FAULT DIAGNOSIS USING SYSTEM IDENTIFICATION FOR CHEMICAL PROCESS PLANT

Prepared By

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FINAL REPORT

Submitted to the Electrical & Electronics Engineering Programme
in Partial Fulfillment of the Requirements
for the Degree
Bachelor of Engineering (Hons)
(Electrical & Electronics Engineering)

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CERTIFICATION OF APPROVAL

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Approved:

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December 2009

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.

Anan Kamal Abdalla Bon

ABSTRACT

Fault detection and diagnosis have gained an importance in the automation process industries over the past decade. This is due to several reasons; one of them being that sufficient amount of data is available from the process plants. The goal of this project is to develop such fault diagnosis systems, which use the input-output data of the realm process plant to detect, isolate, and reconstruct faults. The first part of this project focused on developing a different prediction models to the real system. Moreover, a linearized model using Taylor Series Expansion approach and ARX (Autoregressive with external input) model of the real system have been designed. In addition, the most accurate identification model which describes the dynamic behavior of the monitored system has been selected.
Furthermore, a technique Statistical Process Control (SPC) used in fault diagnosis. This method depends on central limit theorem and used to detect faults by the analysis of the mismatch between the ARX model estimation and the process plant output.

Finally the proposed methodology for fault diagnosis has been applied in numerical simulations to a non-isothermal CSTR (continuous stirred tank reactor) and the results and conclusion have been reported and showed excellent estimation of ARX model and good fault diagnosis performance of SPC.

ACKNOWLEDGEMENTS

First of all, I would like to express my greatest thankful to Allah *for his uncountable* blessings and for giving me the strength to success and finish my final year project.

I would like to express my gratitude to my supervisor, Dr. Vijanth Sagayan Asirvadam , whose support, encouragement, expertise, understanding, and patience, added considerably to my graduate experience during my final year. Since the first day I started until the moment I finished my final version of the final project report.

I would also like to thank my parents and family members for always supporting me and believing in me, not just for this work, but everything in my life and provided me through my entire life and in particular.

I must also acknowledge all the lecturers of electrical and electronic engineering department for their advices and all my friends in Universiti Teknologi PETRONAS for helpfulness and sharing experiences

In conclusion, I recognize that this project would not have been possible without the good environment offered by Universiti Teknologi PETRONAS (UTP), the Department of Electrical and Electronics Engineering.

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Chapter 1

INTRODUCTION

1.1 Problem Statement

Fault diagnosis becomes one of the critical issues of process plants and industrial automation due to the growing complexity of automation systems. Therefore, the growing demand for performance efficiency, reliability, dependability and safety of process plants creates the need of fault detection and isolation of the design system.

1.2 Background study

Since the early 70's, the model based fault diagnosis technique has developed remarkably since then. Its efficiency in detecting faults in a system has been demonstrated by a great number of successful applications industrial process and automatic control system.[1]

1.3 Project Objectives

The purpose of this project to develop a fault diagnosis approach that can detect, isolate and identify the system fault using system identification technique.

Chapter 2

LITERATURE REVIEW

2.1 Model Based Fault Diagnosis

The concept of fault diagnosis is based on the following three important tasks [1]

- Fault detection: to detect of the existence of fault in the process system.
- Fault isolation: to determine the fault location.
- Fault analysis/ estimation: to determine the type, size and cause of fault.[1]

The concept of model based fault diagnosis is to run a process model in parallel to the process which is driven by the same process inputs. Moreover, the process model is implemented in a software form and describes the process dynamic and steady state of the system , which can be obtained using system identification technique.[1]

In addition, a comparison of the measured process variables with the model process's output will be made to detect any fault in the process. The difference between the measured and the estimated output signals is referred as residual which carries the most critical message for fault diagnosis.[2]

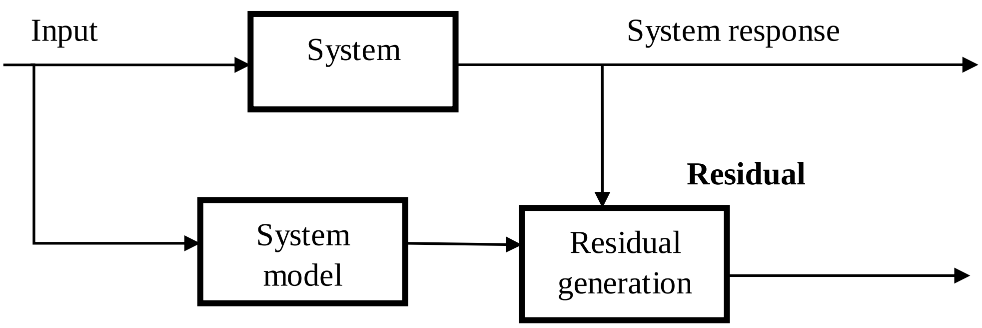
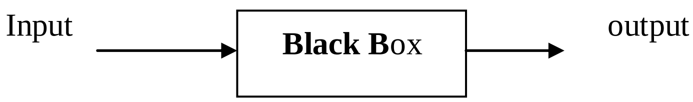


Figure 1: model based fault diagnosis block diagram

2.2 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 principles 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).

