Ministry of Higher Education
& Scientific Research
University of Technology
Chemical Engineering Department

Neuro-Fuzzy Control for Methanol Recovery Distillation Column

A Thesis Submitted to the Department of Chemical Engineering of the University of Technology in Partial Fulfillment of the Requirements for The Degree of Master of Science

In

Chemical Engineering/Petroleum Refinery Engineering and Gas Technology

By

Ghydaa Majeed Jaid

(B.Sc. in Chemical Engineering 2009)

Supervised by

Prof. Dr. Safa A. Al-Naimi

February 2012

SUPERVISOR CERTIFICATION

I certify that this thesis entitled " **Neuro-fuzzy control for methanol recovery distillation plant** " presented by **Ghydaa Mjeed Jaeed** was prepared under my supervision in partial fulfillment of the requirements for the degree of **Master of Science** in **Chemical Engineering** at the **Chemical Engineering Department**, **University of Technology**.

Signature:

Prof. Dr. Safa A. Al-Naimi

(Supervisor)

Date: 2011

In view of the available recommendations I forward this thesis for debate by the Examination Committee.

Signature:

Date: 2011

SUPERVISOR CERTIFICATION

I certify that this thesis entitled " **Neuro-fuzzy control for methanol recovery distillation plant** " presented by **Ghydaa Mjeed Jaeed** was prepared under my supervision in partial fulfillment of the requirements for the degree of **Master of Science** in **Chemical Engineering** at the **Chemical Engineering Department**, **University of Technology**.

Signature: S Al Naimi

Prof. Dr. Safa A. Al-Naimi

(Supervisor)

Date: 2012

In view of the available recommendations I forward this thesis for debate by the Examination Committee.

Signature:

Ass. Prof. Dr. Mohamed I. Mohamed

(Deputy of Head of Department For Scientific and Post Graduated Affairs)

Date: 2012

Certificate of Examiners

We certify, as an examining committee, that we have read this thesis entitled" **Neuro-fuzzy control for methanol recovery distillation plant** ", examined the student **Ghydaa Mjeed Jaeed in** its content and found that the thesis meets the standard for the degree of Master of Science in chemical engineering.

Signature: SA l Naimi
Name: Prof. Dr. Safa A. AL-Niami
Data: / /2012
(Supervisor)

Signature:
Name: Ass. Prof. Dr.Azad R.kareem
Data: / /2012
(Member)

Signature: Kar
Name:Dr.Karima.M. Putrus
Data: / /2012
(Member)

Signature: Duraid f. A.
Name: Prof. Dr. Duraid F. Ahmed
Data: / /2012
(Chairman)

Approved by the Head of the Chemical Engineering Department

Signature: M. Zablouk
Name: Prof. Dr. Mumtaz A.Zablouk
Head of Chemical Engineering Department
Data:18/3/2012

بسم الله الرحمن الرحيم

"إقرأ بإسم ربك الذي خلق، خلق الإنسان
من علق، إقرأ وربك الأكرم الذي علم
بالقلم، علم الإنسان ما لم يعلم".

صدق الله العظيم

سورة العلق
(الآية من 1–5)

Acknowledgments

In the name of **Allah**. Above all**,** praise is to **Allah** Who created us and gave us the power to work and the ability to think.

I would like to express my sincere appreciation and thanks to my supervisor **Prof. Dr. Safa A. Al-Naimi**, for his constant guidance and valuable comments, without which, this thesis would not have been successfully completed.

Also I would like to convey my sincere appreciation to all staff of the Chemical Engineering Department at the University of Technology .

Finally, deep thanks are expressed to my family especially for my brother Khalid for his consistent backing, and also for their continuous encouragement and to all my friends.

Ghydaa

DEDICATION

For my parents And Brothers:

Your love and support are endless.

*I could never say **"Thank you"** enough for what*

you have given me.

Ghydaa

Abstract

The distillation column is difficult to control due to the nonlinearity, Substantial coupling of manipulated variables, and No stationary behavior and therefore the different control strategies were used to control the distillate and bottom compositions of the packed distillation column to separate the mixture of methanol (CH_3OH) and water (H_2O).

Different control strategies; such as conventional feedback controls (PI, PID), artificial neural network (ANN) control , fuzzy logic (FLC)control, adaptive fuzzy logic control, PID fuzzy logic control and adaptive neuro-fuzzy inference system (ANFIS) were used to control the distillate and bottom compositions of the distillation column.

The performance criteria used for different control strategies is the integral time-weighted absolute error (ITAE) as a primary objective, as well as overshoot value and settling time to evaluate the performance of different control strategies.

The tuning of control parameters were determined for PI and PID controllers using three different methods; Internal Model Control (IMC), Ziegler-Nichols (Bode diagram), and Cohen-Coon (process reaction curve) to find the best values of gains. The (IMC) method gave better results than that of the other two methods and it was recommended to be the tuning method in this work.

The degree of loops interaction was determined based on Relative Gain Array (RGA) and a decoupling system was suggested to eliminate the interaction effects which showed a good non-interacting behavior.

The low values of ITAE of 61.3 for distillate product composition and 54 for bottom composition were obtained which represent the ANFIS method and assure the feasibility of this method as a control strategy among other methods.

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

Contents

Chapter Four: Results and Discussion

List of Tables

List of Figures

List of Abbreviations

Symbol	***Definition***
ANFIS	Adaptive Neuro-Fuzzy Inference System
ANN	Artificial Neural Network
AD-FLC	Adaptive Fuzzy Logic controller
AV	Auxiliary variable
BP	Back-Propagation
CI	Computational Intelligence
CSTR	Continuous Stirred-Tank Reactor

CE	Change of Error
E	Error
Er	Relative Error
FIS	Fuzzy Inference System
FLC	Fuzzy Logic control
FNN	Fuzzy Neural Networks
GM	Gain Margin
G_{PRC}	Process Reaction Curve Transfer Function
GRNN	General Regression Neural Network
IMC	Internal Model Control
ITAE	Integral Time-weighted Absolute Error
LSE	Least Square Estimates
MF	Membership Functions
MIMO	Multi-input & Multi-output
MLBP	Multi-Layer Back Propagation
MLP	Multi Layer Perceptron
MPC	Model Predictive Control
N	Negative
NARMA-L2	Nonlinear Auto Regressive-Moving Average
NB	Negative Big
NF	Neuro-Fuzzy
NNS	Neural Networks
NNMPC	Neural Network Model Predictive Control
NS	Negative Small
P	Positive
p	Proportional
PB	Positive Big
PI	Proportional-Integral

PID	Proportional-Integral-Derivative
PID-FLC	Proportional Integral Derivative -Fuzzy Logic controller
PRC	Process Reaction Curve
PS	Positive Small
RGA	Relative Gain Array
SISO	Single Input-Single Output
TCDS	Thermally coupled distillation sequences
Tri3lin	three triangular MFs for each input and linear output MF
TS	Takagi — Sugeno
z	Zero
Z.N	Ziegler-Nichols

Nomenclature

Symbol	***Definition***	***Units***
D	Decoupler system	–
$D_1(s)$	Dynamic element (Decoupler) for loop 1	–
$D_2(s)$	Dynamic element (Decoupler) for loop 2	–
G	Transfer function	–
G_c	Transfer function of controller	–
G_m	Transfer function of measurment	–
G_p	Transfer function of process	–
G_v	Transfer function of control valve	–

H	reboiler heat duty	kJ/sec
$H_{ij(s)}$	Transfer functions between output and input	–
$H_{11(s)}$	Transfer functions between X_D(s) and R(s)	–
$H_{12(s)}$	Transfer functions between X_D(s) and H(s)	–
$H_{21(s)}$	Transfer functions between X_B(s) and R(s)	–
$H_{22(s)}$	Transfer functions between X_B(s) and H(s)	–
K	Steady-state gain of the process reaction curve method	sec
K_c	Proportional gain	%/ sec
K_D	Derivative gain	%/ sec
K_I	Integral gain	%/ sec
K_u	Ultimate gain	–
p_u	Ultimate period of sustained cycling	sec/cycle
R	reflux flow rate	m^3/sec
s	Laplacian variable	–
S	Slop of the tangent at the point of inflection of the process reaction curve method	–
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***
μ	Membership function	–
Λ	Relative gain array	–
λ_{ij}	Elements of relative gain array	–
λ_{11}	Relative gain between X_D and R	–
λ_{12}	Relative gain between X_D and H	–
λ_{21}	Relative gain between X_B and R	–
λ_{22}	Relative gain between X_B and H	–
τ	Time constant of the process reaction curve method	sec
τ_D	Derivative time constant	sec
τ_I	Integral time constant	sec
τ_p	Lag time constant	sec
ψ	Damping coefficient	–
ω	Crossover frequency	rad/sec

Chapter One

Introduction

1.1 Distillation columns

Distillation column is often considered as the most significant and most common separation technique used in the processing of chemical engineering for separating feed streams and for the purification of final and intermediate product streams. It comprises 95 percent of the separation processes for the refining and chemical industries.

The aim of a distillation column is to separate a mixture of components into two or more products of different compositions. The physical principle of separation in distillation is the difference in the volatility of the components. The separation takes place in a vertical column where heat is added to a reboiler at the bottom and removed from condenser at the top. A stream of vapor produced in the reboiler rises through the column and is forced into contact with a liquid stream from the condenser flowing downwards in the column. The volatile (light) components are enriched in the vapor phase and the less volatile (heavy) components are enriched in the liquid phase. A product stream taken from the top of the column therefore mainly contains light components, while a stream taken from the bottom contains heavy components [1, 2].

There are many types of distillation columns where each plant is designed to perform specific types of separation and also depends on the complexity of the process. Commonly, the distillation column types are classified by looking at how the plant is operated.

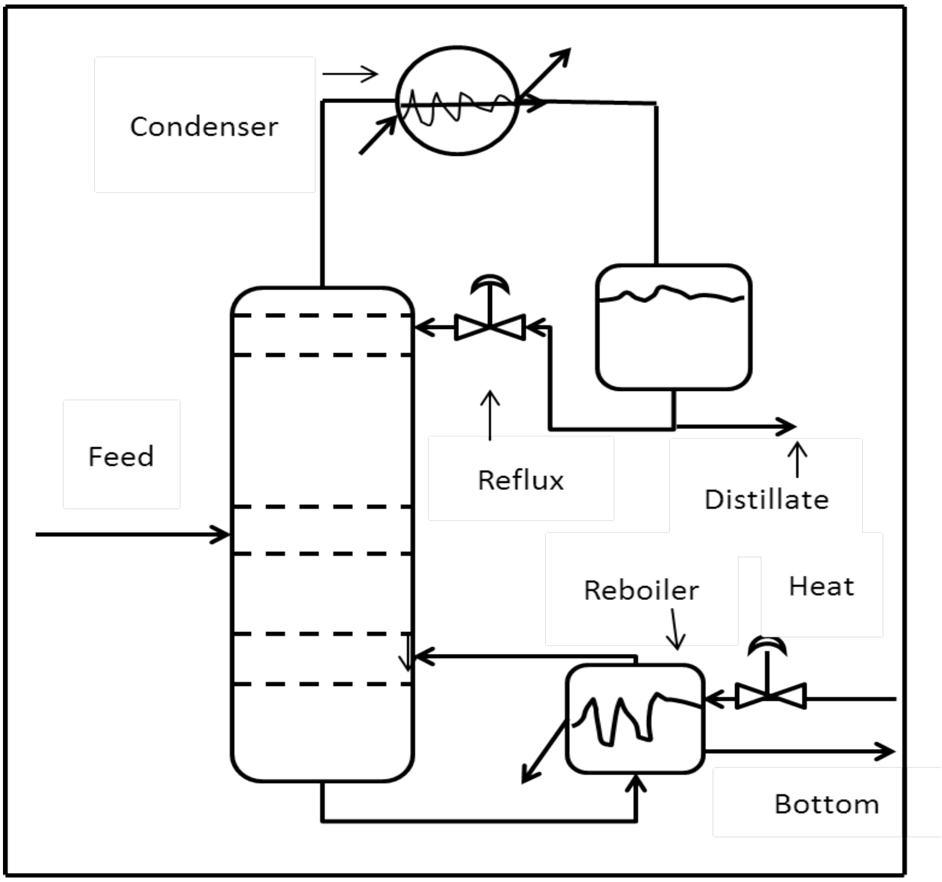


Fig. (1.1) Basic design of distillation column

1.2 Control of a Distillation Column:

Distillation columns are important separation technique in the chemical process industries around the world. For these reasons, improved distillation control can have a significant impact on reducing energy consumption is 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 (the nonlinear dynamics behavior occurs due to the Nonlinear vapor liquid equilibrium relationships, the complexity of the processing configurations and high product purities)

• Substantial coupling of manipulated variables (where reflux flow rate use to control distillate composition would effect on bottom composition and in the same way heat duty use to control bottom composition would effect on distillate composition thus show a certain degree of interaction);

• Severe disturbances; and

• No stationary behavior (their characteristics change with time).

Accordingly, most researches in both the private and public sector has focused on control methods that use modern computing power to cope with these control related difficulties [2-4].It has a major impact upon the product quality, energy usage, and plant throughput of these industries. It was also reported that an effective control of the distillation column is the best way to reduce the operating costs of existing units since the distillation process consumes enormous amounts of energy both in terms of cooling and heating requirements. It also contributes to more than 50 percent of the plant operating costs.

The objective of the control system of distillation columns is to move the process to the new optimal operating point. At the same time, the objective of the control system is to cancel the effect of the disturbances on the controlled variables by making the minimal changes in the manipulated variables from their optimal values [5].

Control technique involves decoupling control which is applied to multivariable processes, where there is interaction between control loops. This technique eliminates the effect of this interaction by designing suitable decouples for the loops .It requires a wide knowledge of the dynamic behavior of the controlled variables for change in disturbance and manipulated variables[6,7].

1.3 Scope of the present work:

This work is concerned with process control implemented using different control strategies through the following steps:

1- Studying the open loop system (without control) where the transfer functions between the controlled variable and manipulated variables and transfer functions between the controlled variable and disturbance are to be determined.

2- The dynamic model of the packed distillation column is to be studied by introducing step changes in; reflux rate and reboiler heat duty and then measuring the top and bottom concentration of the distillation column.

3- Studying the Interaction between the variables by best implementing and relative gain array (RGA) is used as an interaction measurement to decide the best pairing of the control loops.

4-Decoupling control will be applied to the two point composition control scheme.

5- Selecting the best control parameters by carrying a tuning procedure using the integral of the time-weighted absolute error (ITAE). As well as the parameter of the step performance of the system such as overshoot and settling time value are to be used to evaluate the performance of different control strategies.

6- Applying different control strategies such as conventional feedback control, fuzzy logic control, artificial neural network control, adaptive fuzzy control and Adaptive nero-fuzzy inference system and carrying out a comparison between them.

Chapter Two

General Review and Literature Survey

2.1 Introduction

Distillation is probably the most studied unit operation in terms of control. Control of distillation columns refers to the ability of keeping certain variables at or near their set points whenever there is a disturbance or set point change in the plant. Many papers and books have been devoted to the investigation and exploration of different aspects of distillation column control over the last half century [7].

This chapter reviews the literature and studies that deal with different control strategies (conventional feedback, fuzzy logic, artificial neural network and neuro-fuzzy systems).

2.2. Feedback control:

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 difference between these to eliminate any difference between them. A feedback control system consists of five basic components; input, process being controlled, output, sensing elements, controller and actuating devices. The most important types of industrial feedback controllers include**:** Proportional (P), Proportional-Integral (PI) and Proportional-integral-derivative controller (PID) [8]. Feedback control can be used very effectively to stabilize the state of a system, while also improving its performance. It can be easily duplicated from one system to another and

improved reference tracking performance. The Weaknesses of FeedbackControl depends on the accuracy of the mathematical model of the systems, at highly non-linear Feedback control systems may fail and Feedback control designed for high performance increases the complexity of the design and hence the cost.

Hale, *et .al.*[9] studied the efficiency of the strategies PID feedback and self-tuning PID in controlling the composition of a packed distillation column. The controller parameters were estimated using three different closed loop response tuning criteria for discrete controllers; the best Conventional PID action is compared with self-tuning PID control. It was shown that self-tuning PID control provides better control than conventional PID action for the cases studied.

Rohit[10] 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.

2.3 Loops Decoupling:

Due to the dynamic characteristics of the distillation process, the control design by process decoupling is suited especially for two point composition case. The proposed decoupling method is a theoretical - experimental procedure that can be applied as a rule to two inputs -two outputs processes.

Sanda [12] tested decoupling of two binary distillation columns. The designed decoupler has a standard general structure, which can be implemented in 4x4 distinct variants, corresponding to the dynamic

characteristics of process direct and crossed channels. It has six tuning parameters: two time constants, two dead times and two gains. The simulation results showed that the proposed decoupling method was a useful tool for composition decoupling.Whereas RGA elements for different configurations are relatively small and larger than one. The decoupled process was sensitive to large condition changes but performs well and even very well to medium and small condition changes.

Juan , *et.al.*[13] showed that the use of thermally coupled distillation sequences (TCDS) can provide significant energy savings with respect to the operation of sequences based on conventional distillation columns. He made comparisons between the TCDS in optimal operation and the TCDS in non-optimal conditions .The results indicated that TCDS with side column operated at some non-optimal operating conditions have the best controllability and the lower energy consumption.

Qasim[14] designed the decoupling method to eliminate the interaction effects between the control loops for the composition of both distillate and side stream product. He found that the decouplers were greatly improved the response of the system and made the system stable.

2.4 Fuzzy Logic Control

Fuzzy logic was developed for representing uncertain and imprecise knowledge. Its provides an approximate but effective means of describing the behavior of systems that are too complex, ill-defined, or not easily analyzed mathematically. A typical fuzzy inference system consists of membership functions, a rule base and an inference procedure [15, 16]. The advantages of Fuzzy Logic Control are Simplicity of control and Smooth operation, High degree of tolerance, Low cost, Reduce the effect of Non-

linearity and Possibility to design without knowing the exact mathematical model of the process. Weaknesses of Fuzzy Logic Control are the rules of the fuzzy logic, which apply everyday life, have to be determined by expert experiences, It is difficult to make analysis of determination of a system designed according to the fuzzy logic That is, it cannot be estimated how the system reacts beforehand and As the membership functions are determined according to the trial and error learning, they take a long time.

The concept of fuzziness was first proposed by Zadeh. He aimed to describe complex and complicated systems using fuzzy approximation and introduced fuzzy sets. 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 [17, 18].

Maidi , *et .al.*[4] evaluated the proposed a fuzzy multi loop control design for a distillation column , which exhibits a strong interaction between the distillation column variables. The fuzzy multi loop control was compared in simulation with that provided by the classical PID controllers. The results showed the fuzzy multi loop control achieves better control performance than those obtained using the conventional multi loop control for the feed composition disturbance.

Fuzzy classifier that can be used as an adequate and reliable expert system to perform quality qualifications in chemical engineering system was proposed by Evren [19].The method builds a fuzzy logic model, which infers the quality variables from other accurately measured system parameters. It was applied to two chemical engineering problems; the wine distillate maturation and the tissue making process and compared with a

feed forward NN methodology and a fuzzy identification method. It was confirmed that classifications of proposed fuzzy logic model were more accurate.

Eranda[20] designed Linear PI and fuzzy PI controller for (3x3 variables)distillation column. Based on simulation results, fuzzy PI controller has better performance compared to its counterpart and it fulfills the operating requirements while maintaining inputs/outputs constrains.

José , *et.al.*[21] applied Mamdani fuzzy control for a simulated oil distillation system. The designed fuzzy system disposes of two inputs (error and error variance), and one output (sets points of the reflux flow controller). The membership functions were adjusted based on experiments, so efforts to achieve a better adjust is an alternative that must be considered. The error in steady state can be reduced. This work investigates the efficiency of fuzzy controllers on set points generation.

Qasim [14] designed PI-fuzzy logic controller for a ternary distillation column separating benzene- toluene- o-xylene mixture. PI-fuzzy logic control gave a marked improvement over feedback controller. In general PI-fuzzy logic gave better results than feedback controller and the PI-Fuzzy was the effective one.

2.5Artificial Neural Network Control

Artificial neural network (ANN) takes their name from the network of nerve cells in the brain. Recently, ANN has been found to be an important technique for classification and optimization problem. 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 [22]. The advantages of artificial neural network control are Learning ability, its individual units can function in parallel. This corresponds to increase in speed that can be used effectively in applications requiring real-time decision making, Fast adaptation, Inherent approximation capability and High degree of tolerance. the disadvantages of Artificial neural network control are Unlike statistical modeling where estimates of sample size can be initially computed the number of samples of observations needed for training ANN models cannot be determined in advance, Assessing the internal operation of the network is difficult and Instability to explain any results that they obtain. Networks function as "black boxes" whose rules of operation are completely unknown.

Hui [23] used of a mathematical tool called soft sensors to distillation column and the neural network implemented and used. The results showed that the neural network can be an interesting tool to operate as a sensor to avoid mathematical manipulation and possible loss of physical meaning of variables in the modeling of the distillation column. The proposed soft sensor, represented by a wavelet neural network was able to predict, within the desired precision, the variables of interest during the startup procedure.

Chen [24] implemented ANN in process estimation and control using an industrial fatty acid distillation column as Case study. In this study, two types of network namely feed forward and Elman was trained using different training algorithms. The results showed that ANN was an efficient and effective empirical modeling tool for estimating the chemical process variable. The estimation and control performance of ANN model within its training data range was excellent.

Mujtaba and Greaves [25] developed ANN based dynamic optimization framework for batch reactive distillation using very little computational effort. The optimal product yield, optimal heat load, optimal maximum conversion and optimal reflux ratio profiles are predicted using ANN techniques that are only dependent on purity and batch time inputs. This reduces the computational time down from minutes to under a second.

Bahar[26] designed ANN estimator to estimate the distillate composition values of the column from available four temperature measurements. The performance of the designed neural network is found to be good in open-loop. It was possible to control the compositions in this reactive distillation column by using the designed ANN estimator, by refining the errors in estimation whenever they pass their tolerance levels.

Konakom , et.al.[27] used neural network-based model predictive control (NNMPC) for a batch reactive distillation column. Multi-layer feed forward neural network model and estimator were developed and used in the model predictive control algorithm. The NNMPC performance was compared with the performance of the conventional P controller. In the presence of plant/model mismatches in reaction rate and vapor-liquid equilibrium constants, the NNMPC was more robust than the conventional P controller. The NNMPC can maintain the distillate product purity on its specification whereas the conventional P controller lets the product out of specification in the presence of plant/model mismatches.

2.6 Neuro Fuzzy Systems

Neuro-Fuzzy systems are the systems that neural networks (NNS) are incorporated in fuzzy systems, which can use knowledge automatically by learning algorithms of NNS. Therefore, the combination of these two outperforms either neural network or fuzzy logic method used exclusively and becomes an ideal partner in control area, medicine, time series forecasting, and decision making[28,29].

Evren [19] designed ANFIS estimators to infer the top and bottom product compositions in a continuous distillation column and to infer the reflux drum compositions in a batch distillation column from the measurable tray temperatures. Designed estimator performances were further compared with the other types of estimators such as ANN. That results showed that the Best performance was obtained by Tri3lin (three triangular MFs for each input and linear output MF) ANFIS structure for both top and bottom product estimation. Tri3lin ANFIS estimator performance was compared with ANN estimator and it was seen that performance of the ANFIS was better than that of ANN In batch distillation column. It was concluded that convergence of ANFIS with back propagation algorithm was slower than that of ANN.

Jelenka[30] investigated a neural-fuzzy control of the top product composition and the reflux flow rate of the ethanol recovery distillation plant. The controller design has been based on the process inverse dynamic modeling. The simulated results illustrate the feasibility of using a neural-fuzzy controller for controlling state variables. The obtained control results showed improving quality control with time delay and a troubleshooting day to day operating problem. Non stationary characteristics of the process were handled by feeding information of the state variables. This was the

major advantage of the neural-fuzzy controller compared to the other well established control algorithms.

Boumediene, et.al. [29] Presented an application of adaptive neuro-fuzzy inference system (ANFIS) control for DC motor speed optimized with swarm collective intelligence. The controller was designed according to fuzzy and an adaptive neuro-fuzzy the ANFIS has the advantage of expert knowledge of the fuzzy inference system and the learning capability of neural networks.

Fikar and Kvasnica [31] presented the intelligent control system design via the combination of the predictive and the neuro-fuzzy controller type of ANFIS. The neuro-fuzzy controller works in parallel with the predictive controller. This controller adjusts the output of the predictive controller, in order to enhance the predicted inputs. The performance of their proposal was demonstrated on the Continuous Stirred-Tank Reactor (CSTR) control problem. Experimental results confirmed control quality improvement in the combined controller over the original predictive and PID controller. Neuro-fuzzy control scheme showed the best performance.

Sivakumar and Balu[32] designed and used ANFIS controller in an adaptive way in the distillation column control scheme. The performance of ANFIS controller was compared with the ANN, conventional multi loop PI controller and MPC controller for the same system under study. The process controlled with ANFIS controller was faster and reaches the steady state values with minimum oscillations in both top and bottom product Composition control.

Chapter Three

Theoretical Analysis

3.1 Introduction

This chapter contains two main sections, which deal with the dynamic model for a packed distillation and the methods of different control strategies that are used.

3.2 Dynamic Model

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 [33]. 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.

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.

From a process control viewpoint, the independent variables for the process are reflux flow rate (R) and reboiler heat duty (H) can be used as manipulated variables. The dependent variables for the process are distillate composition (X_D) and bottom composition (X_B) can be used as controlled variables.the steady state conditions of the column are given in table (3.1)

Table (3.1) Data of Steady state conditions[34].

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

The dynamic model of the packed distillation column was studied by introducing step changes in; reflux rate and reboiler heat duty and then measuring top and bottom concentration out of the distillation column. A model for the packed distillation column was developed based on the step response curve method and a process reaction curve method (PRC) was used to determine the process variables [34]. The method is described in appendix (A).

