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Neural Network Control for a Batch Distillation Column

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Abstract

The present work deals with studying the dynamic behavior of a batch distillation column and implemented two types of control strategies for the separation different types of binary systems. The model was derived and then simulated using "MATLAB" program. The experimental data of dynamic behavior were to tune the parameters of PID controller and developed the training of neural networks controller by using supervised learning algorithms. The simulation results show a qualitatively acceptable behavior. This study shows also that the response of PID controller was oscillatory behavior with high offset value while neural network controller gave less offset value and less time to reach the steady state. In general, a good improvement is achieved when the neural network controller is used compared with PID control.

Keywords: Mathematical modeling, batch distillation column, Neural network controller, "MATLAB" simulation, PID controller.

سيطرة الشبكة العصبية على برج التقطير الدفعي

الخلاصة

تناول البحث دراسة السلوك الديناميكي لبرج التقطير الدفعي وتطبيق نوعين من طرق السيطرة لعملية فصل أنواع مختلفة من الأنظمة الثنائية. تم اشتقاق أنموذج رياضي ومحاكاته باستخدام برنامج ماتلاب.تم استخدام التجارب العملية في حساب معاملات المسيطر التقليدي (PID) وكذلك تطوير مسيطر الشبكة العصبية. كانت نتائج المحاكاة ضمن الحدود المقبولة. وكذلك بينت النتائج إن استجابة المسيطر التقليدي متذبذب وقيمة الحيد عالية بينما كان مسيطر الشبكة العصبية اقل حيد واقل زمن للوصول إلى حالة الاستقرار. وبشكل عام تم الحصول على نتائج أفضل عند استخدام مسيطر الشبكة العصبية بالمقارنة مع المسيطر التقليدي.

الكلمات الدالة: النمذجة الرياضية، برج تقطير دفعي، مسيطر الشبكة العصبية، المحاكاة باستخدام برنامج الماتلاب، مسيطر تناسبي–تكاملي– تفاضلي.

Nomenclature

b: Bias value.
D: Distillate molar flow rate (mol/s)
d_k : Actual output of the process
H : Vapor mixture enthalpy (J/mol)
h : Liquid mixture enthalpy (J/mol)
L: Liquid molar flow rate (mol/s)
L_{NT+2}: Liquid molar flow rate input to the condenser (mol/s)
M: Molar liquid holdup (mol)
M_1: Still holdup (mol)
M_L: Packed section holdup (mol)

M_{NT+2}: Reflux drum holdup (mol)
Q_1 : Still heat load (J/mole.s)
Q_{NT+2}: Condenser heat load (J/mol .s)
R: Reflux ratio
T_t: Neural Network temperature (°C).
t: Time (s)
V: Vapor molar flow rate (mol/s)
V_{NT+2}: Vapor molar flow rate input to the condenser (mol/s)
W_{ij}: Weight value between input and hidden layer
W_{jk}: Weight value between output and hidden layer.
x: Liquid mole fraction (mol/mol)
y: Vapor mole fraction (mol/mol)
γ_i: Activity coefficient
φ : Fugacity coefficient of species (i) in liquid
μ: Momentum rate
η: Learning rate

Introduction

Batch Distillation is one of the most commonly used separation processes in chemical and petroleum industries and it is a process in which miscible liquids are separated based on their physical properties, specifically, relative volatilities. The boiling of the more volatile components of the mixture drives the distillation process [1]. The distillation process can be carried out in a continuous, batch or in semi-batch (or semi continuous) mode. The choice of the type of operation of distillation, as batch or continuous depends on the feed amount and on the characteristics of the feed components. The batch distillation is more commonly used due to its convenience for low volume, fine chemicals and bio chemicals [2], and its advantages like “flexibility, high product purity and possibility of multiple fraction operation [3].

