Identify Time varying Concentration of CSTR System Using

B-Spline Network

by:

Majda Bakheit Obaid

Dissertation submitted in partial fulfillment of

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Approved by,

_____

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TRONOH, PERAK

DECEMBER 2010

CERTIFICATION OF ORIGINALITY

This is to certify that I am responsible for the work submitted in this project, that the original work is my own except as specified in the references and acknowledgements, and that the original work contained herein have not been undertaken or done by unspecified sources or persons.

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MAJDA BAKHEIT OBAID

ABSTRACT

Continuous Stirred Tank Reactor System (CSTR) is a typical chemical reactor system with complex nonlinear dynamic characteristics. The system is SISO, the output being the concentration of a product compound C and the input being the coolant flow rate. There has been considerable interest in its state estimation and real time control based on mathematical modeling. The mathematical model works for all fluids: liquids and gases. An efficient control of the product concentration in CSTR can be achieved through accurate model. A time varying concentration of CSTR system has been identified throughout various techniques. The project life cycle combined a number of stages, each stage is a complement or enhancement of the previous stage starting from building the basic model for CSTR depending on its two main equations using SIMULINK then applying different levels of ARX models to determine the best model that represent the real output, then using some RBF functions and other functions from Neural Network toolbox and finally examine the response of those functions by training them and observing their response on the training window's performance and regression to evaluate them and their error rates. B-spline network is under progress and by that, the project has succeeded in achieving its target.

ACKNOWLEDGMENT

All thanks due to Allah for his blessing & grace to complete this report in ease & success.

Without the valuable supervisory efforts from my honorable supervisor Dr. Vijanth Sagayan, this project would not complete in such way. So, much respectful regards are carried to him.

My deepest heart gratitude is to my parents who haven't hesitated to sacrifice anything to ensure my success in my life.

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TABLE OF CONTENTS

LIST OF FIGURES

LIST OF ABBREVIATIONS

CSTR Continuous Stirred Tank Reactor

ARX Autoregressive with external input

RBF Radial Basis Function

SISO Single Input Single Output

CHAPTER 1

INTRODUCTION

1.1 Background of Study

Since early 60s, developing mathematical models of non-linear systems is a central topic in many disciplines of engineering. In control system the plant displaying nonlinearities has to be described accurately in order to design an effective controller. In obtaining the mathematical model, the designer follows two methods. The first one is to formulate the model from the first principles using the laws governing the system. This is generally refers to as mathematical modeling. The second approach requires experimental data obtained by exciting the plant and measuring its response. This is called system identification and is preferred in the case where the plant or process involves extremely complex physical phenomena or exhibits strong nonlinearity.[1]

The continuous stirred-tank reactor (CSTR) is one of those non-linear systems. It is also known as vat- or backmix reactor is a common ideal reactor type in chemical engineering. A CSTR often refers to a model used to estimate the key unit operation variables when using a continuous agitated-tank reactor to reach a specified output. The mathematical model works for all fluids: liquids, gases, and slurries.[2]

1.2 Problem Statement

Obtaining a mathematical model that works for complex nonlinear system like CSTR which works for all fluids: liquid, gases, and slurries was complex and time

consuming. It often requires some assumptions such as defining an operating point, important variables and some constants. This fact has leaded the researcher to go through a set of methods to identify time varying concentration of CSTR system. The modern CSTR models are often used to simplify engineering calculations and can be used to describe the behavior of CSTR system no matter how complex it is.

1.3 Objectives

The objective of this project is to model and simulate CSTR system throughout various techniques in order to identify its time varying concentration. It is required to figure out the best technique that can give the most accurate representation for the real plant output and that could never be achieved without a systematic procedures that should be followed starting from building the main CSTR model using SIMULINK block diagrams and varying the coolant flow rate -which represents the input of the system- to determine the stability range of input data that can work with ARX system. Three different levels of ARX have to be applied and each level should be evaluated in term of its response. The third stage is applying some RBF Network functions, two functions were applied and results were analyzed but since the number of neurons was very large RBF Network was not satisfactory and a better network that can overcome such problem was required. As a result, Neural Network is the best alternative since it can deal with large input data more efficiently.

1.4 Scope of Study

This projects aims to obtain a practical model that identifies time varying concentration of the complex nonlinear CSTR system through number of stages. This target can never be achieved without following a systematic guideline and since CSTR is SISO system that deals with single input which is the flow of the coolant (q_c), and single output being the concentration of the product (C), the first step is to linearize the system by varying its input coolant flow to determine the

best range for ARX system. For better and more accurate results the project has to experience some functions from RBF Network as well as Neural Network toolbox.

CHAPTER 2
LITERATURE REVIEW

2.1 Theory

Continuous Stirred Tank Reactor System (CSTR) is a typical chemical reactor system with complex nonlinear dynamic characteristics. The system is SISO, the output being the concentration of a product compound C and the input being the coolant flow rate.

Past researches have proven that CSTR is a highly nonlinear plant. The product concentration can be controlled by introducing the coolant flow which allows the manipulation of reaction temperature. The reaction takes place in a container of fixed volume.

Figure 4 bellow illustrates the diagram of a continuous stirred tank reactor system with concentration of the compound as the output:

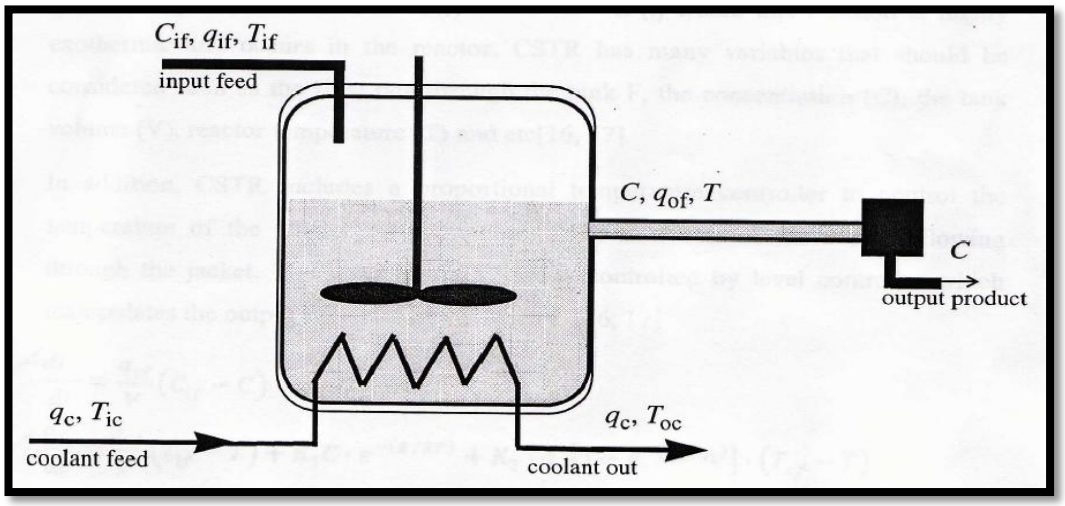

Figure 1: CSTR with C as the input & q as output

The figure shows typical input (coolant flow) and output (concentration of the product) signals for the system when it is excited about its nominal operating point using band limited white noise.

The chemical reaction to produce the compound that takes place inside the insulated tank is considered to be exothermic process which raises the temperature inside the tank and hence reduce the reaction rate.[4]

The behavior of a CSTR is often approximated or modeled by that of a Continuous Ideally Stirred-Tank Reactor (CISTR). All calculations performed with CISTRs assume perfect. In a perfectly mixed reactor, the output composition is identical to composition of the material inside the reactor, which is a function of residence time and rate of reaction. If the residence time is 5-10 times the mixing time, this approximation is valid for engineering purposes. The CISTR model is often used to simplify engineering calculations and can be used to describe research reactors. In practice it can only be approached, in particular in industrial size reactors.[2]

2.2 The operational concept of CSTR:

One or more fluids are introduced into a tank reactor equipped with an impeller. The impeller stirs fluids by circulating the liquid upward and downward to ensure proper mixing. Vertical heat exchangers are used.[5] Sometimes a coolant jacket around the tank is used as heat exchanger. The type of heat exchanger depends on the applications of the CSTR wither industrial application or wastewater treatment units etc.

Simply dividing the volume of the tank by the average volumetric flow rate through the tank gives the residence time, or the average amount of time a discrete quantity of reagent spends inside the tank. Using chemical kinetics, the reaction's expected percent completion can be calculated.[5] Figure1 bellow shows a very basic structure of CSTR system.

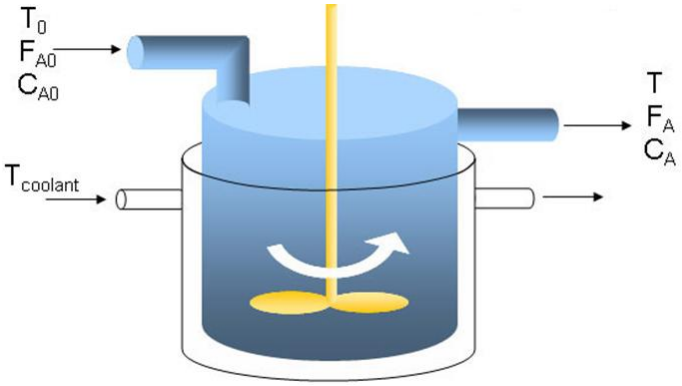

Figure 2: CSTR Structure

2.3 Input-Output Data

System identification experiment design for many nonlinear systems is typically much more involved than for linear systems. This is also true for the CSTR, where on one hand it is desired that the controllable input (q_c) is such that it excites the system sufficiently and on the other hand it must be chosen to be "plant-friendly" (the chemical process must be kept stable, the duration of the test should be as short as possible so as to influence the production least, and so forth). To discuss the choice of input signals to the CSTR, there it is an argument that a multi-sinusoidal input (q_c) is advantageous to a multi-level pseudo random input signal for several reasons.[3] In this project many kinds of input signals will be presented to CSTR. Firstly a step function with various values will be introduced and its response is going to be evaluated in order to linearize the system and prepare it for ARX model. Then five different functions which are, two pulse generators, two sine waves and one step function, will be added together and introduced to the input of CSTR as a form of noise to get the maximum feedback from ARX system even if the system is completely nonlinear.[3]

2.4 Important aspects of CSTR:

1) "At steady-state, the flow rate (in) must equal the mass flow rate (out), otherwise the tank will overflow or go empty (transient state). While the reactor is in a transient state the model equation must be derived from the differential mass and energy balances.