3.2.a.Controlled variables:

- Reflux rate
- Reboiler heat duty

3.2.b.Manipulated variables:

- Distillate composition (X_D)
- Bottom composition (X_B)

The following step changes in open loop are considered.

1-Step change in reflux rate: The reflux rate was increased by (22%, 30 %, 60% and 90%).

2-Step change in reboiler heat duty: The heat duty was increased by (30 %, 70%, 100%, and 150%).

3.3 Control Strategies

In this section, the application of conventional PI and PID control to the distillation process is described and discussed as well as the implementation of the PID control in place of the controller. The neural network control, fuzzy logic, and adaptive neuro-fuzzy inference system are also described and employed to improve the response.

3.3.1 Conventional Feedback Control:

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 difference between these to eliminate any difference between them [35]. Fig (3.1) shows the block diagram of feedback control system.

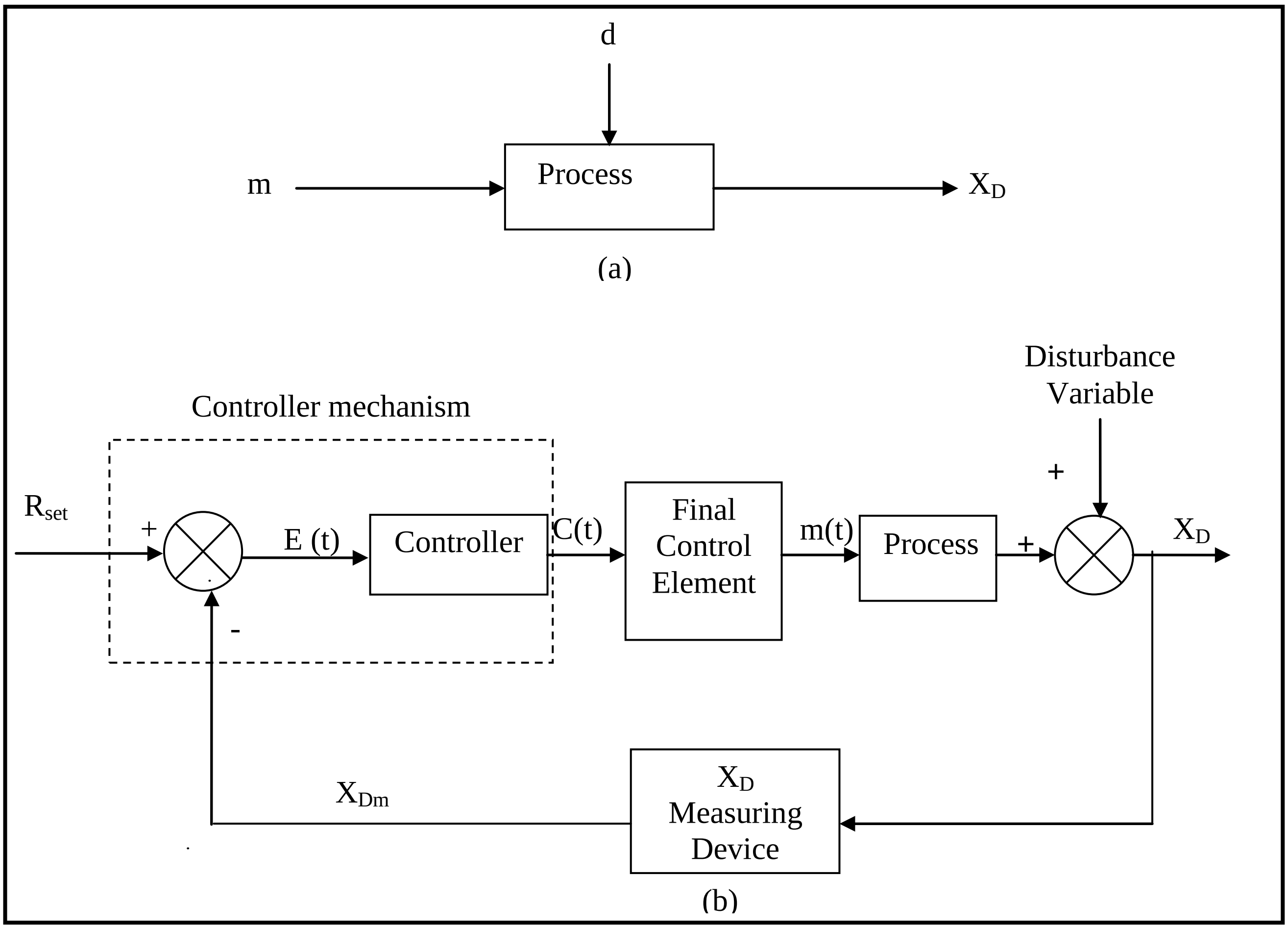


Fig. (3-1) (a) Process, (b) Feedback control loop.

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

3.3.1. a. Proportional Controller: (*P*)

The output of a proportional controller changes only if the errors signal changes. Since a load change requires a new control valve position, the controller must end up with a new error signal.

The proportional control action may be described mathematically as:

$$c(t)=K_c E(t)+c_s \qquad \text{----------- (3-1)}$$

Where
Kc = the proportional gain of the controller.

E (t) = the error.

c_s = the controller's bias signal (i.e., its actuating signal when E = 0 (at steady state) [35].

3.3.1.b. Proportional-Integral Controller: (PI)

The PI controller combines the proportional and integral modes:

$$c(t) = K_C\, E(t) + \frac{K_C}{\tau_I}\int_0^t E(t)\,dt + c_s \qquad \text{----------- (3-2)}$$

Where τ_I is the integral time constant or reset time in minutes. This combination provides stability with elimination of offset.The transfer function of a proportional-integral controller is given by [35]:

$$G_C = K_C\,(1 + \frac{1}{\tau_I\, s}) \qquad \text{------------- (3-3)}$$

3.3.1c. Proportional-Integral-Derivative Controller :(PID)

In the industrial practice it is commonly known as proportional-plus-reset-plus-rate controller. The output of this controller is given by

$$c(t) = K_C\, E(t) + \frac{K_C}{\tau_I}\int_0^t E(t)\,dt + K_C\,\tau_D\,\frac{dE}{dt} + c_s \qquad \text{----------- (3-4)}$$

Where τ_D is the derivative time constant in minutes. From equation (3-4) one can easily derive the transfer function of a PID controller [36].

$$G_C = K_C\;(1 + \frac{1}{\tau_I\, s} + \tau_D\, s) \qquad \text{---------- (3-5)}$$

3.3.1. d. Controller Tuning

Performance of feedback controllers depends on the values of their chosen parameters. If these parameters are properly chosen, they offer the highest flexibility to achieve the desired controlled response and stability. The process of choosing these parameters is known as controller tuning [37].

In this work, three methods were chosen to find the optimum values of K_C, τ_I and τ_D. These methods are:

1. Frequency Curve Method (Bode diagram).
2. Internal Model Control (IMC).
3. Process Reaction Curve (PRC).

These methods are described in Appendix (A). Internal model control (IMC) has gained high popularity due to the good disturbance rejection capabilities and robustness properties of the IMC structure. Furthermore, the controller design is simple and straightforward such that the controller can easily be tuned by the process engineer [38].

The main two methods of the time integral performance criteria are:

- **Integrated Square Error (ISE)**[39]

This error uses the square of the error, thereby penalizing large errors more than small errors. This gives more conservative response (faster return to set point).

$$ISE = \int_0^\infty e^2\,dt \qquad \text{---------- (3.6)}$$

❖ **Integrated Time-Weighted Absolute Error (ITAE)** [39]

This criterion is based on the integral of the absolute value of the error multiplied by time. It results in errors existing over time being penalized even though may be small, which a result in a more heavily damped response and these performance criteria is using in this work.

$$ITAE = \int_0^{\infty} t\,|e|\,dt \qquad \text{---------- } (3.7)$$

3.4.2 Loops Interactions [40]:

Processes which are multivariable in nature, i.e. processes where the variables to control and the variables available to manipulate cannot be separated into independent loops where one input only would affect one output, constitute a major source of difficulty in process control multivariable processes and thus show a certain degree of interaction. One control loop affects other loops in some way. As this interaction increases, so do the potential control problems multivariable processes in industrial and other applications are often of higher order.

3.4.2.1 RGA analysis [6]:

The RGA is a matrix of numbers. The ijth elements in the array are called relative gain (λ_{ij}). It is a ratio of the steady-state gain between the ith controlled variable and the jth manipulated variable when all other manipulated variables are constant Divided by the steady-state gain between the same two variables when all other controlled variables are constant. The relative gain array indicates how the input should be coupled with the output to form loops with the smallest amount of interaction.

Process with two controlled output and two manipulated variables are shown in Fig (3.2)

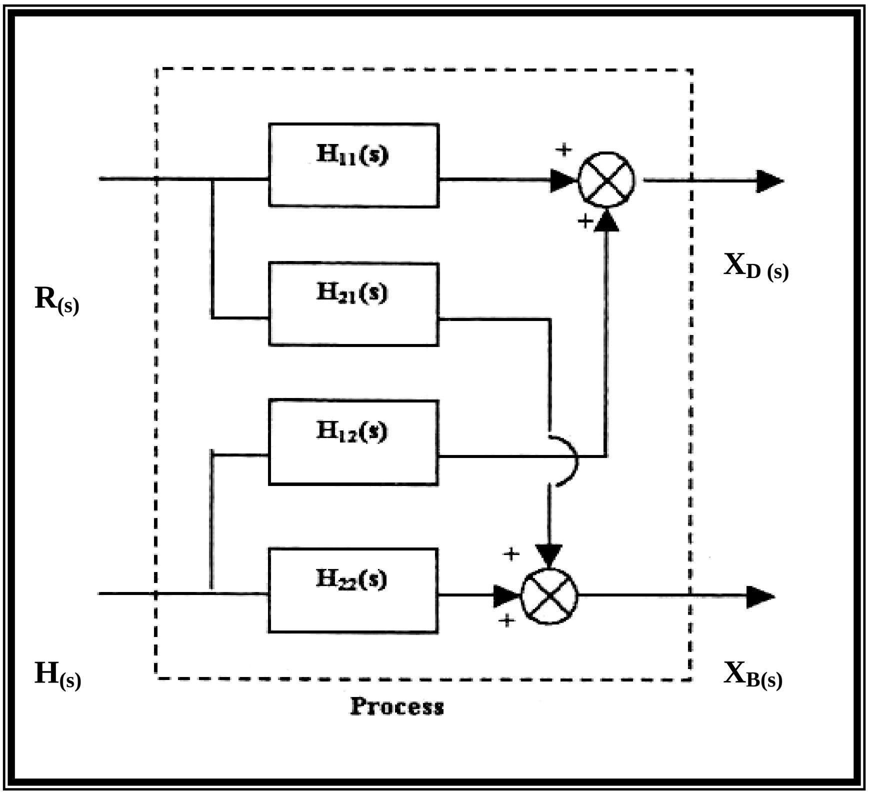


Fig (3.2) Block diagram of Process with two Controlled output and two manipulated variables

3.4.2.2 Decoupling:

The purpose of decouples is to cancel the interaction effect between the two loops and thus render two non-interacting control loops.

To design decouplres for a distillation, Equations (B.5) and (B.6) have been used in appendix (B). From Equation (B.5), in order to keep X_D constant (i.e. X_D=0), R should be changed by the following:

$$0 = H_{11}(s)\, R(s) + H_{12}(s)\, H(s) \qquad \text{-----------} \ (3.8)$$

$$R(s) = -\frac{H_{12}(s)}{H_{11}(s)}\ H(s) \qquad \text{----------- } (3.9)$$

Equation (3.8) implies that dynamic element is introduced with a transfer function:

$$D_1(s) = -\frac{H_{12}(s)}{H_{11}(s)} \qquad \text{----------- } (3.a10)$$

It uses the value of H as input and provides as output the amount by which it should change R, in order to cancel the effect of H on X_D.

This dynamic element (decoupler) when installed in the control system cancels any effect that loop 2 might have on loop 1, but not vice versa.

To eliminate the interaction from loop 1 and loop 2, the same reasoning as above has been followed and the transfer function of the second decoupler is given by:

$$D_2(s) = -\frac{H_{21}(s)}{H_{22}(s)} \qquad \text{----------- } (3.b10)$$

When the designer is encounters with two interacting loops, it is recommended to use decoupling. The best system design is to reject or to minimize any possible interaction between control loops.

The control loop two-way decoupler is shown in fig (3.3), and the block diagram of the process with two Feedback control loops, and with Complete Decouplller is given in fig (3.4).

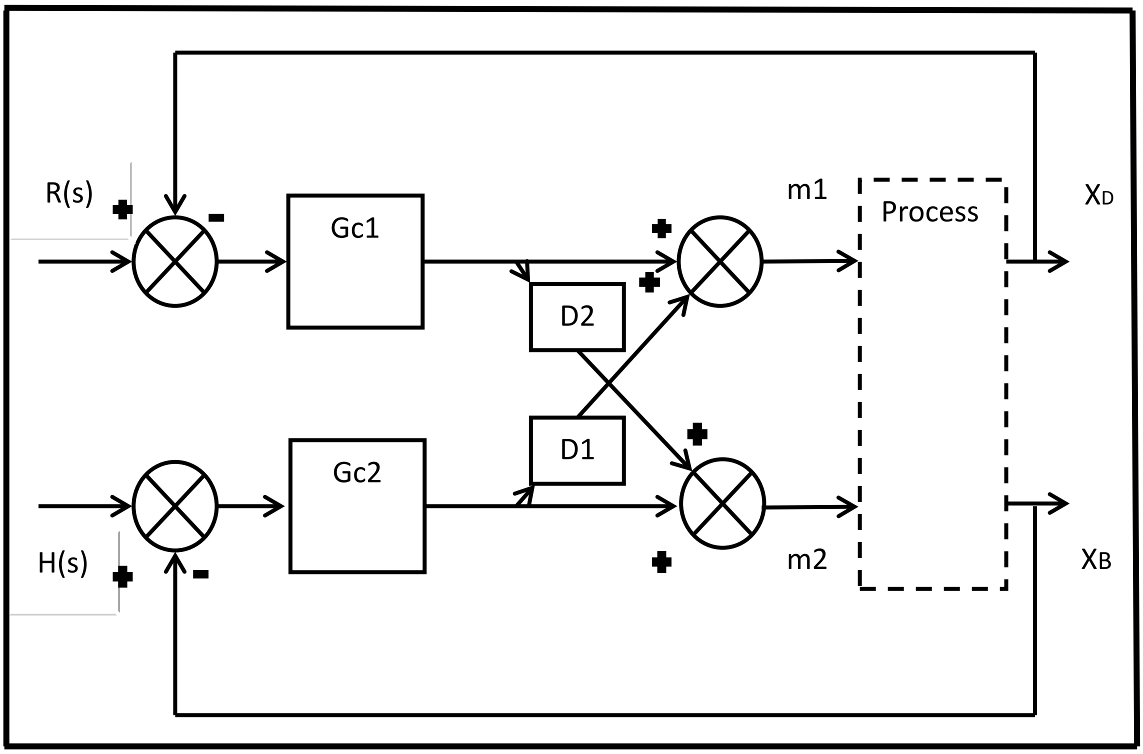


Fig (3.3): A 2×2 Processes with Two Decoupler

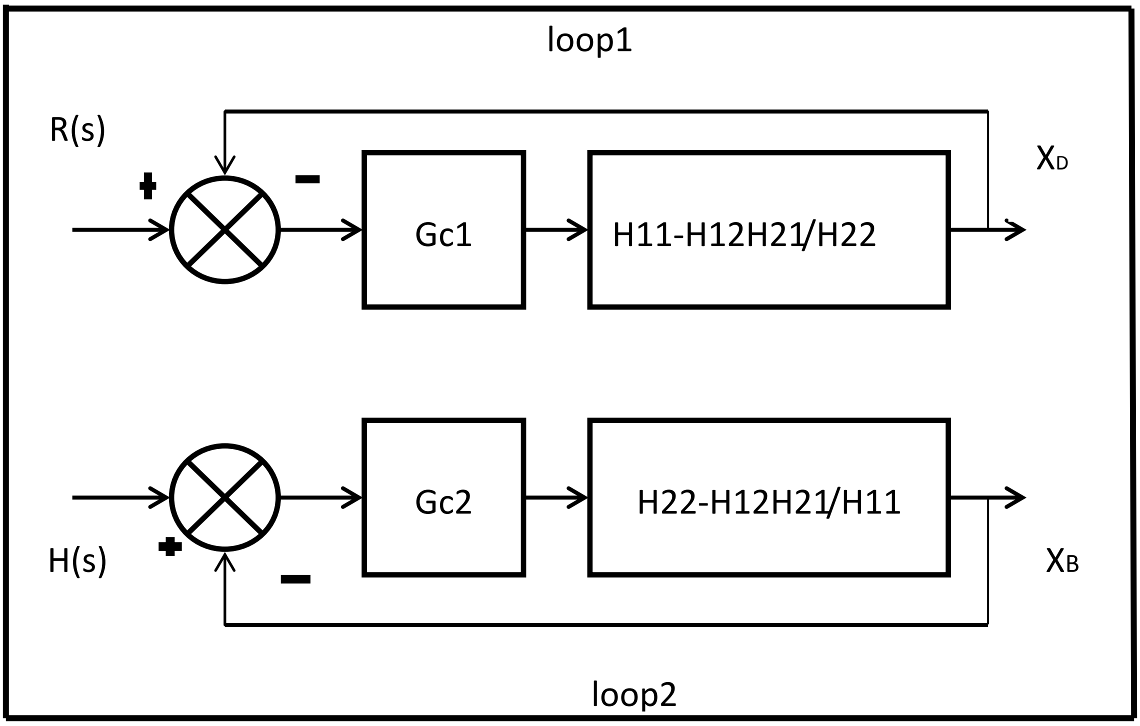


Fig (3.4): Equivalent Block diagram with Complete Decouppller

From Figure (3.4) the following two closed loop input-output relationships are developed as:

$$X_D = \frac{Gc_1[H_{11} - H_{12}H_{21}/H_{22}]}{1 + Gc_1[H_{11} - H_{12}H_{21}/H_{22}]} R_{,sp} \qquad \text{-----------} \; (3.11)$$

$$X_B = \frac{Gc_2[H_{22} - H_{12}H_{21}/H_{11}]}{1 + Gc_2[H_{22} - H_{12}H_{21}/H_{11}]} H_{,sp} \qquad \text{-----------} \; (3.12)$$

Where $R_{,sp}$ and $H_{,sp}$ are the set point value of X_D and X_B respectively G_{c1} and G_{c2} are the controller transfer functions of the first and second loops respectively. The last two equations demonstrate complete decoupling of the two loops[11, 35] .

3.4.3 Fuzzy Logic Control.

Fuzzy logic control is a control algorithm based on a linguistic control strategy, which 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 FLC system is shown in Fig. (3.5)

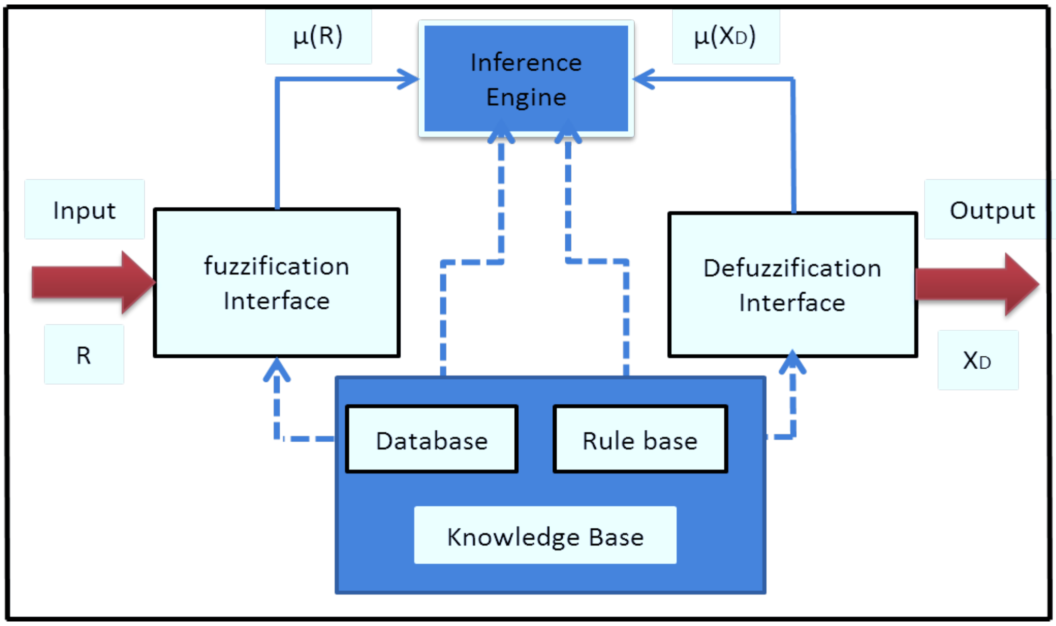


Figure (3.5) Architecture of a fuzzy logic controller

The fuzzy controller is composed of the following four elements:

- A fuzzification interface, which converts controller inputs into information that the inference mechanism can easily use to activate and apply rules. This transformation is performed using membership functions. The membership functions can take many forms including triangular, Gaussian, bell shaped, trapezoidal, etc.

- Knowledge base consists of the data base and the linguistic control rule base. The data base provides the information which is used to define the linguistic control rules and the fuzzy data manipulation in the fuzzy logic controller. The rule base defines (expert rules) specifies the control goal actions by means of a set of linguistic rules. There are three distinct classes of fuzzy models[41]:

– Fuzzy linguistic models (Mamdani models) where both the antecedent and consequent are fuzzy propositions.

– Fuzzy relational models are based on fuzzy relations and relational equations.

– Takagi — Sugeno (TS) fuzzy models where the consequent is a crisp function of the input variables

Each rule in general can be represented in the following manner:

If (antecedent) Then (consequence)

The set of fuzzy rule for FLC can be written in a table as shown in table (3.2).

Table(3.2) the set of fuzzy rules

E \ CE	N	Z	P
N	P	P	Z
Z	P	Z	N
P	Z	N	N

➢ Inference engine has the capability both of simulating human decision making based on fuzzy concepts and inferring fuzzy control actions by using fuzzy implications and fuzzy logic rules of inference. In other words, once all the monitored input variables are transformed into their respective linguistic variables, the inference engine evaluates the set of if then rules and thus a result is obtained which is again a linguistic value for the linguistic variable.

➢ A defuzzifier compiles the information provided by each of the rules and makes a decision from this basis. In linguistic fuzzy models the defuzzification converts the resulted fuzzy sets defined by the inference engine to the output of the Model to a standard crisp signal [42, 43, and 44].

3.4.4 Artificial Neural Network Control.

Neural networks have been applied successfully in the identification and control of dynamic systems. There are three popular neural network architectures for prediction and control that have been implemented in the Neural Network Toolbox software:

- Model Predictive Control
- NARMA-L2 (Non-linear Auto-regressive Moving Average) or Feedback Linearization Control
- Model Reference Control [45].

NARMA-L2 algorithm is implemented using back-propagation networks in this work

3.4.4.a Mathematical Model of a Neuron

Artificial neural networks (ANN) have been developed as generalizations of mathematical models of biological nervous systems. The basic processing elements of neural networks are called artificial neurons, or simply neurons or nodes [46].

The mathematical model of the neuron, which is usually utilized under the simulation of NNs. The neuron receives a set of input signals x_1, $x_2 \ldots x_n$ (vector X) which are usually the output signals of other neurons.

Each input signal is multiplied to a corresponding connection weight, w, and analogue of the synapse's efficiency.

In addition, the artificial neuron has a bias term, wk_0, a threshold value that has to be reached for the neuron to produce a signal. Weighted input signals come to the summation module corresponding to cell body,

where their algebraic summation is executed and the excitement level of neuron is determined:

$$a = w_0 x_{k0} + x_1 w_{k1} + x_2 w_{k2} + \text{------} + x_n w_{kn}$$

----------- *(3-13)*

$$a = x_0\, w_{k0} + \sum_{i=0}^{n} x_i w_{ki}$$

----------- *(3-14)*

The output signal of a neuron is determined by conducting the excitement Level through the function f, called activation function as in Equation (3.14) [19, 26, and 37].

$$y_k = f(a)$$

---------- *(3-15)*

Typical activation functions include sigmoidal functions, hyperbolic tangent function, sine or cosine function. So far, there are no rules for the selection of transfer function but the sigmoidal function (functions called threshold functions), is the most popular choice.

A sigmoid function is defined as $f(a) = \frac{1}{1+e^{-\beta a}}$ the output of this function is guaranteed to be in (0, 1).

Sigmoid function is used for the activation function due to some of its advantages

1. Nonlinearity makes the learning powerful.
2. Differential is possible and easy with simple equations.
3. Negative and positive value makes learning fast [24, 47].