The main objectives of distillation control are maintaining product purity and quality, constraint satisfaction, and energy reduction. Distillation control is a complex due to the inherent nonlinearity of distillation, multivariable interaction, non-stationary behavior and severity of disturbances. Mohanad and Ramasamy (2009)[4] developed a neural network based soft sensor to be used in an inferential control scheme of a pilot-scale binary distillation column. The performance of different networks is discussed and developed soft sensor can be utilized in an inferential control scheme on the distillation column. Almıla and Canan (2010)[5] designed an Artificial Neural Network (ANN) estimator system, which utilizes the use of several ANN estimators, to predict the product composition values of the distillation column from temperature measurements inferentially. It is found that, it is possible to control the compositions in this dynamically complex system by using the designed ANN estimator system with error refinement whenever necessary. Feng (2011)[6] designed a dynamic neural network (DNN) to control the top and bottom compositions of a distillation column. The effectiveness of the control strategy is demonstrated using simulation results.

In this paper a dynamic model for batch distillation column is developed. Thus, both theoretical and experimental studies are carried out. Two control methods, neural network and PID controllers were applied to control the top product temperature of the batch distillation column. The simulation of control methods and dynamic model of the batch distillation process are built by using "MATLAB" program to study the response of the process.

Dynamic Modeling

Modeling of batch distillation systems is complex due to the unsteady state nature of the system. The dynamic behavior of the batch distillation has been modeled by the following set of nonlinear equations based on the mass and energy balances for the batch distillation sections. A schematic view of the studied batch packed distillation column is shown in Figure (1). In this figure the packed column with its still, condenser, reflux drum are shown. The parameter (i) defines the differential element starting with i = 1 at still to i=NT+2 at reflux drum and condenser.

In the proposed packed distillation column model the following assumptions are considered [7]:

1. Negligible vapor holdup throughout the system.

2. Equimolar counter diffusion between the phases.
3. Constant volume of reflux drum and packed section liquid holdup.
4. Negligible fluid dynamics lags.
5. Adiabatic column operation.
6. Constant flow rate for the liquid and the vapor.
7. Total condensation.
8. Negligible effect of maldistribution of liquid and vapor flow rates.
9. Packed section divided into segments. Each of these segments can be looked at as a "stage".

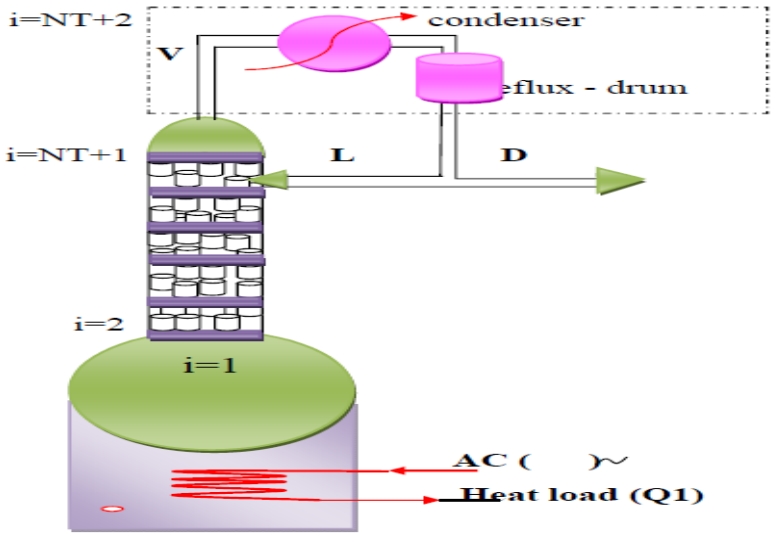

Fig. 1. Schematic View of Studied Batch Packed Distillation Column

Total material balance equation for still:

$$\frac{dM_1}{dt} = L_2 - V_1 \quad \dots\dots\dots\dots\dots\dots\dots (1)$$

Material balance on component (j) gives:

$$\frac{d(M_1 x_{1j})}{dt} = L_2 x_{2j} - V_1 y_{1j} \quad \dots\dots\dots\dots (2)$$