2.2.1 Linearization of process mode

A non-linear system can be linearized via several methods such as[3]:

1. Taylor series expansion method (local linearization method).
2. Feedback linearization method.

In this section, we will focus in Taylor series method only

Considering a nonlinear system dynamics as follows:

$$\frac{dX}{dt} = F(X, U, D)$$

And Y=G(X)

A linear model of the nonlinear system can be obtained using local linearization technique around a steady state operation point (X^o, U^o, D^o) as following:

$$\frac{dx}{dt} = Ax + Bu + Hd$$

$$y = Cx$$

Where

$$x(t) = X(t) - X^o \;\; ; \; u(t) = U(t) - U^o$$

$$d(t) = D(t) - D^o \; ; \; y(t) = Y(t) - Y^o$$

And

$$A = \frac{\partial F}{\partial X} \; ; B = \frac{\partial F}{\partial U}$$

$$H = \frac{\partial F}{\partial D} \; ; C = \frac{\partial G}{\partial X}$$

Computed at the steady state operating point (X^o, $U^{o,}$ D^o)

2.2.2 ARX Model

A brief description of system identification using ARX (Autoregressive with exogeneous input[4]) model with parameters which are functions of input output. The ARX model that is the most widely applied linear dynamic model represented as follow:

$$y[k] + a_1 y[k-1] + a_i y[k-i] + \cdots + a_n y[k-n] \\ = b_1 u[k-1] + b_i u[k-i] + \cdots + b_n u[k-n] + e(t) \qquad (2.5)$$

Where y[k] and u[k] are autoregressive variable or system output and exogeneous variable or system input at time k respectively, a_i and b_i are coefficients where i = 1,2,3,…,n and n is the system order .the coefficients of the ARX model depend only on y[j] and input u[j] : = k-n, k-n+1,…,k at time k[5],[6].

Now, rewrite the ARX model in equation (2.5) as follow:

$$A(q)y(t) = B(q)u(t) + e(t) \qquad (2.6)$$

Where

$$A(q) = 1 + a_1 q^{-1} + a_2 q^{-2} + \cdots + a_n q^{-n}$$

$$B(q) = b_1 q^{-1} + b_2 q^{-2} + \cdots + b_n q^{-n}$$

In addition, the operator q^{-1} can be considered as a unit delay operator (Z^{-1}) in the conventional z-transformation[4, 7].by taking the z-transform of equation (2.5), we can obtain the following [8]

$$\begin{aligned} Y(z) + a_1 Z^{-1} Y(z) + \cdots + a_{n-1} Z^{-n+1} Y(z) + a_n Z^{-n} Y(z) \\ = b_1 Z^{-1} U(z) + \cdots + b_{n-1} Z^{-n+1} U(z) + b_n Z^{-n} U(z) \end{aligned} \qquad (2.7)$$

2.2.3 ARX parameters estimation

The identification of the ARX model depends only on the information of the input and output as stated previously. In this technique, the system is identified by estimating the parameters of the ARX model using input-output data[5].

Parameter estimation using least square approach is the most popular used technique in system identification[9] .moreover, for N available data samples, we can identify the following:

$$y = [y[n+1] \;\; y[n+2] \;\; \ldots \;\; y[N]\,]^T$$

In addition, ARX model parameters are defined by the least square method as follows:

$$\theta = (\varphi^T \; \varphi)^{-1} \varphi^T \; Y$$

Where

$$\theta = [a_1 \, a_2 \, \ldots \, a_n \, b_1 \, b_2 \, \ldots \, b_n \,]^T$$

$$\varphi = \begin{bmatrix} y[k-1] & y[k-2] & \cdots & u[k-1] & u[k-2] & \ldots \\ \vdots & \vdots & \ldots & \vdots & \vdots & \ldots \\ y[k-n] & y[k-n+1] & \ldots & u[k-n] & u[k-n+1] & \ldots \end{bmatrix}$$

$y(t) = \theta^T \varphi = \varphi^T \theta$

The parameters is identified by repeating the identification of the ARX over the given range of input-output data[5, 6]. Further, In order to estimate the ARX model parameters, ($\varphi^T \varphi$) has to be non-singular[4, 8].