A graphical representation of an artificial neuron is shown in fig. (3.6)

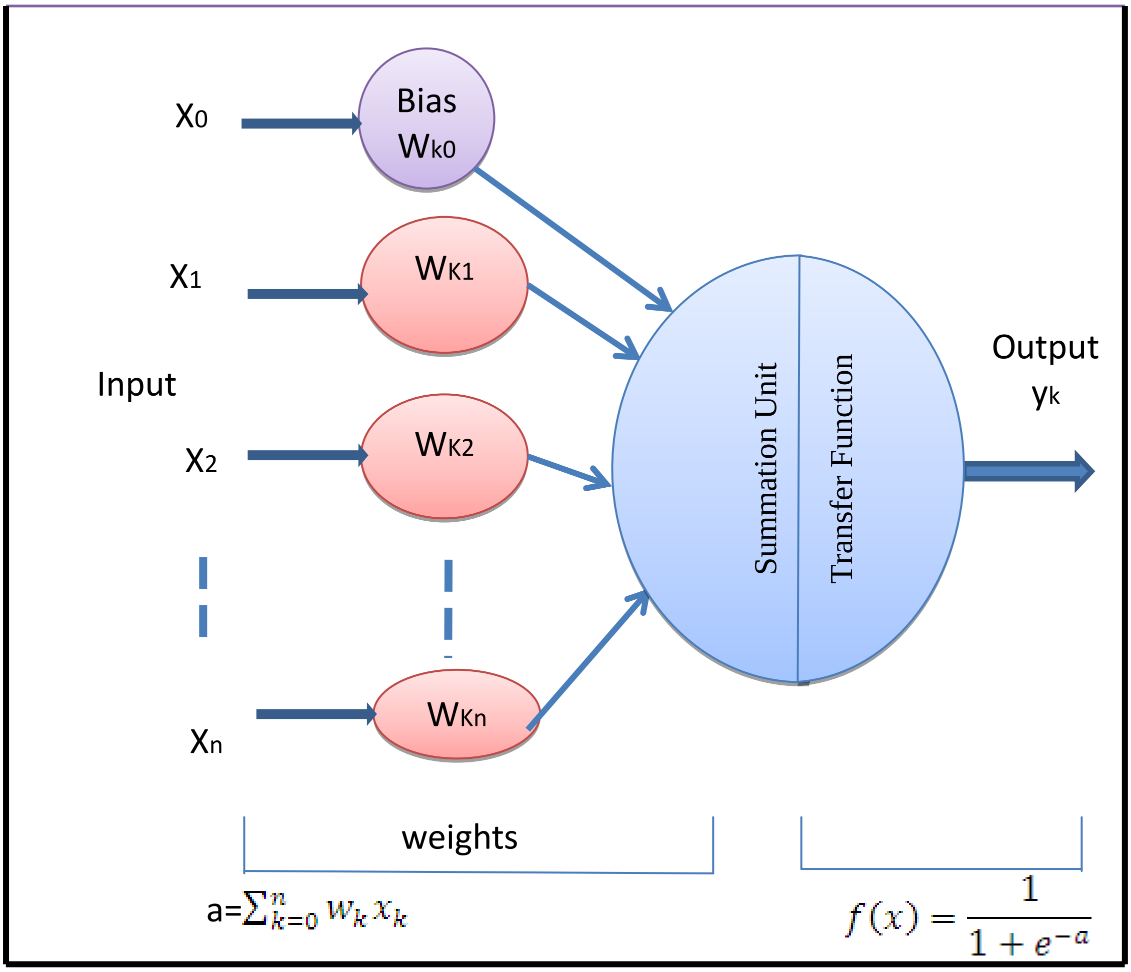


Fig (3.6) A graphical representation of an artificial neuron

Neural networks generally have at least three layers containing the artificial neurons: input, hidden (or middle), and output. Each layer in a layered network is an array of processing elements or neurons. The input layer receives an input signal, manipulates it and forwards an output signal to the hidden layer receives the weighted sum of incoming signals sent by the input units and processes it by means of an activation function. The units in the output layer receive the weighted sum of incoming signals and process it using an activation function. A common example of such a network is the Multilayer Perceptron (MLP).

3.4.4.b Back Propagation (BP) Algorithm Artificial Neural Network

Back propagation get its name from the fact that, during training, the output error is propagated backward to the connections in the previous layers, where it is used to update the connection weights in order to achieve a desired output. Typical back propagation is a gradient descent optimization method, which is executed iteratively with implicit bounds on the distance moved in the search direction in the weight space fixed via learning rate, which is equivalent to step size. The back propagation technique adjusts each variable (weight) individually according to the size along the path of the steepest descent to minimize the objective function [48].

The back propagation learning algorithm is performed in the following steps:

1. Initialize network weight values.
2. Repeat the following steps until some criterion is reached: (for each training pair).
3. Sums weighted input and apply activation function to compute output of hidden layer.

$$h_i = f\left(\sum_i X_i \, W_{ij}\right) \qquad \text{----------- (3-16)}$$

4. Sums weighted output of hidden layer and apply activation function

to compute output of output layer.

$$y_K = f\left(\sum_j h_j \, W_{jK}\right) \qquad \text{---------- (3-17)}$$

5. Compute back propagation error.

$$\delta_K = \left(d_K - y_K\right) f'\left(\sum_j h_j \, W_{jK}\right) \qquad \text{---------- (3-18)}$$

6. Calculate weight correction term.

$$\Delta W_{jK}(n) = \eta\ \delta_K h_j + \alpha\ \Delta W_{jK}(n-1) \qquad \text{---------- } (3\text{-}19)$$

7. Sums delta input for each hidden unit and calculate error term.

$$\delta_j = \sum_K \delta_K\ W_{jK}\ f'\left(\sum_i X_i\ W_{ij}\right) \qquad \text{---------- } (3\text{-}20)$$

8. Calculate weight correction term.

$$\Delta W_{ij}(n) = \eta\ \delta_j X_i + \alpha\ \Delta W_{ij}(n-1) \qquad \text{---------- } (3\text{-}21)$$

9. Update weights.

$$W_{jK}(new) = W_{jK}(old) + \Delta W_{jK} \qquad \text{---------- } (3\text{-}22)$$

$$W_{ij}(new) = W_{ij}(old) + \Delta W_{ij} \qquad \text{---------- } (3\text{-}23)$$

10. End.

Where:

ΔW_{ij} : Amount of Change Added to The Weight Connection Wij.

y_K : Output Signal of an Output Neuron (K) at Time (n).

d_K : Desired (Target) Output Neuron (K) at Time (n).

η : Learning Rate Coefficient.

h_j : Output Signal of Hidden Neuron (j) at Time (n).

δ_j : Delta Quantity for Hidden Neuron (j).

δ_K : Delta Quantity for Output Neuron (K).

α : Momentum Constant[5,14].

3.4.5 Neuro-Fuzzy Control

Neuro-Fuzzy systems allow incorporation of both numerical and linguistic data into the system. The Neuro-Fuzzy system is also capable of extracting fuzzy knowledge from numerical data [49].

There are several ways to combine neural networks and fuzzy logic Efforts at merging these two technologies may be characterized by considering three main categories: neural fuzzy systems, fuzzy neural networks and Adaptive-Neuro-Fuzzy Inference System.

3.4.5.a. Neuro- fuzzy Systems:[50]

Neuro- fuzzy systems are characterized by the use of neural networks to provide fuzzy systems with a kind of automatic tuning method, but without altering their functionality. One example of this approach would be the use of neural networks for the membership function elicitation and mapping between fuzzy sets that are utilized as fuzzy rules as shown in Fig (3.7) . In the training process, a neural network adjusts its weights in order to minimize the mean square error between the output of the network and the desired output. In this particular example, the weights of the neural network represent the parameters of the fuzzification function, fuzzy word membership function, fuzzy rule confidences and defuzzification function respectively. In this sense, the training of this neural network results in automatically adjusting the parameters of a fuzzy system and finding their Optimal values.

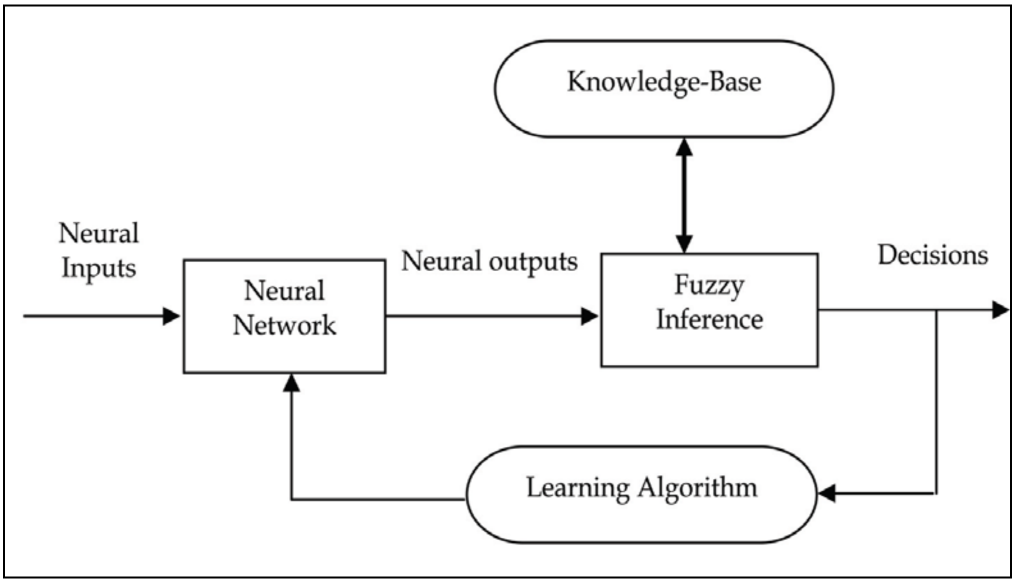


Fig (3.7) Block diagram of Neural fuzzy system

3.4.5.b. Fuzzy- neuro systems:[50]

The main goal of this approach is to 'fuzzify' some of the elements of neural networks, using fuzzy logic (Fig (3.8)). In this case, a crisp neuron can become fuzzy. Since fuzzy neural networks are inherently neural networks, they are mostly used in pattern recognition applications. In these fuzzy neurons, the inputs are non-fuzzy, but the weighting operations are replaced by membership functions. The result of each weighting operation is the membership value of the corresponding input in the fuzzy set. Also, the aggregation operation may use any aggregation operators such as min and max and any other t-norms and t-conorms.

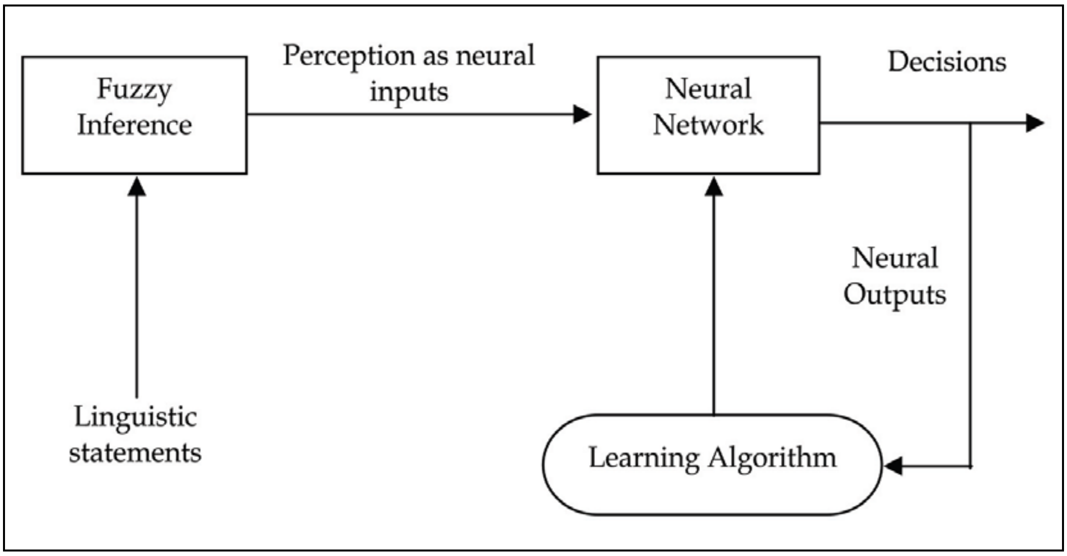


Fig (3.8) Block diagram of fuzzy neural system

3.4.5.c. 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.

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. Output variables are obtained by applying fuzzy rules to fuzzy sets of input variables [51].

Adaptive-Neuro-Fuzzy Inference System is implemented in this work.

3.4.5.c.1 Adaptive-Neuro-Fuzzy Inference System controller

ANFIS's network organizes two parts like fuzzy systems. The first part is the antecedent part and the second part is the conclusion part, which are connected to each other by rules in network form. If ANFIS in network structure is shown, that is demonstrated in five layers. It can be described as a multi-layered neural network as shown in Figure (3.16).

Where, the first layer executes a fuzzification process, the second layer executes the fuzzy AND of the antecedent part of the fuzzy rules, the third layer normalizes the Membership Functions (MF), the fourth layer executes the consequent part of the fuzzy rules, and finally the last layer computes the output of fuzzy system by summing up the outputs of layer fourth [52].

Basic ANFIS architecture that has two inputs x and y and one output z is shown in Figure 3.9. The rule base contains two Takagi-Sugeno if then rules as follows:

- **Rule1**: If X is A_1 and y is B_1, then $f_1 = p_1x + q_1y + r_1$

- **Rule2**: If X is A_2 and y is B_2, then $f_2 = p_2x + q_2y + r_2$

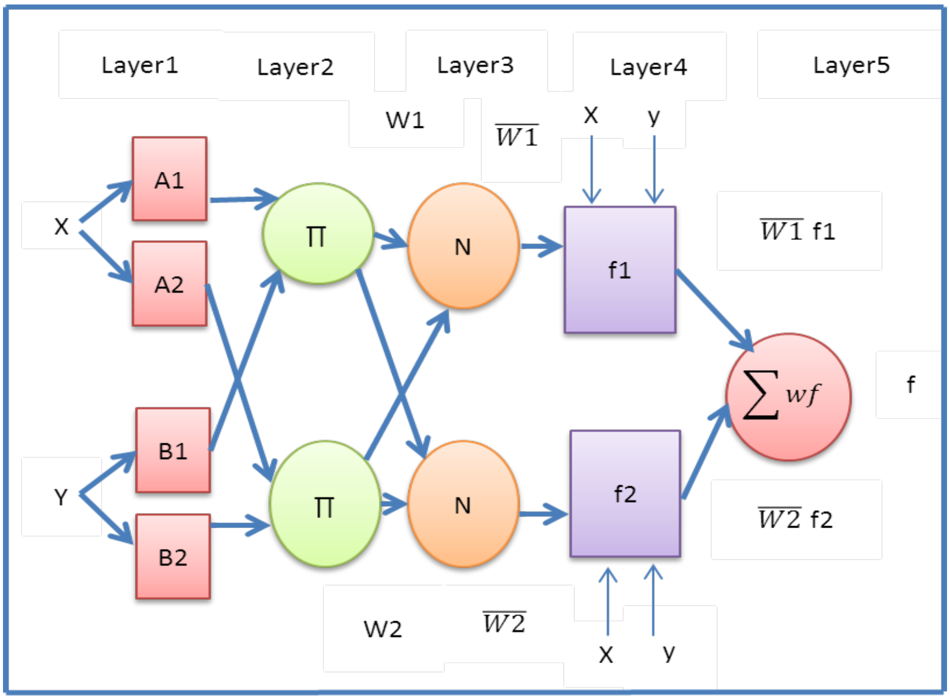


Fig (3.9) Basic structure of ANFIS

The node functions in the same layer are the same as described below [49, 52, and 53]:

Layer 1: Every node i in this layer is a square node with a node function as:

$$O_{1,i} = \mu_{Ai}(x)$$

For i=1, 2 ---------- *(3-24)*

$$O_{1,i} = \mu_{Bi-2}(y)$$

---------- *(3-25)*

Where X is the input to node i, and i A (or i–2 B) is a linguistic label (such as “small” or “large”) associated with this node. In other words, $0_{1,i}$ is the membership grade of a fuzzy set A and it specifies the degree to which the given input x satisfies the quantifier A . The membership function for A can be any appropriate membership function, such as the Triangular or Gaussian. When the parameters of membership function changes, chosen membership function varies accordingly, thus exhibiting various forms of

membership functions for a fuzzy set A . Parameters in this layer are referred to as “premise parameters”.

Layer 2: Every node in this layer is a fixed node labeled as Π, whose output is the product of all incoming signals:

$$O_{2i}=w_i=\mu_{Ai}(x)\mu_{Bi-2}(y)$$

i=1, 2 --------- *(3-26)*

Each node output represents the firing strength of a fuzzy rule.

Layer 3: Every node in this layer is a fixed node labeled N. The ith node calculates the ratio of the rule’s firing strength to the sum of all rules’ firing strengths:

$$O_{3i} = \overline{w_i} = \frac{w_i}{w_1 + w_2}$$ ---------- *(3-27)*

Outputs of this layer are called “normalized firing strengths”.

Layer 4: Every node i in this layer is an adaptive node with a node function as:

$$O_{4i}=\overline{w_i}f_i=\overline{w_i}\ \ (p_i x + q_i y + r_i)$$

----------- *(3-28)*

Where $\overline{W_i}$ is a normalized firing strength from layer 3 and (p_i, q_i, r_i) is the parameter set of this node. Parameters in this layer are referred to as Consequent parameters.

Layer 5: The single node in this layer is a fixed node labeled Σ that computes the overall output as the summation of all incoming signals:

$$O_{5i}=\sum \overline{w_i}f_i = \frac{\sum_i w_i f_i}{\sum_i w_i}$$

---------- *(3-29)*

Thus an adaptive network, which is functionally equivalent to the Takagi- Sugeno type fuzzy inference system, has been constructed.

3.4.5. C.2 Adaptive Neuro-Fuzzy Inference System Learning Algorithm: [45].

From the proposed ANFIS architecture above, the output can be defined as:

$$O_{4i}=\overline{w_i}f_i=\overline{w_i}\;\;(p_i x + q_i y + r_i)$$

---------- *(3-30)*

Where p, q, r are the linear consequent parameters. The methods for updating the parameters are listed as below:

1. Gradient decent only: All parameters are updated by gradient decent back propagation.
2. Gradient decent and One pass of Least Square Estimates (LSE): The LSE is applied only once at the very beginning to get the initial values of the consequent parameters and then the gradient descent takes over to update all parameters.
3. Gradient and LSE: This is the hybrid learning rule. Since the hybrid learning approach converges much faster by reducing search space dimensions than the original back propagation method, it is more desirable. In the forward pass of the hybrid learning, node outputs go forward until layer 4 and the consequent parameters are identified with the least square method. In the backward pass, the error rates propagate backward and the premise parameters are updated by gradient descent. This method is implemented in this work because give smaller error than other mthods.

Chapter Four

Results and Discussion

4.1 Introduction

This chapter presents the results obtained from the computer programs using MATLAB program version 7.80 cited in appendix (C) for dynamic model and control.

The first part of this chapter 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

4.2 Open loop process

The results of the transient response based on open loop system are shown in Figure (4.1) 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) .

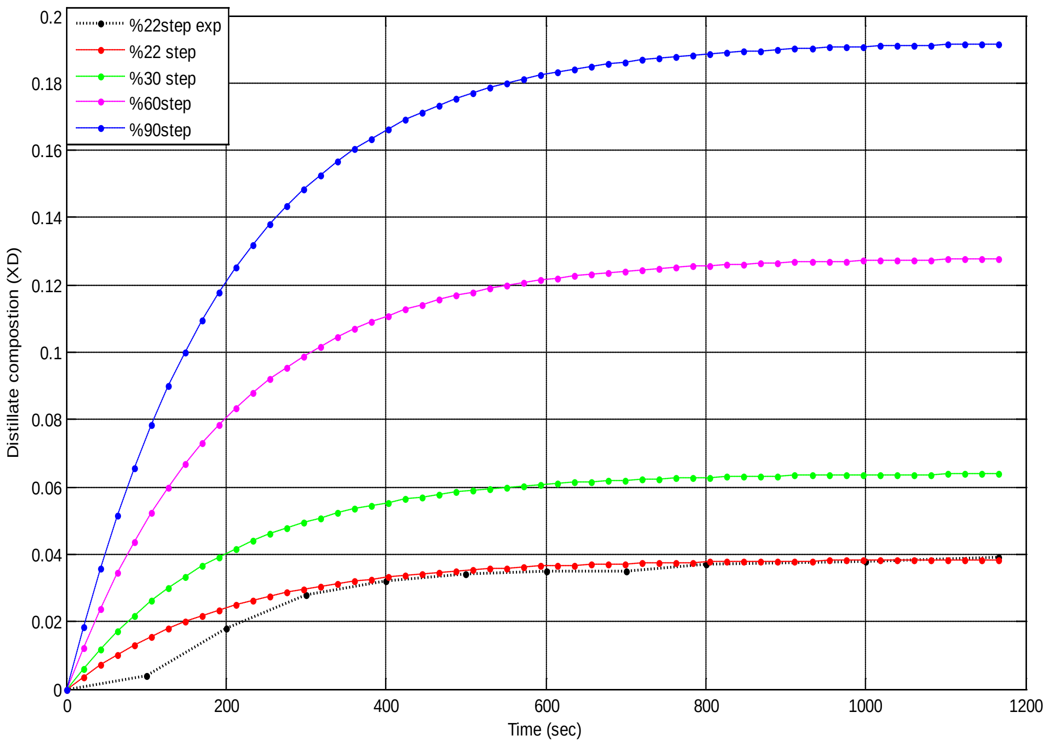


Fig (4.1.a) Effect of reflux ratio on distillate composition for different step change) .The second

part s trol

strateg

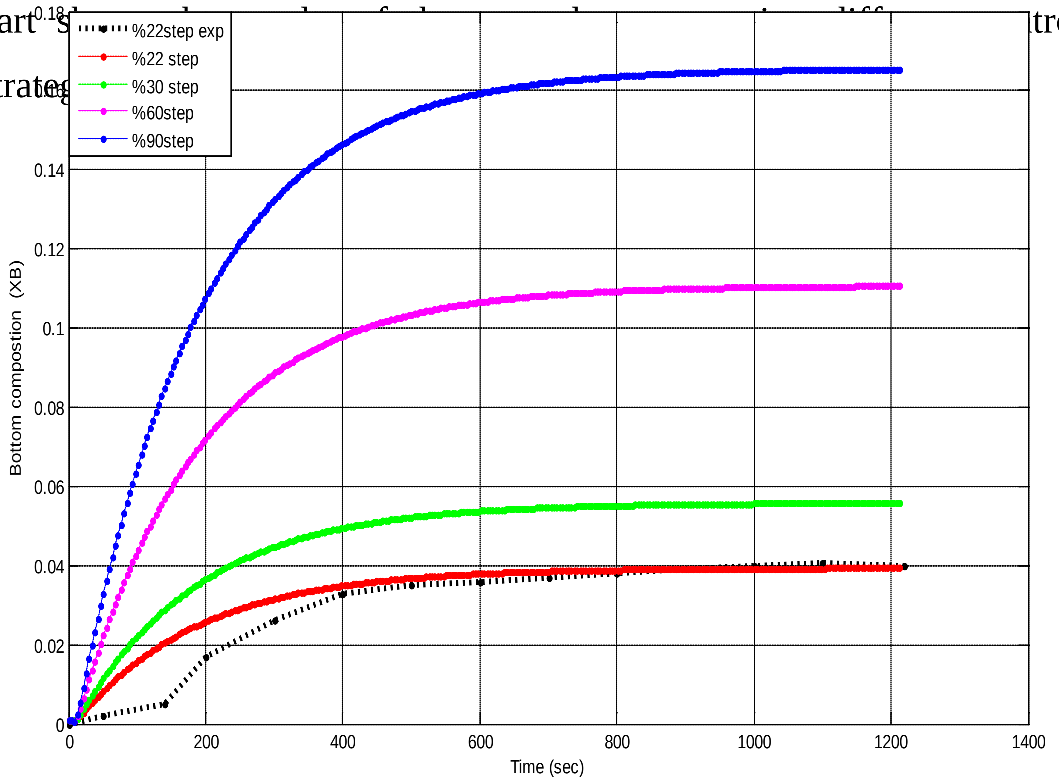


Fig (4.1.b) Effect of heat duty on distillate composition for different step change

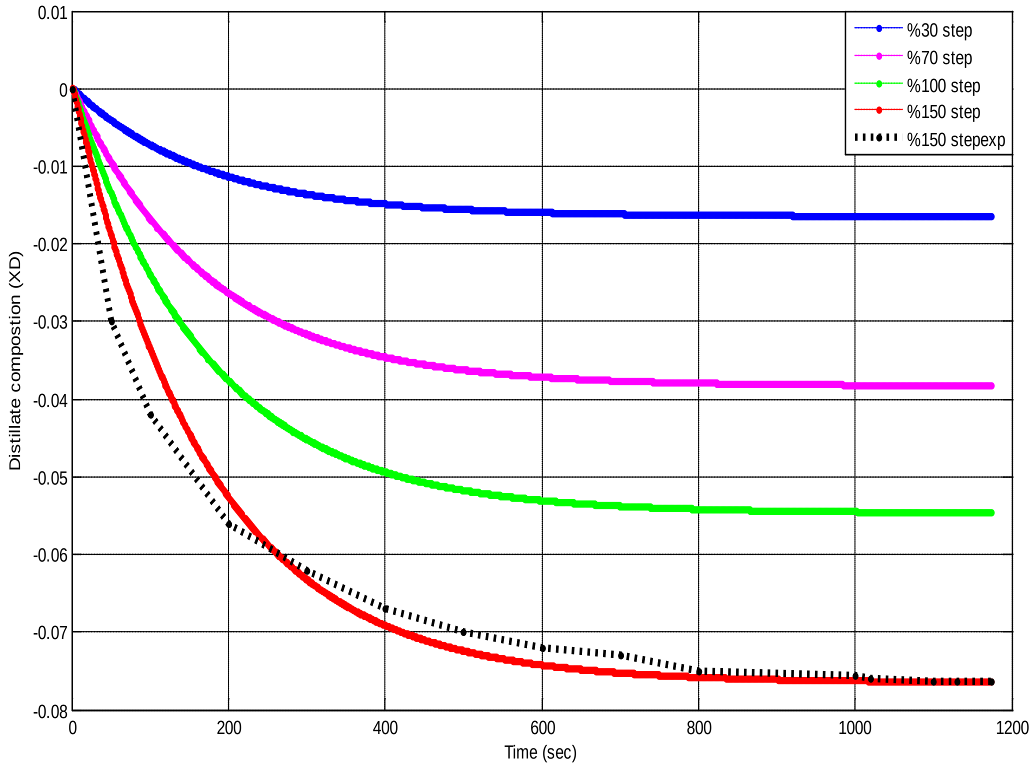


Fig (4.1.c) Effect of reflux on bottom composition for different step change

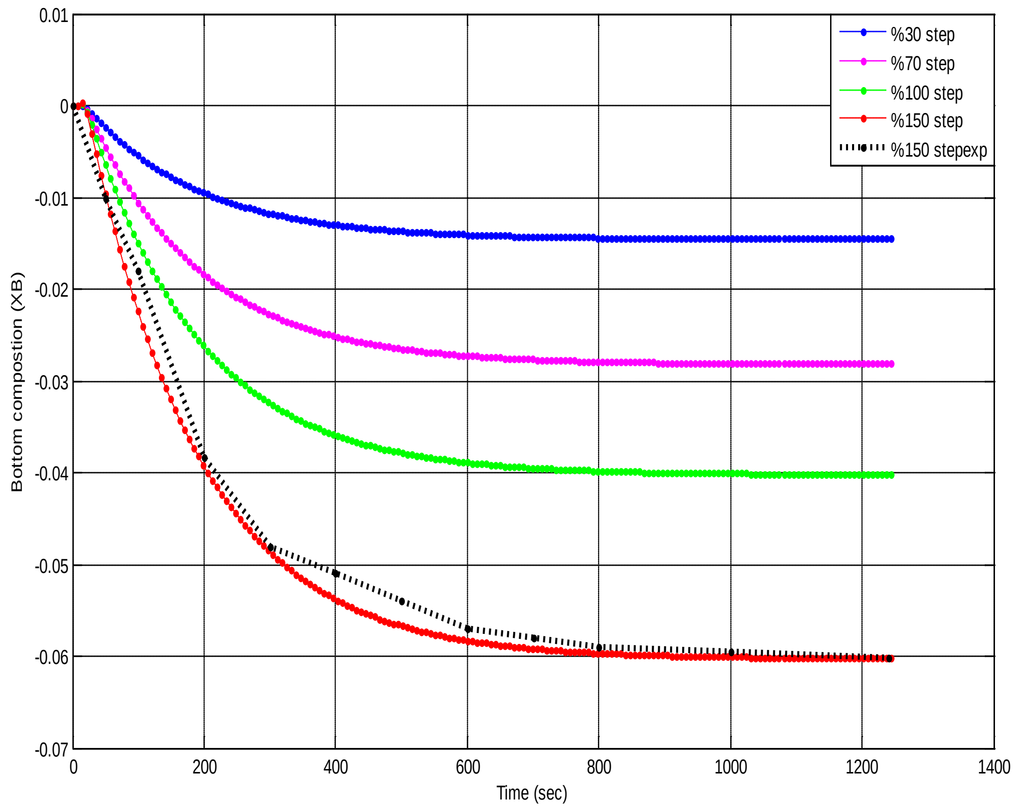


Fig (4.1.d) Effect of heat duty on bottom composition for different step change

Figure (4.1.a) shows the response of distillate composition (X_D) for different step changes on reflux flow rate (R). The results show that distillate composition (X_D) increases with increasing reflux flow rate (R) and then reaches the steady state value. This is because the liquid hold up and the contact time between liquid and vapor is increased.