A heat balance can be written as:

$$\frac{d(M_1 h_1)}{dt} = L_2 h_2 - V_1 H_1 + Q_1 \dots\dots (3)$$

If the assumption of divided the packed section into stages is employed then total material balance equations can be written as:

$$\frac{dM_i}{dt} = L_{i+1} + V_{i-1} - L_i - V_i \dots\dots\dots (4)$$

Material balance on component (j) gives:

$$\frac{d(M_i x_{ij})}{dt} = L_{i+1} x_{i+1,j} + V_{i-1} y_{i-1,j} - L_i x_{ij} - V_i y_{ij} \dots\dots\dots (5)$$

A heat balance across can be written as:

$$\frac{d(M_i h_i)}{dt} = L_{i+1} h_{i+1} + V_{i-1} H_{i-1} - L_i h_i - V_i H_i \dots (6)$$

Total material balance equation of reflux drum and condenser gives:

$$\frac{dM_{NT+2}}{dt} = V_{NT+2} - L_{NT+2} - D \dots\dots (7)$$

Material balance on component (j) gives:

$$\frac{d(M_{NT+2}\, x_{NT+2,j})}{dt} = V_{NT+2}\, y_{NT+2,j} - L_{NT+2}\, x_{NT+2,j} - D\, x_{NT+2,j} \dots\dots\dots\dots (8)$$

A heat balance can be written as:

$$\frac{d(M_{NT+2}h_{NT+2})}{dt} = V_{NT+2}H_{NT+2} - L_{NT+2}h_{NT+2} - D\,h_{NT+2} - Q_{NT+2} \quad (9)$$

Extracting left- side (L.S.) of eq. (2)

$$\frac{dM_1x_{1j}}{dt} = M_1\frac{dx_{1j}}{dt} + x_{1j}\frac{dM_1}{dt} \ldots\ldots(10)$$

And inserting Eq.(1)

$$\frac{dM_1x_{1j}}{dt} = M_1\frac{dx_{1j}}{dt} + x_{1j}(L_2 - V_1) \quad (11)$$

$$M_1\frac{dx_{1j}}{dt} = L_2x_{2j} - V_1y_{1j} - L_2x_{1j} + V_1x_{1j} \ldots(12)$$

Rearranging eq.(12) gives time derivative of the compositions in the still as:

$$\frac{dx_{1j}}{dt} = \frac{[L_2(x_{2j} - x_{1j}) - V_1(y_{1j} - x_{1j})]}{M_1} \ldots\ldots(13)$$

Combining Eq. (4) and Eq. (5) gives the time derivative of the compositions at the stages as:

$$\frac{dx_{ij}}{dt} = 1/M_i[V_{i-1}(y_{i-1,j} - x_{ij}) + L_{i+1}(x_{i+1,j} - x_{ij}) - V_i(y_{ij} - x_{ij})] \ldots\ldots(14)$$

If the assumption of Constant flow rate for the liquid and the vapor is employed.

$$\frac{dx_{ij}}{dt} = \frac{[L(x_{i+1,j} - x_{ij}) - V(y_{ij} - y_{i-1,j})]}{M_i} \ldots\ldots(15)$$

If the assumption of constant molar liquid holdup in the reflux drum and condenser is employed, Eq. (7) becomes:

$$V_{NT+2} = L_{NT+2} + D \ldots\ldots\ldots\ldots(16)$$

and inserting Eq. (16) to Eq. (8) gives state equation for compositions at the distillate compositions.

$$\frac{dx_{NT+2,j}}{dt} = \frac{[V_{NT+2}(y_{NT+2,j} - x_{NT+2,j})]}{M_{NT+2}} \ldots\ldots\ldots(17)$$

The equilibrium temperature and the composition of vapor phase at equilibrium with the liquid phase is represented by:

$$\bar{f}_j^L = \bar{f}_j^V \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots(18)$$

$$\bar{f}_j^L = x_j\gamma_j\varphi_j^{sat.}P_j^{sat.}\exp\left(\int_{P_j^{sat.}}^{P}\frac{V_j^L}{RT}dP\right) \ldots\ldots\ldots\ldots\ldots(19)$$

$$\bar{f}_j^V = y_j\varphi_j^V P \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots(20)$$

$$x_j\gamma_j\varphi_j^{sat.}P_j^{sat.}\exp\left(\int_{P_j^{sat.}}^{P}\frac{V_j^L}{RT}dP\right) = y_j\varphi_j^V P \ldots.(21)$$