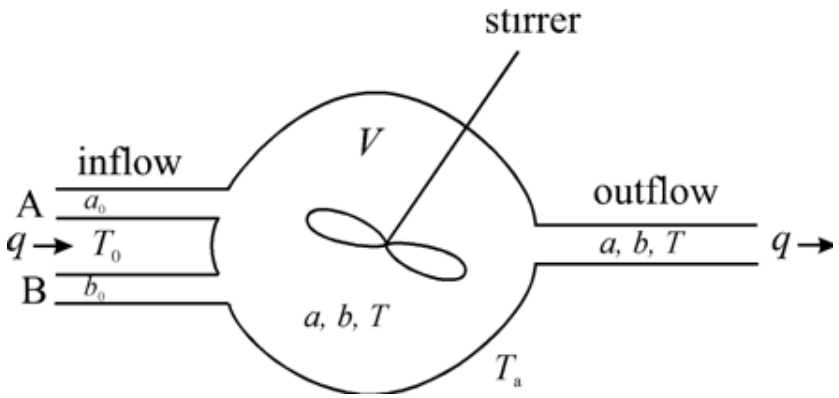

Figure 3: Inflow = outflow of CSTR

2) The reaction proceeds at the reaction rate associated with the final (output) concentration.
3) The materials (i.e. a,b,T) are assumed to be completely mixed.
4) Often, it is economically beneficial to operate several CSTRs in series. This allows, the first CSTR to operate at a higher reagent concentration and therefore a higher reaction rate.

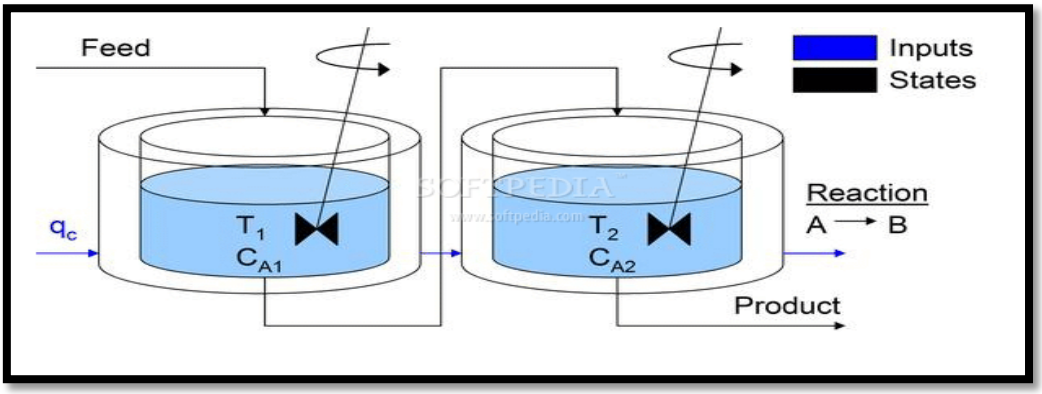

Figure4: series CSTRs for economic reasons

In these cases, the sizes of the reactors may be varied in order to minimize the total capital investment required to implement the process." [5]

2.5 System Identification

"System identification is a general approach to determine a mathematical model of process from measured data and describe the dynamic behavior of the process. In addition, the system identification models can be built using one of the following approaches:

- White box model: that based on the first principles such as physical laws, energy and material balances. This model valid over wide range of operating points.
- Gray box model: this model developed from the first principle and part of it developed from experimental data.
- Black box model: which is built from experimental data of the input and the output and the internal system parameters are hidden.

Furthermore, two common approaches of system identification are Auto Regressive with Exogenous input (ARX) and Auto Regressive Moving Average with Exogenous input (ARMAX)."[6]

2.6 ARX Model

A brief description of system identification using ARX model with parameters which are functions of input output. The ARX model that is the most widely applied linear dynamic model represented by the following equation:

$$y[k] + \alpha_1 y[k-1] + \alpha_i y[k-i] + \ldots + \alpha_n y[k-n] = \beta_1 u[k-1] + \beta_i u[k-i] + \ldots + \beta_n u[k-n] + e(t) \quad (2.1)$$

Where y[k] and u[k] are autoregressive variables or system output and system input at time k respectively, α_i and β_i are coefficients where i= 1,2,3, …,n and n is the system order. [6]

2.7 RBF Design

A Radial Basis Function (RBF) neural network consists of two layers: a hidden radial basis layer of S^1 neurons and an output linear layer of S^2 neurons. The neurons in the hidden layer contain Gaussian transfer functions whose outputs are inversely proportional to the distance from the center of the neuron.

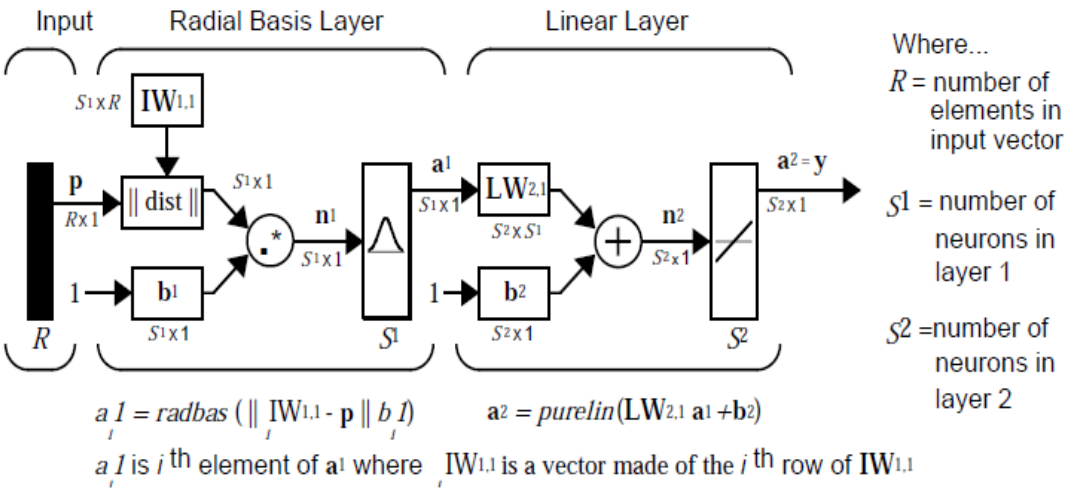

Figure 5: RBF contents

The transfer function for a radial basis neuron is $radbase(n) = e^{-n2}$

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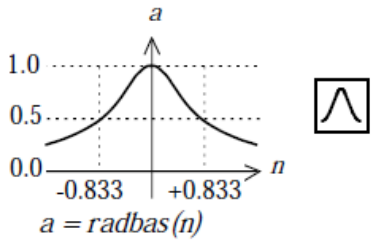


Figure 6: A plot of the radbas transfer function [4]

Radial basis networks can be designed with function (newrbe). This function is preferred because it produces a network with zero error on training vectors. It is called in the following way:

```
net= newrbe(P,T, SPREAD)
```

The function (newrbe) takes matrices of input vectors P and target vectors T, and a spread constant SPREAD for the radial basis layer, and returns a network with weights and biases such that the output are exactly T when the inputs are P.[7]

At this stage of the project life cycle RBF was applied using (newrbe) function and results are shown on the results and discussion chapter 4.

2.8 Neural Network Toolbox

Control Systems describes three practical neural network control system applications, including neural network model predictive control, model reference adaptive control, and a feedback linearization controller. Neural networks are good at fitting functions and recognizing patterns. In fact, there is proof that a fairly simple neural network can fit any practical function.

To define a fitting problem for the toolbox, arrange of Q input vectors has to be used as columns in a matrix. Then, another set of Q target vectors should be arranged (the correct output vectors for each of the input vectors) into a second matrix.

