Neuro-Fuzzy Controller for Methanol Recovery Distillation Column

Dr. Safa A. Al-Naimi
Chemical Engineering Department, University of Technology/Baghdad
Email: Chemo_sIay@yahoo.com
Ghydaa M. Jaid

Received on: 1/4/2012 & Accepted on: 4/10/2012

ABSTRACT

Distillation columns are widely used in chemical processes as separation systems in industries. In order to gain better product quality and lower the energy consumption of the distillation column, an effective control system is needed to allow the process to be operated over larger operating ranges. In this study Different control strategies were used to control the distillate and bottom compositions of a packed distillation column to separate the mixture of methanol (CH_3OH) and water (H_2O). The tuning of control parameters were determined for PI and PID controllers using three different methods; Internal Model Control (IMC), Ziegler-Nichols (Z.N), and Cohen-Coon (PRC) to find the best values of proportional gain (K_C), integral time (τ_I) and derivative time (τ_D). The Internal Model Control (IMC) method gave better results than that of the other two methods thus it was recommended to be the tuning method in this work. The low values of ITAE of 61.3 for distillate product composition and 54 for bottom composition were obtained which represent the adaptive neuro-fuzzy inference system (ANFIS) method and assure the feasibility of this method as a control strategy among other methods (conventional feedback controllers (PI, PID), artificial neural network (ANN) , adaptive fuzzy logic and PID fuzzy logic controllers).

Keywords: distillation, conventional feedback, artificial neural network, adaptive fuzzy Logic and PID fuzzy logic.

السيطرة على برج التقطير باستخدام نظام الشبكة العصبية المتضببة

الخلاصة:

برج التقطير يستخدم بصورة واسعة لعمليات الفصل في الصناعات الكيميائية ولضمان الحصول على افضل انتاج بصرفيات طاقة قليلة نحتاج الى نظام سيطرة فعال يسمح لبرج التقطير بالعمل بظروف مختلفة .تم استخدام طرق سيطرة مختلفة للسيطرة على التراكيز الخارجة من اعلى واسفل برج التقطير الحشوي لعملية الفصل بين مزيج الماء والميثانول. وتم ضبط محددات السيطرة لمسيطرين PI و PID بأستخدام ثلاث طرق

https://doi.org/10.30684/etj.31.6A2
2412-0758/University of Technology-Iraq, Baghdad, Iraq

Internal Model Control (IMC) و Ziegler-Nichols و Cohen-Coon لايجاد افضل القيم للكسب التناسبي (Kc) وزمن التكامل (τ_I) والزمن التفاضلي (τ_D) وجد ان طريقة Internal Model Control كانت افضل من بقية الطرق وتم اعتمادها في هذا العمل. تم الحصول على اقل قيمة لمعيار التكامل الزمني للخطأ المطلق (ITAE) للمسيطر الشبكة العصبية الأصطناعية الضبابية المتكيفة(ANFS) لتركيز الناتج العلوي لبرج التقطير بنتيجة٦١,٣ و ٥٤ لتركيز الناتج السفلي والذي يؤكد على انه افضل مسيطر من بين المسيطرات الأخرى (المسيطر التقليدي,مسيطر الشبكة العصبية الأصطناعية (NARMA-L2), مسيطر (PID fuzzy), مسيطر الضبابي المنطقي المتكيف(Adaptive fuzzy logic).

INTRODUCTION

Distillation columns are important separation technique in the chemical process industries around the world. Improved distillation control can have a significant impact on reducing energy consumption to improve the distillation unit's efficiency and operation, improving product quality and protecting environmental resources. However, distillation control is a challenging problem, due to the following factors: process nonlinearity, substantial coupling of manipulated variables, severe disturbances; and no stationary behavior [1-3].

The objective of the control system of distillation columns is to move the process to the new optimal operating point. In order to determine control strategies, it is necessary to gain a quantitative understanding of the dynamic behavior that the process will exhibit. Dynamic simulations can be used to provide a picture of how the plant will behave when there is a set point change and disturbances. This is best achieved by having a model of the process [4]. The information on the dynamic characteristic can be obtained by:

1-Developing mathematical models based on the physics and the chemistry of the process.

2-Experimentally, by injection known disturbance and measuring the system response.

Conventional Feedback control in general is the achievement and maintenance of a desired condition by using an actual value of this condition and comparing it to a reference value (set point) and using the difference between these to eliminate the error. Hale, *et .al*.[5] studied the efficiency of the strategies PID feedback and self-tuning PID in controlling the composition of a packed distillation column. It was shown that self-tuning PID control provides better control than conventional PID action for the cases studied. Rohit[6] designed the PI controllers of the ethyl acetate reactive distillation column. The dual-PI composition controls of six different control configurations were studied. The overall results for dual-PI composition control shown satisfactory control performance for each configuration.

Fuzzy logic was developed for representing uncertain and imprecise knowledge. The concept of fuzziness was first proposed by Zadeh. He aimed to describe complex and complicated systems using fuzzy approximation and introduced fuzzy sets[7]. Mamdani's development of fuzzy controllers gave rise to the utilization of these controllers in ever expanding capacities, particularly in Japan where many industrial processes now employ fuzzy control [8].

A neural network is a data processing system consisting of a large number of simple, highly interconnected processing elements (artificial neurons) in an architecture inspired by the structure of the cerebral cortex of the brain. Artificial neural networks (ANN) have been developed as generalizations of mathematical models of biological nervous systems. Bahar[9] designed ANN estimator to estimate the distillate composition values of the column from available four temperature measurements.

Neuro-Fuzzy systems are the systems that neural networks are incorporated in fuzzy systems, which can use knowledge automatically by learning algorithms of ANN. Sivakumar and Balu[10] designed and used Adaptive Neuro-Fuzzy Inference System (ANFIS) controller in the distillation column control scheme. The performance of ANFIS controller was compared with the ANN, conventional multi loop PI controller and Model Predictive Control (MPC) controller for the same system under study.