Then eq. (21) simplified to:

$$y_j = \frac{x_j\gamma_j P_j^{sat.}}{P} \ldots\ldots\ldots\ldots\ldots\ldots\ldots(22)$$

γ_j: Is the activity of a species in a liquid which computed in this paper using Van Laar, model

Neural Network Controller

The “neural network” referred to in this research is a "Artificial Neural Network", which is collections of mathematical models that emulate the real neural structure of the brain. In general, ANN is made up of individual interconnected simple processing elements called neurons, arranged in a layered structure to form a network. There are a wide variety of neural network structures, but each type consists of the same basic features which are, neurons, layers and weighted connections. The basic element of the network is a neuron. Each neuron has an input, a body and an output.These neuron, organized in three layers which are, Input layer, Hidden layers and Output layer. These layers are interconnected and produce a final output for the whole network .An example of artificial neuron is illustrated in Figure (2).

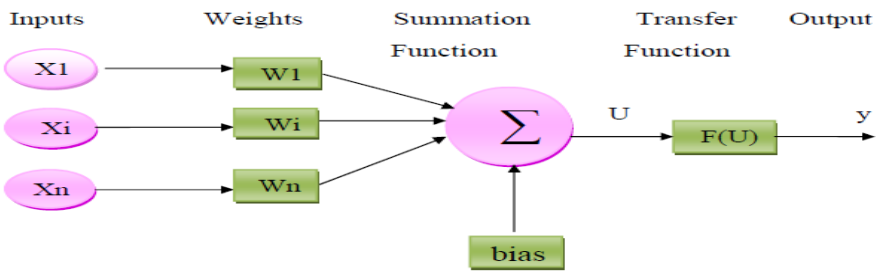

Fig. 2. Artificial Neuron

The neuron input, xi, is multiplied by the corresponding weight factor, wi, before being sent to the neuron. This is followed by performing summation of all input in the neuron body. An internal bias, b is also introduced to enhance performance of the network. The result is passed through a nonlinear activation transfer function to obtain the output y:

$$y = f\left(\sum_{i=1}^{i=n} X_i W_i + b\right) \dots\dots\dots\dots\dots (23)$$

Typical activation transfer functions include sigmoidal function, hyperbolic tangent function, sine or cosine function. So far, there are no rules for the selection of transfer function but the sigmoidal function is the most popular choice. Therefore we used it in this study. Neural networks can be broadly classified as feed forward networks where the signal flows only in the forward direction, recurrent networks where the signal flows in both the forward and backward directions and self-organizing network. In this study feed forward neural network was applied with three inputs and single output (MISO) to control the temperature of the top product temperature in the batch distillation column. Figure (3) show schematic diagram of the control system.

Training of Neural Networks

Training is a systematic adjustment of weights to get a chosen neural network to predict a desired output and the algorithm used for training is called a "learning algorithm". Two types of learning algorithms exist as supervised and unsupervised learning algorithms [8].

Learning Algorithm

Learning algorithm is a mathematical tool that outlines the methodology and the speed for NN to reach the steady state of its parameters, weights and thresholds successfully. It starts with an error function (energy function), which is expressed in terms of weights. The objective is to minimize the error in the set of weights. The decrease may be accomplished with different optimization techniques such as the Delta rule, Boltzman's algorithm, the Backpropagation learning algorithm and simulation annealing. Backpropagation learning algorithm [8], which is used in this paper, is the basic learning mechanism and it is very popular in the literature. The algorithm of the error back-propagation training for training the studied network shown in Figure (3) is given below.

Step1: Initialize network weight value randomly in the range of (-1,1).

Step2: sum weighted input and apply activation function to compute output of hidden layer.

$$h_j = f\left[\sum_{i=1}^{i=N} X_i W_{ij} + b\right] \dots\dots\dots\dots\dots (24)$$

h_j: output of hidden neuron j.