In this stage, data consisting of input vectors and target vectors is loaded as following:

```
load house_dataset
```

A feedforward network is created with the default tan-sigmoid transfer function in the hidden layer and linear and transfer function in the output layer. This structure is useful for functions approximation problems. [7] In this project different

numbers of neurons are applied but the best result was found when using neurons range from 50 to 70 as will be shown later in Chapter4. The network has one output neuron, because there is only one target value associated with each input vector:

```
net=newfit(net, houseInputs, house Targets)
```

Or;

```
net=newff(net, houseInputs, house Targets)
```

CHAPTER 3
METHODOLOGY

3.1 Procedure Identification

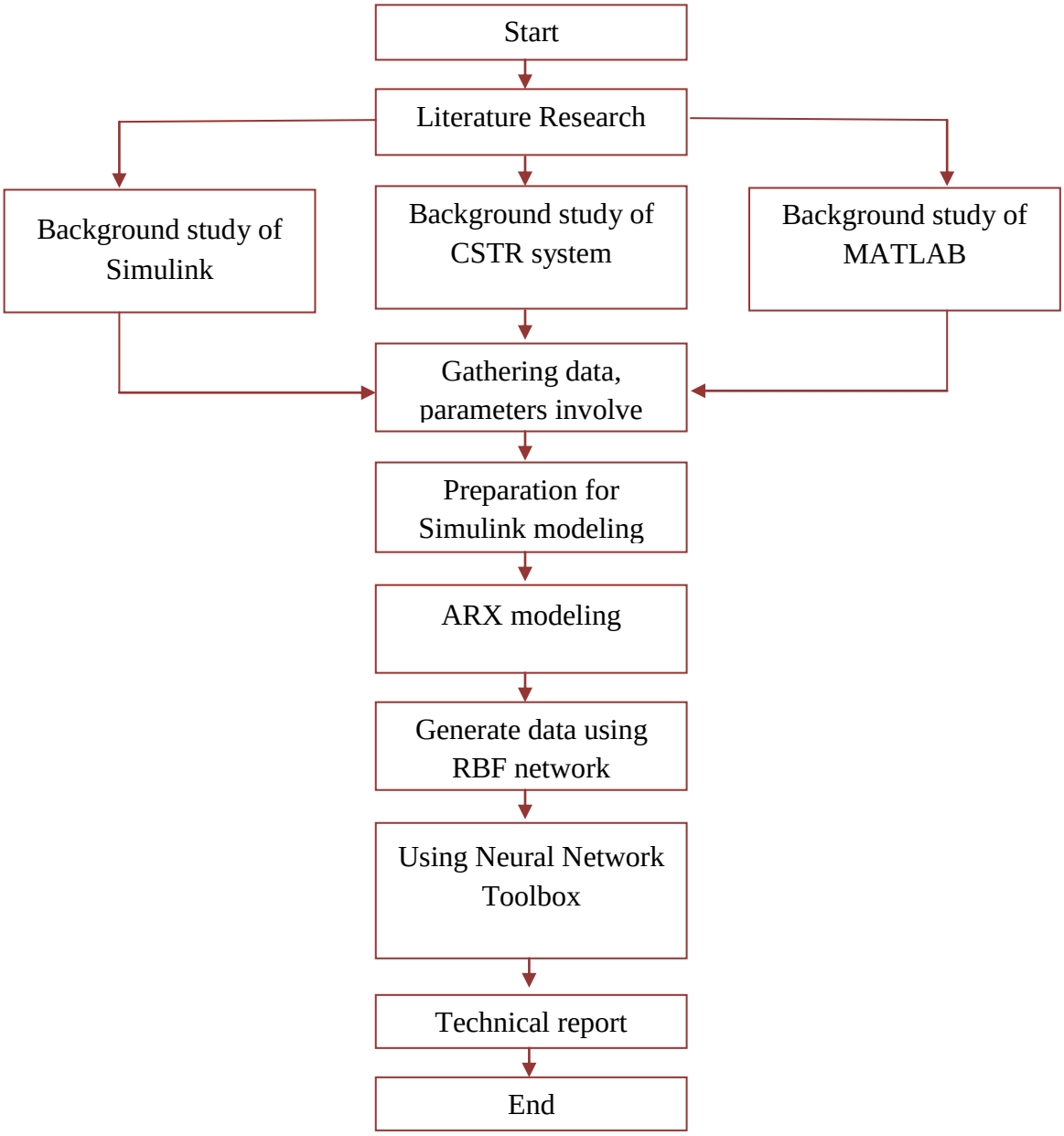


Figure7: Flowchart of the project

3.2 Tools and Equipments Used

There are many techniques used to reach the target of this project such as;

I. SIMULINK/ MATLAB
II. ARX model
III. RBF Network
IV. Neural Network Toolbox

3.3 CSTR Main Equations

“

$$\frac{dT}{dt} = \frac{q_{if}}{V}(T_{if} - T) + K_1 C \cdot \exp\left(\frac{-E}{R \cdot T}\right) + K_2 q_c \cdot \left[1 - \exp\left(-\frac{K_3}{q_c}\right)\right] \cdot (T_{cf} - T) \quad (3.1)$$

$$\frac{dC}{dt} = \frac{q_{if}}{V}(C_{if} - C) - K_o C \cdot \exp\left(\frac{-E}{R \cdot T}\right) \quad (3.2)$$

Where:

q_{if} = product rate = 100 l/min C_{if} = input product concentration = 1 mol/l

T_{if} = input temperature = 350K T_{cf} = Temperature of coolant = 350 K

V = container volume = 100 l/min E/R = Activation Energy = 10^4 K

K_0 = plant constant = 7.4×10^{10} K_1 = Plant constant = 1.44×10^{13}Kl/min/mol

K_2 = plant constant = 0.01/l K_3 = plant constant = 700 l/min

The important variables are:

q_c = coolant flow rate – the plant input

T= temperature of the product compound – internal plant state

C= product concentration (mol/i) – the plant output" [4]

3.4 Actual CSTR Plant Simulation

A SIMULINK diagram for nonlinear complete CSTR plant is shown in APPENDIX-I.

For the sake of simplicity, the graphs of Concentration (C) and temperature (T) are shown separately as subsystems for the actual system:

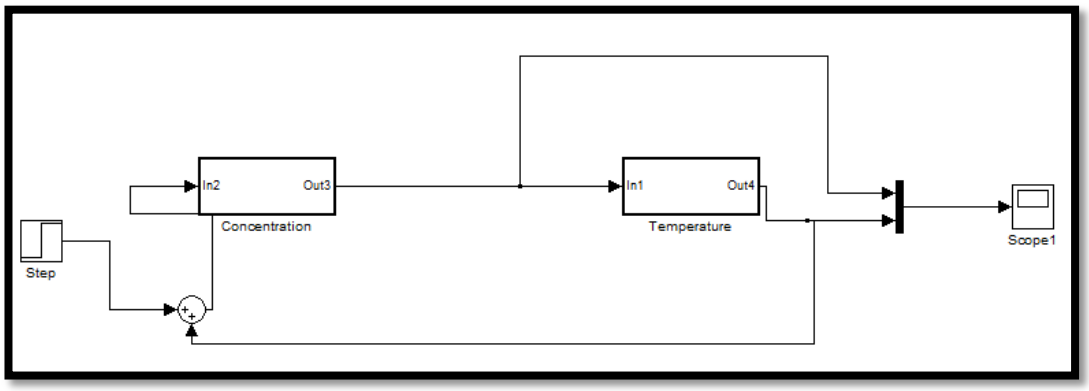


Figure 8: Concentration (C) and Temperature (T) inside the subsystem.

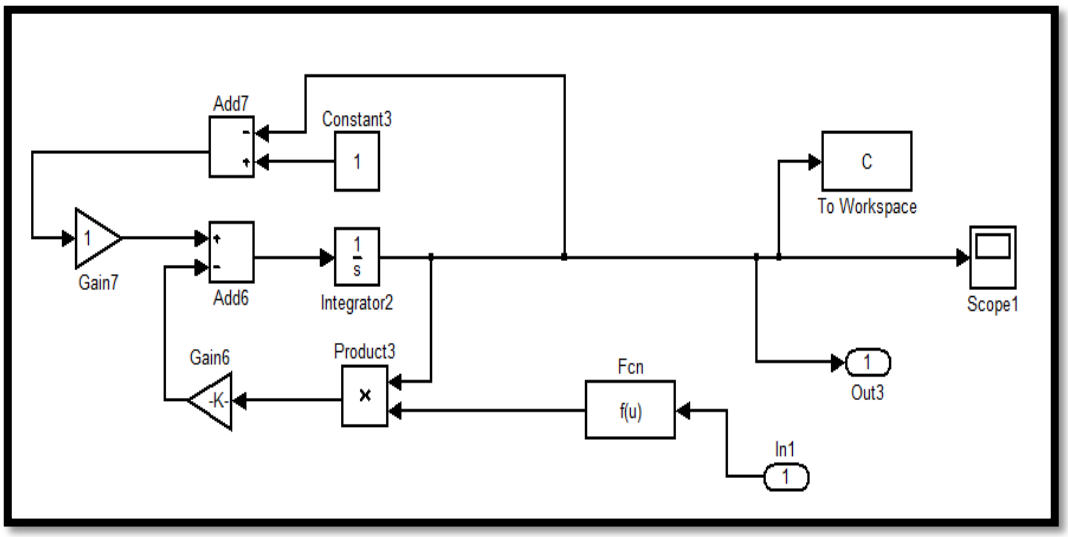


Figure 9: Concentration (C) SIMULINK blocks

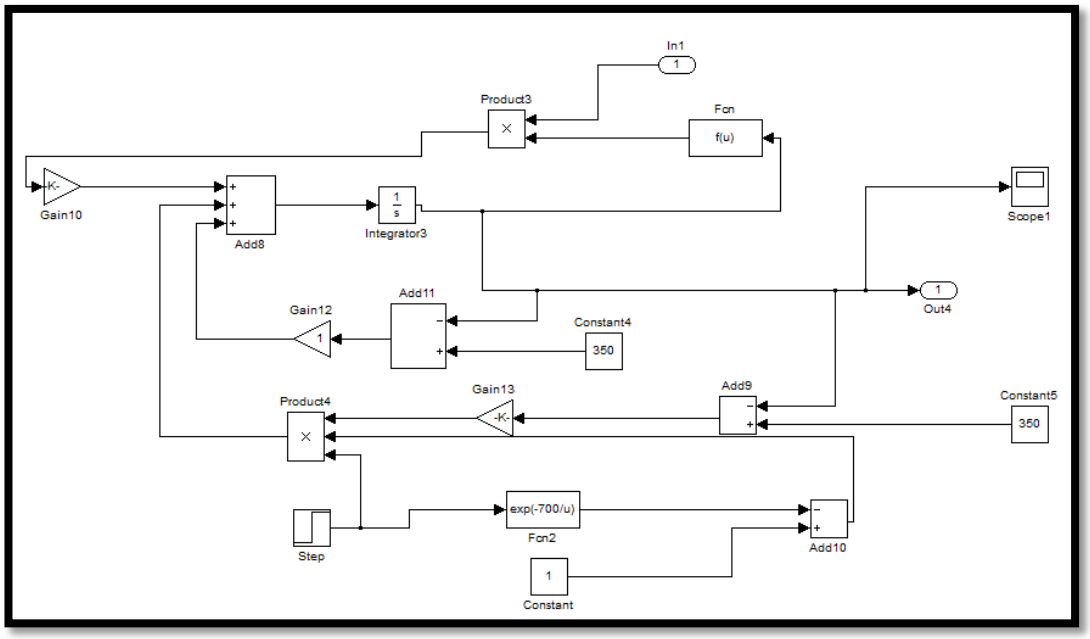


Figure 10: Temperature (T) SIMULINK blocks

3.5 Identification of linear ARX black-box model

The accuracy of the prediction or the estimation of the ARX model depends on the sampling frequency of the measured input-output data of the real system (CSTR plant). Moreover, the sampling frequency should be sufficiently large enough. However, having a large sampling frequency to obtain an accurate identification of the real system will result in difficulties and problems in the CSTR plant identification due to:

- Very large sampling frequency leads to that the values of the observed output to the neighbor output y(k) and y(K+1) respectively, are very close and near equal to each other which leads to a poor prediction of the ARX model.
- In addition, it also results in the matrix R will have a singular value.[6]

The figure bellow shows the linear CSTR model after applying the ARX concept. For more details on the subsystem content, refer to Appendix-I which shows the three ARX level block diagrams.

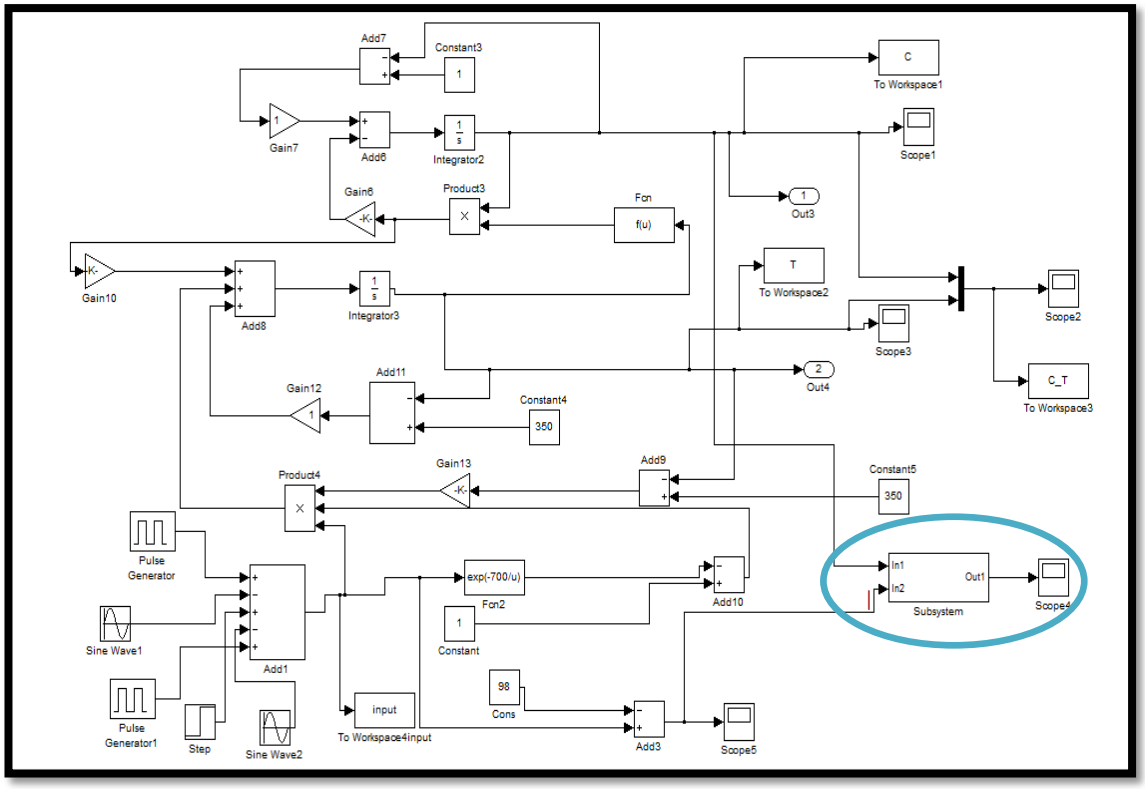


Figure 11: CSTR with ARX enhancement

3.6 RBF (newrbe)

Radial basis networks can be designed with function (newrbe). This function is preferred because it produces a network with zero error on training vectors.[7] It is called as following:

```
net= newrbe(P,T, SPREAD)
```

This function (newrbe) creates as many `radbas` neurons as there are input vectors in P, and sets the first layer weights to P'. Thus, there is a layer of

`radbas` neurons in which each neuron acts as a detector for a different input vector. If there are Q inputs vectors, then there will be Q neurons.

3.7 Neural Network Toolbox Command Line Functions

There are facts that have to be considered before applying Neuron Network. More neurons require more complicated problems. More layers require more computation, but their use might result in the network solving complex problems more efficiently.[7]

The common steps of demonstrating our linear CSTR system using Neural Network toolbox are as following:

- The first step is to define a set of input vectors and a set of associated desired output vectors called *target vectors*. The input vectors define data regarding real—estate properties and the target values define relative values of the properties.
- Load the data using the following command `load house_dataset`. Loading this file creates two variables. The input matrix `houseInputs` consists of 506 column vectors of 13 real estate variables for 506 different properties. The target matrix `houseTargets` consists of the corresponding 506 relative valuations.
- The next step is to create a network and train it until it has learned the relationship between the inputs and targets using (newfit) or (newff) functions.
  1. `net=newfit(net, houseInputs, house Targets)`
  2. `net=newff(net, houseInputs, house Targets)`
- Train the network. The uses the default Levenberg –Marquardt algorithm for training. The application randomly divides input vectors and target vectors into three sets as follows:
  1. 60% are used for training.

2. 20% are used to validate that the network is generalizing and to stop training before overfitting.
3. The last 20% are used as completely independent test of network generalization.

To train the network, we use:

```
net= train(net,houseInputs,houseTargets)
```

CHAPTER 4
RESULTS AND DISCUSSION

4.1 Theory

In order to develop an appropriate model for the CSTR plant, several models have been designed. Firstly, a linearized model was built through a number of stages bellow are some steps that were followed in order to reach to the best range of values for the ARX model.

4.2 Linearization of Process Mode:

The first step is to linearize the system by varying its input coolant flow to determine the stability range for ARX system. Linearization was achieved through the following steps:

1. At q_c = 85 l/min, the Concentration (C) graph represents a first order system that reaches steady state within 20minutes. Temperature (T) experiences very high over-shoot then settles down to steady state. The figure bellow shows the graphs for C and T;

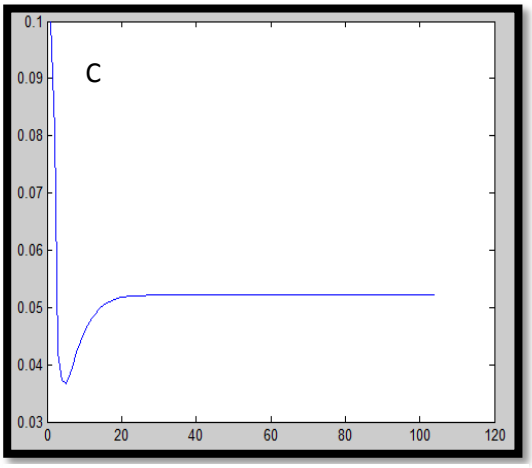


Figure 12: Concentration at qc = 85

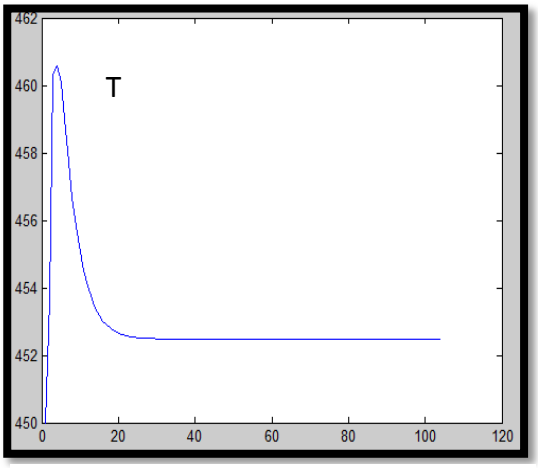


Figure 13: Temperature at qc = 85

Although the system is first order linear system but Concentration is very small and Temperature overshoot may damage plant equipments.