There are many different control strategies that have been used such as conventional feedback control [11], adaptive fuzzy control [12], artificial neural network (ANN) control [13],PID fuzzy control and adaptive nero-fuzzy inference system (ANFIS)[14].

THEORY

Conventional Feedback Control [11]

Figure (1) shows the block diagram of a feedback control system.

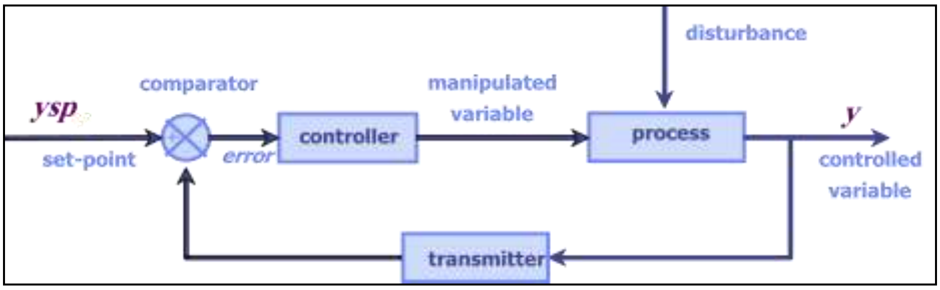


Figure (1) Feedback control system.

There are three basic types of a feedback controllers which described briefly as follow:

a. Proportional Controller: (P)

The proportional control action may be described mathematically as:

$$G_C = K_C \qquad \dots (1)$$

b. Proportional-Integral Controller: (PI)

The transfer function of a proportional-integral controller is given by:

$$G_C = K_C\left(1+\frac{1}{\tau_I s}\right) \qquad \dots (2)$$

c. Proportional-Integral-Derivative Controller :(PID)

The transfer functions of a PID controller.

$$G_C = K_C\left(1+\frac{1}{\tau_I s}+\tau_D s\right) \qquad \dots (3)$$

Fuzzy Logic Control [15]:

Fuzzy logic control is derived from expert knowledge into an automatic control strategy. The operation of a FLC is based on qualitative knowledge about the system being controlled .It doesn't need any difficult mathematical calculation like the others control system. A block diagram of a fuzzy control system is shown in Figure (2).

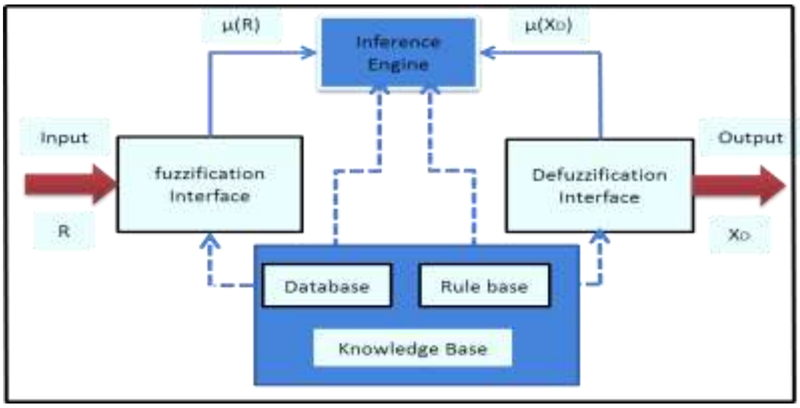


Figure (2) Architecture of a fuzzy logic controller.

The fuzzy controller is composed of the following four elements:

1) A rule-base (a set of if-then rules), which contains a fuzzy logic quantification of the expert's linguistic description of how to achieve good control.

2) An inference mechanism (also called a fuzzy inference engine), which emulates the expert's decision making in interpreting and applying knowledge about how best to Control the plant.

3) A fuzzification interface, which converts controller inputs into information that the inference mechanism can easily use to activate and apply rules.

4) A defuzzification interface, which converts the conclusions of the inference mechanism in to actual inputs for the process.

The design of fuzzy controller is still considered premature in general; it remains a difficult task due to the fact that there is insufficient analytical design technique in contrast with the well-developed linear control theories. In this work PID fuzzy and Adaptive fuzzy controllers were used.

a.PID Fuzzy Controller

The parameters of the conventional PID controllers were determined by system response curve method and the PID controllers then inter to fuzzy controller and then the parameters of the conventional PID controllers were optimized by simulation to use appropriate control parameters.

b.Adaptive fuzzy controller [12]

Adaptive is called a control, which can adjust its parameters automatically in such a way as to compensate for variations in the characteristics of the process it controls. To design an adaptive fuzzy controller (multi regional fuzzy controller) that gives satisfactory performance for different regions of gain nonlinearity, a fuzzy controller with three inputs is used. In addition of using the error (E) and the change in error (CE) as inputs for fuzzy, an auxiliary variable is used as another input to select the region in which the process is operating. Auxiliary variable (AV) is used to indicate different regions of the nonlinear process.

The functional relationship of such a controller can be described by:

$$\Delta u = FLC\,(CE, E, AV) \qquad \ldots (4)$$

Artificial Neural Network Controller:

A neural network is a collection of mathematical models that emulate some of the observed properties of biological nervous systems and draw on the analogies of adaptive biological learning. It is composed of a large number of highly interconnected processing elements that are analogous to neurons and are tied together with weighted connections that are analogous to synapses [13].

There are three popular neural network architectures for prediction and control that have been implemented in the Neural Network Toolbox software:

- Model Predictive Control
- 0NARMA-L2 (Non-linear Auto-regressive Moving Average) or Feedback
- 0Linearization Control
- 0Model Reference Control [16].

Adaptive Neuro-Fuzzy Inference System (ANFIS)

ANFIS is an adaptive network which permits the usage of neural network topology together with fuzzy logic. It not only includes the characteristics of both methods, but also eliminates some disadvantages of their lonely-used case. Operation of ANFIS looks like feed-forward back propagation network. Consequent parameters are calculated forward while premise parameters are calculated backward [14].
There are two learning methods in neural section of the system: Hybrid learning method and back-propagation learning method. In fuzzy section, only zero or first order Sugeno inference system or Tsukamoto inference system can be used [17].