X_i: Input signals which are reflux ratio, the past value of the controlled temperature and still temperature.

f : The activation function.

i : Number of input layer neuron =3.

j : Number of hidden layer neuron

Step3: sum weighted output of hidden layer and apply activation function.

$$T_t = f[\sum_j h_j W_{jk} + b] \dots\dots\dots\dots\dots (25)$$

T_t: The actual output of output neuron k which represent controlled temperature (top product temperature).

k : number of output layer neuron =1.

Step4: compute back propagation error.

Error (E)= $(d_k - T_t)$

Step 5: calculate weight correction term.

$$\Delta W_{jk}(n) = \eta E h_j + \mu \Delta W_{jk}(n-1) .. (26)$$

$$\Delta W_{ij}(n) = \eta E X_i + \mu \Delta W_{ij}(n-1) \dots (27)$$

Step 6: update weights.

$$W_{jk}(n+1) = W_{jk}(n) + \Delta W_{jk}(n) .. (28)$$

$$W_{ij}(n+1) = W_{ij}(n) + \Delta W_{ij}(n) \dots . (29)$$

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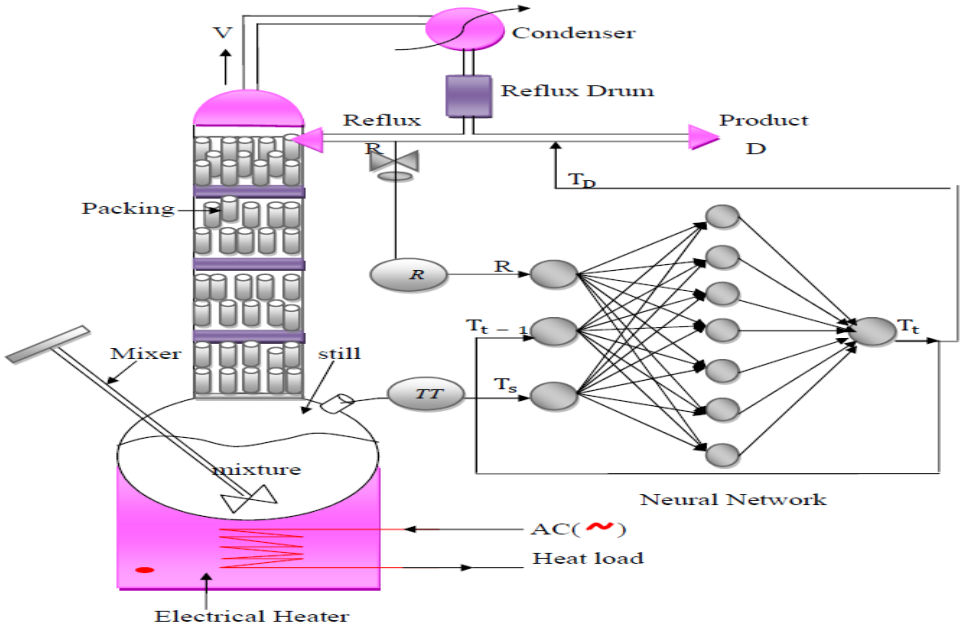

Fig. 3. Schematic Diagram of the Control System

Experimental Work

The experiments were carried out in a laboratory scale batch distillation column consists of a still pot, packed column and condenser as shown in Figure (1).

The still pot of a (5L) volume, made from glass, equipped with mixer and heated using an electrical heater to supply energy to the system. The 0.4m height and 0.05m diameter glass packed column was located above the still pot and made of glass. Column was filled with 0.01m diameter glass rasching rings .At the top of the packed column, the condenser was connected. Three thermocouples with measuring range of (-210-1200)℃ was located at the still pot (T1), packed section (T2) and the top product (T3) to measuring the temperature. Each of these thermocouples was connected to the ADC by means of an amplifier to make the signal larger before it was sent to the interface unit (ADC).The amplifier receive an analog signal from the thermocouple in the range of (-0.02 to 2.4)V and make the signal larger (0 to +10)V before it was sent to the interface unit. The interface unit receives an analog signal from the amplifier and converts it to a digital signal through an ADC then sends it to the computer. The ADC channels have been set to give (0V to 10V) voltage range. The computer receives a digital voltage signal from ADC and it has

been provided with supervision software "LAB VIEW" which is used to reading voltage signal received from ADC and convert it to temperature signal.