2. At q_c = 100 l/min the graphs give better output responses. The Concentration (C) shows a first order response to the coolant flow. Temperature overshoot is acceptable and it reaches saturation as well. The system is first order and linear. The figures bellow show C and T at q_c = 100 l/min;

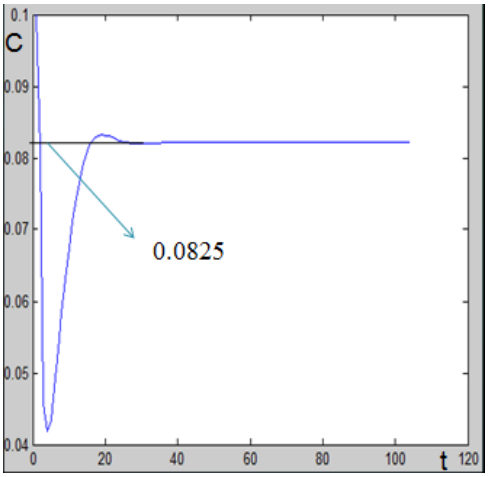


Figure 14: Concentration at qc = 100

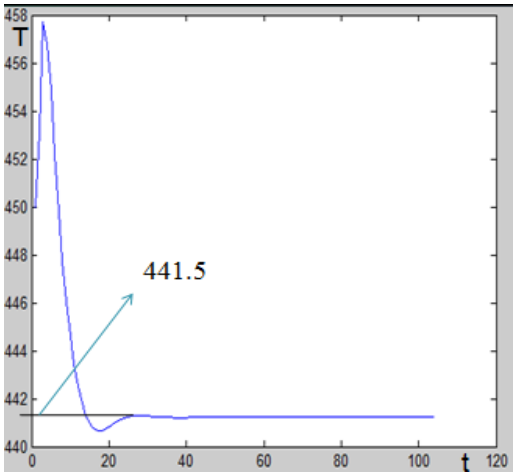


Figure 15: Temperature at qc = 100

3. At q_c =110 l/min, the Concentration (C) graph represents a second order oscillatory system that never reaches steady state. Temperature (T) experiences very obvious oscillation as well. This system is completely undesired. The figure bellow shows the graphs for C and T;

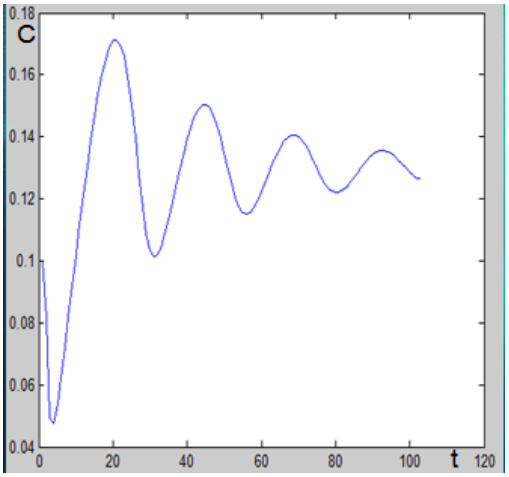


Figure 16: Concentration at qc = 110

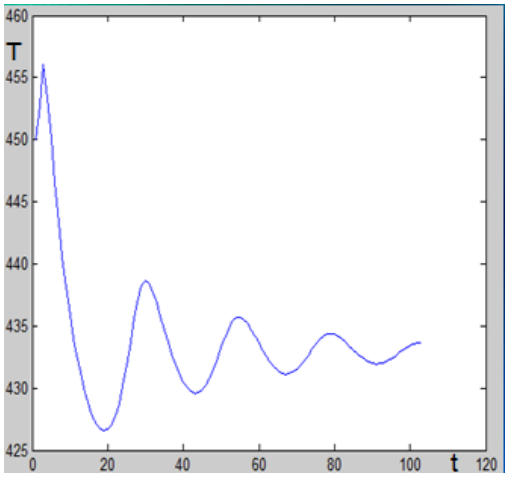


Figure 17: Temperature at qc = 110

Findings:

- The output of the system shows a first order response for the coolant flow rate (input) at qc=95 l/min to qc=100 l/min.
- As the coolant flow rate increases beyond 100 l/min, the system starts showing a second order behavior (oscillation) before settling down to steady state.
- The nonlinear CSTR plant is linearized around the following operation points;

  qc= (95 -100) l/min, T=441.5 K, C=0.0825 mol/l

Analysis:

- The range of operation for ARX (Black box model) is between qc= 95 to 100 l/min.
- Next stage: Apply ARX model for various values of qc within the appropriate range and study the effect of each input (qc) on the system output (Concentration)

4.3 ARX parameter estimation

The identification of the ARX model depends only on the information of the input and output as it is a black-box model as mentioned earlier. In this technique the system is identified by estimating the parameters of the ARX model using input-output data. In this model;

$$\text{ARX-1} = \alpha_1 Y_{(t-1)} + \beta_1 U_{(t-1)} + E_{(t)} \quad (4.1)$$

$$\text{ARX-2} = \alpha_1 Y_{(t-1)} + \alpha_2 Y_{(t-2)} + \beta_1 U_{(t-1)} + \beta_2 U_{(t-2)} + E_{(t)} \quad (4.2)$$

$$\text{ARX-3} = \alpha_1 Y_{(t-1)} + \alpha_2 Y_{(t-2)} + \alpha_3 Y_{(t-3)} + \beta_1 U_{(t-1)} + \beta_2 U_{(t-2)} + \beta_3 U_{(t-3)} + E_{(t)} \quad (4.3)$$

4.4 ARX Results

The estimation of the parameters for different orders of ARX model is achieved and the estimated output is compared with the real output for different orders of ARX model as shown in the following figures. Figure 18 shows the real plant output (CSTR) and the predicted output for first order ARX model.

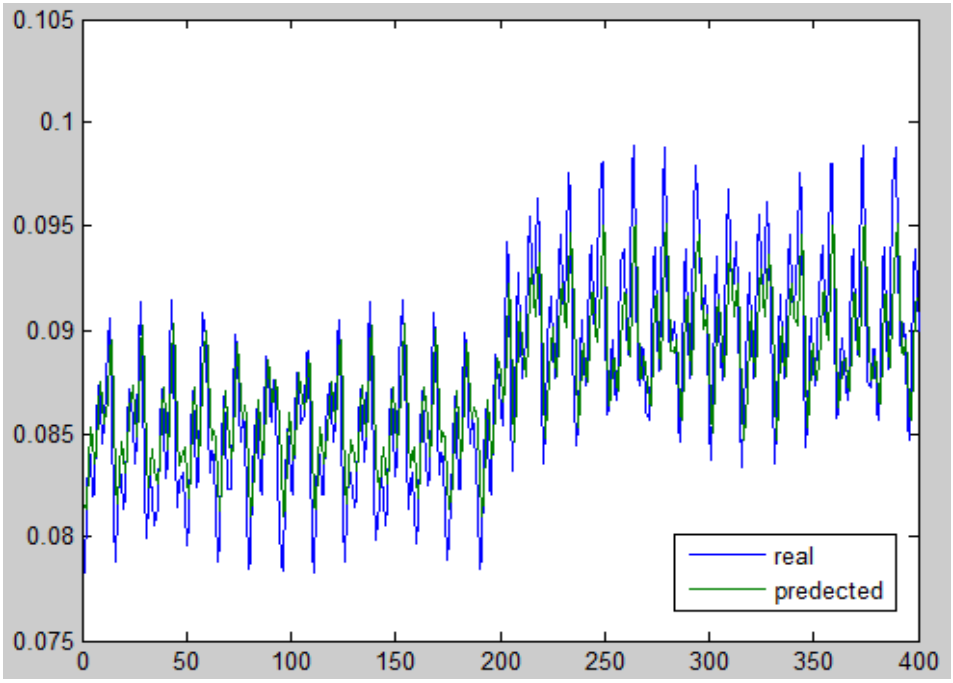


Figure 18: Comparison of the real output and the predicted by ARX-1model

In addition an ARX-2 has been implemented also for the prediction of CSTR output as shown in figure 18. Last but not least, Figure 19 presents ARX-3 response.