THE PACKED DISTILLATION COLUMN [18]:

The packed distillation column tested in this work was 2m high, 8cm in diameter filled with packing of hight 1.5m.The subcooled feed was introduced to the column from constant head tank at mid of the column. The vapours produced from the column were condensed at the top in a condenser; the distillate was separated into reflux.The cooling water flowrate to the cooler and top condenser with capacity (0 - $25*10^{-5}$ m^3/sec). The feed was kept in a 25 liter size vessel .The feed rate is over a range of ($83*10^{-8}$-$15*10^{-6}$ m^3/sec). The solution with the desired concentration of (methanol-water system) was prepared by using distilled water in the feed container.

Table (1) Data of Steady state conditions [18].

Flow rate of cooling water	$8*10^{-5}$ m^3/sec
Feed rate	$33*10^{-7}$ m^3/sec.
Reflux rate	$61*10^{-8}$ m^3/sec.
Reboiler heat duty	2.1 kJ/sec

RESULTS AND DISCUSSION

The obtained results from the computer programs using MATLAB program version 7.8 for dynamic model and control. The first part of this work shows the results of the open loop experimental and theoretical response for different step changes of reflux flow rate (R) and reboiler heat duty (H) on the controlled variables the distillate composition (X_D) and bottom composition (X_B) .The second part shows the results of the control system using different control strategies

Open loop process

The results of the transient response based on open loop system are shown in Figures (3) for different step changes of reflux flow rate (R) and reboiler heat duty (H) on the controlled variables the distillate composition (X_D) and bottom composition (X_B).

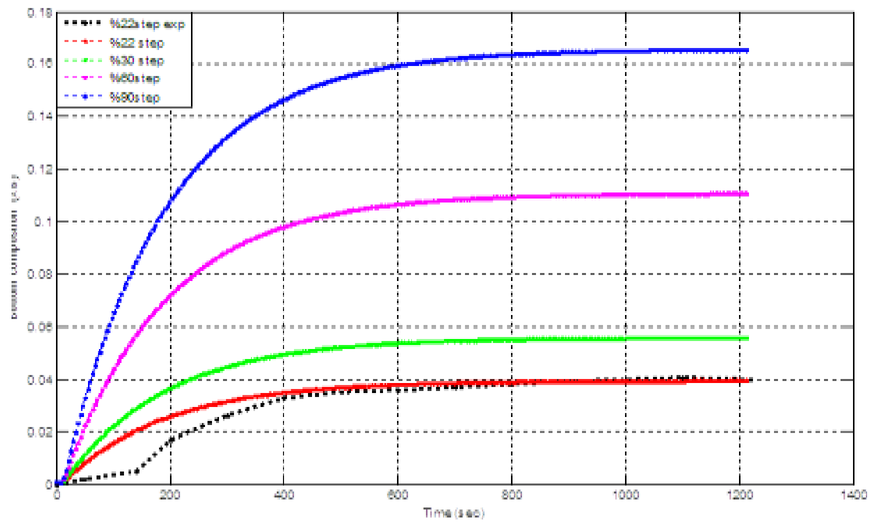


Figure (3.a) Effect of reflux ratio on distillate composition for Different Step change.

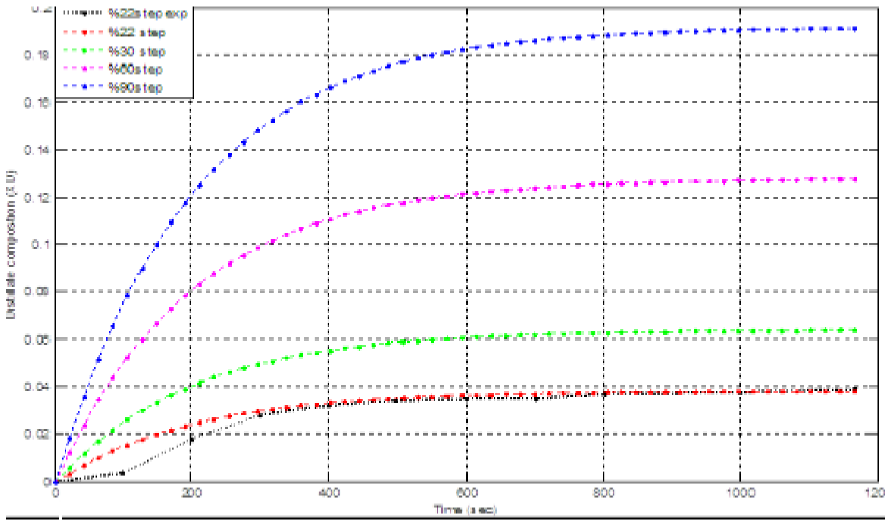


Figure (3.b) Effect of heat duty on distillate composition for different step change.

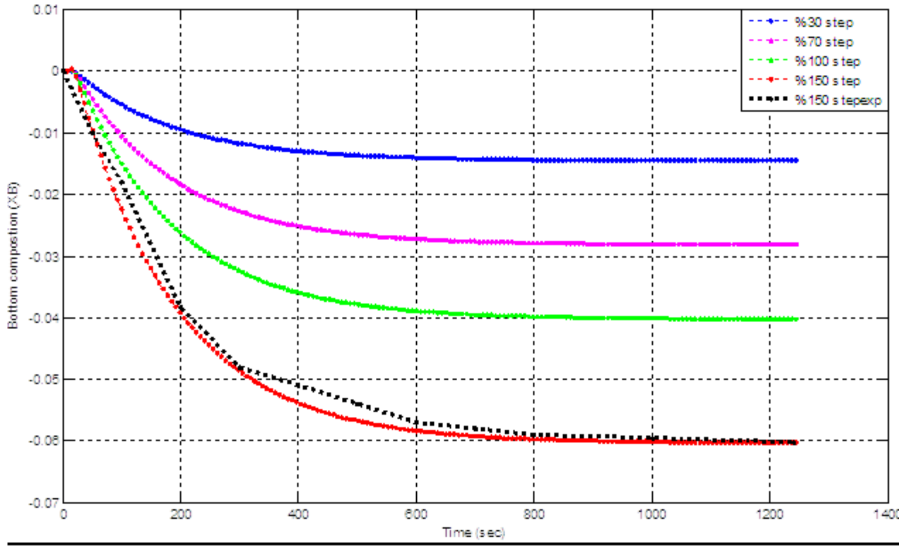


Figure (3.c) Effect of reflux on bottom composition for Different step change.