Moreover, it is possible to estimate the ARX model parameters via least square criterion function as follow

$$V_N(\theta, Z^N) = \frac{1}{N}\sum_{t=1}^{N} \frac{1}{2}[y(t) - \varphi^T \theta]^2$$

$$\hat{\theta} = \arg V_N(\theta, Z^N) = [\frac{1}{N}\sum_{t=1}^{N} \varphi\varphi^T]^{-1} \frac{1}{N}\sum_{t=1}^{N} \varphi y(t)$$

Where

$V_N(\theta, Z^N)$ is a defined scalar valued function of the ARX model parameter for given Z^N.=[u(1), y(1) u(1), y(1),…, u(2), y(2), u(N), y(N)]

2.2.4 Statistic Process Control

The rapidly growing demand for quality and productivity improvement of chemical process plants results in implementation of statistical process control (SPC) approach in process industry[10].

In addition, SPC technique has been proposed to monitor batch process with empirical models that built using Multi-way Principle Component Analysis (MPCA)[11], Principle Component Analysis (PCA), or Partial Least Squares (PLS)[10, 12].

The MPCA or the ordinary PCA are models that can be expressed as linear combination of the original variable values weighted by the corresponding eigenvectors[10].

In addition, many obstacles have been faced I the application of SPC approach in the process industries such as:

1. The dynamic behavior of most of the process plants is usually represented by

more than one output variable that very difficult to monitor all of them[13].

2. Most alarms will not go off until the fault is actually happened in the outputs, and it may be too late to prevent product quality from being fatally affected[13].
3. Measured noise on the outputs will often be large enough to cover any incipient faults until they become fatal[13].

In [14], an approach of multivariate control charts have been presented to monitor electrostatic separation process. Moreover, two output variables considered were the masses of product recovered in the middling and conductive compartments of the collector. The results shows that multivariate control charts can consider the existing correlations between the output variables of complex electrostatic separation processes. And it has been found that they can be implemented to monitor the global performances of process and detect any out-of-control states.

A multivariate monitoring model has been built based on Principal Component Analysis (PCA) in [15].in addition, a monitoring strategy using multiple PCA models has been presented based on the soft-partition algorithms. The application was implemented to a three-tank plant to show the effectiveness of the method. Finally, the results demonstrate the feasibility of method.

In [12], multivariate statistical process control (SPC) charts have developed using principal component analysis (PCA)for a batch process. Measured data from a sulfite batch digester was used to develop a reference model. The result showed that an outlier could be detected quickly and easily using control charts and the contribution plot .statistical Process control for the batch digesters can be simplified via PCA/PLS and that leads to, reducing the number of bad batches by acting as an early stage of detection for operators.

2.2.5 Output error

Together with ARX and ARMAX the output error model is widely used. It is the simplest representative of the output error model class. Output error models are often more realistic models of reality and thus they often perform better than equation error models. However, because the noise model do not include the process denominator 1/A(q) all output models are nonlinear in their parameters and consequently they are harder to estimate.

The OE model is generally described by

$$y(k) = \frac{B(q)}{F(q)}u(k)+v(k)$$

Chapter 3
METHODOLOGY

3.1 CSTR System description

In order illustrate the idea of fault detection a non-isothermal continuous Stirred Tank Reactor (CSTR) is considered. CSTR is a mixer that used as an industrial chemical reactor where chemical components of a flow steam reside for some time in the tank before the final product. Hence, in this case the residence time distribution is a measure of extent of a chemical reaction. In addition, the process involves liquid phase reaction A $_{(1)}$ $\longrightarrow$ B $_{(1)}$ where this reaction is highly exothermic and occurs in the reactor. CSTR has many variables that should be considered such as the flow rate through the tank F, the concentration (C), the tank volume (V), reactor temperature (T) and etc[16, 17]

In addition, CSTR includes a proportional temperature controller to control the temperature of the reactor by manipulating the flow rate of the coolant flowing through the jacket. The level in the CSTR is controlled by level controller which manipulates the output flow rate of the reactor. [16, 17]

$$\frac{dC}{dt} = \frac{q_{if}}{V}\left(C_{if} - C\right) - K_0\, C \cdot e^{-(E/RT)}$$

$$\frac{dT}{dt} = \frac{q_{if}}{V}\left(T_{if} - T\right) + K_1 C \cdot e^{-(E/RT)} + K_2 \cdot q_c\left[1 - e^{-(K_3/q_c)}\right] \cdot \left(T_{cf} - T\right)$$