The experimental work was performed by measuring the temperatures in the still pot, packed section and the top product. Seventeen runs were carried out for the batch distillation system using four systems (Acetic acid-water, Acetone-water, Ethanol-water and Benzene-toluene) as shown in Table (1).

Table 1. Experimental Runs for the Batch distillation Process dynamic

Run No.	Systems	Mole fraction of more volatile component	Reflux ratio	MSE at top	MSE at bottom
1	Benzene-toluene	0.4	0.5	57.055	133.77
2	Benzene-toluene	0.6	0.5	70.94	89.045
3	Benzene-toluene	0.8	0.5	23.38	102.09
4	Benzene-toluene	0.4	0.75	26.055	133.045
5	Benzene-toluene	0.4	1	59.5	115.95
6	Acetone-Water	0.3	0.3	35.125	67.86
7	Acetone-Water	0.5	0.3	72.09	122.9
8	Acetone-Water	0.7	0.3	41.37	99.44
9	Acetone-Water	0.3	0.5	13.31	127.54
10	Acetone-Water	0.3	0.8	33.27	88.88
11	Acetic Acid-Water	0.2	1.5	57.05	127.86
12	Acetic Acid-Water	0.4	1.5	71.5	202.03
13	Ethanol-Water	0.4	0.1	47.04	229.55
14	Ethanol-Water	0.6	0.1	39.31	185.5
15	Ethanol-Water	0.8	0.1	11.72	140.64
16	Ethanol-Water	0.4	0.3	18.77	87.94
17	Ethanol-Water	0.4	0.5	12.70	117.16

Results and Discussion

In this section the experimental results of the open –loop response in the top and still temperature of batch distillation column for our runs which are shown in Table (1) were compared with simulated top and still temperature response which were extracted from (MATLAB simulator) of the batch distillation.

Figures (4) to (7) show the comparison for top and bottom temperature for (benzene-toluene) system. It can be seen that mole fraction of benzene increase from 0.4 to 0.6 the top and still temperatures also increase because the boiling point of benzene is lower than boiling point of toluene then lead to decrease the boiling point of mixture. Also it can be seen that the time delay of the response for temperature of top product decrease from 15 to 10 minutes at the same reasons. From Table (1) it can be seen that under all conditions and all systems that the mean square error (MSE) for top product temperature is smaller than mean square error (MSE) for still temperature and this due to the assumption of considering the column is packed do not effect on the temperature of the top product temperature. But in the packed column change all stages temperature in the packed section and the still temperature is depend on the temperature of stages in packed section. Also it can be seen that (MSE) for top and still temperature for (acetic acid - water) systems is higher than (MSE) for other systems. Mean square error for all runs is listed in Table (1).

$$(\mathrm{MSE}) = \frac{1}{N}\sum \left(T_{exp.} - T_{sim.}\right)^2 \ldots . (30)$$

The present work also includes application of neural network and PID controllers for the control of the top product temperature of the batch distillation column. The Cohen &Coon

and Internal model setting were applied for tuning of the PID controller. The resulting values for controller parameters are given in Table (2). From Table (2) it can be seen that for all studied systems the mean square error (MSE) using Cohen & Coon setting is smaller than mean square error (MSE) when using Internal model setting, Also in this section a comparison was made between the two control methods results which were extracted from "MATLAB" simulators shown in Figures (8) to (11). From these results, it is clear that neural controller is the best and gives better results than PID controller because neural controller has less offset value and oscillation, more suitable, the temperature response reach the steady state value in less time and it has lower over-shoot.