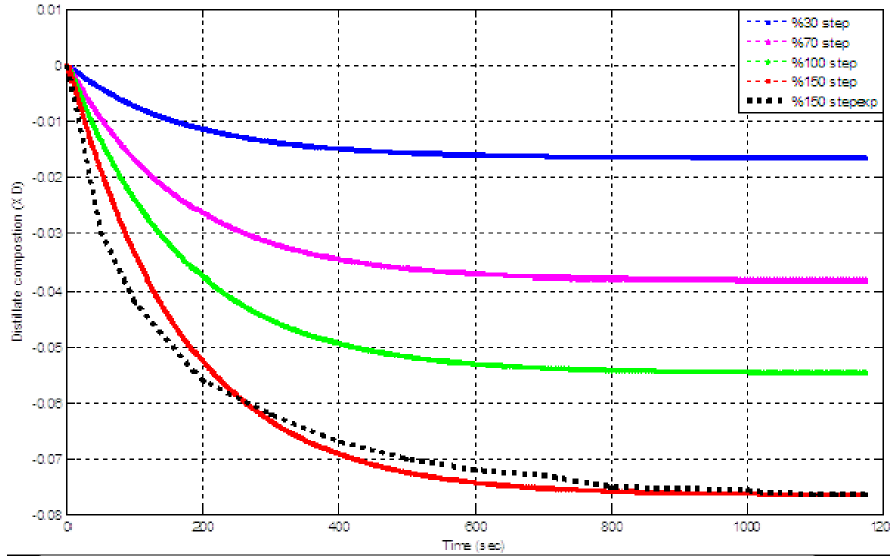


Figure (3.d) Effect of of heat duty on bottom composition for Different step change.

A 30% step change in heat duty and reflux flow rate is taken to study the effect of using different control strategies in this work, using process reaction curve (PRC) [19] to determine the transfer function for the system. The following transfer functions were found:

$$\begin{matrix} X_D \\ X_R \end{matrix} = \begin{bmatrix} \dfrac{.061}{230S+1} e^{-2S} & \dfrac{-.01658}{175S+1} e^{-.2S} \\ \dfrac{.0525}{220S+1} e^{-1.6S} & \dfrac{-.0103}{180S+1} e^{-.2S} \end{bmatrix} \begin{matrix} R \\ H \end{matrix}$$

CLOSED LOOP SYSTEM

Conventional Feedback Control

Conventional feedback control was applied using PI and PID modes to control the distillation process. The tuning of the control parameters were applied using Internal Model Control (IMC)[20], Ziegler-Nichols (Z.N), and Cohen-Coon (PRC) [19]methods. Figures (4) show the control responses for PI and PID modes for three different criteria's and the comparison between two control modes.

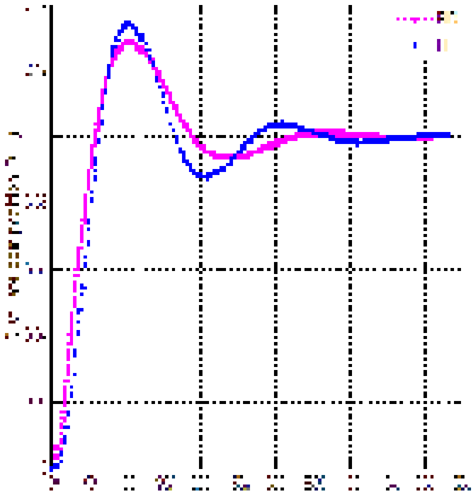


Figure (4.a) Transient response for PI controller of distillate composition with respect to refiux flow rate .

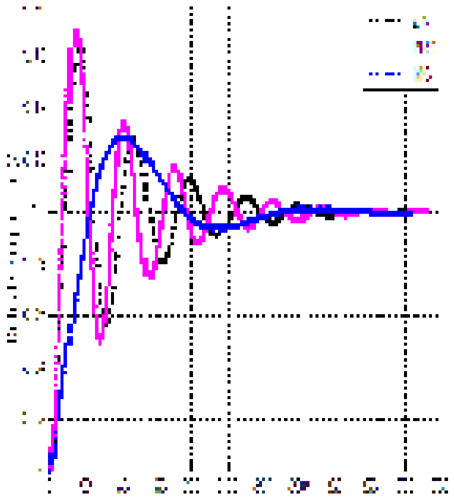


Figure (4.b) Transient response for PID controller of distillate composition with respect to refiux flow rate.

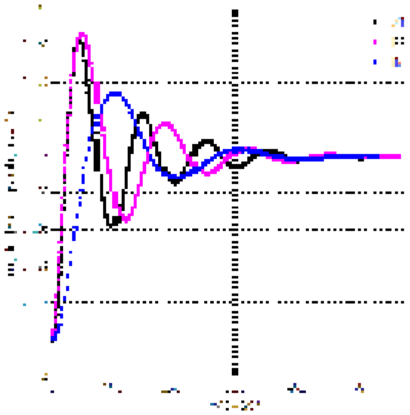


Figure (4.c) Transient response for PI and PID controller of distillate composition with respect to refiux flow rate.