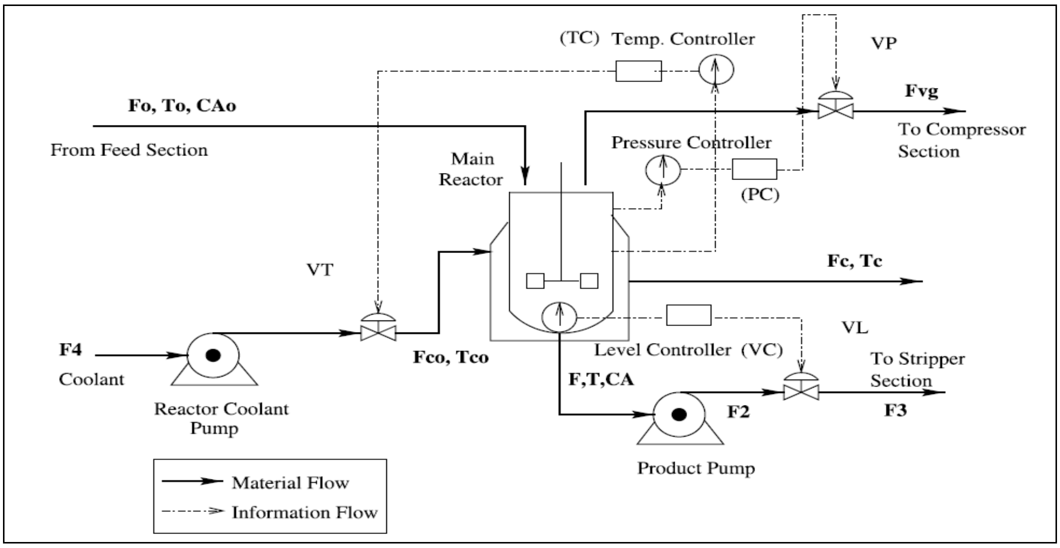


Figure 2: schematic of CSTR[16]

Table 1: CSTR parameters

Process parameters	**value**
Process flow rate (q)	100 l/min
Reactor volume (V)	100 l
Activation energy (E/R)	$1X10^4$ K
Feed temperature (T_o)	350 K
Inlet coolant temperature (T_{co})	350 K
Inlet coolant concentration (C_{ao})	1.0 mol/l
Reactive rate constant (K_0)	$7.2x10^{10}$ min^{-1}
K_1	$1.44x10^{13}$
K_2	0.01
K_3	700

3.2 Actual CSTR plant simulation

A non-linear CSTR plant SIMULINK diagram is shown in Figure 3.and the non-linear plant has multiple steady states, as shown in Figure 4.

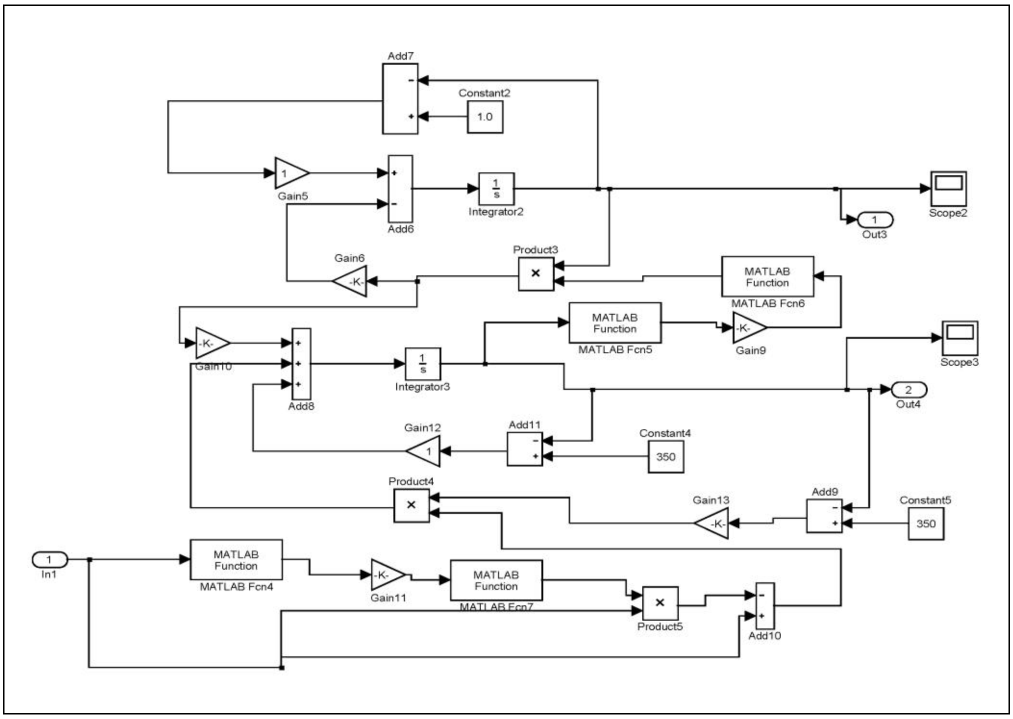


Figure 3:non-linear CSTR Plant simulation

As illustrated in Figure 4, the output of the system shows a first order response for the coolant flow rate (input) at q_c=85 l/min to q_c=95 l/min. moreover, as the coolant flow rate increased beyond 100 l/min the system starts showing a second order behavior (oscillations) before settling down to its steady state.