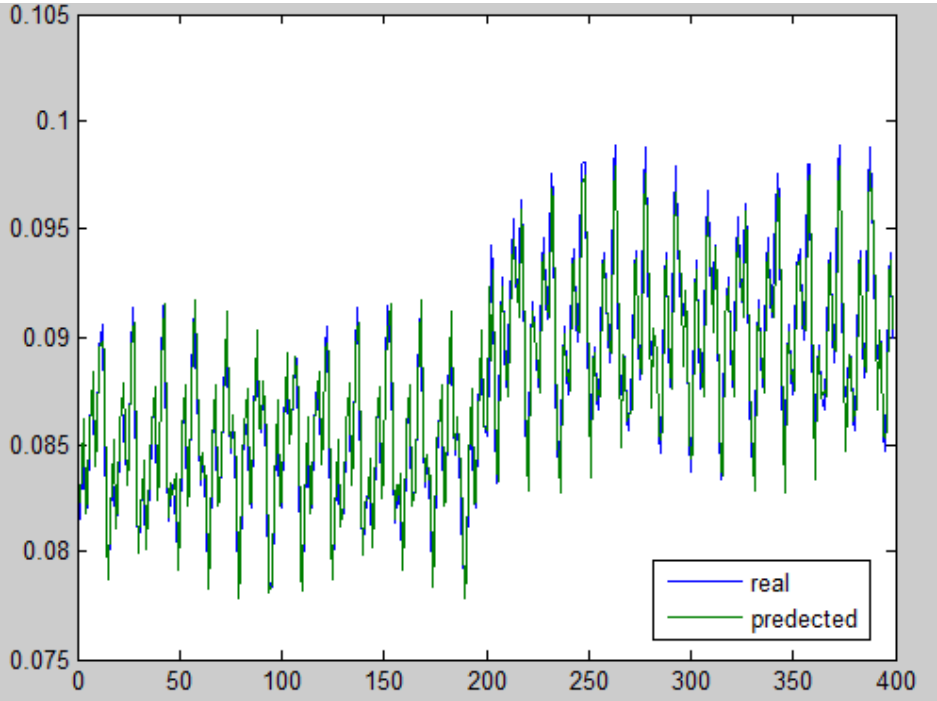


Figure 19: Comparison of the real output and the predicted by ARX-2 model

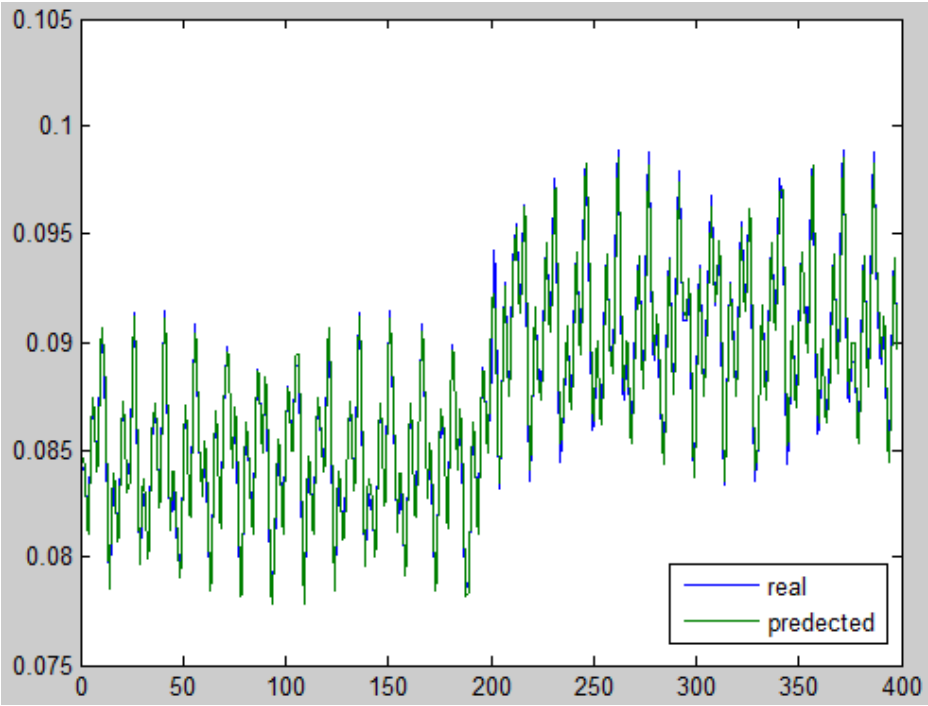


Figure 20: Comparison of the real output and the predicted by ARX-3 model

In order to have accurate and well-conditional least square estimated parameters, it is required that both input and output have the same level of amplitude. [6] Based on that, ARX-3 model is chosen to be the most accurate representation for the actual plant output.

Note: For more details on ARX model block diagrams and M-files, refer to APPENDIX-II and APPENDIX-III respectively.

Furthermore, it is recommended after the ARX model has been identified the system gain should be adjusted or rescaled to cancel the effect of the scaling process in the estimated output.[6]

4.5 Applying RBF and Neuron Network Toolbox on CSTR System

4.6.1 RBF (newrbe)

Below are the MATLAB codes for this function;

```
P=Ut_1;
Px=P(1:40);
Cx=C(1:40);
SPREAD=5;
net=newrbe(Px,Cx,SPREAD)
Py=P(201:240);
Yp=sim (net,Py);
plot([Cx Yp])
```

Where:

Ut_1= ARX-1 input

C= CSTR output (Concentration)

The graphs cover a small portion of data, only 40 inputs & 40 outputs. (newrbe) function loses its accuracy with increasing number of data. Therefore, Neural Network toolbox is the next step as it is good at fitting functions and recognizing patterns for large number of neurons.

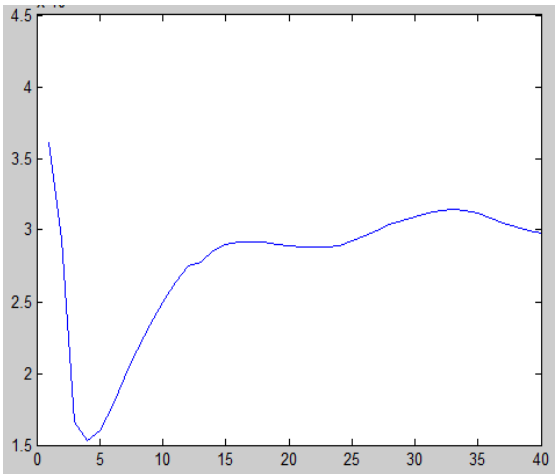


Figure 21: graph for Yp

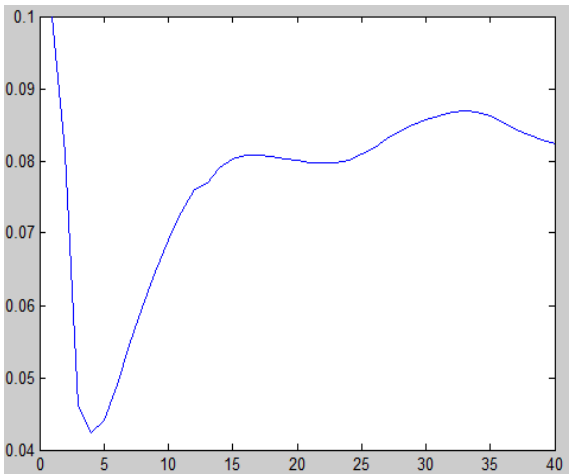


Figure 22: graph for Cx

It is very obvious that Cx graph is very similar to Yp graph with some difference in the range where Yp ranges from 1.5 to 3.6 while Cx ranges from 0.043 to 0.1.

4.6.2 Using Neural Network Toolbox Command Line Functions

The program will be as following;

```
P=Uarx;
C=Yarx;
net= newfit (P',C', 200);
net=train(net,P',C');
```

During training, the following training window opens. This window displays training progress and allows you to interrupt training at any point by clicking Stop training.

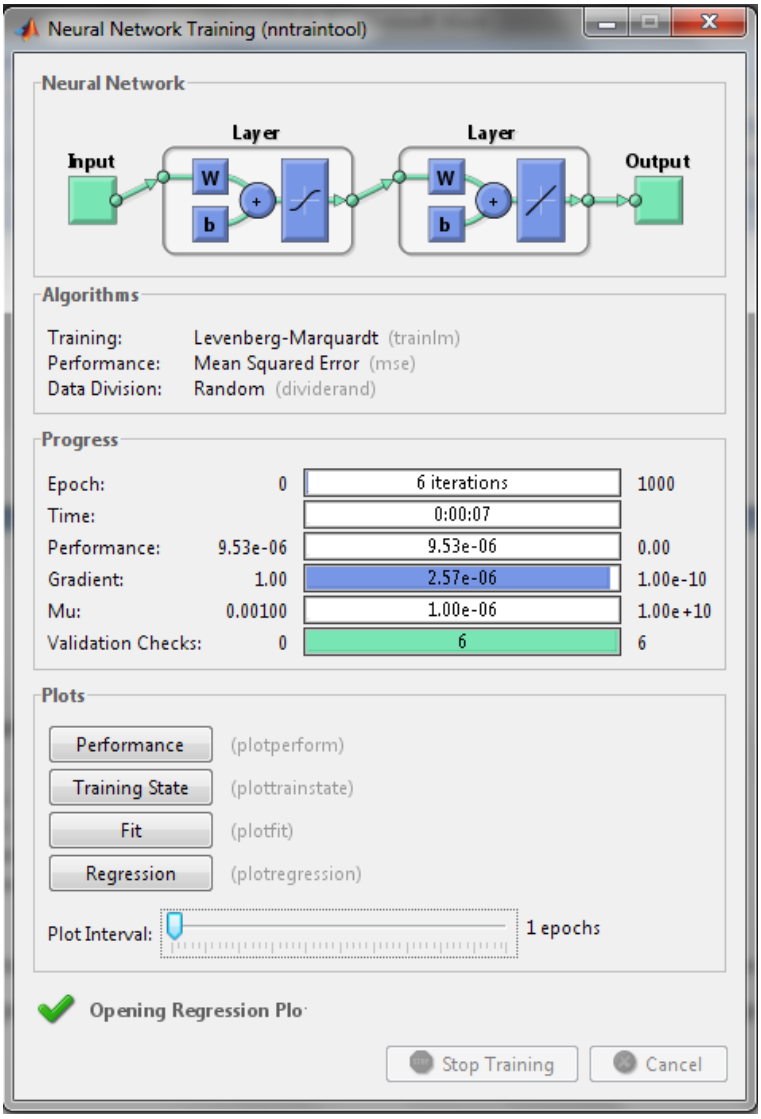


Figure 23: Neural Network Training window

Training on the training vectors continues as long as he training reduces the network's error on the validation vectors. After the network memorizes the training set, training is stopped. This technique automatically avoids the problem of overfitting , which plagues many optimization and learning algorithms.

When Performance is clicked in the training window, a plot of the training errors, validation errors, and test errors appears as shown in the following figure.