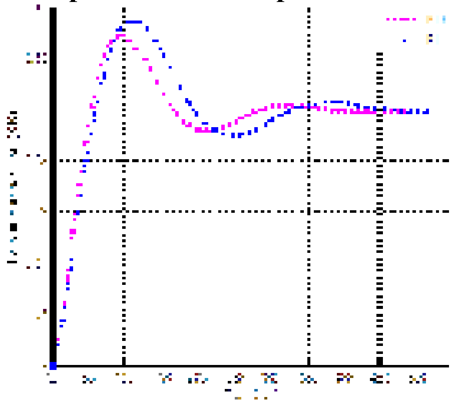


Figure (4.d) Transient response for PI controller of bottom composition with respect to rebutter heat duty.

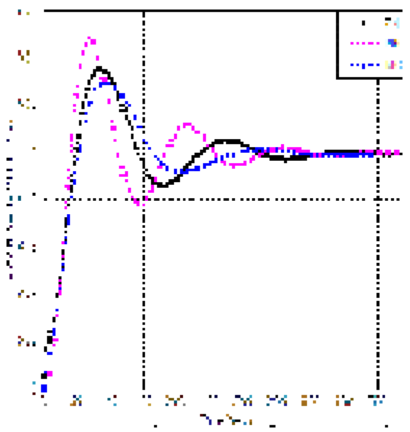


Figure (4.e) Transient response for PID controller of distillate composition with respect to rebutter heat duty.

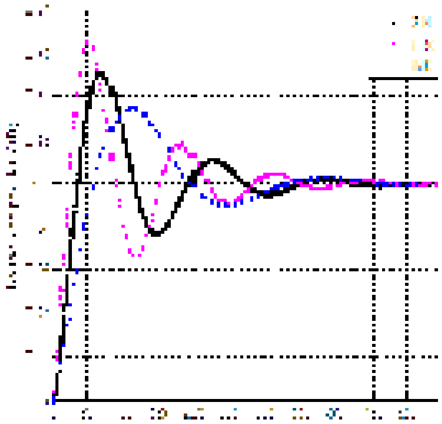


Figure (4.c) Transient response for PI and PID controller of distillate composition with respect to rebutter heat duty.

PID (IMC) controller is better than PI controller because it gives smaller ITAE, overshoot, and settling time values as shown in Figure (4).

PID Fuzzy Controller

The parameters of the conventional PID controllers was determined by system response curve method and the PID controllers used in fuzzy controller then the parameters of the conventional PID controllers were optimized by fuzzy simulation to use appropriate control parameters as shown in Figure (5).

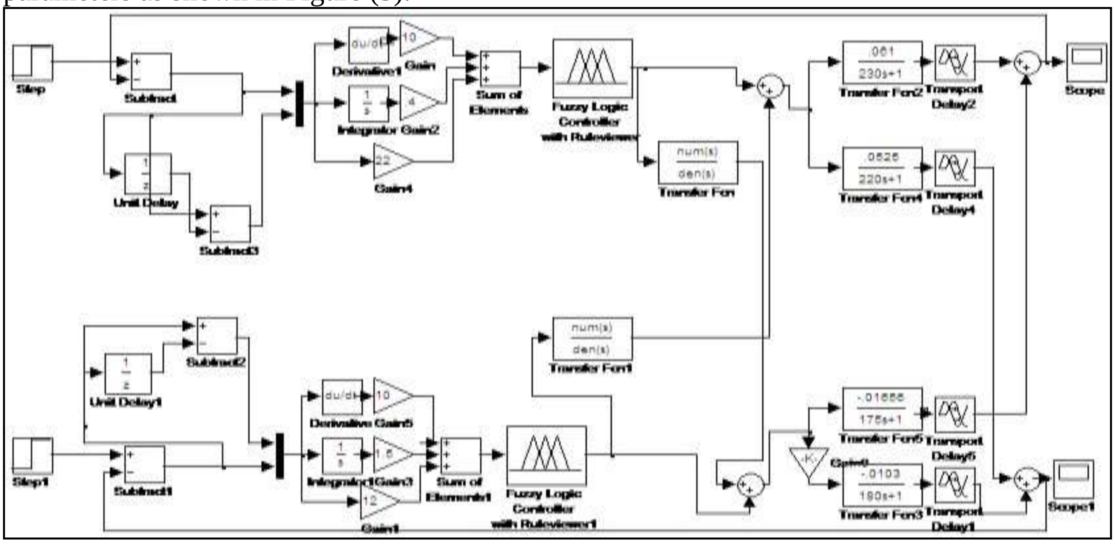


Figure (5) Block diagram of PID fuzzy controller.

The inputs of the PID fuzzy control are defined as the proportional gain (K_C), integral time (τ_I) and derivative time (τ_D). The output variable is called the control action (u). The transient response for the PID fuzzy controller for both distillate composition and bottom composition are shown in Figures (6)

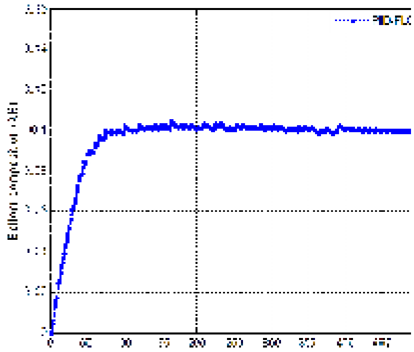


Figure (6.a) Transient response of distillate composition with respect to refiux flow rate in PID-FLC .