Figure (4.1.b) shows the response of the distillate composition (X_D) with different step change on reboiler heat duty (H). The result shows that the distillate composition (X_D) decreases with increasing reboiler heat duty (H), and then reaches the new steady state value.

Figure (4.1.c) shows the response of bottom composition (X_B) for different step change on reflux flow rate (R). The results show that bottom composition (X_B) increases with increasing reflux flow rate (R), and then reaches the steady state value.

Figure (4.1.d) shows the response of bottom composition (X_B) via different step change on reboiler heat duty (H). The result shows that bottom composition (X_B) decrease with increasing reboiler heat duty (H).

A 30% step change is taken in order to study the Control Strategies in this work, due to less non linearity, less variation between the manipulated and controlled the variables.

The transfer function for the distillation column at 30% given below is:

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

4.3 Closed Loop System

4.3.1 Interactions of the Control Loops:

Whenever a single manipulated variable can significantly affect two or more controlled variables, the variables are said to be coupled and there is interaction between loops, this interaction can be troublesome.

The following figures (4.2) show the response of the interaction between loops when applying PID controller on the system.

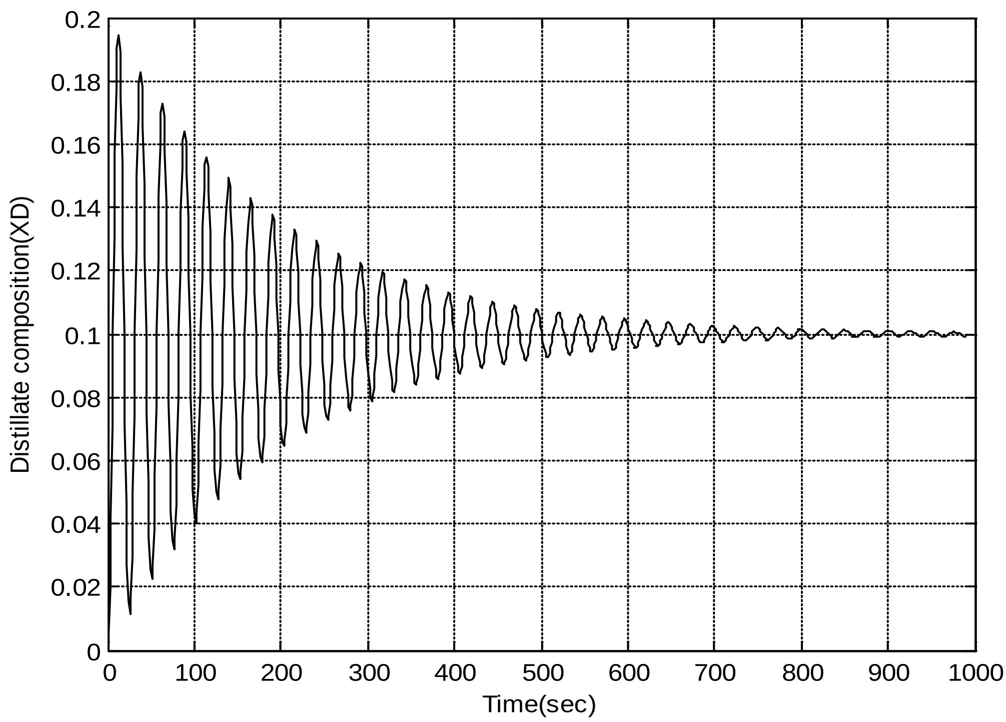


Fig (4.2.a) Transient response of distillate composition with respect to reflux flow rate with interaction effect

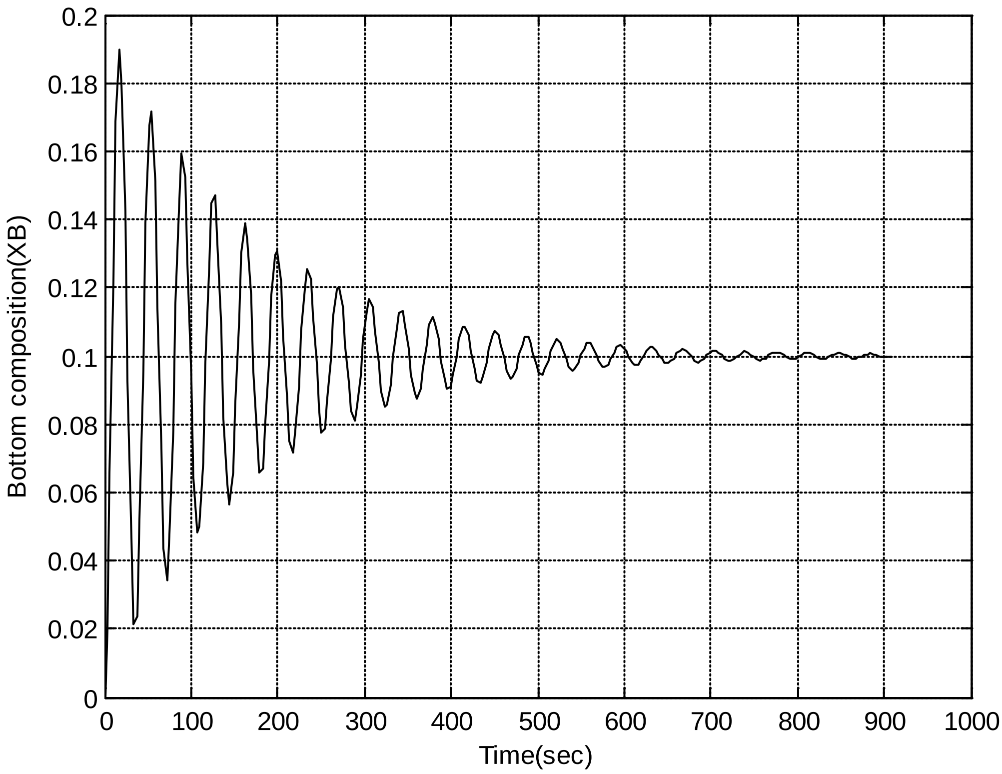


Fig (4.2.b) Transient response of bottom composition with respect to reboiler heat duty with interaction effect

4.3.2 Relative Gain Array (RGA) Calculations:

RGA must be calculated to choose the best pairing of the two controlled variables (X_D and X_B) and the two manipulated variables (R and H) before applying the control techniques. In this work, the results of RGA calculation were obtained by using computer simulation program MATLAB. The resulted array is given as:

$$\text{RGA}= \begin{array}{cc} R & H \\ \end{array}$$

$$\text{RGA}= \begin{bmatrix} \lambda_{11} & \lambda_{12} \\ \lambda_{21} & \lambda_{22} \end{bmatrix} \begin{matrix} X_D \\ X_B \end{matrix} = \begin{bmatrix} 3.606 & -2.606 \\ -2.606 & 3.606 \end{bmatrix}$$

Therefor the best coupling are obtained by pairing the distillate composition (X_D)with the reflux flow rate(R), and the bottom composition (X_B) with the reboiler heat duty(H), since λ_{11i} has the largest positive number of the array.In this case, the interaction is very dangerous, when λ_{12} and λ_{21}

4.3.3Decoupler design:

The decoupler of loop1 (D_1) was designed to eliminate the effect of interaction of loop2 on loop1 by using equation (3.a10) .On substitution the values; the decoupler shows the following value:

$$D_1 = \frac{3.809s + 0.01656}{10.68s + 0.061}$$

The value of D_1 is coupled with the value of the reflux flow rate (R) to get the non-interacted final value.

In the same way, the decoupler of loop2 (D_2) was designed to eliminate the effect of interaction of loop1 on loop2 by using equation (3.b10).

$$D_2 = \frac{9.45s + 0.0525}{2.66s + 0.0103}$$

The decoupler was obtained to justify the reboiler heat duty.

4.4 Control Strategies:

In this work, different control strategies used: conventional feedback controls (PI, PID), ANN control, classical FL control, adaptive fuzzy logic control, PID fuzzy logic control and adaptive neuro-fuzzy Inference system (ANFIS).

4.4.1Conventional 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), Frequency Curve Method (Z.N), and Process Reaction Curve (PRC) methods.The optimum values of the controller parameters (k_c, $\tau_{I,}$ τ_D) were tuned by using computer simulation programs based on minimum integral of the

time-weighted absolute error (ITAE). The Matlab code is listed in appendix (C).To evaluate the performance of the PI and PID controllers, the two parameters of the step response and the parameters overshoot, and settling time were implemented.

4.4.1.2 Results of control tunings:

- Distillate composition:

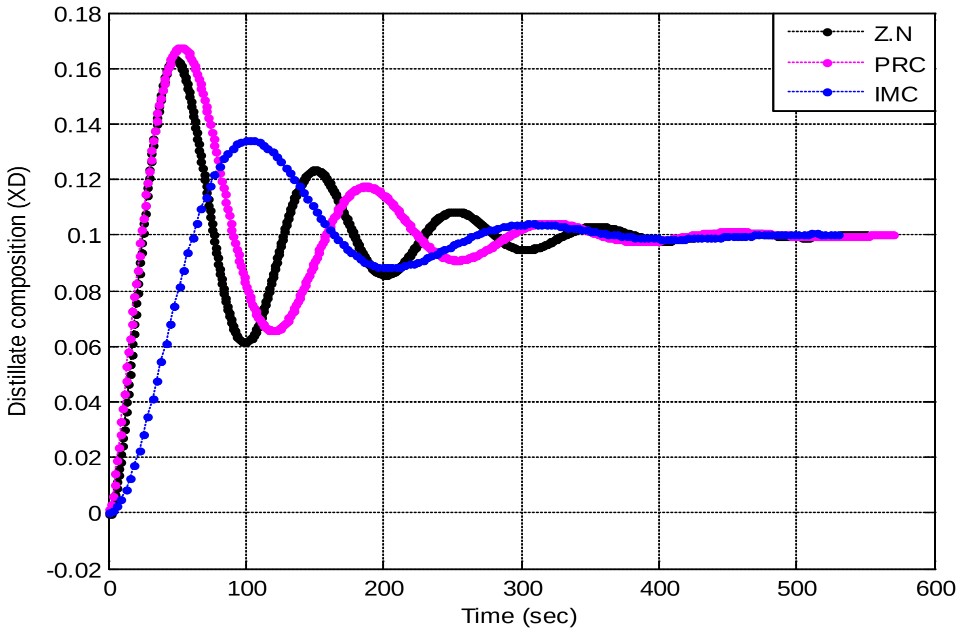


Fig (4.3.a) Transient response for PI controller of distillate composition with respect to reflux flow rat

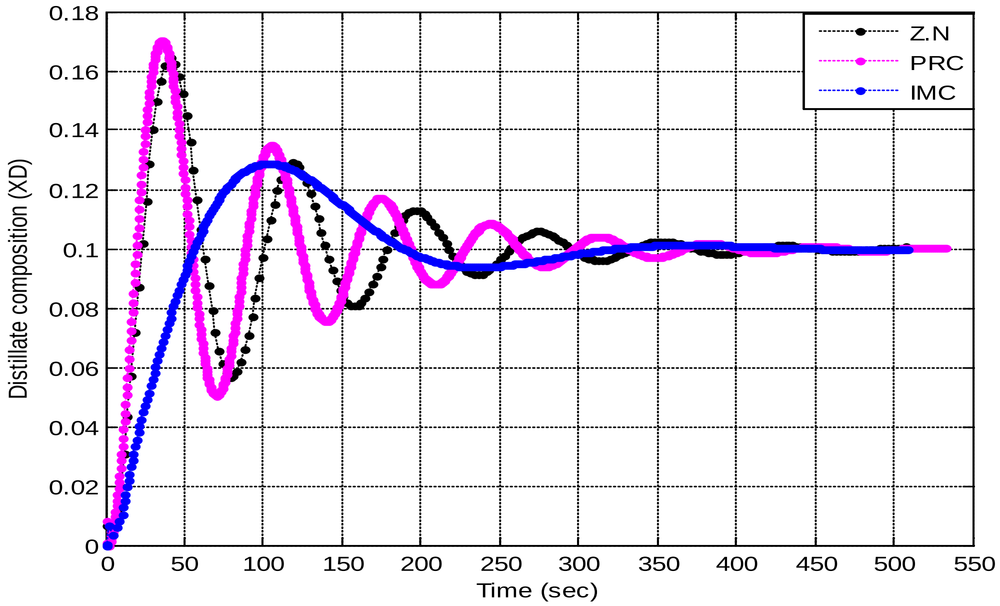


Fig (4.3.b) Transient response for PID controller of distillate composition with respect to reflux flow rate

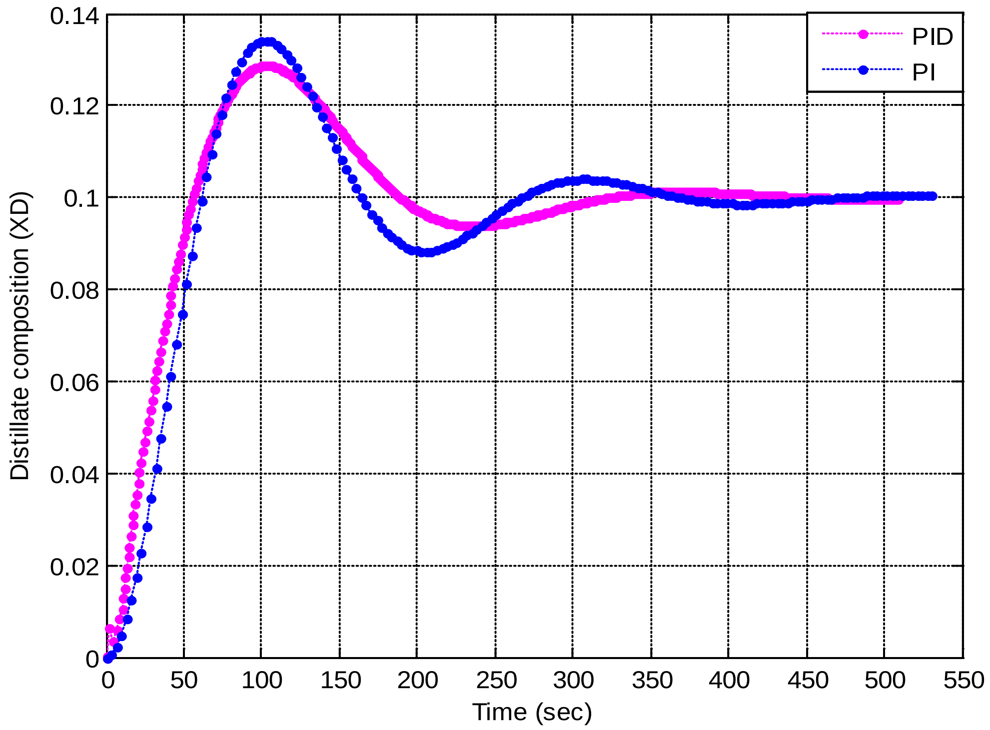


Fig (4.3.c) comparison between the transient response for PI and PID controllers of distillate composition with respect to reflux flow rate

Figure (4.3.a), (4.3.b), (4.4.a) and (4.4.b) show the control responses for PI and PID modes for three different criteria's. As shown in the figures, it is clear that the overshoot and settling time of IMC are less than of Z-N and PRC methods for both PI and PID modes for distillate and bottom composition.

Figure (4.3.c) and (4.4.c) show the comparison between two control modes. It is clear that PID mode gave better response which is clear through the lower values of the overshoot and response time.

Tables (4.1.a),(4.1.b),(4.2.a) and (4.2.b) show that the control tuning was found in three different methods therefore; it can be seen that the tuning by using the Internal Model Control tuning method is better than other methods .ITAE values of IMC are less than that of the Z-N and PRC methods ,In this work, the ITAE is implemented because it uses the time to determine its value which states the faster criteria to reach the new steady-state value.

Tables (4.1.c) and (4.2.c) show clearly that the PID controller is better than the PI controller because it gives smaller overshoot and settling time values than that of PI controller.

It is clear that the PID and the (IMC) mode give better response; this is shown clearly through the lower values of the overshoot and the response time. Therefore the PID (IMC) controller is used in this work as a feedback mode for comparison with the other modes.

Table (4.1.a) Control parameters of PI for distillate composition control.

Control tuning methods	**Controller parameters**			***ITAE***
	K_c	τ_I	τ_D	
Internal Model Control tuning	7.261	6.1	_	590.8
Ziegler-Nichols tuning	12.82	1.0514	_	666.06
Cohen-Coon tuning	10.9	1.725	_	716.5

Table (4.1.b) Control parameters of PID for distillate composition control.

Control tuning methods	**Controller parameters**			***ITAE***
	K_c	τ_I	τ_D	
Internal Model Control tuning	10.909	6.415	.2995	474.4
Ziegler-Nichols tuning	18.67	.63	0.1577	575.5
Cohen-Coon tuning	16	1.4863	.22495	607.2

Table (4.1.c) Comparison between of PI(IMC) and PID(IMC) for distillate composition controllers.

Parameters	PI(IMC) controller	PID(IMC) controller
Overshoot	.3423	.2878
Settling time	302	270

- Bottom composition:

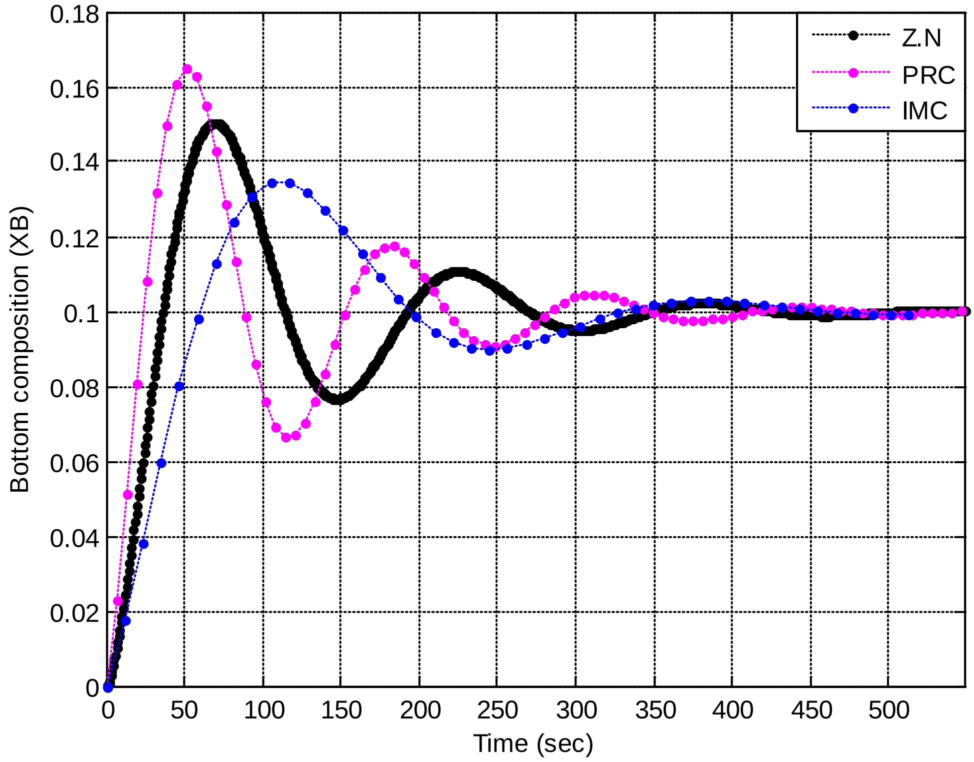


Fig (a) Transient response for PI controller of bottom composition with respect to reboiler heat duty

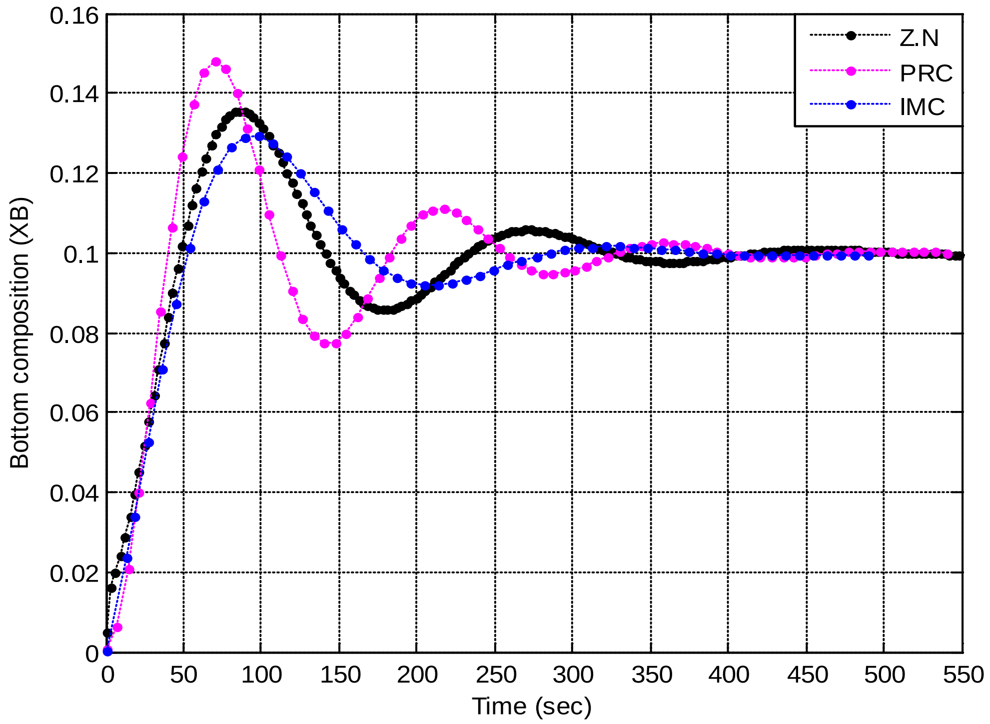


Fig (b) Transient response for PID controller of bottom composition with respect to reboiler heat duty

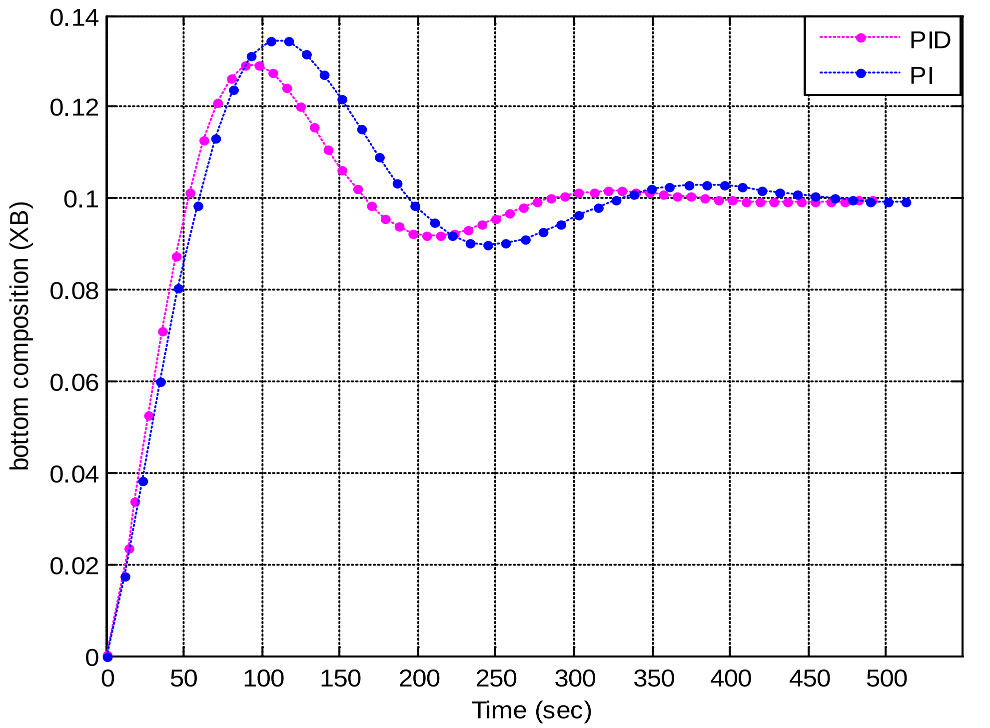


Fig (4.4.c) comparison between the transient response for PI and PID controllers of bottom composition with respect to reboiler heat duty

Table (4.2.a) Control parameters of PI for bottom composition control.