3.3 Linear CSTR model simulation

The equations of CSTR non-linear plant are

$$F_1(C,T) = \frac{dC}{dt} = \frac{q_{if}}{V}(C_{if} - C) - K_0\, C \cdot e^{-(E/RT)}$$

$$F_2(C,T,q_c) = \frac{dT}{dt} = \frac{q_{if}}{V}(T_{if} - T) + K_1 C \cdot e^{-(E/RT)} + K_2 \cdot q_c\left[1 - e^{-(K_3/q_c)}\right] \cdot (T_{cf} - T)$$

The developing of the linearized system matrices A, B and C as following:

$$A = \begin{bmatrix} \frac{\partial F_1}{\partial C} & \frac{\partial F_1}{\partial T} \\ \frac{\partial F_2}{\partial C} & \frac{\partial F_2}{\partial T} \end{bmatrix}$$

$$B = \begin{bmatrix} 0 & \frac{\partial F_2}{\partial q_c} \end{bmatrix}^T$$

$$C = [1 \quad 0]$$

$$\frac{\partial F_1}{\partial C} = -\frac{q_{if}}{V} - K_0\, e^{-(E/RT)}$$

$$\frac{\partial F_1}{\partial T} = -K_0\, C \cdot \left(\frac{E}{R \cdot T^2}\right) \cdot e^{-(E/RT)}$$

$$\frac{\partial F_1}{\partial q_c} = 0$$

$$\frac{\partial F_2}{\partial C} = K_1 \cdot e^{-(E/RT)}$$

$$\frac{\partial F_2}{\partial T} = -\frac{q_{if}}{V} + K_1 \cdot \left(\frac{E}{R \cdot T^2}\right) \cdot e^{-(E/RT)} - K_2 \cdot q_c\left[1 - e^{-(K_3/q_c)}\right]$$

$$\frac{\partial F_2}{\partial q_c} = K_2 \cdot \left(T_{cf} - T\right) - K_2 \cdot e^{-(K_3/q_c)} \cdot \left(T_{cf} - T\right) - K_2 \cdot q_c \cdot \left(\frac{K_3}{{q_c}^2}\right) \cdot e^{-(K_3/q_c)} \cdot \left(T_{cf} - T\right)$$

As a result the linearized model is

$$\begin{bmatrix} \dot{C} \\ \dot{T} \end{bmatrix} = \begin{bmatrix} \frac{\partial F_1}{\partial C} & \frac{\partial F_1}{\partial T} \\ \frac{\partial F_2}{\partial C} & \frac{\partial F_2}{\partial T} \end{bmatrix} \begin{bmatrix} C \\ T \end{bmatrix} + \begin{bmatrix} 0 \\ \frac{\partial F_2}{\partial q_c} \end{bmatrix} q_c$$

$$y = [1 \quad 0] \begin{bmatrix} C \\ T \end{bmatrix}$$

As mentioned in section 3.1, the non-linear CSTR plant is linearized around the following operation points

q_c^o= 100 l/min , T^o= 438.54 K , C^o=0.103 mol/l

As a result CSTR system matrices are obtained by linearizeing the actual CSTR plant around the chosen steady state.

$$\begin{bmatrix} \dot{C} \\ \dot{T} \end{bmatrix} = \begin{bmatrix} -10 & -0.0456 \\ 1800 & -2.96887 \end{bmatrix} \begin{bmatrix} C \\ T \end{bmatrix} + \begin{bmatrix} 0 \\ 0.8775 \end{bmatrix} q_c$$

$$y = [1 \quad 0] \begin{bmatrix} C \\ T \end{bmatrix}$$

In addition, Figure 5 shows the linear CSTR model SIMULINK diagram. And Figure 6 shows an acceptable estimation to the response of non-linear CSTR at the operation point. Moreover, Figure 6 illustrates an internal system parameter (reactor temperature T) that shows a non-linear behavior.