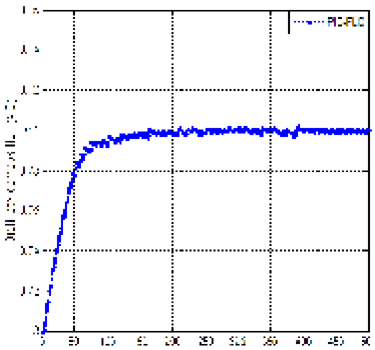
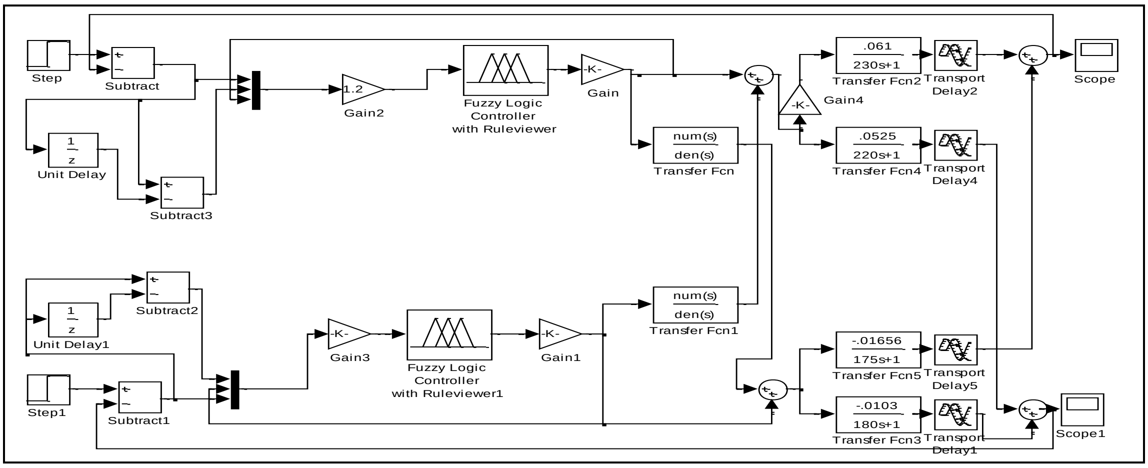


Figure (6.b) Transient response of bottom composition with respect to rebutter heat duty in PID-FLC .

Figures (6) show that the PID fuzzy gave a good control performance with low values of ITAE as well as low overshoot and low settling time for distillate and bottom compositions, when compared with PID and classical fuzzy**.** Oscillations remain around the set point in a constant, growing, or decaying sinusoid, the high value of the rise time in the distillate and the bottom composition and the high settling time show the disadvantages in the PID-FLC. The rule base for PID-FLC controller is shown in Appendix A.

Adaptive fuzzy controller

For the Adaptive fuzzy controller the input variable are the error (*E*) , change of error (*CE*) and auxiliary variable (AV), where the output variable is the control action (*u*).The optimum values of the scaled factors were tuned using Simulink program as shown in Figure (7).



Figure(7)Block diagram of Adaptive fuzzy controller.

The transient response for the adaptive fuzzy controller for both the distillate composition and the bottom composition are shown in Figure (8).

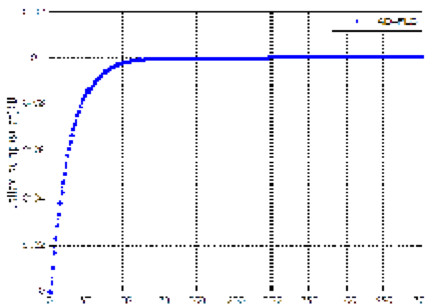


Figure (8.a) Transient response for adaptive fuzzy controller of distillate composition with respect to refiux flow rate.

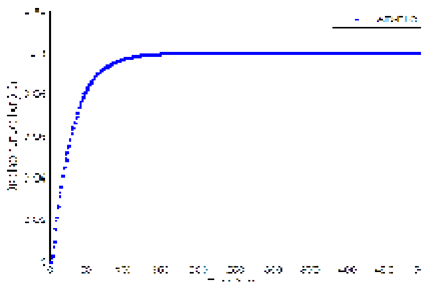
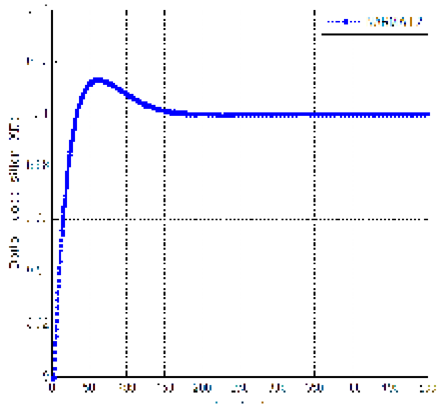


Figure (8.b) Transient response for adaptive fuzzy controller of Bottom composition with respect to reboter heat duty.

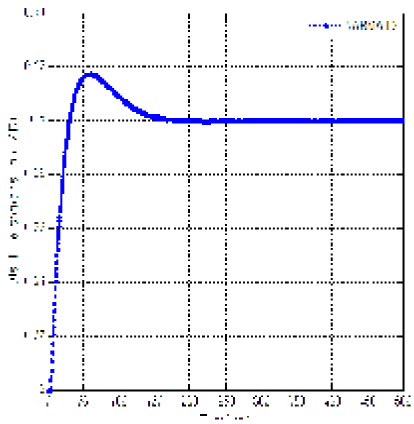
The transient response for adaptive fuzzy controller for both distillate and bottom composition are shown in Figures (8)with low values of ITAE ,low settling time and no overshoot took place when compared to the PID fuzzy, PID, and the classical fuzzy. The rule base for adaptive fuzzy controller is given in Appendix.A.

Artificial Neural Network Controller

NARMA-L2 algorithm is implemented using back-propagation networks in this work. One hidden layer of seven neuron which was found as a best neuron number in this work and an output layer of one neuron by using trial and error which gave a good performance controller for neural network controller for both distillate and bottom composition . The transient response for neural network controller for both the distillate and the bottom composition are shown in Figures (9).



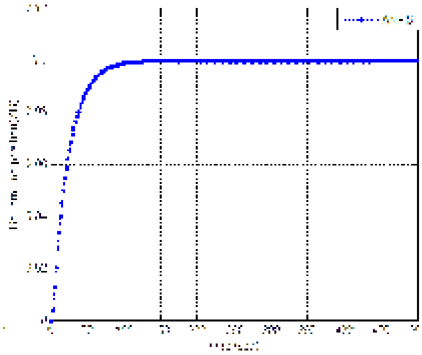
Figures (9.a) transient response for NARMA-L2 controller of distillate composition with respect to rellex flow rate.