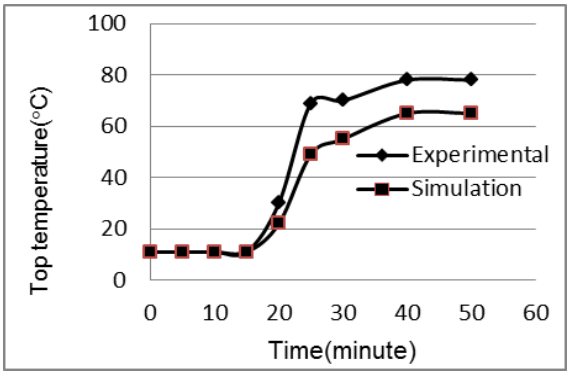

Fig. 4. Comparison of simulation and experimental of response of top product temperature for (benzene-toluene) system at mole fraction of benzene=0.4 & R=0.5

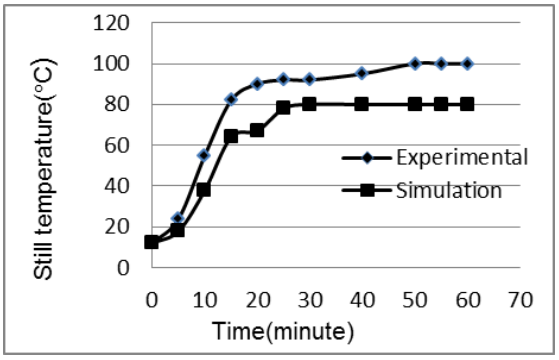

Fig. 5. Comparison of simulation and experimental of response of still temperature for (benzene-toluene) system at mole fraction of benzene=0.4 & R=0.5

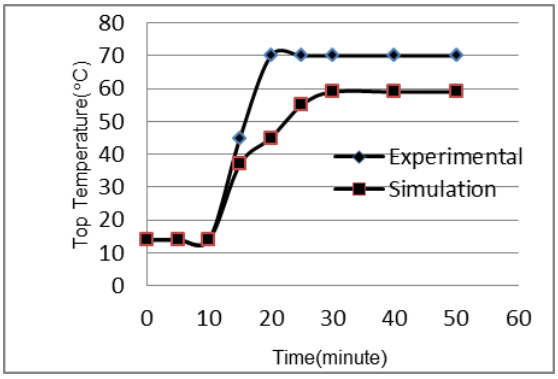

Fig. 6 Comparison of simulation and experimental of response of top product temperature for (benzene-toluene) system at mole fraction of benzene=0.6 & R=0.5

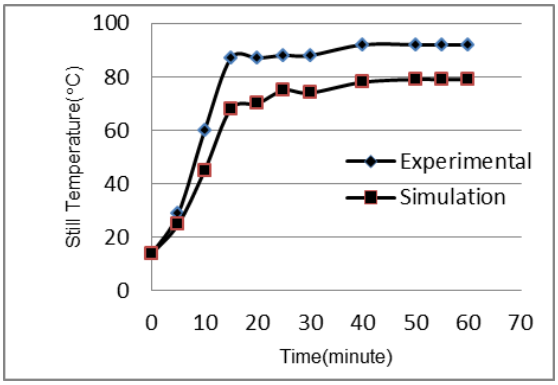

Fig. 7. Comparison of simulation and experimental of response of still temperature for (benzene-toluene) system at mole fraction of benzene=0.6& R=0.5

Table 2. Controller Setting for Top Temperature of Batch Distillation

system	Controller action	Cohen & Coon	Internal model	MSE using Cohen & Coon		MSE using Internal model	
				C°60	C°70	C°60	C°70
Benzene& Toluene	P	K_C= 0.082					
	PI	K_C= 0.0724 τ_I=1.468min	K_C= 0.048 τ_I= 7.8min				
	PID	K_C= 0.108 τ_I= 1.12min τ_D= 0.18min	K_C= 0.0708 τ_I= 8.05min τ_D= 0.242min	5.69	6.21	12.1	10.1
Acetone & Water	P	K_C= 0.135					
	PI	K_C= 0.1205 τ_I=1.383 min	K_C= 0.08 τ_I=11.2min				
	PID	K_C= 0.18 τ_I=1.09 min τ_D=0.163 min	K_C= 0.117 τ_I=11.425min τ_D=0.221 min	8.23	5.15	13.7	16.3
Acetic Acid &Water	P	K_C= 0.0514					
	PI	K_C= 0.045 τ_I=1.134 min	K_C= 0.03 τ_I=4.8 min				
	PID	K_C= 0.067 τ_I= 0.951min τ_D= 0.143min	K_C= 0.044 τ_I=5 min τ_D=0.192 min	4.46	8.53	9.38	12.6
Ethanol & Water	P	K_C= 0.268					
	PI	K_C= 0.24 τ_I= 0.97min	K_C=0.16 τ_I=17.8 min				
	PID	K_C= 0.356 τ_I=0.733min τ_D=0.108 min	K_C= 0.23 τ_I=17.95 min τ_D=0.148 min	2.92	9	12.8	11.3