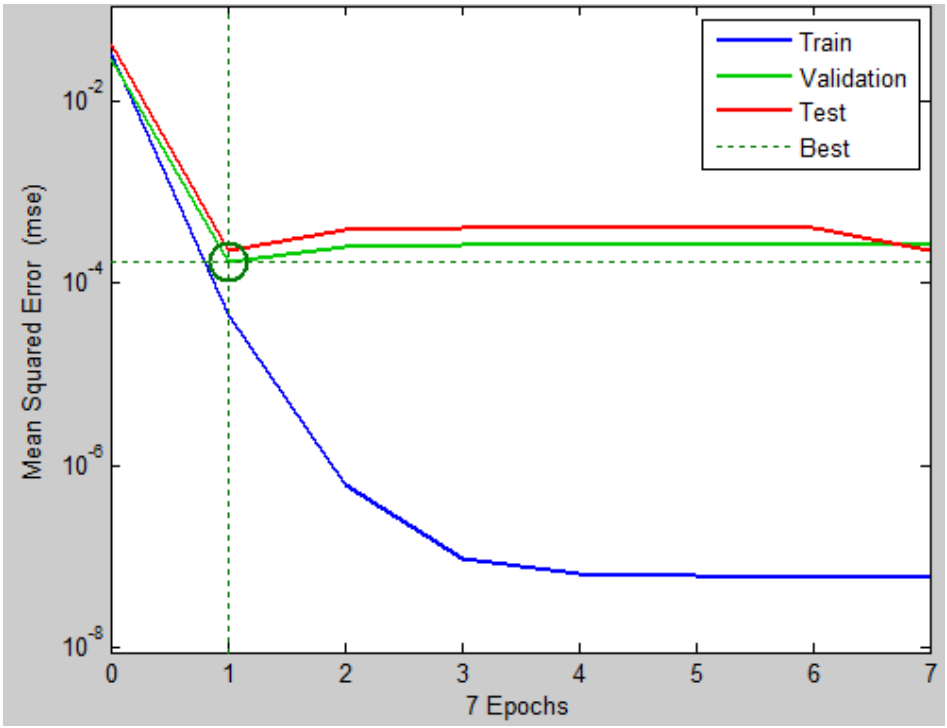


Figure 24: Performance plot from training window

The result is reasonable because of the following considerations.

- ✓ The final mean square error is small.
- ✓ The test set error and the validation set error have similar characteristics.
- ✓ No significant overfitting has occurred by iteration.

If Regression in the training window is clicked, a linear regression between the network outputs and corresponding targets. The following figure shows the results.

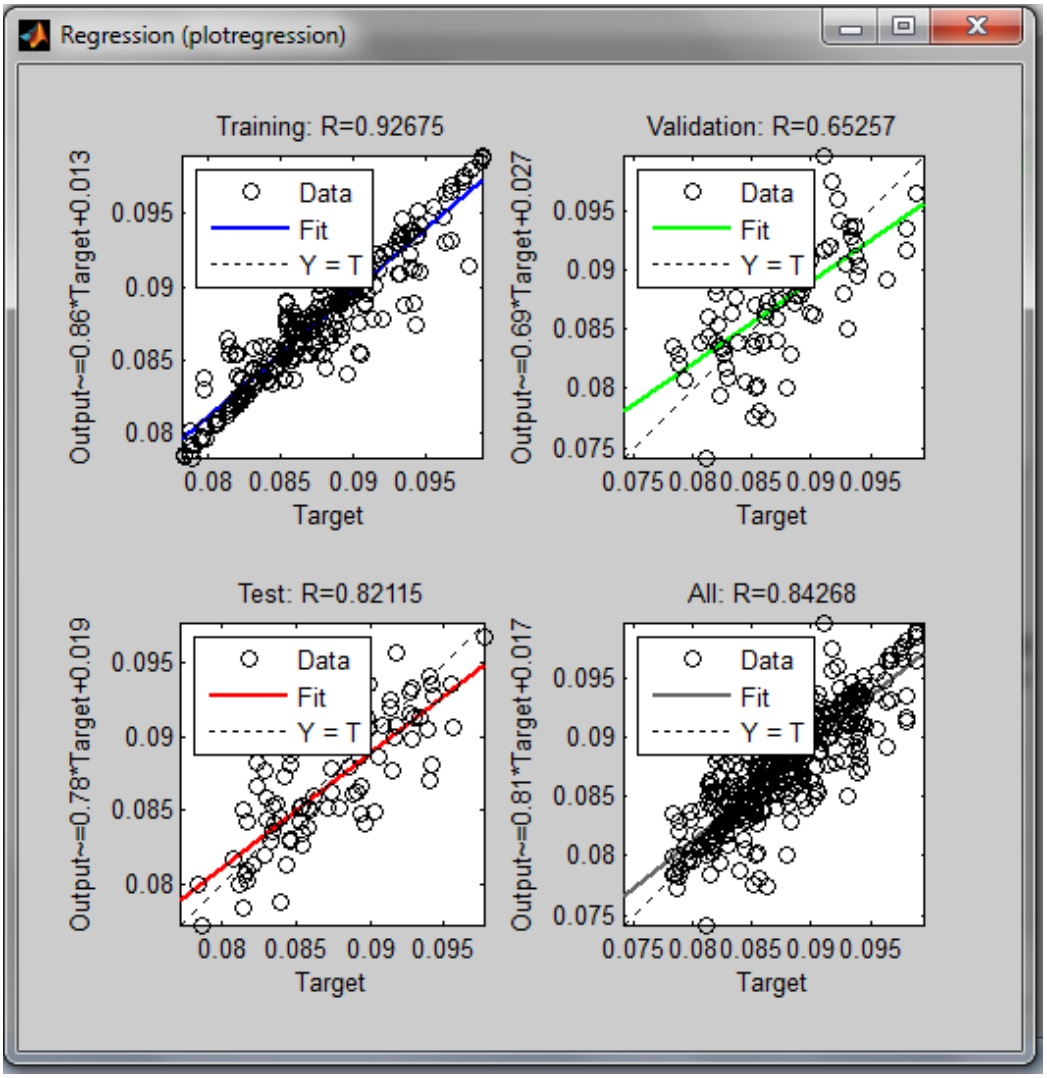


Figure 25: Regression plot from training window

The output takes the target very well for training, testing, and validation, and the R-value is over 84% for the total response. In this case the result is satisfactory and considered excellent. If even more accurate results are required, any of the approaches in recommendation chapter 5 can be applied.

CHAPTER 5
CONCLUSION AND RECOMMENDATION

5.1 Conclusion

Continuous Stirred Tank Reactor System (CSTR) is a typical chemical reactor system with complex nonlinear dynamic characteristics. The system is SISO, the output being the concentration of a product compound C and the input being the coolant flow rate.

A time varying concentration of CSTR system has been identified throughout various techniques. Linearization of the model was achieved at qc= (95 -100) l/min. three orders of ARX model were applied and ARX-3 gave the best representation for the real plant output. Two RBF functions were used and (newrbe) function is preferred because it produces a network with zero error on training vectors. It was found that RBF functions lose their efficiency with increasing number of input data. It was required to find a suitable alternative for RBF functions that can fit large data and gives accurate results on training vectors so Neural Network Toolbox functions were targeted. Two functions were applied which are (newff) and (newfit). These functions have been trained and the results of training were analyzed. The output takes the target very well for training, testing, and validation, and the R-value is over 84% for the total response

5.2 Recommendations

To achieve more accurate results, on the training window any of these approaches may be followed:

I. Reset the initial network weights and biases to new values with (init) and train again.

```
net= init(net);
net= train (net, houseInput,houseTargets)
```

II. Increase the number of hidden neurons.

III. Increase the number of training vectors.

IV. Increase the number of input values, if more relevant information is available.

V. During the training, open a plot window such as regression and watch it animate.[4]

In addition, it is recommended to use M-files and SIMULINK subsystem blocks when dealing with ARX model because it consists of three levels each has its own program and structure which makes it difficult and time consuming to build their blocks and run their programs due to the large amount of data involved. Last but not least, this project is based on simulation via MATLAB using various functions. It is recommended to examine the real plant by exciting it with the input data obtained from simulation and observe its output response and compare the experimental data with the real plant reaction to give a significant feedback and better chance for improvement.

REFERENCES

[1] Suja Malar, R.M, Thyagarajan.T, "Modelling of Continuous Stirred tank reactor Using Artificial Intelligence Techniques"

[2] Schmidt, Lanny D. "The Engineering of Chemical Reactions". New York (1998). Oxford University.

[3] M.W Braun, R.Ortiz-Mojica and DE. Rivea, "Application of Minimum crest factors multisinusoidal signals for "Plant-Friendly" identification of nonlinear systems", in "Control Engineering Practice", (2002)

[4] Vijanth S. Asirvadam, Sean F. McLoone, George W.Irwin, "Computationally efficient Sequential Learning algorithms for direct Link"

[5] http://en.wikipedia.org/wiki/Chemical_reactor

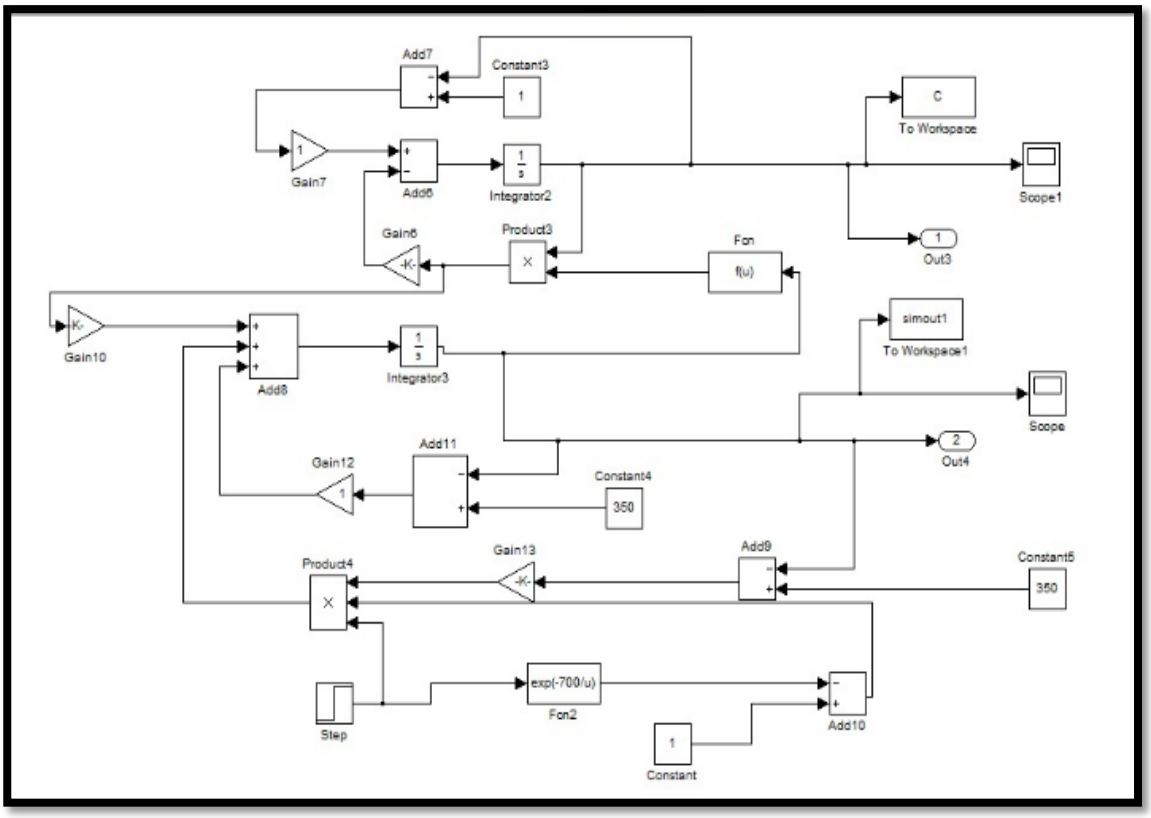
[6] Anan Kamal. Bon, "Fault Diagnosis Using System Identification For Chemical Process Plant", (2009)