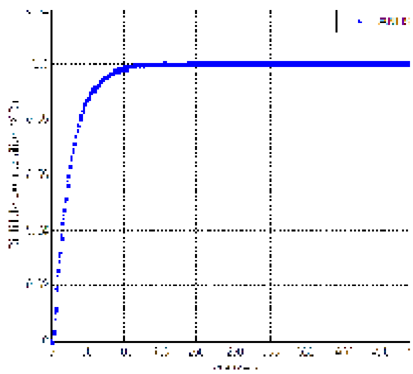
Figures (9.b) transient response for NARMA-L2 controller of distillate composition with respect to reboter heat duty.

Adaptive Neuro-Fuzzy Inference System (ANFIS)

The fuzzy logic toolbox of MATLAB 7.8 was used to train the ANFIS and obtain the results. A total of 75 network nodes and 25 Fuzzy rules were used to build the Neuro -Fuzzy inference system. A triangular membership functions and the Sugeno Inference System were used to train the ANFIS [17]. The ANFIS was tuned using a hybrid system which contains a combination of the back propagation and least-squares-type methods. An error tolerance of 0 was used and the ANFIS was trained with 100 epochs. The transient response for the ANFIS controller for both distillate composition and bottom composition are shown in Figures (10).



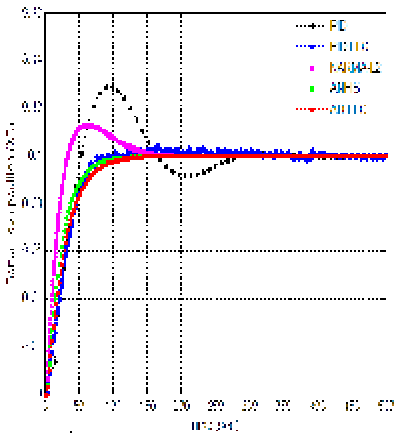
Figures (10.a) transient response for NARMA-L2 controller of distillate composition with respect to rellex flow rate.



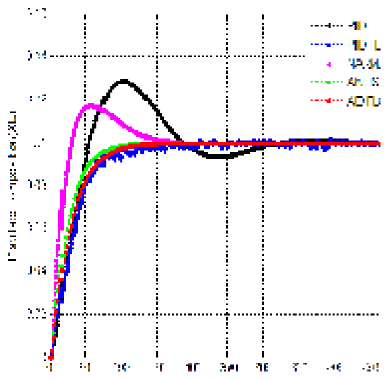
Figures (9.b) transient response for NARMA-L2 controller of distillate composition with respect to reboter heat duty.

Comparisons among Feedback, PID-Fuzzy, Artificial Neural Network, Adaptive Fuzzy and Adaptive Neuro-Fuzzy Inference System Controllers

This section shows a comparison among different control strategies of the transient response for both distillate and bottom composition with PID, NARMA-L2, AD-FLC**,** PID-FLC and ANFIS controllers as shown in Figures (11) .In all the five controllers the performance indices of different controllers is the ITAE as well as the parameters are evaluated and comparative studies of their performance are tabulated in the Tables (2).



Figures (11.a) Comparisons among transient response for PIDE, NARMA-L2, PID FLC, AD-FLC .In all the five controllers the controller of distillate composition with respect to rellex flow rate.



Figures (11.b) the Comparisons among transient response for PID, NARMA-L2, PID FLC, and ANFIS **AD-FLC controllers of bottom with respect to rebutter heat duty .**

Table (2.a) Comparison of different performance indices and different parameters in controllers of distillate composition.

Parameters	PID controller	PID-FLC controller	NARMA-L2 controller	AD-FLC controller	ANFIS controller
ITAE	474	187.34	108	83.2	61.3
Overshoot	.12878	.022	.174	0	0
Settling time	270	116	120	88	75

Table (2.b) Comparison of different performance indices and different parameters in controllers of bottom composition.

Parameters	PID controller	PID-FLC controller	NARMA-L2 controller	AD-FLC controller	ANFIS controller
ITAE	435.7	184.8	93	75.23	54
Overshoot	.12922	.043	.132	0	0
Settling time	249	65	118	70	70

The simulation results clearly show that the ANFIS controller gives better control for both distillate and bottom composition than Adaptive fuzzy, NARMA-L2, PID fuzzy, and PID controllers.

CONCLUSIONS

1- The control tuning was carried using three different methods therefore; the tuning technique using the Internal Model Control method gave better results than frequency curve method and process reaction curve which gives smaller ITAE values.
2- Adaptive fuzzy logic controller is better than feedback, PID fuzzy logic and Artificial neural network controllers because it uses an auxiliary variable used as another input to select the region in which the process is operating, while artificial neural network controller gave better values than feedback, and PID fuzzy logic controllers because the artificial neural network controller is a learning system with
3-The ANFIS controller gives a much better control performance for both distillate and bottom composition because gave the low values of ITAE of 61.3 for distillate product composition and 54 for bottom composition than feedback (PI, PID), PID fuzzy logic, Artificial neural network and Adaptive fuzzy logic controllers because ANFIS controller combines the advantages of fuzzy logic controller and an Artificial neural network controller.

