and Astolfi A., "Continuous Stirred Tank Reactors Easy to Stabilize", a Department of Electrical and Electronic Engineering, Imperial College, London, UK, 2001.

[8] Zadeh L.A., " Fuzzy Sets as A Basis for a Theory of Possibility", Computer Science Division, Department of Electrical Engineering and Computer Sciences and the Electronics Research Laboratory, University of California, Berkeley, U.S.A. , 1977.

[9] Ge S.S., Hang C.C., Zhang T.," The Nonlinear Adaptive Control Using Neural Networks and Its Application to CSTR Systems", Department of Electrical Engineering, National University of Singapore, Singapore, 1999.

[10] Mircea Lazar and Octavian Pastravanu," A Neural Predictive Controller For Non-linear" Systems, Technical University “Gh. Asachi” of Iaşi, Department of Automatic Control and Industrial Informatics , Iaşi, Romania, 2002.

[11] Martin T. Hagan, Howard B. Demuth, and Orlando De Jesús, "An Introduction to the Use of Neural Networks in Control Systems", Electrical & Computer Engineering, Oklahoma State University, Stillwater, Oklahoma, USA, 2002.

[12] JaroslavaŽilková, Jaroslav Timko, Peter Girovský,"Nonlinear System Control Using Neural Networks", Department of Electrical Drives and Mechatronics, Technical University of KošiceLetná, Slovak Republic, 2006.

[13] DaudaOlurotimi ARAROMI, TinuadeJolaade AFOLABI, and Duncan ALOKO, " the Neural Network Control of CSTR for Reversible Reaction Using Reverence Model Approach", Department of Chemical Engineering ,LadokeAkintola University of Technology, Ogbomoso, Oyo State, Nigeria, 2007.

[14] Suja Malar, R.M. and Thyagarajan, T., "The Modeling of Continuous Stirred Tank Reactor Using Artificial Intelligence Techniques", Department of Electrical and Electronic Engineering, PET Engineering College, Tamil Nadu, India, 2009.

[15] Bahman ZareNezhad, Ali Aminian, "The Application of the Neural Network Based Model Predictive Controllers in Nonlinear Industrial Systems", School of Chemical, Petroleum and Gas Engineering, Semnan University, Semnan, Iran, 2011.

[16] Sastry S.V.A.R., and Ravi Kumar K.S., "The Application of Fuzzy Logic for the Control of CSTR", Department of Chemical Engineering, M.V.G.R.College of Engineering, Vizianagaram, India, 2012.

[17] Kajan S., "Neural Controllers for Nonlinear Systems in Matlab ", Institute of Control and Industrial Informatics, Faculty of Electrical Engineering and Information Technology, Slovak University of Technology in Bratislava, Slovak Republic, 2012.

[18] KhyatiSahu, and G N Pillai, " Type-2 Fuzzy Logic Control of Continuous Stirred Tank Reactor ", Department of Electrical

Engineering, Indian Institute of Technology RoorkeeUttarakhand, INDIA, 2013.
[19] MahaNazarEsmaeel,"Fuzzy logic Control of Continuous Stirred Tank Reactor", Chemical Engineering Department, Tikrit University, Iraq, 2013.
[20] Yingming Liu, Guoqing Chen, and Mingsheng Ying, Fuzzy Logic, Soft Computing & Computational, Intelligence(Volume I、II、III), International Fuzzy Systems Association, 2005, P (844)
[21] William S.Levine, "The Control Handbook: Control System Fundamental ", Second Edition, Electrical Engineering, 2011, P (166).

دراسه سيطرة المفاعل الكيمياوي المستمر CSTR بأستخدام أستراتيجيات ذكيه

خالد مخلف موسى
قسم الهندسه الكيمياويه/جامعه النهرين

زينب عصام عبدالله
قسم الهندسه الكيمياويه / جامعه النهرين

الخلاصة:

الا خطية، والتداخل والتعقيد في النمذجة تؤدي إلى صعوبات كبيرة في نظام المفاعل الكيمياوي المستمر (CSTR)، هذا البحث يهتم في السيطرة على المفاعل الكيمياوي المستمر (CSTR) باستخدام المسيطر التقليدي ذو الاطوار الثلاثة (PID) المنطق الضبابي (fuzzy logic) واستراتيجيات التحكم الذكي. وقد تم اختيار معدل تدفق الماء وخلات الإيثيل كمتغيرات مؤثرة في حين خلات الصوديوم ودرجة حرارة المفاعل كمتغيرات استجابة(المسيطر عليها). وقد أجريت مجموعة من التجارب العملية في البداية لتحديد تماثلية النظام واظهرت النتائج أن النظام ذو المدخلات والمخرجات المتعددة يمكن أن تمثله المصفوفة التالية:

$$\begin{matrix} C_D \\ T \end{matrix} = \begin{bmatrix} \dfrac{0.022e^{-0.33s}}{15S+1} & \dfrac{5e^{-0.33s}}{21S+1} \\ \dfrac{0.0056e^{-6s}}{21S+1} & \dfrac{5.9e^{-0.33s}}{21S+1} \end{bmatrix} \begin{matrix} F \\ F_c \end{matrix}$$

تم مقارنة نتائج الاستراتيجيات وتبين افضلية سيطرة المنطق الضبابي (fuzzy logic).