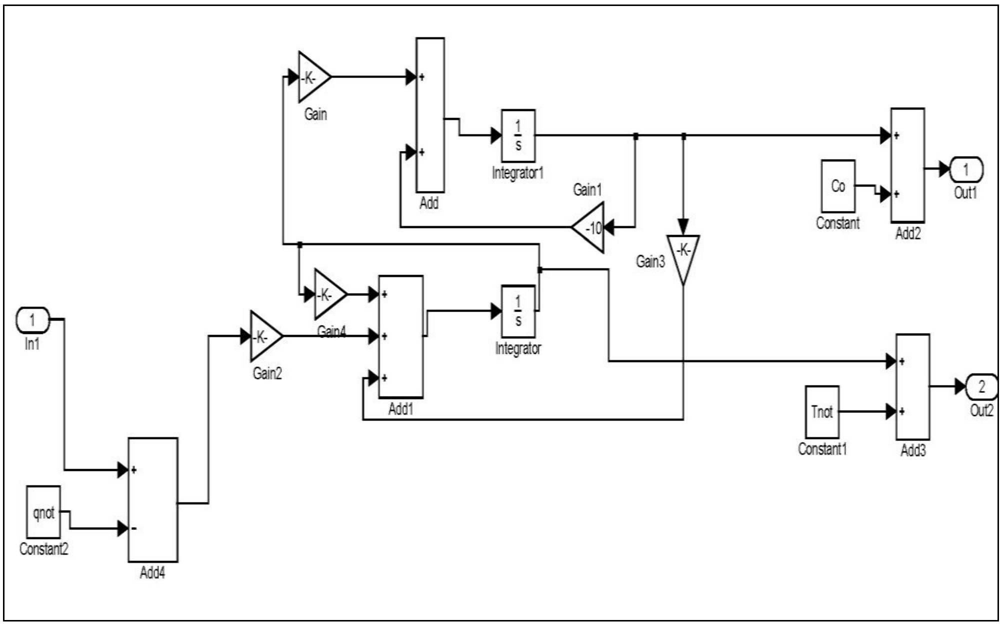


Figure 4: linear model CST simulation

3.4 Identification of linear ARX model

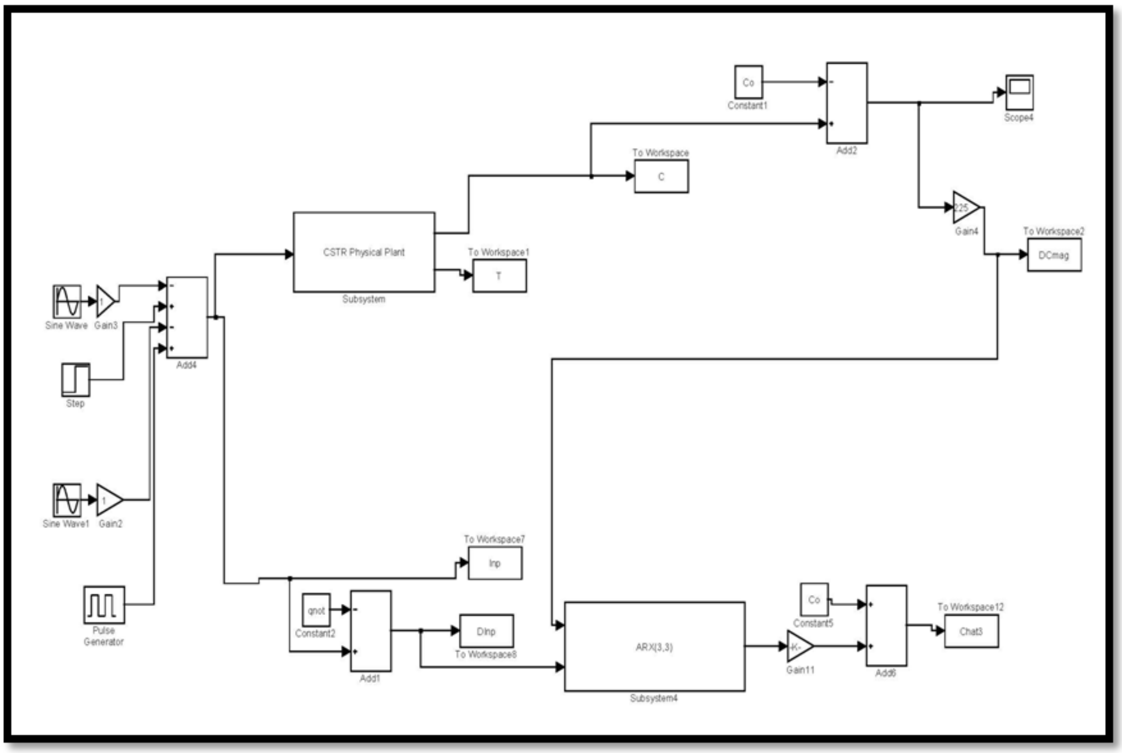


Figure 5: ARX (3, 3) model Identification scheme

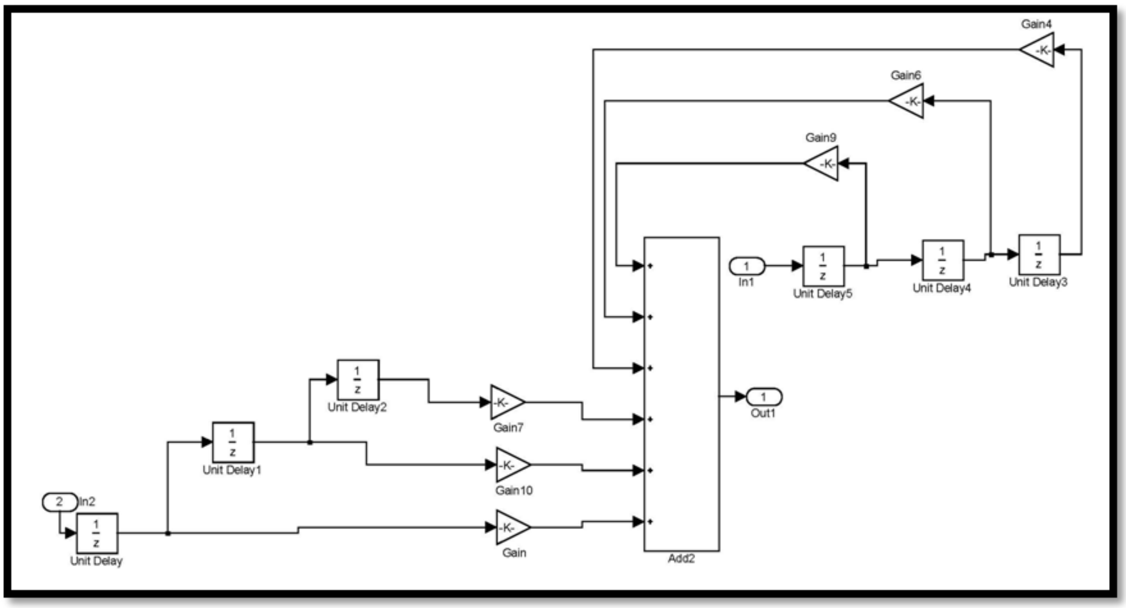


Figure 6: ARX (3,3) model simulation

3.5 Practical consideration on parameter estimation

The accuracy of the least-square estimated parameters depends on the sampled data of the input u(k).therefore, the input must have the following criteria:

1. The input should be rich enough in order to ensure that the matrix R is non-singular. In addition, that requires the following:
    - Single sinusoids input must be avoided. In order to be able to distinguish between different transfer functions with exactly the same value at $Z = e^{j\Omega}$ [8].
    - Sufficient input should include: sum of sinusoids with different amplitudes, frequencies, and phases and square wave[8].
2. The amplitude of the measured output y(k) should be greater than the measurement noise[8].

3.5.1 Input-output Signal Scaling

In order to have accurate and well-conditioned least-square estimated parameters, it is required that both input and output have the same level of amplitude. In addition, it is leads to scale the input, the output, or both of them.

Furthermore, 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.

3.5.2 Choice of sampling frequency

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 sample frequency to obtain an accurate identification of the real system will result in difficulties an problems in the CSTR plant identification due to[8]:

- 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 is also results in that the matrix R will have a singular value.

3.6 Statistical process control (SPC) approach

The proposed technique used in fault diagnosis is the Statistical Process Control (SPC). This method depends on central limit theorem and used to detect faults by the analysis of the mismatch between the ARX or OE model estimation and the real CSTR process plant output.

Upper Limit= $\bar{X} + 3\sigma$

Lower Limit= $\bar{X} - 3\sigma$

Where $\bar{X}$ is the mean and sigma (σ) is the standard deviation.