Control tuning methods	Controller parameters			*ITAE*
	K_c	τ_I	τ_D	
Internal Model Control tuning	8.035	1.5	_	557.3
Ziegler-Nichols tuning	19.695	.5011	_	676.2
Cohen-Coon tuning	12.5	1.5	_	557.3

Table (4.2.b) Control parameters of PID for bottom composition control.

Control tuning methods	Controller parameters			*ITAE*
	K_c	τ_I	τ_D	
Internal Model Control tuning	12.244	1.6	0.0938	435.7
Ziegler-Nichols tuning	19.6623	.1899	.0474	551.3
Cohen-Coon tuning	18.3	.4664	0.071	594.6

Table (4.2.c) Comparison between PI and PID for bottom composition controllers.

Parameters	PI(IMC) controller	PID(IMC) controller
Overshoot	.3137	.2922
Settling time	290	249

4.4.1.3 Comparison between the Interaction and the decoupler of Feedback Control:

The comparison between the transient response for PID and PID decoupler controller for distillate composition and bottom composition are

Shown in Figure (4.5.a) and (4.5.b). The comparison between the transient response for PID and PID decoupler controller for distillate and bottom composition, show clearly that the decoupling system is better than the interaction system as well as the overshoot and the settling time are shorter.

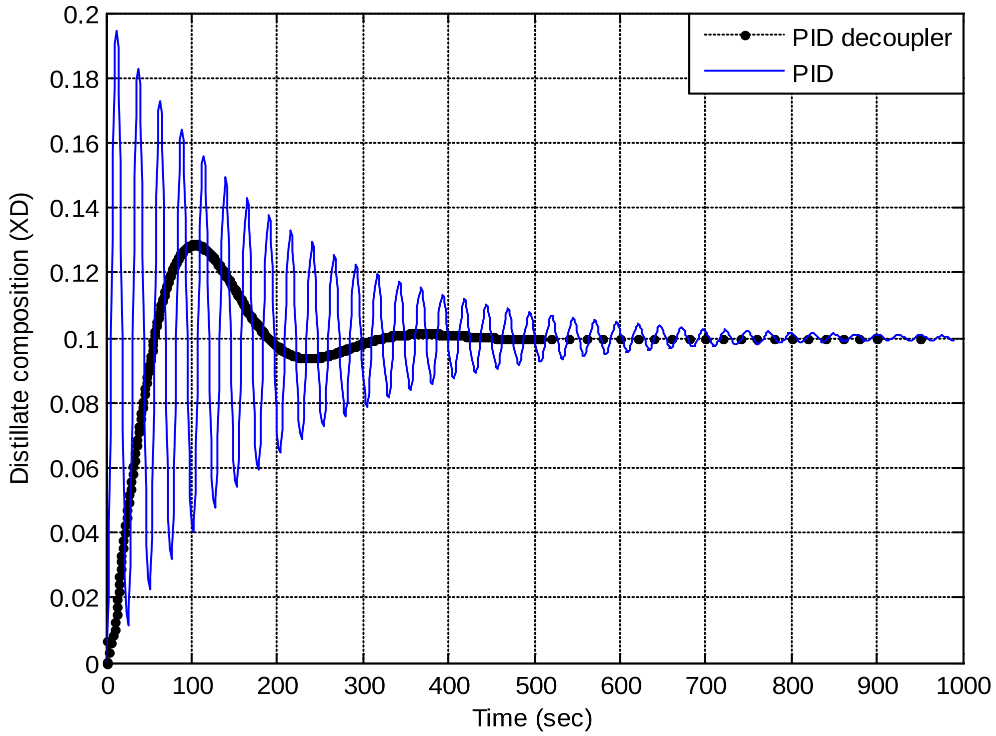


Fig (4.5.a) Transient response for PID and PID decoupler controller for distillate composition

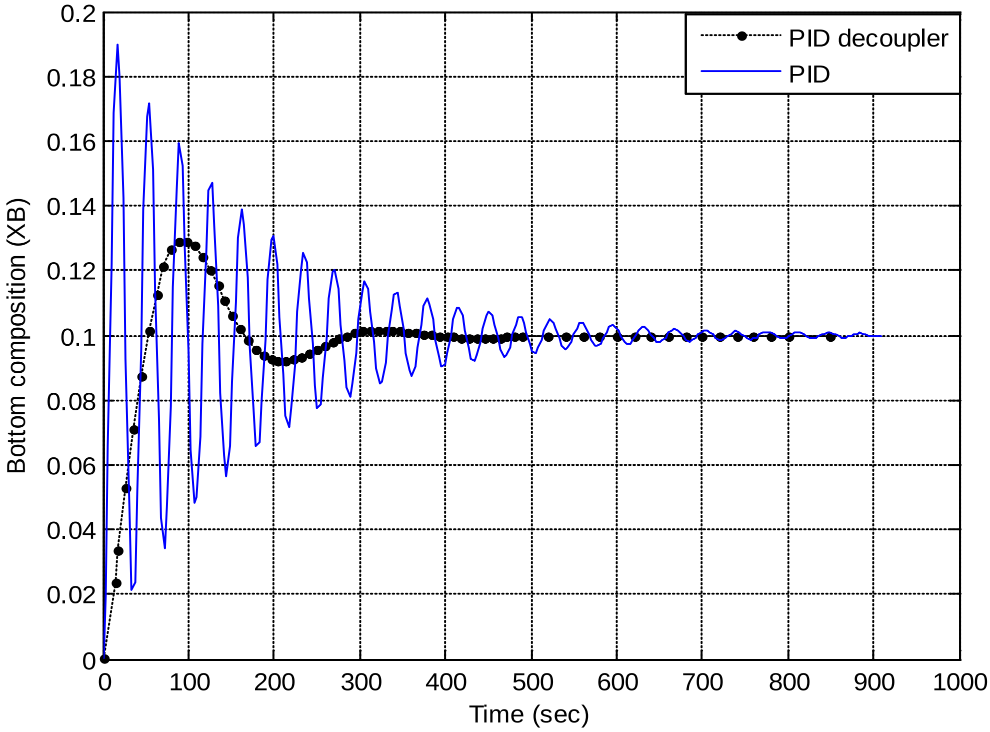


Fig (4.5.b) Transient response for PID and PID decoupler controller for bottom composition

Figure (4.5.a) and (4.5.b) show good decoupling controller to eliminate the strong interactions and cancels the effect of the distillate composition to the change of the bottom composition and the effect of the bottom composition by the distillate composition.

4.4.2 Fuzzy Logic Controller:

The control tuning of the FLC controller depends on the trial and error in order to find the scaled factors for each variable. The main difficulties of implementing this FL C is the number of tuning parameters: the scaled factors for each variable, the membership functions and the rules. The best values of the scaled factors were tuned using Simulink program as shown in figure (4.6).

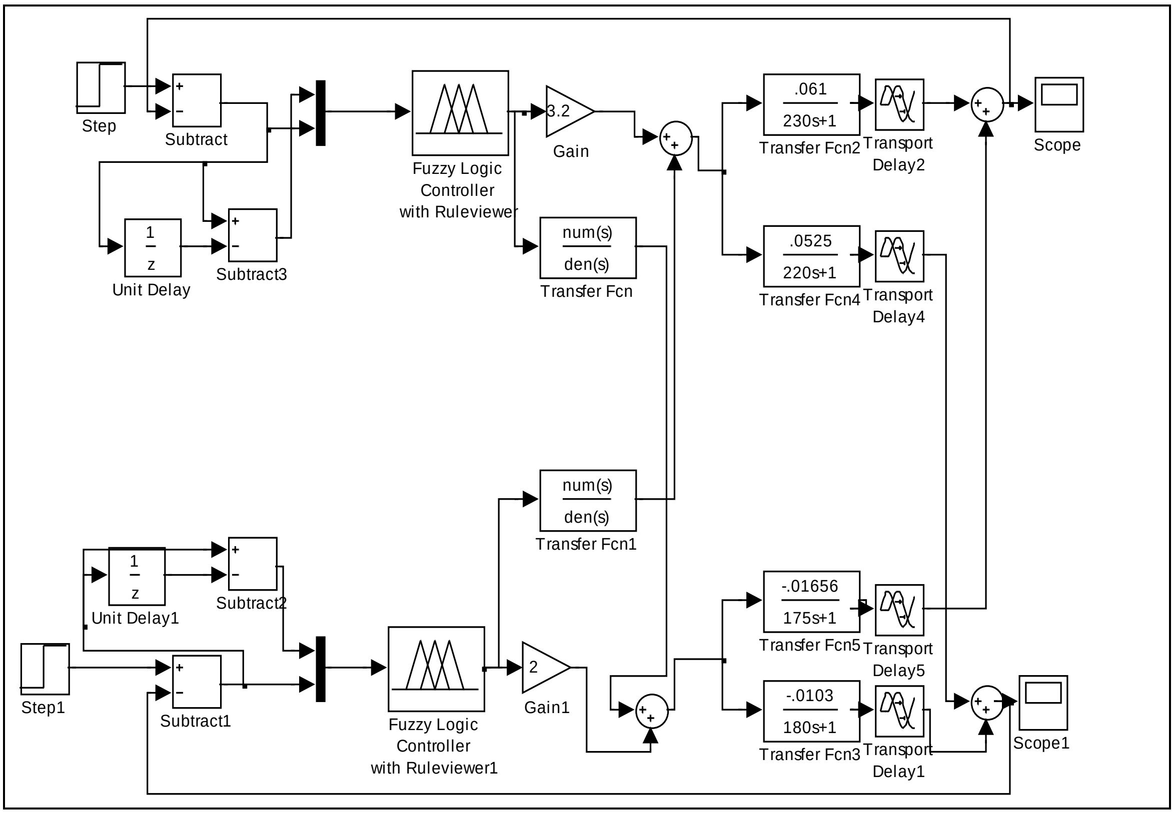


Fig (4.6) Block diagram of FLC

For the FLC, the input variables are error (*E*), the change of error (*CE*), and the output variable is the control action (*u*).

Gaussian membership functions are used for input variables simulations while for the output variable the triangular membership function was used. The universe of discourse of error, delta error and output for distillate composition are [-20, 20], [-2, 2] and [-80, 80] respectively and bottom composition are [-20, 20], [-2, 2] and [-100, 100] respectively. The universe of discourse of error, delta error and output of the fuzzy controller depends on the trial and error to find the best values by using simulink program.

The membership function for the error and the change of error consist of negative big (NB), negative small (NS), zero (Z), positive small (Ps) and positive big (PB). Meanwhile, membership function for the control action consist of negative big (NB), negative small (NS), zero (Z),

positive small (PS) and positive big (PB). The complete set of classical FLC control rules are given in table (4.3).

Table (4.3) IF-THEN rule base for 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

The table is read in the following way:

IF *E* is PB AND *CE* is NB THEN *u* is Z.

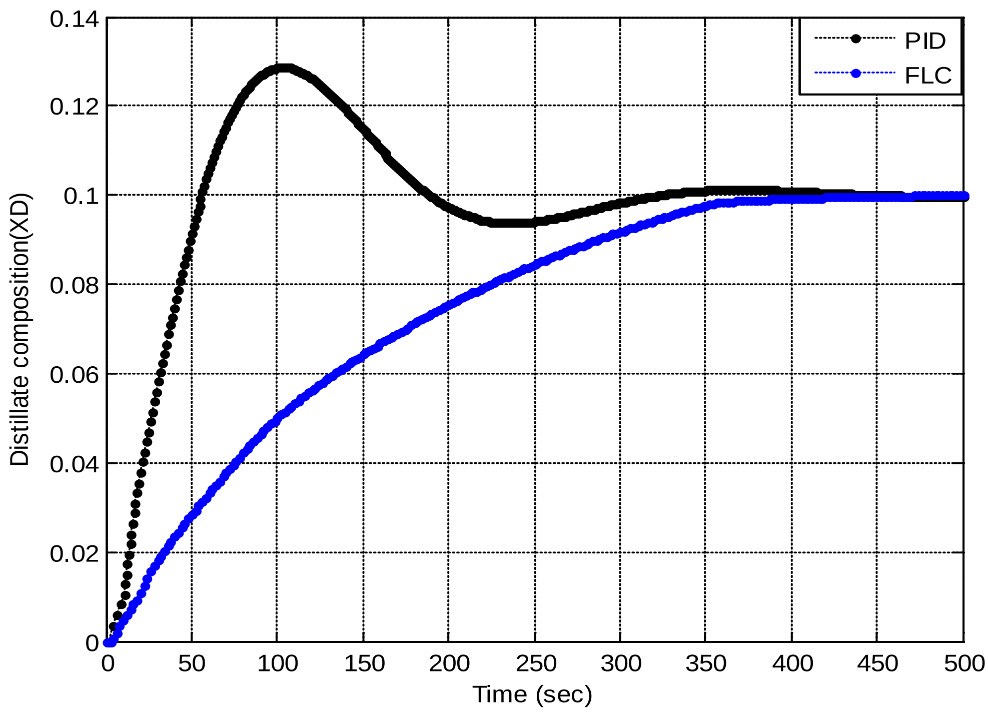


Fig (4.7) Comparison between the transient response for PID(IMC) and fuzzy controllers of distillate composition with respect to reflux flow rate

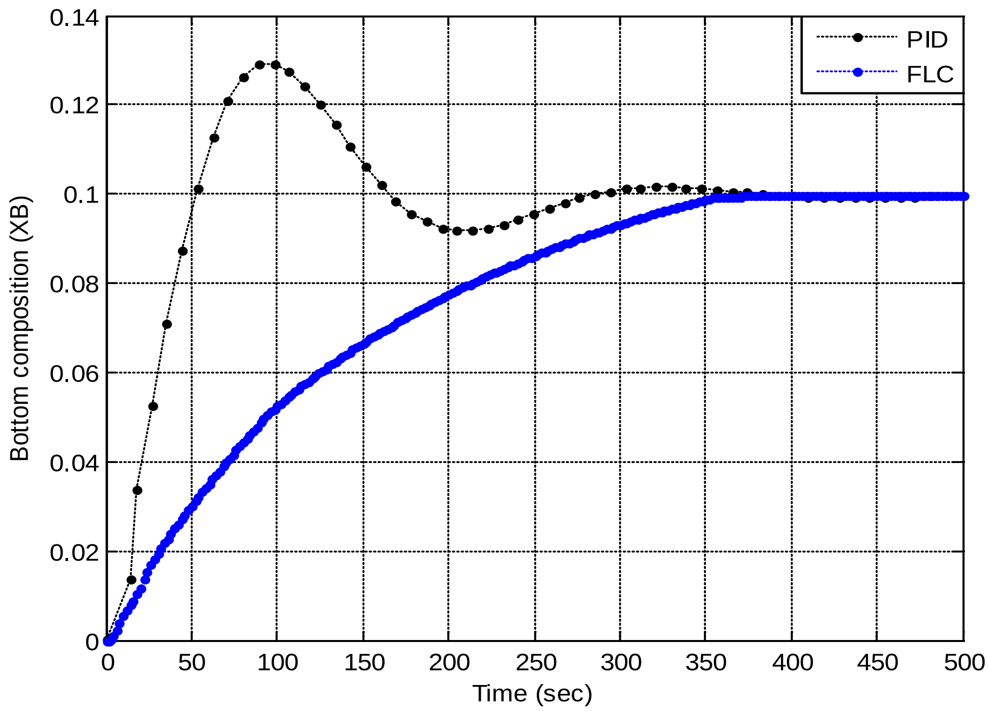


Fig (4.8) Comparison between the transient response for PID (IMC) and fuzzy controllers of bottom composition with respect to reboiler heat duty

Table (4.4) Comparison between the performance of fuzzy controller and PID(IMC) controller of distillate and bottom compositions.

Parameters	**FLC(X_D)**	**PID(X_D)**	**FLC(X_B)**	**PID(X_B)**
ITAE	1341.4	474.4	1230	435.7
Overshoot	.003	.2878	.011	.2922
Settling time	332	270	312	249

The comparison between the transient response for PID(IMC) and FLC for distillate composition and bottom composition are shown in Figure (4.7) and (4.8).

Figure (4.7), (4.8) and table (4.4) show clearly that the PID(IMC) controller performs better results when compared with fuzzy controller, except that the overshoot is lower in the fuzzy control.

When comparing the ITAE and settling time of both controllers, the PID(IMC) controller performs better due to the trial and error depending on fuzzy controller tuning process and decoupler process. Also there are several reasons that make the PID(IMC) controller better than fuzzy controller:

• The fuzzy controller is generally nonlinear. It does not have a simple equation like the PID, and it is more difficult to analyze mathematically; where approximations are required.

• The fuzzy controller has more tuning parameters than the PID controller. Furthermore, it is difficult to trace the data flow during execution, which makes error correction more difficult.

4.4.3 PID Fuzzy Controller:

The design for classical fuzzy controller is still considered premature in general, significant progress has been gained recently in the pursuit of this technology and 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 .The fuzzy controller structure can be classified into different types, and the most popular one is PID fuzzy controller. The control tuning of the PID fuzzy controller depends on the trial and error to find the scaled factors for each variable. The best values of the scaled factors were tuned using Simulink program as shown in figure (4.9).

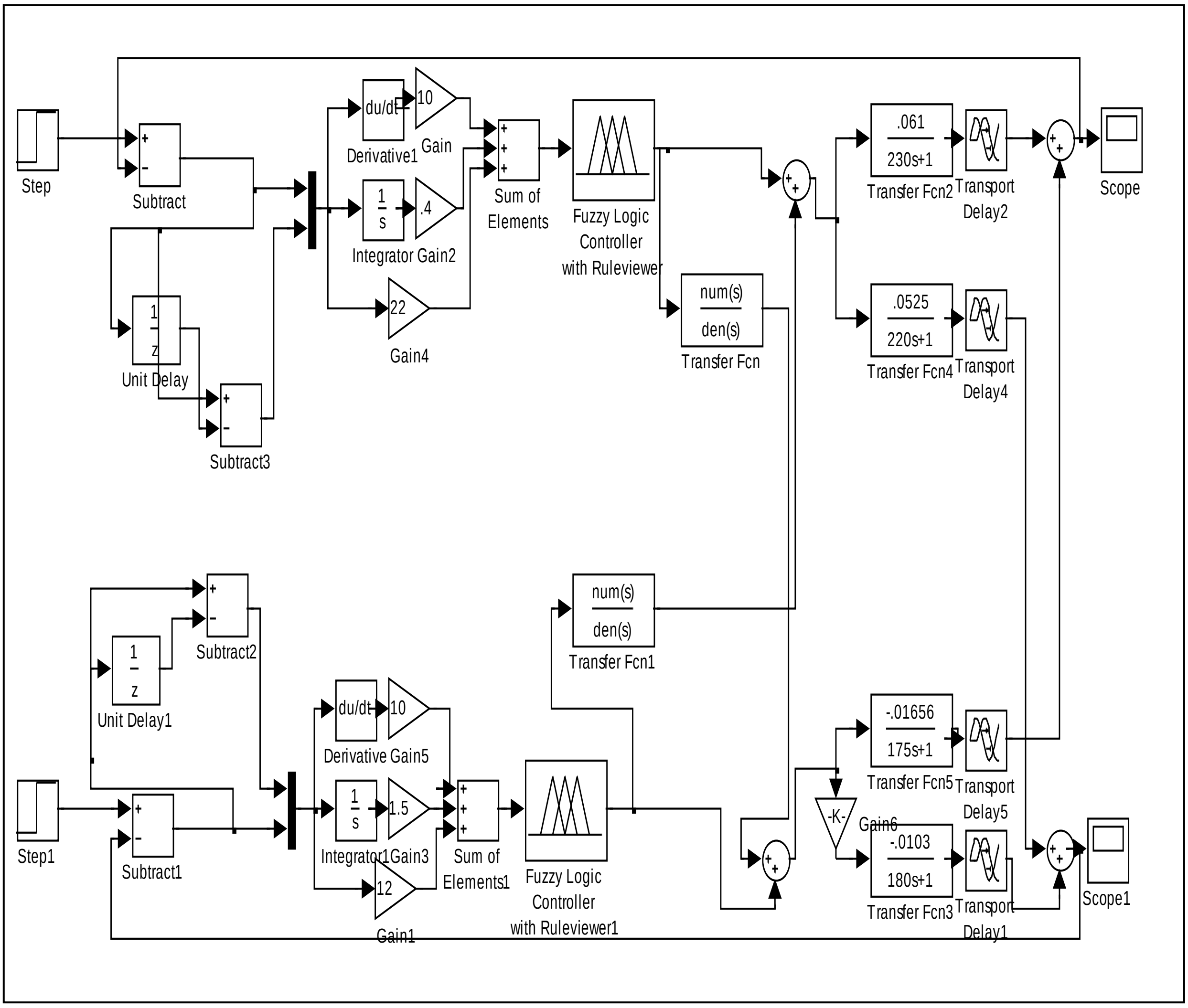


Fig (4.9) Block diagram of PID fuzzy controller

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).

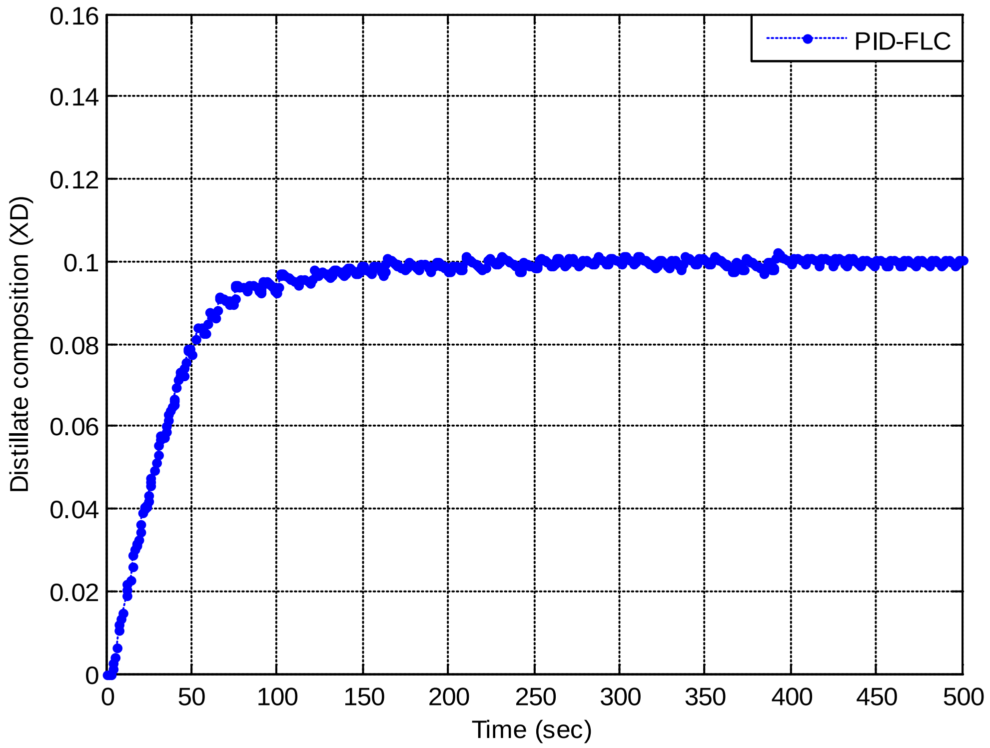


Fig (4.10) Transient response of distillate composition with respect to reflux flow rate in PID-FLC

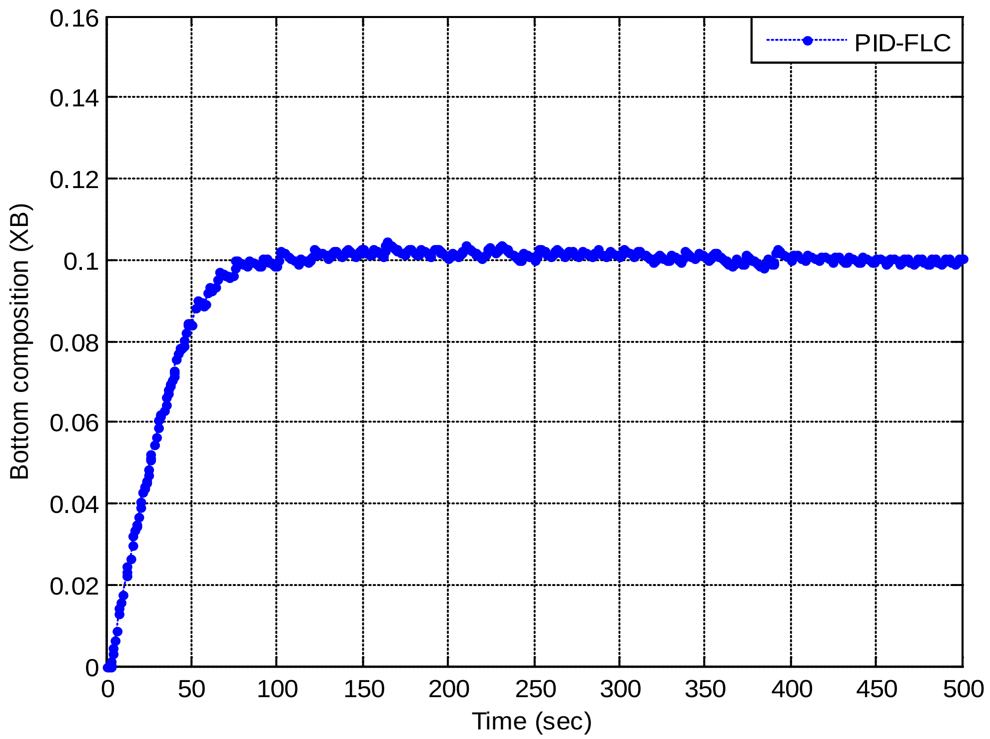


Fig (4.11) Transient response of bottom composition with respect to reboiler heat duty in PID-FLC

Table (4.5) ITAE value and different parameters in PID fuzzy controller of distillate and bottom compositions.