LIST OF ABBREVIATIONS

Symbol	*Definition*
ANFIS	Adaptive Neuro-Fuzzy Inference System
ANN	Artificial Neural Network
AD-FLC	Adaptive Fuzzy Logic controller
AV	Auxiliary variable
CE	Change of Error
E	Error
FLC	Fuzzy Logic control
IMC	Internal Model Control
ITAE	Integral Time-weighted Absolute Error
MPC	Model Predictive Control
NARMA-L2	Nonlinear Auto Regressive-Moving Average
p	Proportional
PI	Proportional-Integral
PID	Proportional-Integral-Derivative
PID-FLC	Proportional Integral Derivative -Fuzzy Logic controller
PRC	Process Reaction Curve
Z.N	Ziegler-Nichols

NOMENCLATURE

Symbol	*Definition*	*Units*
G	Transfer function	–
G_c	Transfer function of controller	–
H	reboiler heat duty	kJ/sec
K_c	Proportional gain	%/ sec
R	reflux flow rate	m^3/sec
s	Laplacian variable	–
t	Time	sec

t_d	Time delay	sec
u	Control Action	–
X_B	Bottom composition	–
X_D	Distillate composition	–
y	Output variable	–
y_{st}	Desired set point of controlled output	–

Greek Symbols

Symbol	*Definition*	*Units*
τ_D	Derivative time constant	sec
τ_I	Integral time constant	sec
τ_p	Lag time constant	sec

Appendix.A:

Table (A.1) IF-THEN rule base for PID-FLC.

CE / E	NB	NS	Z	PS	PB
PB	Z	PS	PS	PB	PB
PS	NS	Z	PS	PS	PB
Z	NB	NS	Z	PS	PB
NS	NB	NS	NS	Z	PS
NB	NB	NB	NS	NS	Z

Table (A.2) Adaptive fuzzy rule.

CE	E	AV	Δu
PB	*NB*	*Z*	*Z*
PB	*NS*	*PS*	*PB*
PB	*Z*	*PB*	*PB*
PB	*PS*	*PB*	*PB*
PB	*PB*	*PB*	*PB*
PS	*NB*	*NS*	*NB*
PS	*NS*	*Z*	*Z*
PS	*Z*	*PS*	*PS*
PS	*PS*	*PS*	*PS*
PS	*PB*	*PB*	*PB*
Z	*NB*	*NS*	*NB*
Z	*NS*	*NS*	*NS*
Z	*Z*	*Z*	*Z*
Z	*PS*	*PS*	*PS*
Z	*PB*	*PS*	*PB*
NS	*NB*	*NB*	*NB*
NS	*NS*	*NS*	*NS*
NS	*Z*	*NS*	*NS*
NS	*PS*	*Z*	*Z*
NS	*PB*	*PS*	*PB*

NB	*NB*	*NB*	*NB*
NB	*NS*	*NB*	*NB*
NB	*Z*	*NB*	*NB*
NB	*PS*	*NB*	*NB*
NB	*PB*	*Z*	*Z*

REFERENCES

[1].Ramesh,K.," Nonlinear Model Predictive Control of A Distillation Column Using Hammerstein Model and Nonlinear Autoregressive Model With Exogenous Input", PhD Thesis, Chemical Engineering, University of Sains Malaysia ,March ,2009.

[2].Mohd, F.," Fuzzy Modeling and Control for a Nonlinear Reboiler System of a Distillation Column", MSc Thesis, Electrical Engineering, University of Technology Malaysia, May, 2006.

[3].Maidi, A., Diaf, M., Khelassi, A., and Bouyahiaoui, C.," Non–Interacting Fuzzy Control System Design for Distillation Columns", www.sciencedirect.com , 2001.

[4].Seborg, D.E, Edgar, T.F.,Melichamp, D.A., and Doyle, F.J.,"Process Dynamics and Control", International Student version, ISBN:978-0-470-64610-6, www.wiley.com/go/global/seborg ,2011.

[5].Hale, H., Can ,E. B., Antony ,P. W.," Self-Tuning and Conventional Control of an Industrial Scale Packed Distillation Column", Journal of Engineering and Environmental Sciences, Chemical Engineering Department, Ankara-Turkey,1998.

[6].Rohit K.," Nonlinear Model Predictive Control of A Reactive Distillation Column", PhD Thesis, Chemical Engineering, University of Texas Technology, May, 2004.

[7]Zadeh, L.A., “Fuzzy Sets”, Information and Control, vol. 8, pp. 338-353, 1965

[8]. Mary , P.M. and N.S. Marimuthu; “Design of self-tuning fuzzy logic controller for the control of an unknown industrial process”, IET control theory & applications, vol. 3, pp. 428-436, 2009.

[9].Bahar, A.," Modeling and Control Studies for a Reactive Batch Distillation Column", PhD Thesis, Chemical Engineering, University of Middle East Technical, May, 2007.

[10].Sivakumar , R., Balu ,K.," ANFIS Based Distillation Column Control", IJCA Special Issue on “Evolutionary Computation for Optimization Techniques”, 2010.

[11]."PID controller", Wikipedia, the free encyclopedia,
http://en.wikipedia.org/wiki/PID_controller , 2006.

[12].Zahwar, Z. F.,"Adaptive and Fuzzy Logic Controls of a pH Neutralization Process", MSc Thesis, Chemical Engineering, University of Technology, 2007.

[13].Mohamad, N.," Use of Soft Computing Techniques for Transducer problems", MSc Thesis, Electronics and Communication Engineering, National Institute of Technology Rourkela, 2008.

[14].Ozgur, K.," Suspended sediment estimation using neuro-fuzzy and neural network approaches", Hydrological Sciences–Journal–des Sciences Hydrologiques, February, 2006

[15].Amanpreet ,K.," Adaptive Neuro Fuzzy Inference System In Distillation Column", MSc Thesis, Electronics Instrumentation and Control Engineering, University of Thapar, June ,2009.

[16].Mark, H. B., Martin, T. H., Howard, B. D.," Neural Network Toolbox™ 7User’s Guide, www.mathworks.com , April, 2011

[17]."Fuzzy Logic Toolbox™ 2 User’s Guide"www.mathworks.com, September, 2010.

[18].Hameed, A.M.,"A Study Into the Dynamic Behavior of A packed distillation column", MSc Thesis, Chemical Engineering, University of Technology, August- 2003.

[19].Stephanopoulos, G., Chemical Process Control: an Introduction to Theory and Practice, Prentice-Hall India, 1984.

[20].Kumar ,M. P.," Analysis of Self Tuning Fuzzy PID Internal Model Control", MSc Thesis, Electronics Instrumentation and Control Engineering , Thapar University , July, 2010.