[7] Howard Demuth, Mark Beale, Martin Hagan" Neural Network Toolbox ™ 6"

APPENDICES

APPENDIX-I:

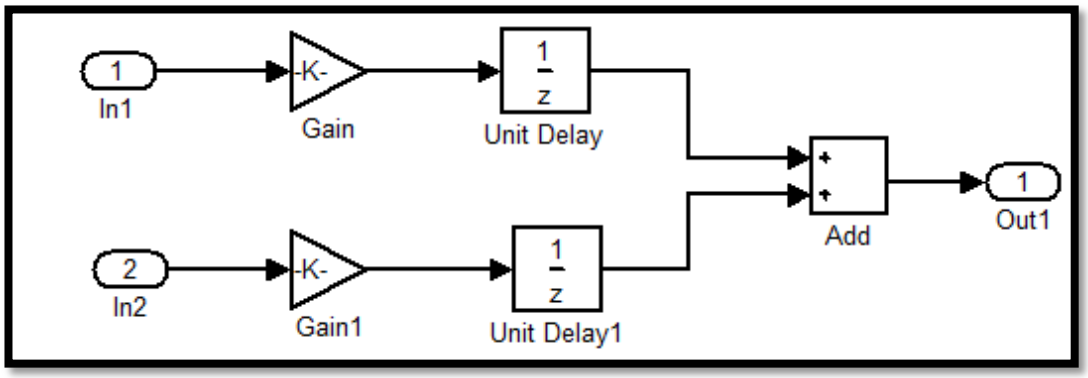
Nonlinear CSTR Plant Diagram



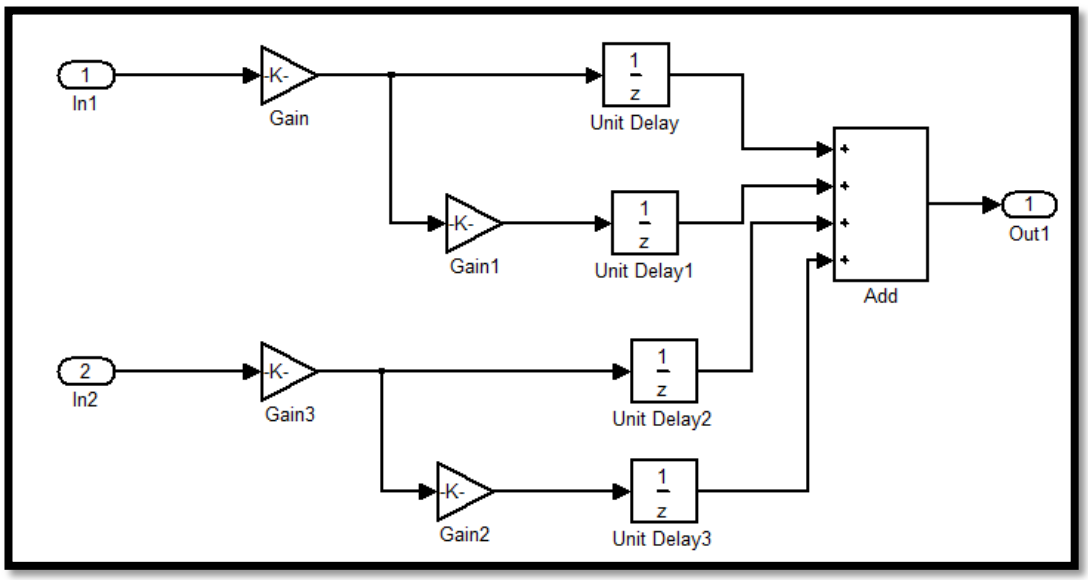
This graph shows Concentration (C) and Temperature (T) as tow outputs. Our main concern in this project is Concentration with regarding Temperature as the major element in the control process of the product Concentration (C).

APPENDIX-II:

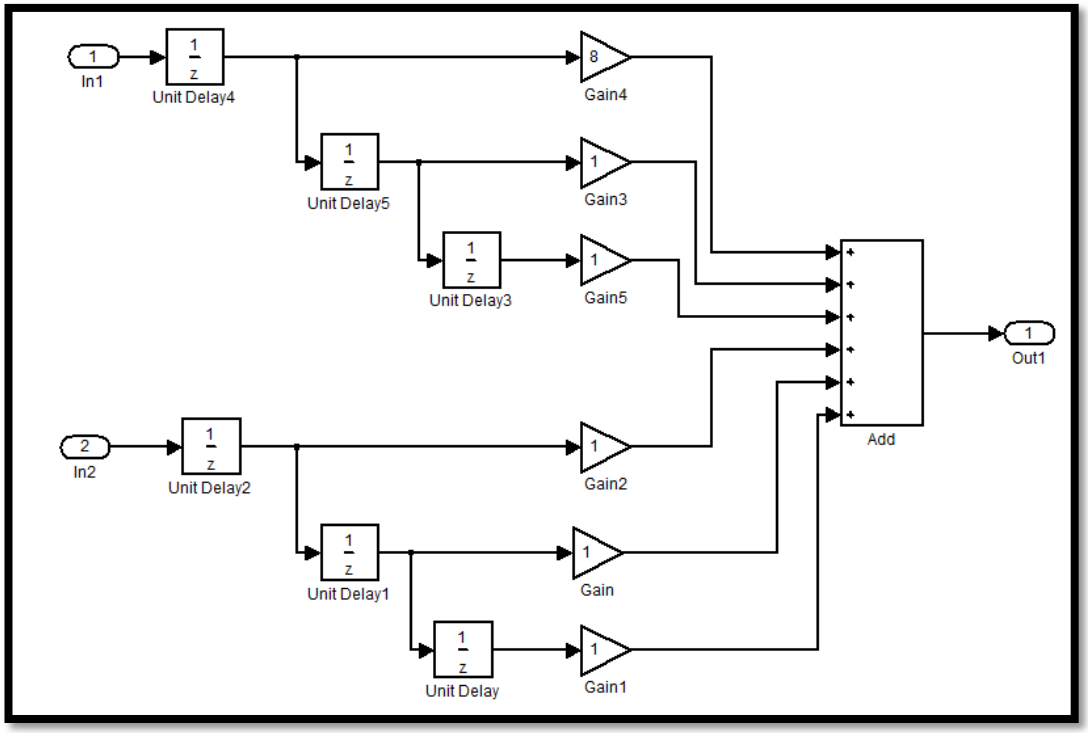
a. ARX-1 block diagram,



b. ARX-2 block diagram



c. ARX1 block diagram



Appendix-III:

M-files used for the project

```
function par1=ARX1(Yarx,Uarx)
Yt = Yarx(2:401)
Yt_1 = Yarx(1:400)
Ut_1 = Uarx(1:400)
X = [Yt_1 Ut_1]
Par1 = pinv(X)*Yt
Ypred = X*Par;
plot([Yt Ypred])
```

```
function par2=ARX2(Yarx,Uarx)
Yt= Yarx(3:401);
Yt_1=Yarx(2:400);
Yt_2=Yarx(1:399);
Ut_1=Uarx(2:400);
Ut_2=Uarx(1:399);
X=[Yt_1 Yt_2 Ut_1 Ut_2];
par2= pinv(X)*Yt
Ypred=X*par;
plot([Yt Ypred])
error=(Yt-Ypred);
error.^2;
mean(error.^2)
```

```
function par3=ARX3(Yarx,Uarx)
Yt=Yarx(4:401)
Yt_1=Yarx(3:400)
Yt_2=Yarx(2:399)
Yt_3=Yarx(1:398)
Ut_1=Uarx(3:400)
Ut_2=Uarx(2:399)
Ut_3=Uarx(1:398)
X=[Yt_1 Yt_2 Yt_3 Ut_1 Ut_2 Ut_3]
par3=pinv(X)*Yt
Ypred=X*par
plot([Yt Ypred])
```

APPENDIX-IV

FYP-II Schedule

No.	Detail/ Week	1	2	3	4	5	6	7		8	9	10	11	12	13	14
1	Building ARX model for CSTR system															
2	Submission of Progress Report 1															
3	Gathering data Using RBF Network															
4	Submission of Progress Report 2															
5	Gathering data using Neural Network Toolbox															
6	Draft Report Submission															
7	Final Report Submission															
8	Technical Report Submission															

Submission dates

Project Progress