Parameters	PID fuzzy controller(X_D)	PID fuzzy controller(X_B)
ITAE	187.34	184.8
Overshoot	.022	.043
Settling time	116	65

The transient response for the PID fuzzy controller for both distillate composition and bottom composition are shown in Figure (4.10) and (4.11)

Table (4.5) shows the performance ITAE for both distillate composition and bottom composition.

The transient response of the distillate composition with respect to the reflux flow rate in the PID-FLC is shown in Figure (4.10) and the Transient response of the bottom composition with respect to reboiler heat duty in the PID-FLC are shown in Figure (4.11) and the performance indices used of the PID fuzzy controller is the ITAE as well as the performance of the PID fuzzy controller of the step response of the distillate and bottom compositions are given in table (4.5).

Figures (4.10) and (4.11) 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 the distillate composition, and the PID fuzzy gave a good control performance with low values of ITAE as well as low overshoot with high settling time for the bottom composition when compared with PID(IMC) 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 disadvantages in the PID-FLC.

The reason for that is the significant time investment needed to correctly tune the membership functions and adjust rules to obtain a good solution. The more rules suggested, the more increasing difficulty obtained. It does not have simple equation like the PID and it is more difficult to analyze mathematically. Therefore approximations are required. Instability and oscillation are caused by excess gain.

Figure (4.10), (4.11), table (4.5) show clearly that the PID fuzzy controller is improved over to classical FLC and PID(IMC) controllers used in this work.

4.4.4 Adaptive fuzzy controller:

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. The various types of adaptive control systems differ only in the way the parameters of the controller are adjusted.

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, 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:

$$\Delta u = FLC\ (CE, E, AV) \qquad \text{-----------} \ (4\text{-}1)$$

The control tuning of the Adaptive fuzzy depends on the trial and error in order to find the scaled factors for each variable (E, CE, AV and Δu). The main difficulties of implementing this fuzzy controller are the number of tuning parameters: the scaled factors for each variable, the membership functions and the rules. The optimum values of the scaled factors were tuned using Simulink program as shown in figure (4.12).

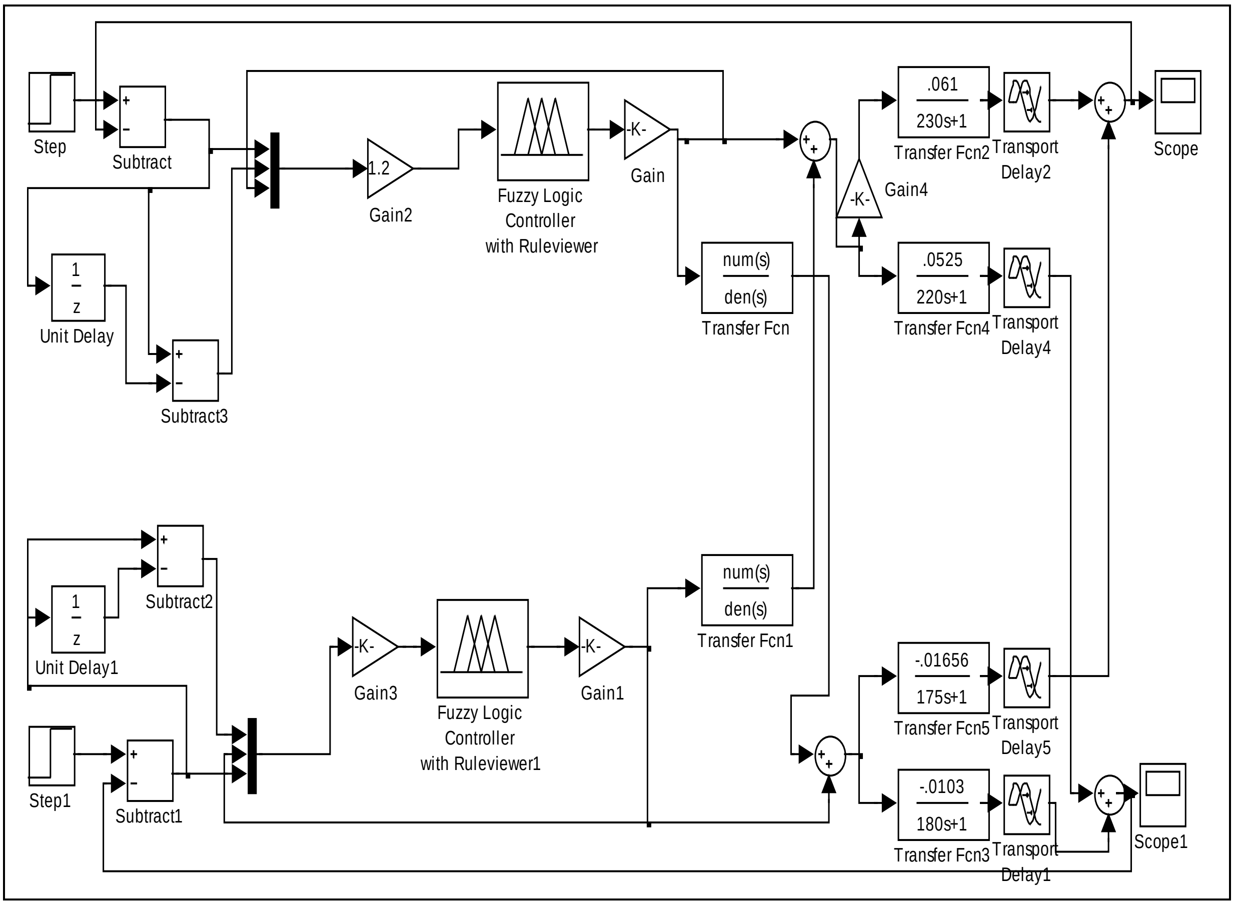


Fig (4.12) Block diagram of Adaptive fuzzy controller.

For the Adaptive fuzzy controller the input variable are error (*E*) , change of error (*CE*) and auxiliary variable (AV), the output variable is the control action (*u*).

Rule definition: a general fuzzy inference rule for this controller that has three inputs and a single output is:

IF E is PB AND CE is NB AND AV is Z THEN u is Z

The rule base for Adaptive fuzzy controller is shown in Appendix (D).For this process; five regions of non-linear gains can be identified: NB, NS, Z, PS and PB.

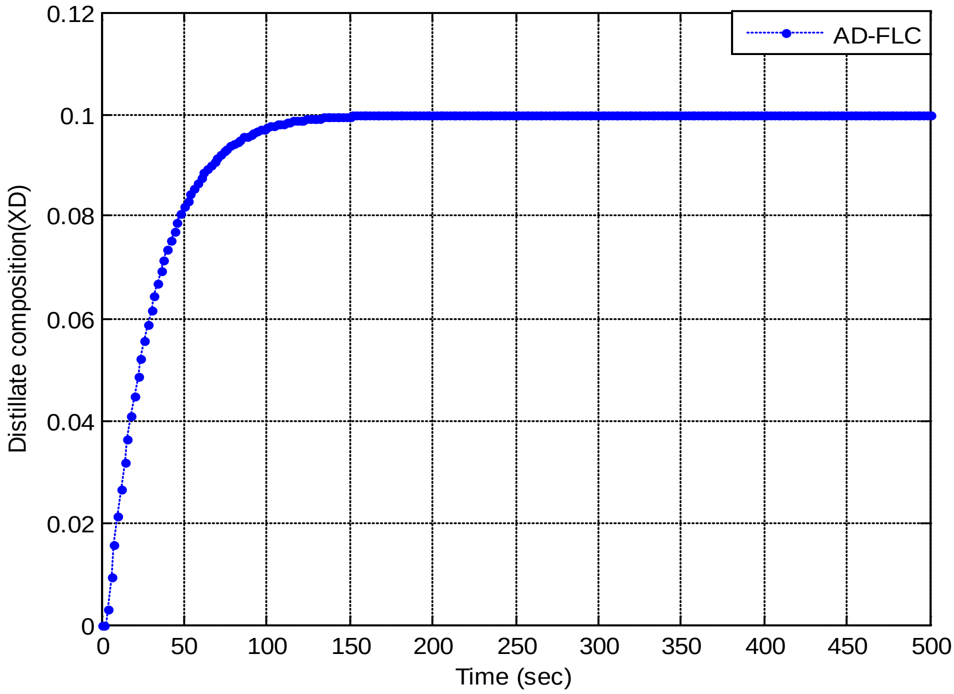


Fig (4.13) Transient response for Adaptive fuzzy controller of distillate composition with respect to reflux flow rate

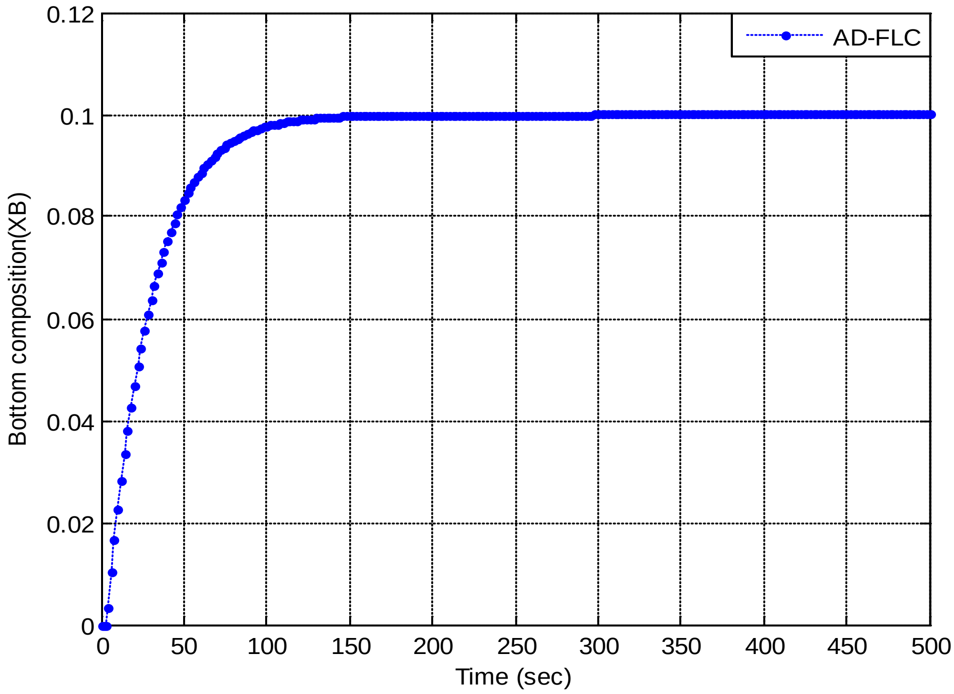


Fig (4.14) Transient response for Adaptive fuzzy controller of bottom composition with respect to reboiler heat duty

Table (4.6) ITAE value and different parameters in Adaptive fuzzy controller of distillate and bottom compositions.

Parameters	Adaptive fuzzy controller (X_D)	Adaptive fuzzy controller (X_B)
ITAE	83.2	75.23
Overshoot	0	0
Settling time	88	78

The transient response for the adaptive fuzzy controller for both the distillate composition and the bottom composition are shown in Figure (4.13) and (4.14) .Table (4.6) show the performance ITAE for both the distillate composition and the bottom composition.

The transient response for adaptive fuzzy controller for both distillate and bottom composition are shown in Figure (4.13) and Figure (4.14) show the excellent improvement in controlling by shortening time to reach the set point with low values of ITAE . For distillate composition the adaptive fuzzy controller gave a good control performance with low settling time and no overshoot took place when compared to the PID fuzzy , PID(IMC), and the classical fuzzy for the distillate composition. For the bottom composition no overshoot took place, low settling time than the PID (IMC) and the classical fuzzy.

The obtained figures indicate that the adaptive fuzzy gives the best performance among the three controllers PID (IMC), classical FLC, and PID- FLC) controllers because an auxiliary variable is used as another input to select the region in which the process is operating.

4.4.5 Artificial Neural Network NARMA-L2 Controller.

In order to evaluate the effectiveness of the NARMA-L2 control, the controller is implemented and applied to control the distillation process. NARMA-L2 control is one of the popular neural network architectures that have been implemented as Simulink block in the MATLAB software version 7.8 contained in the neural network toolbox block set. The optimum values of the scaled factors were tuned using Simulink program as shown in figure (4.15).

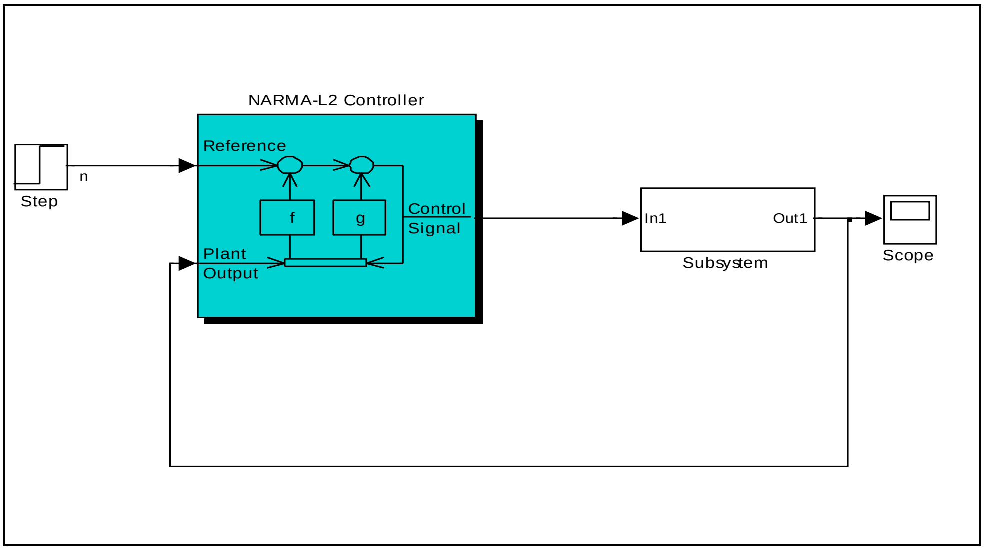


Fig (4.15) Simulation model with ANN NARMA-L2 controller.

The plant model neural network has 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 . ANN architecture with single hidden layer is sufficient for the distillation process of binary mixture of methanol and water and also gives satisfactory results.

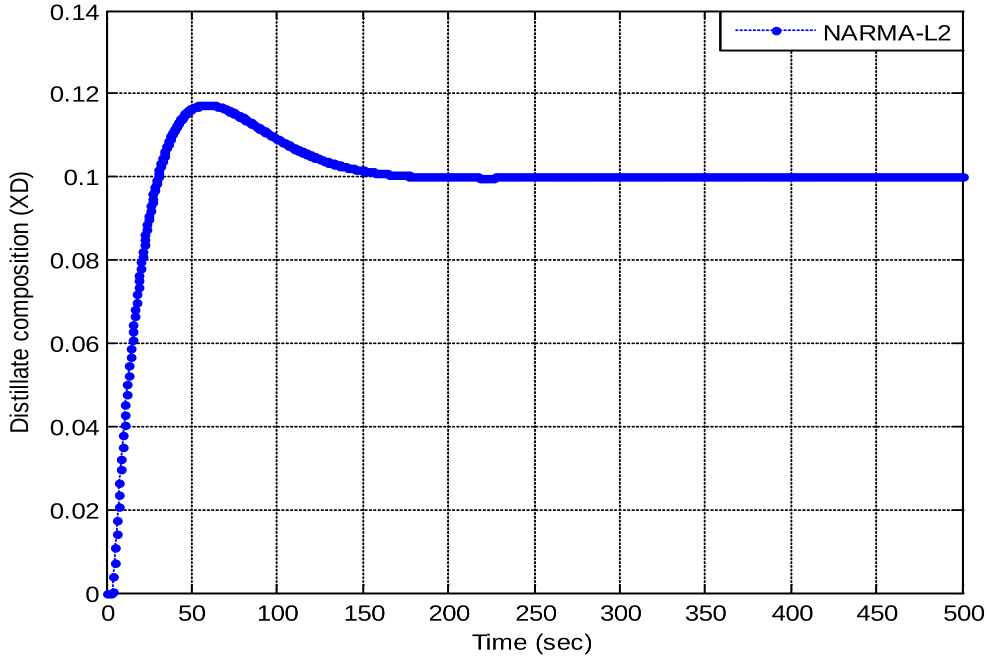


Fig (4.16) Transient response for NARMA-L2 controller of distillate composition with respect to reflux flow rate

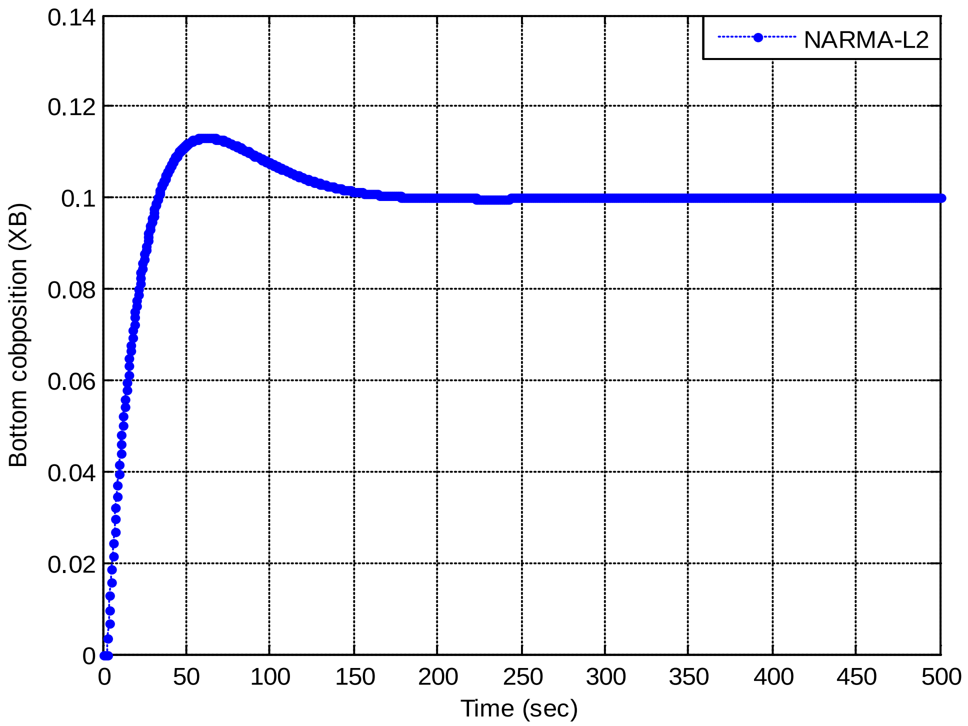


Fig (4.17) Transient response for NARMA-L2 controller of bottom composition with respect to reboiler heat duty

Table (4.7) ITAE value and different parameters in NARMA-L2 controller of distillate and bottom compositions.

Parameters	NARMA-L2 controller(X_D)	NARMA-L2 controller(X_B)
ITAE	108	93
Overshoot	.174	.132
Settling time	120	118

The transient response for neural network controller for both the distillate and the bottom composition are shown in Figure (4.16) and (4.17). Table (4.7) shows the performance ITAE for both the distillate and the bottom composition.

4.4.6 Adaptive Neuro-Fuzzy Inference System (ANFIS):

In this part, the behavior of distillation process has been assessed with the presence of ANFIS controller. The fuzzy logic toolbox of MATLAB 7.8 was used to train the ANFIS and obtain the results. Different ANFIS parameters were tested as training parameters in order to achieve the perfect training and the maximum prediction accuracy. Two inputs and one output were used. 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.

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 Figure (4.17) and (4.18).

Table (4.8) shows the performance ITAE for both distillate composition and bottom composition.

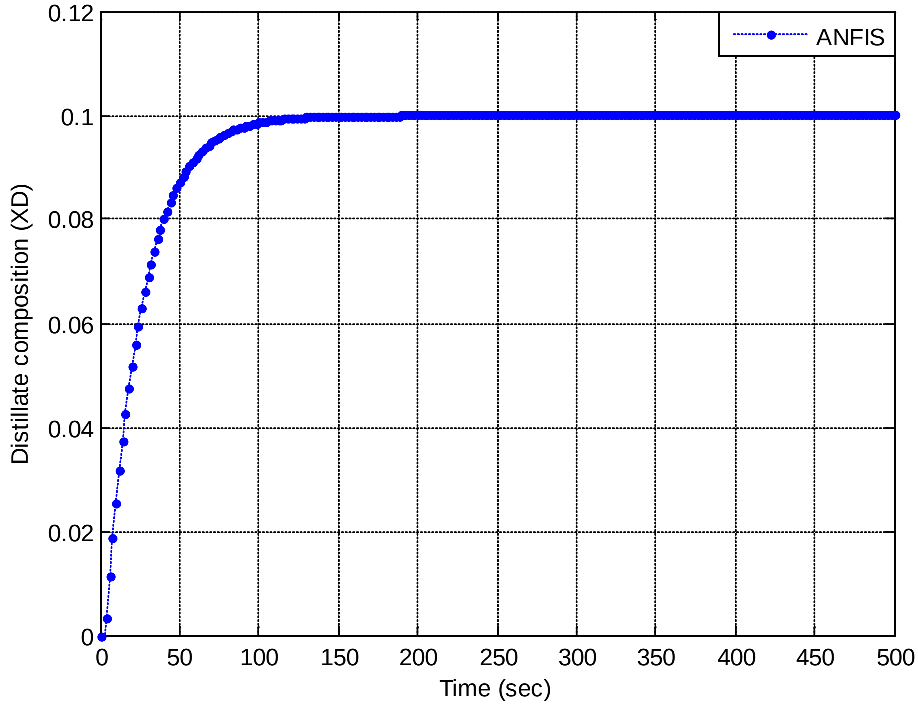


Fig (4.18) Transient response for ANFIS controller of distillate composition with respect to reflux flow rate

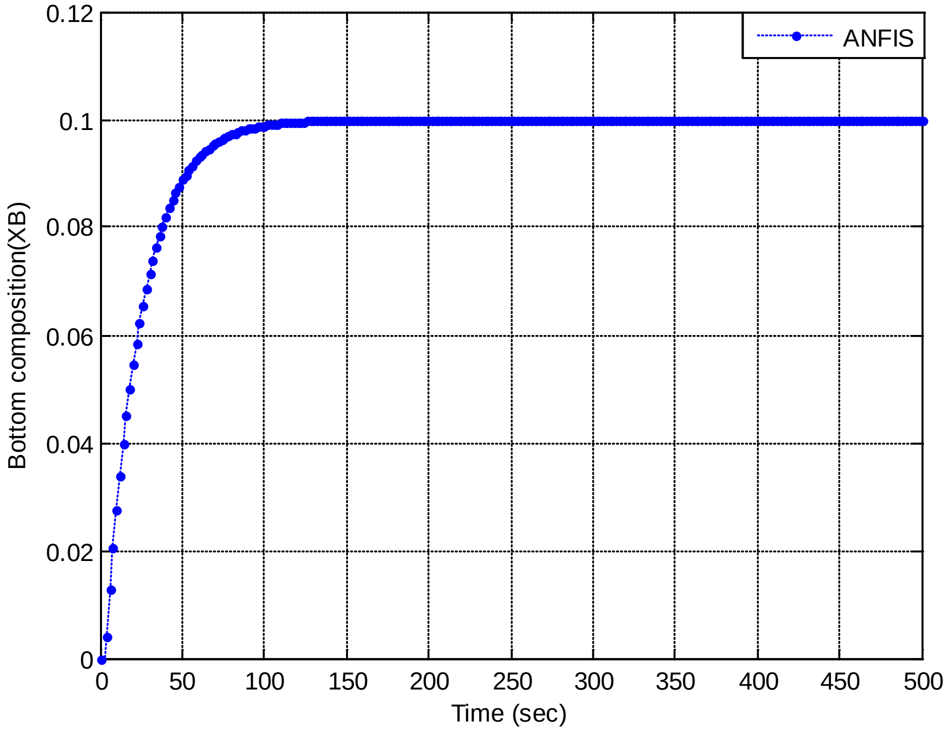


Fig (4.19) Transient response for ANFIS controller of bottom composition with respect to reboiler heat duty

Table (4.8) ITAE value and different parameters in ANFIS controller of distillate and bottom compositions.

Parameters	ANFIS controller(X_D)	ANFIS controller(X_B)
ITAE	61.3	54
Overshoot	0	0
Settling time	75	70

The performance of ANFIS controller is compared with NARMA-L2 controller in figure (4.16), (4.17), (4.18), and (4.19).

The process controlled with ANFIS controller is faster and reaches the steady state values with low settling time ,no overshoot took place and with low values of ITAE in both distillate and bottom composition control when compared to The ANN controller . The ANFIS is the best controller which presented satisfactory performances and possesses good robustness than the NARMA-L2 controller. The reasons that make the ANFIS controller better than NARMA-L2 controller: the fuzzy interference system cannot only take linguistic information from human experts, but also adapt itself to numerical data (input/output), it takes an edge over neural networks which cannot take linguistic information directly.

The advantages of the ANFIS controller are that it determines the number of rules automatically, reduces computational time, learns faster and produces lower errors than other method.