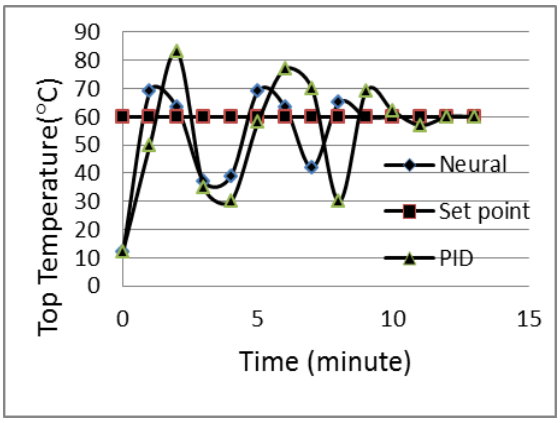

Fig. 9. Comparison between Neural Network and PID controller setting by Internal model setting method for (benzene-toluene) system, (K_C= 0.0708,τ_I= 8.05 min and τ_D= 0.242 min), Set point=60℃

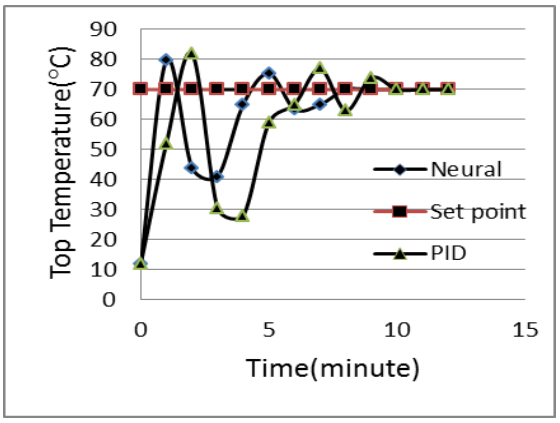

Fig.10. Comparison between Neural Network and PID controller setting by Cohen & Coon setting method for (benzene-toluene) system, (K_C=0.108,τ_I= 1.12 min and τ_D= 0.18min), Set point=70℃

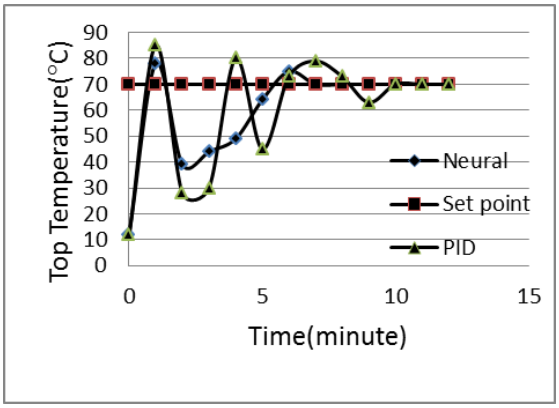

Fig. 11. Comparison between Neural Network and PID controller setting by Internal model setting method for (benzene-toluene) system (K_C=0.0708, τ_I= 8.05 min and τ_D= 0.242 min), Set point=70℃

Conclusions

Based on the results obtained in this study, the main conclusions of this project are as follows:

1. From the dynamic behavior study of the batch distillation column it can be seen that the more effected variables on the batch distillation column were mole fraction of the feed, reflux ratio.
2. The comparison between the experimental data and simulation results gave some agreements.
3. Setting of PID controller parameters was carried out using Cohen –coon & Internal model tuning methods. From the response of the PID controller, it can be seen that Cohen –coon method give better response than internal method.
4. Neural network gave better response than PID controller.

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