4.4.7 Comparison 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(IMC), NARMA-L2, AD-FLC and ANFIS controllers as shown in Figure (4.19), (4.20).

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 table (4.9)

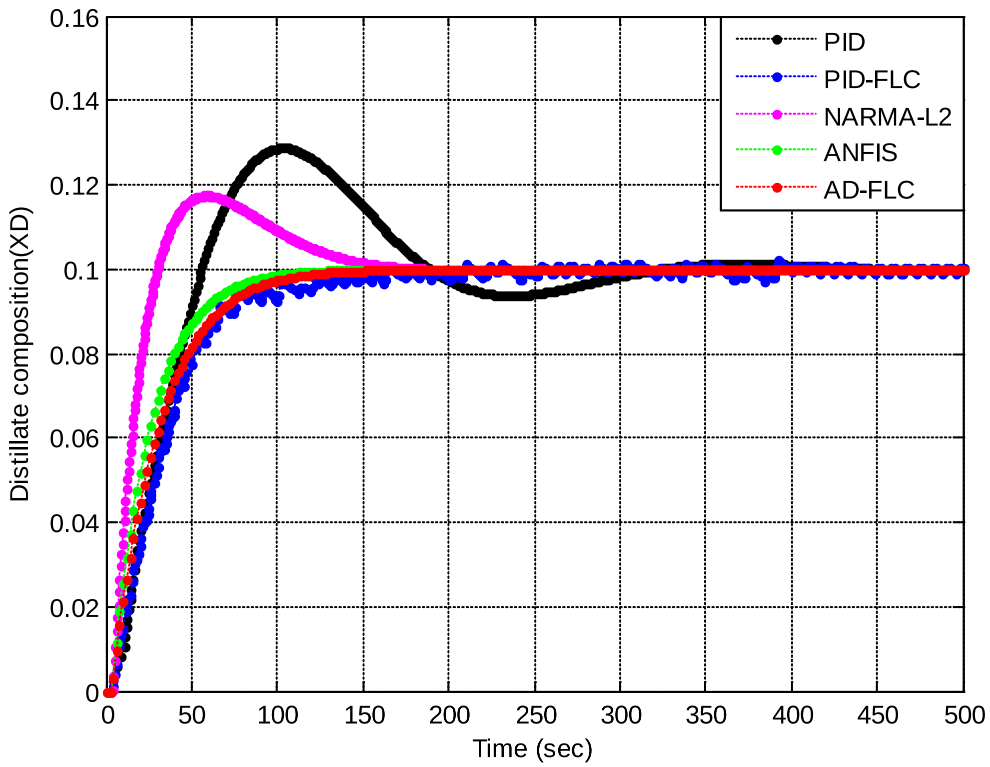
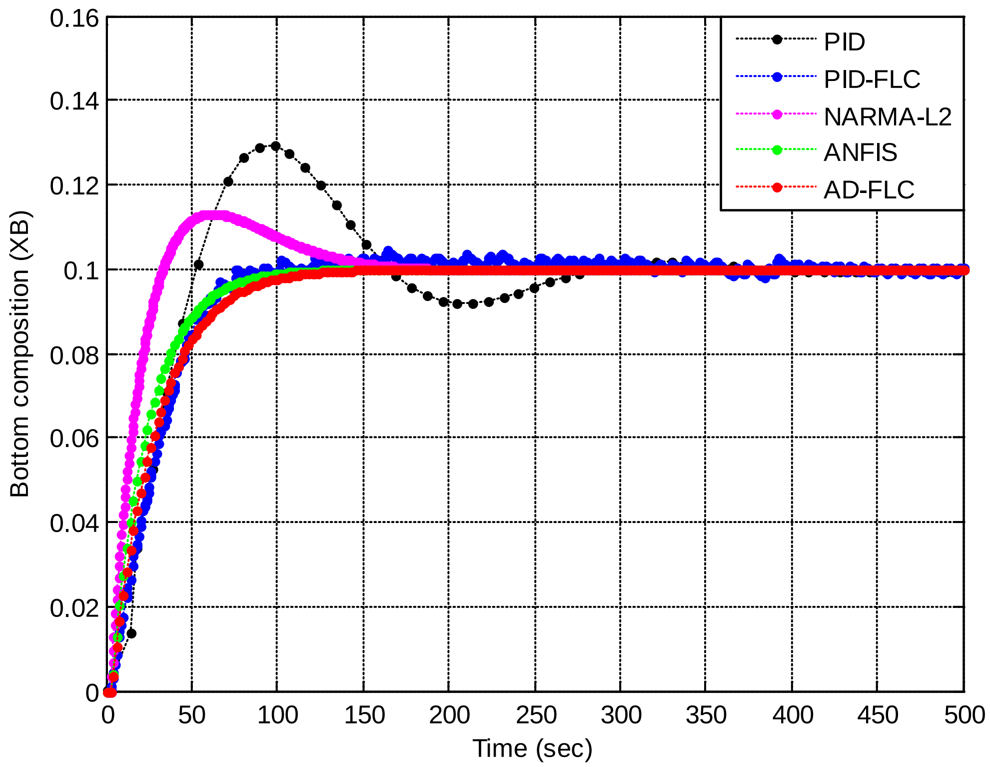


Fig (4.20) comparison among the transient response for PID, NARMA-L2, PID-FLC, ANFIS, AD-FLC controllers of distillate composition with respect to reflux flow rate.



Fig(4.21) The comparison among the transient response for PID, NARMA-L2 , PID - FLC,ANFIS,AD-FLC controllers of bottom composition with respect to reboiler heat duty

Table (4.9) 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 (4.15) 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 controller, NARMA-L2, PID fuzzy, and PID(IMC) controller.

It was observed that the performance of ANFIS controller is slightly better than that of adaptive fuzzy controller in low settling time,and with low values of ITAE in the distillate composition, and with low values of ITAE in the bottom composition. It has been seen that more accurate results were obtained using adaptive fuzzy controller over artificial neural network controller, PID fuzzy, and PID(IMC) controller, further better results were obtained by using NARMA-L2 controller and then PID fuzzy and PID(IMC).

From these observations it is clear that The ANFIS controller gives a much better control performance for both distillate and bottom composition than the feedback, fuzzy logic, PID fuzzy logic, artificial neural network and adaptive fuzzy logic controllers, this because the ANFIS controller combines the advantages of fuzzy logic controller and an artificial neural network controller.

Adaptive fuzzy logic controller is better than the feedback, fuzzy logic, PID fuzzy logic and Artificial neural network controllers, this because an auxiliary variable was used as another input to select the region in which the process is operating.

Artificial neural network controller is better than the feedback, fuzzy logic and PID fuzzy logic controllers, this because the artificial neural network controller learns the system and it has got generalization capabilities.

Chapter Five

Conclusions and Recommendations

5.1 Conclusions:

The main points concluded from the present study are summarized as follows:

1-The decoupler technique suggested in this work greatly improved the response of the interacting system.

2- The control tuning was carried using in 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.

3-PID feedback controller is better than PI feedback controller because it gives smaller ITAE, overshoot, settling time and rise time values.

4- PID fuzzy logic controller is better than feedback ,a classical fuzzy logic controllers because the PID fuzzy logic controller is faster and reaches the steady state values with minimum oscillations in both top and bottom product composition.

5-Artificial neural network controller gave better values than feedback, and fuzzy logic and PID fuzzy logic controllers because the artificial neural network controller is a learning system with generalization capabilities.

6- Adaptive fuzzy logic controller is better than feedback, classical fuzzy logic, PID fuzzy logic and artificial neural network controllers because it

uses an auxiliary variable is used as another input to select the region in which the process is operating.

7-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), classical fuzzy logic, 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.

5.2 Recommendations for Future Work:

The following suggestions for future work can be considered:

1. The same procedure of this work is useful for another type of distillation column that is different in distillation specifications or using the same procedure for other controlled and manipulated variables.
2. Adding other control strategies like cascade control, FFD, genetic algorithms control, PID- genetic algorithms control, PID-ANFIS control, and Fuzzy- genetic algorithms control.
3. Applying the technique of this work on a real distillation column using different (on line) control strategies.

References

1. Zalizawati, B.A.," Development of Multiple-Input Multiple –Output (MIMO) and Multiple-Input Single Output (MISO) Neural Network Models for Continuous Distillation Column ", MSc Thesis, University of Teknologi Malaysia ,November, 2008.

2.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.

3.W. Yu & X. Li, Fuzzy identification using fuzzy neural network with stable learning algorithms, IEEE Transactions on Fuzzy Systems, 12(3), 2004, 411-420.

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

5. Henri, E. Z., and Olatunbosun, A., "Neural Network Controller for A Crude Oil Distillation Column" ARPN Journal of Engineering and Applied Sciences, Vol. 5, No. 6, June, 2010.

6.Taylor, R.; Krishna, R. Chemical Engineering Science. 2000, 55, 5183-5229.

7. Stankiewicz, A. Chem. Eng. Progr. 2003, 42, 137-144.

8. Joe, E.," PID Control", www.pumped101.com , June, 2006.

9. 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.

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

11. Obanifemi, A.," Dynamic Modeling and Control of Reactive Distillation for Hydrogenation of Benzene", MSc Thesis, Chemical Engineering, University of Texas, August, 2008.

12. Sanda , F. F.," Decoupling in Distillation", Journal of Control Engineering and Applied Informatics, Vol. 7, No. 1, pp. 10-19, 2005.

13. Juan, G. S., and Esteban A. H.," Control properties of thermally coupled distillation sequences for different operating conditions", Computers and Chemical Engineering, www.sciencedirect.com , 2007.

14. Qasim, S.A.,"Simulation on Dynamic and Control of Distillation Column", MSc Thesis, Chemical Engineering, University of Nahrain, December, 2009.

15. Manish, K., and Devendra, P. G.," Neuro-Fuzzy control applied to multiple cooperating robots" ,International Journal of Industrial Robot, Department of Mechanical Engineering and Materials Science, Vol. 32 – No. 3 - 234–239,2005.

16. Ashok, K., Kodad, S. F., and Sankar, B. R.," Modeling, Design & Simulation of an Adaptive Neuro-Fuzzy Inference System (ANFIS) for Speed Control of Induction Motor" International Journal of Computer Applications (0975 – 8887), Vol .6– No.12, September, 2010.

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

18. P.M. Mary 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.

19. Evren , G.," Adaptive Neruro Fuzzy Inference System Applications In Chemical Processes", MSc Thesis, Chemical Engineering, University of Middle East Technical, November, 2003.

20. Eranda, H.," Fuzzy PI control system design for distillation column", MSc Thesis, Electrical and Computer Engineering, University of British Columbia, April, 2008.

21. José,M., Fábio, M., and Leandro, L.," Artificial Intelligence Techniques Applied in A Simulated Oil Distillation System", ABCM Symposium Series in Mechatronics, Vol. 3, pp.114-120, 2008.

22. Liu, Z., Zhuang, X., & Wang, S., "Speed Control of a DC Motor using BP Neural Networks". IEEE Transactions, 832-835,2003.

23.Hui , H. C.," All Digitall Design and Implementation of Proportional-Integral-Derivative (PID) Controllers", MSc Thesis, Electrical and Computer Engineering, University of Kentucky, January ,2006.

24. Chen, W. S.," Application OF Artificial Neural Network – Genetic Algorithm in Inferential Estimation and Control of a Distillation Column", MSc Thesis, Chemical Engineering, University of Teknologi Malaysia, July, 2005.

25. Mujtaba , I. M., and Greaves, M. A.," Neural Network Based Modeling And Optimization in Batch Reactive Distillation", Symposium Series No. 152, 2006.

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

27. Kwantip ,K., Paisan, K., Aritsara, S., and Iqbal ,M. M.," Optimal Policy Tracking of a Batch Reactive Distillation by Neural Network-based Model Predictive Control (NNMPC) Strategy",Proceedings of the World Congress on Engineering and Computer Science, Vol. II, San Francisco, 2010.

28.Jyh-Shing R. ," ANFIS: Adaptive-Network-Based Fuzzy Inference System", IEEE Trans, Systems, Man & Cybernetics, Vol. 23, pp 665-685, 1993.

29. Boumediene, A., Abdellah, L., Brahim G., and Abdessalam, A.," Neuro-Fuzzy DC Motor Speed Control Using Particle Swarm Optimization", Leonardo Electronic Journal of Practices and Technologies, ISSN 1583-1078, December, 2009.

30.Jelenka ,B.S,"A Neural-Fuzzy System for Ethanol Recovery Distillation Control ", Bulletin of the Chemists and Technologists of Macedonia, Vol. 24, No. 1, pp. 87–92,2005.

31. Fikar, M.,and Kvasnica, M.," Neuro-Fuzzy Control of Chemical Technological Processes" , In Proceedings of the 17th International Conference on Process Control , Slovak University of Technology in Bratislava, www.kirp.chtf.stuba.sk/pc09/data/abstracts/056.html , June , 2009.

32. Sivakumar , R., Balu ,K.," ANFIS Based Distillation Column Control", IJCA Special Issue on "Evolutionary Computation for Optimization Techniques" , 2010.

33. 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.

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

35. Mehdi,F.A.," Control System of A Fluidized Catalytic Cracking Unit ", MSc Thesis, Chemical Engineering, University of Technology, 2007.

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

37. Kamel, A.H.," Comparative Study of Temperature Control in a Heat Exchanger Process", MSc Thesis, Chemical Engineering, University of Technology, March , 2011.

38. Alexander, F., Oliver, N., and Rolf, I.," Nonlinear Internal Model Control for Miso Systems Based on Local Linear Neuro-Fuzzy Model ", 15th Triennial World Congress, Barcelona, Spain, 2002.

39. Fernando, G. M. , "Tuning PID Controllers using the ITAE Criterion", International Journal of Engng Ed. Vol. 21, No. 5, pp. 867-873, May ,2005.

40. Jonas, B. W.," Directionality and Nonlinearity - Challenges in Process Control", Academic Dissertation, Process Control Laboratory Faculty of Chemical Engineering, University of Abo Academy, 2003.

41.Castillo, O., Melin, P., (2001), “Soft Computing for Control Nonlinear Dynamical System”, Physica-Verlag Heidelberg, New York.

42. Vamsi, M. P.," Fuzzy Logic Controller for an Autonomous Mobile Robot", MSc Thesis, Electrical and Electronics Engineering, University of Jawaharlal Nehru Technological, May, 2005.

43. Seema C., Mitra, R., and Vijay K.," Fuzzy Controller: Choosing an Appropriate and Smallest Rule Set", International Journal of Computational Cognition, VOL. 3, NO. 4, December, 2005.

44. Zeyad, A. O., Nasri, S., Marhaban, M. H., and Hamidon, M. N.," Analysis and Performance Evaluation of PD-like Fuzzy Logic Controller Design Based on Matlab and FPGA", IAENG International Journal of Computer Science, IJCS_37_2_04, May, 2010.

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

46. Peter, H. S., and Richard, T.," Artificial Neural Networks", Handbook of Measuring System Design, ISBN: 0-470-02143-8, 2005.

47.Heaton J.T,. "Introduction to Neural Networks with Java". Heaton Research, Inc, 2000.

48. Boo, C. E., Hong, M. K., Amy, T. S., and Khairiyah, M. Y., "Formulation of Model Predictive Control Algorithm for Nonlinear

Processes", Research Vote No: 71992, Universiti Teknologi Malaysia, 2006.

49. Ali, A., Morteza, S., Vahid , N., Mino, I., And Alireza B.," An Integrated Intelligent Neuro-Fuzzy Algorithm for Long-Term Electricity Consumption: Cases of Selected EU Countries", Acta Polytechnica Hungarica, Vol. 7, No. 4, 2010.

50. Ahmad, T. A.," Adaptive Neuro-Fuzzy Systems", Fuzzy Systems Book, ISBN 978-953-7619-92-3, pp. 216, www.Sciyo.com , February, 2010.

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

52. Eltantawie, M.A.," Forward and Inverse Fuzzy Magnetorheological Damper Models for Control Purposes ", ICGST-ACSE Journal, Vol.10, Issue 1, www.icgst.com , December, 2010.

53. Abdalla , K., and Wing, L. N.," Intraday high-frequency FX trading with adaptive neuro-fuzzy inference systems", Int. J. Financial Markets and Derivatives, Vol. 2, Nos. 1/2, 2011.

54. Sath ,Y. B.," A Study on Neural Network Based System Identification With Application To Heating, Venttil A Ting And Air Conditioning (HVAC) System", MSc Thesis, Electrical Engineering, University of Technology Rourkela, May, 2009.

55. Abd, D.I.," Implementation of Neural Control for Neutralization Process", MSc Thesis, Chemical Engineering, University of Technology, 2009.

A.1 Cohen-Coon Method[47,48]

Cohen-Coon used process reaction curve, that it is a response of the process to a step change in the manipulated variable. Cohen and Coon observed that the response of most processing units to a step change in input variable can be adequately approximated by the response of first order system with dead time, and the transfer function is:

$$G_{PRC}(s) = \frac{K\,e^{-t_d s}}{\tau\,s+1} \qquad \text{----------- (A.1)}$$

The values of K, τ and t_d are calculated from the process reaction curve which is shown in Fig. (A.1). A tangent is drawn to the curve at the point of maximum rate or ascent, and then t_d is the intercept of this tangent with x-axis, and is defined as the time elapsed until the system responds.

$$K = \frac{B}{A} = \frac{Output\ (at\ steady\ state)}{Input\ (at\ steady\ state)} \qquad \text{----------- (A.2)}$$

$$\tau = \frac{B}{S} = \frac{Output\ (at\ steady\ state)}{Slope} \qquad \text{----------- (A.3)}$$

1) For Proportional controller:

$$K_C = \frac{1}{K}\frac{\tau}{t_d}\left(1+\frac{t_d}{3\tau}\right) \qquad \text{----------- (A.4)}$$

2) For Proportional-Integral controller:

$$K_C = \frac{1}{K}\frac{\tau}{t_d}\left(0.9+\frac{t_d}{12\tau}\right) \qquad \text{----------- (A.5)}$$

$$\tau_I = t_d\frac{30+3t_d/\tau}{9+20t_d/\tau} \qquad \text{----------- (A.6)}$$

3) For Proportional-Integral-Derivative controller:

$$K_C = \frac{1}{K}\frac{\tau}{t_d}\left(\frac{4}{3}+\frac{t_d}{4\tau}\right) \qquad \text{----------- (A.7)}$$

$$\tau_I = t_d \frac{32+6t_d/\tau}{13+8t_d/\tau} \qquad \text{----------- (A.8)}$$

$$\tau_D = t_d \frac{4}{11+2t_d/\tau} \qquad \text{----------- (A.9)}$$

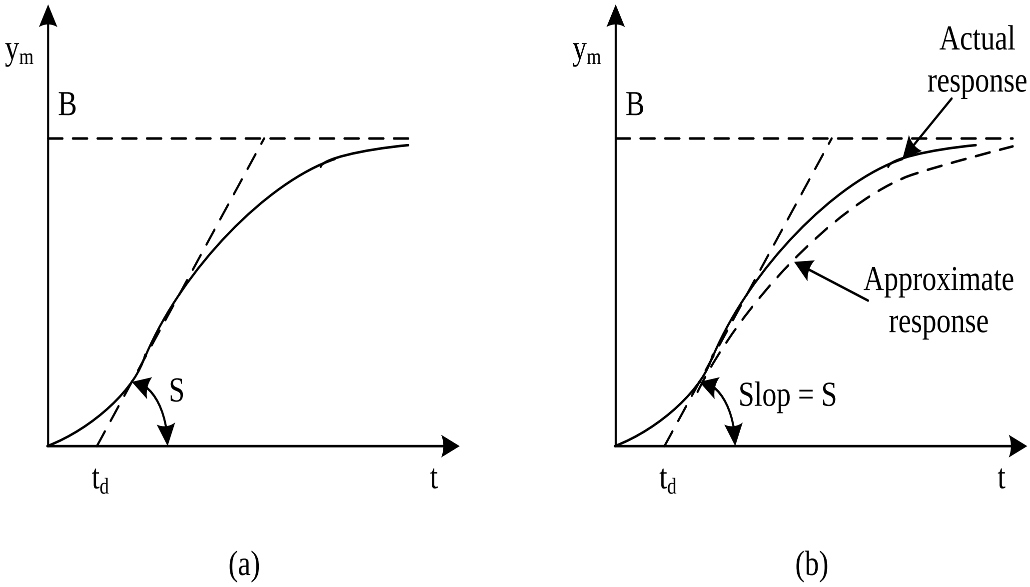


Fig. (A.1) (a) composition curve for Cohen-Coon tuning.
(b) composition curve approximation with a first order dead-time system.

A.2 Ziegler-Nichols Method[47,48]

Ziegler-Nichols used bode diagram of two graphs: one is a plot of the logarithm of the magnitude of sinusoidal transfer function; the other is a plot of phase angle; both are plotted against the frequency on a logarithm scale as shown in Fig. (A.2).

Gain margin (*GM*) and crossover frequency (ω) can be found from two plots therefore, the ultimate gain and period of oscillation are calculated from following:

$$K_u = 20\log(GM) \quad \text{----------- (A.10)}$$

$$P_u = \frac{2\times 3.1428}{\omega} \quad \text{----------- (A.11)}$$

1) For Proportional controller:

$$K_C = \frac{K_u}{2} \quad \text{----------- (A.12)}$$

2) For Proportional-Integral controller:

$$K_C = \frac{K_u}{2.2} \quad \text{----------- (A.13)}$$

$$\tau_I = \frac{P_u}{1.2} \quad \text{----------- (A.14)}$$

3) For Proportional-Integral-Derivative controller:

$$K_C = \frac{K_u}{1.7} \quad \text{----------- (A.15)}$$

$$\tau_I = \frac{P_u}{2} \quad \text{----------- (A.16)}$$

$$\tau_D = \frac{P_u}{8} \quad \text{----------- (A.17)}$$

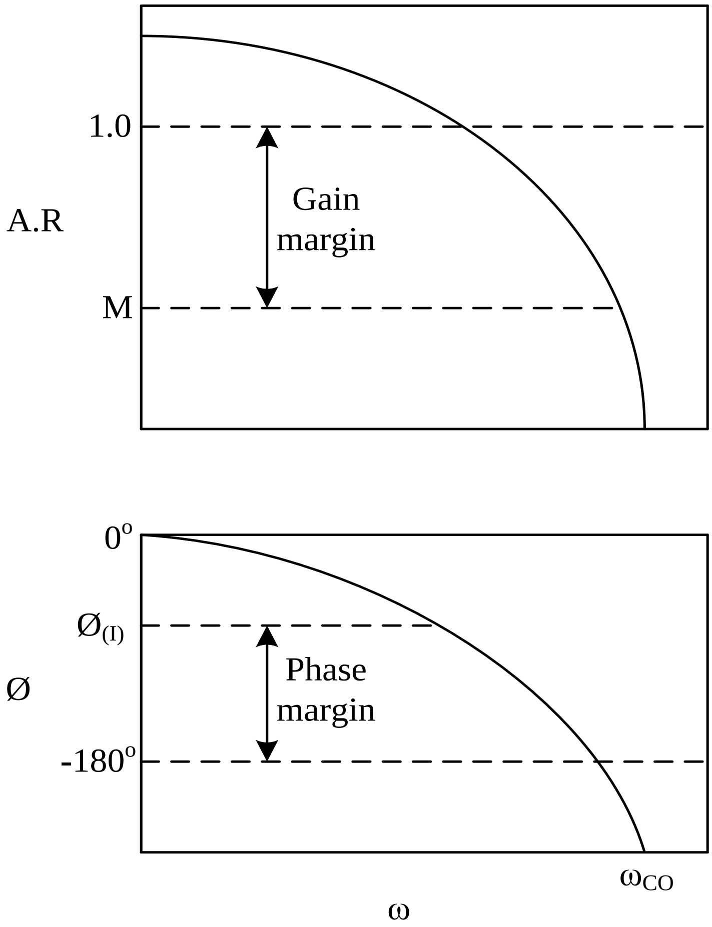


Figure (A.2): Definition of gain and phase margins.

A.3 Internal Model Control Method[49]

The basis for the development of a control strategy that has the potential to achieve perfect control . This strategy, known as Internal Model Control (IMC) has the general structure shown in figure (A.3)

Designing an internal model controller is relatively easy. Given a model of the process,

$G_m(s)$, first, factor $G_m(s)$ into "invertible" and "non-invertible" components.

$Gm(s) = G_m^{+}(s)\,G_m^{-}(s)$. ----------- (A.18)

The non-invertible component, $G_m^{-}(s)$, contains terms which if inverted, will lead to instability and realisability problems, e.g. terms containing positive zeros and timedelays.

Next, set

$G_c(s) = G_m^{+}(s)^{-1}$ ----------- (A.19)

and then

$G_{IMC}(s) = G_c(s)\,G_f(s)$ ----------- (A.20)

where $G_f(s)$ is a low-pass function of appropriate order.

The values of K, τ and t_d are calculated from the process reaction curve which is shown in Fig. (A.1). A tangent is drawn to the curve at the point of maximum rate or ascent, and then t_d is the intercept of this tangent with x-axis, and is defined as the time elapsed until the system responds.

$$K = \frac{B}{A} = \frac{Output\ (at\ steady\ state)}{Input\ (at\ steady\ state)}$$ ----------- (A.2)

$$\tau = \frac{B}{S} = \frac{Output\ (at\ steady\ state)}{Slope}$$ ----------- (A.2)

1) For Proportional-Integral controller:

*Tauc = (2/3)*td* ----------- (A.22)

kc= Tau/(k(Tauc+td))* ----------- (A.23)

ti=Tau ----------- (A.24)

2) For Proportional-Integral-Derivative controller:

*Tauc= (2/3)*td* ----------- (A.25)

*a= ((2*Tau)/td) + 1* ----------- (A.26)

*b= ((2*Tauc)/td) + 1* ----------- (A.27)

kc= (1/k)(a/b)* -----------(A.28)

ti= Tau+(td/2) ----------- (A.29)

td = Tau/a ----------- (A.30)

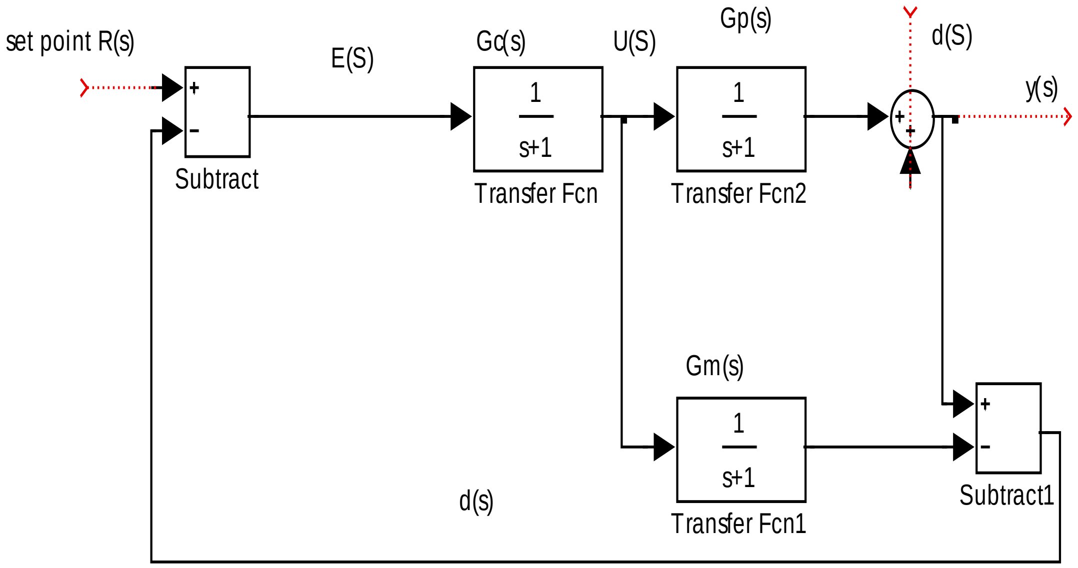


Figure (A.3) Schematic of the IMC scheme

Relative Gain Array (RGA)[35]

The relative gain array is defined as the ratio of open loop gain in terms of (m_j), (i.e., with all other m's constant) to the gain in terms of (y_i), (i.e., with all other y's constant), the term (λ_{ij}) will be used to designate the dimensionless change in (yi) with respect to a change in (mj)[35].

$$\lambda_{ij} = \frac{(\Delta y_i / \Delta m_j)m}{(\Delta y_i / \Delta m_j)y}$$

---------- *(B-1)*

It is convenient to arrange a table of those gains in form of a matrix, the relative gain array of interacting process is:

$$\Lambda = \begin{array}{cc} \text{R} & \text{H} \\ \end{array}$$

$$\Lambda = \begin{bmatrix} \lambda_{11} & \lambda_{12} \\ \lambda_{21} & \lambda_{22} \end{bmatrix} \begin{array}{l} X_D \\ X_B \end{array}$$

---------- *(B-2)*

1-The matrix has the following characteristics:

The sum of the relative gains in any row or column of the array is equal to one

$$\lambda_{11} + \lambda_{12} = 1 \quad , \quad \lambda_{11} + \lambda_{21} = 1$$

---------- *(B-3), (B-4)*

2-The controlled variable is coupled with the manipulated variable that has the largest positive number of relative gain

The Distillation composed of two controlled outputs and two manipulated inputs as shown in Figure (B.3), the input/output relationships are given by:

$X_D (s) = H_{11}(s) R (s) + H_{12}(s) H (s)$ ----------- *(B-5)*

$X_B(s) = H_{21}(s) R (s) + H_{22}(s) H(s)$ ----------- *(B-6)*

Where $H_{11}(S)$, $H_{12}(S)$, $H_{21}(S)$ and $H_{22}(S)$ are the four transfer functions relating the two outputs (X_D and X_B) to the two inputs (R and H). Equations (B.5) and (B.6) indicate that a change in (R or H) will affect both controlled outputs. The relative gain between the controlled variable (X_D) and the manipulated variable (R) will be denoted by (λ_{11}).

$$\lambda_{11} = \frac{\text{open loop gain}}{\text{closed loop gain}}$$ ----------- *(B.7)*

Mathematically, the relative gain can be expressed as:

$$\lambda_{11} = \frac{(\Delta XT / \Delta R)_H}{(\Delta XT / \Delta R)_{XB}} = \frac{H_{11}}{\dfrac{H_{11}H_{22} - H_{12}H_{21}}{H_{22}}}$$ ----------- *(B-8)*

$$\lambda_{11} = \frac{1}{1 - \dfrac{H_{12}H_{21}}{H_{11}H_{22}}}$$ ----------- *(B-9)*

In most cases, the steady state relative gain analysis is a sufficient indicator for control loops combination, so the steady state relative gain could be calculated from the following equations:

$$\lambda_{11} = \frac{1}{1 - \frac{K_{12}K_{21}}{K_{11}K_{22}}} \qquad \text{----------- } (B\text{-}10)$$

The open loop static gain is between (X_D and H) when (R) is kept constant and the other, when (X_B) is constant by the control loop. The values of other relative gains could be calculated from above relative gain (λ_{11}).

Where: $\lambda_{12} = \lambda_{21} = 1- \lambda_{11}$, $\lambda_{11} + \lambda_{12} = 1$ and $\lambda_{11} + \lambda_{21} = 1$

The RGA provides a useful measure of interaction. In particular:

1. If λ_{11}=0, then X_D does not respond to R and H should not be used to control XT.

2. If λ_{11}=1, then H does not affect X_D and the control loop between X_D and H does not interact with loop of X_B and H In this case we have completely decoupled loops.

3. If 0<λ_{11}<1, then an interaction exists and as H varies it affects the steady-state value of X_D. The smaller the value of λ_{11}.the larger the interaction becomes.

4. If λ_{11}<0, then H causes a strong effect on X_D and in opposite direction from that caused by R. In this case, the interaction is very dangerous.

C.1 Introduction

This appendix discusses the computer program developed for the dynamic model and control for both open loop and closed loop of system.

All programs were developed using MATLAB program version 7.8. The use of friendly, easy to use interfaces for these programs were efficient in the implementation of the model procedure that gave dynamic results obtained from the computer programs.

Each program was executed and the results were checked to meet the model requirements, then–if necessary– the design data was modified to meet the requirements of the model.

Table (C.1) lists some functions and commands and their description that were used in computer simulation for dynamic behavior and controller design .

Table (C.1) Summary functions in MATLAB program.

Function Name	Function Description
Pade	Computes the an nth-order approximation to a time delay
Series	Computes a series system connection
Tf	Creates a transfer function model object
Step	Calculates a unit step response of a system
Figure	Creates new figure window
Plot	Generates a linear plot
Xlabel	Add the label to the x-axis of the current graph
Ylabel	Add the label to the y-axis of the current graph
Axis	Specific the manual axis scaling on plot
Title	Add a title to the current graph
Hold on	Holds the current graph on the screen
Legend	Puts a legend on the current screen
Margin	Computes the gain margin, phase margin , and associated crossover frequencies from frequency response data
Bode	Generates bode frequency response plots
Feedback	Computes the feedback interconnection of two systems
Trapz	Computes the integration value
For	Generate loop structure
End	End of loop generated

C.2 Open Loop Program

************************* C.2.a*************************

```
% Matlab program
% for Dynamic behavior of open loop with plotting
```

% Dynamic behavior of open loop between X_D vs. R

```
% define distillate composition at steady state (X_Dss)
X_Dss= value of distillate composition at steady state
% define the transfer function between input R with outputs X_D with
% delay time by using pade function
num=[value of nominator];
den=[value of denominator];
[numdt,dendt]=pade (value of delay time, number of approximation);
% apply series function
[nump,denp]=series (num,den,numdt,dendt);
H11=tf (nump,denp);% where H11 is transfer function between X_D& R
[X_D, x, t]=step (nump,denp);
%plotting X_D vs. Rat step response
figure (1)
plot (t,X_D +X_Dss ,'k-')
ylabel (' Distillate composition ')
xlabel ('Time(sec)')
%
%Or plotting X_D vs. Rat multi-step response
figure (1)
plot (t,y+yss ,'k-')
ylabel (' Distillate composition')
xlabel ('Time(sec)')
hold on
[y,x,t]=step (value of step1*manuipulated variable*nump,denp);
```

plot (t,y+yss,'k:')

[y,x,t]=step (value of step2*manuipulated variable*nump,denp);

plot (t,y+yss ,'k--')

[y,x,t]=step (value of step3*manuipulated variable*nump,denp);

plot (t,y+yss ,'k-.')

[y,x,t]=step (value of step4*manuipulated variable*nump,denp);

plot (t,y+yss,'k:')

legend(' value of step1,' value of step2,' value of step3,' value of step4,1)

grid on

*************************** C.2.b***************************

%Dynamic behavior of open loop between X_D vs. H

% define distillate composition at steady state (X_{Dss})

X_{Dss}= value of distillate composition at steady state

% define the transfer function between input H with outputs X_D

num=[value of nominator];

den=[value of denominator];

H12=tf (num,den);% H12 is transfer function between X_D &H

[X_D, x, t]=step (num,den);

%plotting X_D vs. Hat step response

figure (2)

plot (t,X_D+X_{Dss} ,'k-')

ylabel (' Distillate composition')

xlabel ('Time(sec)')

%

%Or plotting X_D vs. H at multi-step response

figure (2)

plot (t,y+yss ,'k-')

ylabel (' Distillate composition')

xlabel ('Time(sec)')

hold on

[y,x,t]=step (value of step1*manuipulated variable*nump,denp);

plot (t,y+yss,'k:')

[y,x,t]=step (value of step2*manuipulated variable*nump,denp);

plot (t,y+yss ,'k--')

[y,x,t]=step (value of step3*manuipulated variable*nump,denp);

plot (t,y+yss ,'k-.')

[y,x,t]=step (value of step4*manuipulated variable*nump,denp);

plot (t,y+yss,'k:')

legend(' value of step1,' value of step2,' value of step3,' value of step4,1)

grid on

************************** C.2.c**************************

% Dynamic behavior of open loop between X_B vs. R

% define bottom composition at steady state (X_{Bss})

X_{Bss}=value of bottom composition at steady state

% define the transfer function between input R with outputs X_B with

% delay time by using *pade* function

num=[value of nominator];

den=[value of denominator];

[numdt,dendt]=pade (value of delay time, number of approximation);

% apply *series* function

[nump,denp]=series (num,den,numdt,dendt);

H21=tf(nump,denp);% H21 is transfer function between X_B& R

[X_B,x,t]=step (nump,denp);

%plotting X_B vs. Rat step response

Figure (3)

plot (t,X_B +X_{Bss} ,'k-')

ylabel ('Bottom composition ')

xlabel ('Time(sec)')

```
%
%Or plotting XB vs. R at multi-step response
figure (3)
plot (t,y+yss ,'k-')
ylabel (' Bottom composition ')
xlabel ('Time(sec)')
hold on
[y,x,t]=step (value of step1*manuipulated variable*nump,denp);
plot (t,y+yss,'k:')
[y,x,t]=step (value of step2*manuipulated variable*nump,denp);
plot (t,y+yss ,'k--')
[y,x,t]=step (value of step3*manuipulated variable*nump,denp);
plot (t,y+yss ,'k-.')
[y,x,t]=step (value of step4*manuipulated variable*nump,denp);
Plot  (t,y+yss,'k:')
legend (' value of step1,' value of step2,' value of step3,' value of step4,1)
grid on
```

************************** C.2.d**************************

%Dynamic behavior of open loop between X_B vs. H

```
% define bottom composition at steady state (XBSS)
XBss=value of bottom composition at steady state
% define the transfer function between input H with outputs XB with
% delay time by using pade function
num=[value of nominator];
den =[value of denominator];
[numdt,dendt]=pade (value of delay time, number of approximation);
% apply series function
[nump,denp]=series (num,den,numdt,dendt);
H22=tf(nump,denp);% H22 is transfer function between XB& H
[XB,x,t]=step (nump,denp);
```

```
%plotting X_B vs. H at step response
figure (4)
plot (t,X_B +X_Bss,'k-')
ylabel (' Bottom composition ')
xlabel ('Time (sec)')
%
%Or plotting X_B vs. H at multi-step response
figure (4)
plot (t,y+yss ,'k-')
ylabel ('Bottom composition ')
xlabel ('Time(sec)')
hold on
[y,x,t]=step (value of step1*manuipulated variable*nump,denp);
plot (t,y+yss,'k:')
[y,x,t]=step (value of step2*manuipulated variable*nump,denp);
plot (t,y+yss ,'k--')
[y,x,t]=step (value of step3*manuipulated variable*nump,denp);
plot (t,y+yss ,'k-.')
[y,x,t]=step (value of step4*manuipulated variable*nump,denp);
plot (t,y+yss,'k:')
legend(' value of step1,' value of step2,' value of step3,' value of step4,1)
grid on
*************************** C.3***************************
```

C.3 Relative Gain Array (RGA) Program:

```
%Matlab program
%calculation the Relative gain array (RGA)
%give steady-state gain matrix
kp=[kp11 kp12;kp21 kp22];
%calculate matrix inverse
```

```
Kpinverse=inv (kp);
%take transpose
kptranse= inv (kp)';
%Do term by term multiplication using ".*" operator
RGA=kp.*kptranse
```

C.4 Close Loop Programs

*************************** C.4.a****************************

C.4.a Ziegler-Nichols Method

```
% Control tuning in the DIS.
% by using Ziegler-Nichols method (bode diagram).
% define the transfer function of process (DIS) with delay time
num=[value of nomenator];
den=[value of denomenator];
[numdt,dendt]=pade (value of delay time, number of approximation);
% apply series function
[nump,denp]=series (num,den,numdt,dendt);
Gp=tf (nump,denp)
%where Gp is the Transfer function of process with delay time
w=logspace (-1, 2,100);
[Gm,Pm,w]= margin (Gp);
Gmdb=20*log10 (Gm)
figure (1)
bode (Gp,'k')
%calculation the adjusted parameter of controller (PI)
Ku=Gmdb;
%where ku is ultimate gain
Pu= (2*pi)/w;
%where Pu is ultimate period of sustained cycling (sec/cycle)
```

```
kc=Ku/2.2
ti=Pu/1.2
numc=[kc*ti kc];,denc=[ti 0];
Gc=tf(numc,denc)
%or
%calculation the adjusted parameter of controller (PID)
Ku=Gmdb;
%where ku is ultimate gain
Pu= (2*pi)/w;
%where Pu is ultimate period of sustained cycling (sec/cycle)
kc=Ku/1.7
ti=Pu/2
td=Pu/8
numc=[kc*ti*td kc*ti kc];
denc=[0 ti 0];
Gc=tf(numc,denc)
%apply series function
[numol,denol]=series (nump,denp,numc,denc);
GOL=tf(numol,denol)
%where the GOL=GpGc
%apply feedback function
[numcl,dencl]=feedback (numol, denol, 1, 1);
TFCL=tf (numcl,dencl)
%where the TFCL is T.F. of close loop
[y,x,t]=step (numcl,dencl);
figure (2)
%plotting the step response of close loop
plot (t,y,'k-')
xlabel ('Time (sec)')
```

```
ylabel (' Distillate composition')
%or
ylabel ('Bottom composition ')
measured value=y';
%where a is response values
E=set point value- measured value;
%where E is the Error
e=abs (E);
TE=t.*e;
%where TE is the time* absolute error
% use trapz function to calculate the area under the curve
ITAE= trapz(t,TE)
figure (3)
plot (t,TE,'k-')
xlabel('Time (sec)')
ylabel('Time* absolute error')
*************************** C.4.b***************************
```

C.4.b Cohen-Coon Method

```
% Control tuning in the DIS.
% by using Cohen-Coon method (process reaction curve).
% define the transfer function of process (DIS) with delay time
num=[value of nominator];
den=[ value of denominator];
[numdt,dendt]=pade (value of delay time, number of approximation);
% apply series function
[nump,denp]=series (num,  den, numdt, dendt);
Gp=tf (nump,denp)
% where Gp is the Transfer function of process with delay time
[X, x, t]=step (nump,denp);
```

```
figure (1)
plot (t,X,'k')
xlabel ('Time(sec)')
ylabel (' Distillate composition')
%or
ylabel ('Bottom composition ')
hold on
%finding the values of k, Tau and td from figure (1)
k= [values of k];
Tau= [values of Tau];
td=values of td;
[T1, x, t]=step (k,Tau);
plot (t+td,T1,'k--')
hold off
%from figure (1)
k= values of k;
Tau= values of Tau;
td= values of td;
%calculation the adjusted parameter of controller (PI)
kc=(Tau/(k*td))*(0.9+td/(4*Tau))
ti=td*((30+((3*td)/Tau))/(9+((20*td)/Tau)))
numc=[kc*ti kc];,denc=[ti 0];
Gc=tf (numc,denc)
% or  calculation the adjusted parameter of controller (PID)
kc=(Tau/(k*td))*(4/3+td/(4*Tau))
ti=td*((32+((6*td)/Tau))/(13+((8*td)/Tau)))
td=td*((4)/(11+((2*td)/Tau)))
numc=[kc*ti*td kc*ti kc];
denc=[0 ti 0];
```

```
Gc=tf(numc,denc)
%apply series function
[numol,denol]=series (nump,denp,numc,denc);
GOL=tf(numol,denol)
%where the GOL=GpGc
[numcl,dencl]=feedback (numol, denol, 1, 1);
TFCL=tf (numcl,dencl)
%where the TFCL is T.F. of close loop
[y,x,t]=step (numcl,dencl);
figure (2)
%plotting the step response of close loop
plot (t,y,'k-')
xlabel ('Time (sec)')
ylabel (' Distillate composition')
%or
ylabel ('Bottom composition ')
measured value =y';
%where a is response values
E=set point value- measured value;
%where E is the Error
e=abs (E);
TE=t.*e;
%where TE is the time* absolute error
% use trapz function to calculate the area under the curve
ITAE= trapz(t,TE)
figure (3)
plot (t,TE,'k-')
xlabel('Time (sec)')
ylabel('Time* absolute error')
```

************************** C.4.c****************************

C.4.c Internal Model Control Method:

```
% Control tuning in the DIS.
% by using Cohen-Coon method (process reaction curve).
% define the transfer function of process (DIS) with delay time
num=[value of nominator];
den=[ value of denominator];
[numdt,dendt]=pade (value of delay time, number of approximation);
% apply series function
[nump,denp]=series (num,  den, numdt, dendt);
Gp=tf (nump,denp)
% where Gp is the Transfer function of process with delay time
[X, x, t]=step (nump,denp);
figure (1)
plot (t,X,'k')
xlabel ('Time(sec)')
ylabel (' Distillate composition')
%or
ylabel ('Bottom composition ')
hold on
%finding the values of k, Tau and td from figure (1)
k= [values of k];
Tau= [values of Tau];
td=values of td;
[T1, x, t]=step (k,Tau);
plot (t+td,T1,'k--')
hold off
%from figure (1)
k= values of k;
```

```
Tau= values of Tau;
td= values of td;
%calculation the adjusted parameter of controller (PI)
Tauc=(2/3)*td
kc=Tau/(k*(Tauc+td))
ti=Tau
numc=[kc*ti kc];,denc=[ti 0];
Gc=tf(numc,denc)
% or  calculation the adjusted parameter of controller (PID)
Tauc=(2/3)*td
a=((2*Tau)/td)+1;
b=((2*Tauc)/td)+1;
kc=(1/k)*(a/b)
ti=Tau+(td/2)
td=Tau/a
numc=[kc*ti*td kc*ti kc];
denc=[0 ti 0];
Gc=tf(numc,denc)
%apply series function
[numol,denol]=series (nump,denp,numc,denc);
GOL=tf(numol,denol)
%where the GOL=GpGc
[numcl,dencl]=feedback (numol, denol, 1, 1);
TFCL=tf (numcl,dencl)
%where the TFCL is T.F. of close loop
[y,x,t]=step (numcl,dencl);
figure (2)
%plotting the step response of close loop
plot (t,y,'k-')
```

```
xlabel ('Time (sec)')
ylabel (' Distillate composition')
%or
ylabel ('Bottom composition ')
measured value =y';
%where a is response values
E=set point value- measured value;
%where E is the Error
e=abs (E);
TE=t.*e;
%where TE is the time* absolute error
% use trapz function to calculate the area under the curve
ITAE= trapz(t,TE)
figure (3)
plot (t,TE,'k-')
xlabel('Time (sec)')
ylabel('Time* absolute error')
*************************** C.5***************************
```

C.5 Interaction Program:

```
% define the transfer function of process with delay time
num11= [ ];
den11= [ ];
H11=tf (num11, den11); % H11 is transfer function between XD & R
num12= [ ];
den12= [ ];
H12=tf (num12, den12); % H12 is transfer function between XD&H
num21= [ ];
den21= [ ];
H21=tf (num21, den21); % H21 is transfer function between XB& R
num22= [];
```

den22= [];

H22=tf (num22, den22); % H22 is transfer function between X_B& H

G=H11-(H12*H21)/H22

%or G= H22-(H12*H21)/H11

% Apply the Control Tuning

%at interaction by using different three methods

%define the Transfer function of process with delay time

Gpi=H11+H12;

%where Gpi is the Transfer function of process at interaction

% calculate the adjusted parameter of controller (PI)/ (PID) for bode %diagram, IMC and Process Reaction Curve. It is the same in

%previous programs, define the controller then Apply the *series* function

% Apply the *Feedback* function then make step in the %characteristic equation plot and compute the ITAE as in previous %programs

************************** C.6***************************

C.6 Decoupling Program:

% define the transfer function of process with delay time

num11= [ ];

den11= [ ];

H11=tf (num11, den11); % H11 is transfer function between X_D & R

num12= [ ];

den12= [ ];

H12=tf (num12, den12); % H12 is transfer function between X_D&H

num21= [ ];

den21= [ ];

H21=tf (num21, den21); % H21 is transfer function between X_B& R

num22= [];

den22= [];

H22=tf (num22, den22); % H22 is transfer function between X_B& H

G=H11-(H12*H21)/H22

%or G= H22-(H12*H21)/H11

% Apply the Control Tuning

%at interaction by using different three methods

%define the Transfer function of process with delay time

Gpi=H11+H12;

%where Gpi is the Transfer function of process at interaction

% calculate the adjusted parameter of controller (PI)/ (PID) for bode %diagram, IMC and Process Reaction Curve. It is the same in

%previous programs define the controller then apply the *series* function

f=series (G,Gc);

% Apply the *Feedback* function then make step in the

%characteristic equation plot and compute the ITAE as in previous %programs

For the Adaptive fuzzy controller the input variable are error (*e*) , change of error (*de*) and auxiliary variable (AV), the output variable is the control action (*u*).

Rule definition: a general fuzzy inference rule for this controller that has three inputs and a single output is:

IF e is PB AND de is NB AND AV is Z THEN u is Z.

Table (D.1) Adaptive fuzzy rule

e	de	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

الخلاصة

تعتبر السيطرة على برج التقطير عملية صعبة نتيجة للسلوك اللاخطي و التداخل بين المتغيرات اضافة الى عدم الثباتية للسلوك خلال العملية لذالك تم استخدام طرق سيطرة مختلفة للسيطرة على التراكيز الخارجة من اعلى واسفل برج التقطير الحشوي لعملية الفصل بين مزيج الماء والميثانول. تم أستخدام طرق سيطرة مختلفة: المسيطر التقليدي ,المسيطر الضبابي المنطقي التقليدي (Fuzzy logic) ,مسيطر الشبكة العصبية الأصطناعية (NARMA-L2) ,مسيطر (PID fuzzy) ,مسيطر الضبابي المنطقي المتكيف(Adaptive Fuzzy logic) ومسيطر الشبكة العصبية الأصطناعية الضبابية المتكيفة(ANFS) للسيطرة على التراكيز الخارجة من اعلى واسفل البرج.

استعمل معيار الاداء لانواع السيطرة المختلفة وهو معيار التكامل الزمني للخطأ المطلق (ITAE), كذلك تم استعمال معاملات الاداء الخطي للنظام مثل قيمة التطرف (overshoot) وزمن الاستقرار (settling time) لتقييم الاداء لاستراتيجيات السيطرة المختلفة .تم ضبط محددات السيطرة لمسيطرين PI و PID بأستخدام ثلاث طرق Internal Model Control و Ziegler-Nicholsو Cohen-Coon لايجاد افضل القيم للمعاملات ووجد ان طريقة Internal Model Controlكانت افضل من بقية الطرق حيث اعطت معيار التكامل الزمني للخطأ المطلق (ITAE)اقل وتم اعتمادها في هذا العمل

حددت درجة التداخل بالاعتماد على مصفوفة الكسب النسبي (RGA). اختير نظام الرابط المزدوج لالغاء تاثير التداخل في دوائر السيطرة واظهر نتيجة جيدة .

تم الحصول على اقل قيمة لمعيار التكامل الزمني للخطأ المطلق (ITAE) للمسيطر الشبكة العصبية الأصطناعية الضبابية المتكيفة(ANFS) لتركيز الناتج العلوي لبرج التقطير بنتيجة61.3 و 54 لتركيز الناتج السفلي والذي يؤكد على انه افضل مسيطر ستراتيجي من بين المسيطرات الأخرى.

وزارة التعليم العالي والبحث العلمي
الجامعة التكنولوجية
قسم الهندسة الكيمياوية

استخدام مسيطر الشبكة العصبية الضبابية للسيطرة على عملية فصل الميثانول في برج التقطير

رسالة مقدمة الى قسم الهندسة الكيمياوية في الجامعة التكنولوجية
كجزء من متطلبات نيل درجة ماجستير علوم
في
الهندسة الكيمياوية / تكرير النفط والغاز

إعداد
غيداء مجيد جاعد
(بكالوريوس هندسة كيمياوية 2009)
بإشراف
أ.د. صفاء الدين عبد الله النعيمي

ربيع الاول 1432 شباط2012م