3.7 Procedure

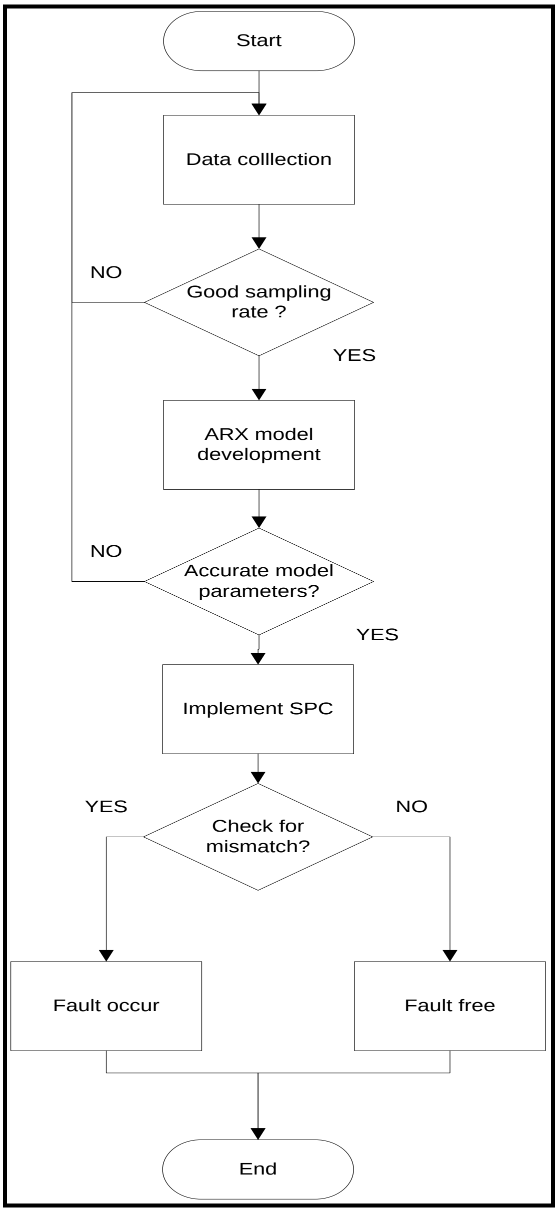


Figure 7: Proposed fault diagnosis scheme

3.8 Tools and equipment

MATLAB SIMULINK has been used as the main tool and software for this project.

Chapter 4

RESULTS AND DISCUSSION

In order to develop an appropriate model for the CSTR plant, several models several model has been designed. Firstly, a linearized model was built as mentioned previously in the methodology chapter.

Figure 7, 8 represent the estimated concentration and temperature respectively around the steady state point.

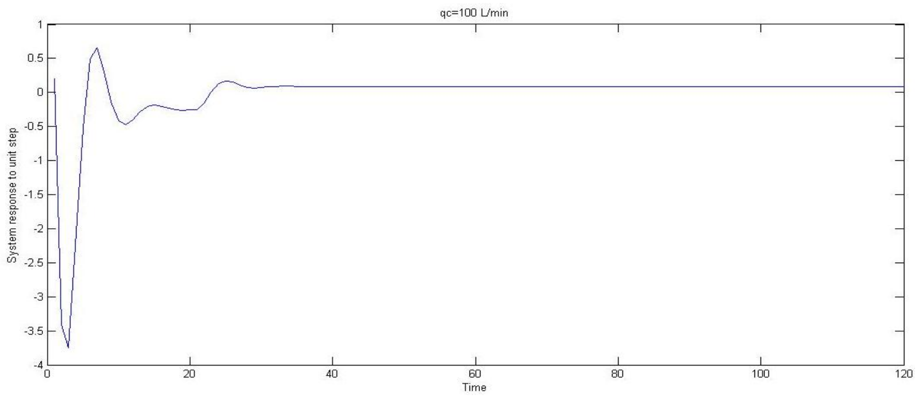


Figure 8: estimated system response to unit step at qc=100 l/min

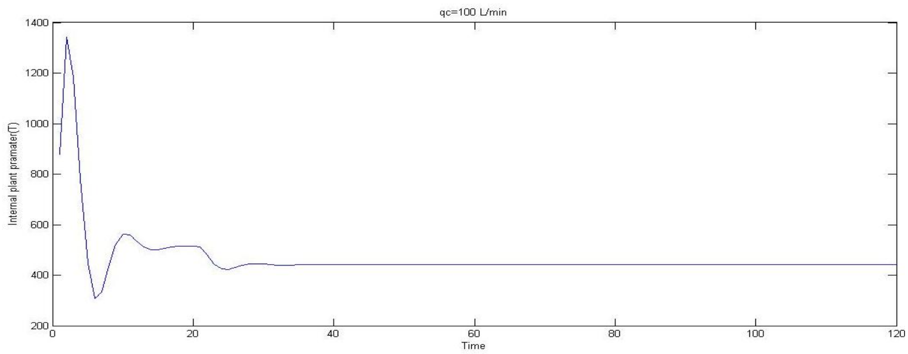


Figure 9: reactor temperature (T): internal system parameter

As shown in figure 9, a comparison of the actual CSTR plant and its linearized model is made. Moreover, for large step change the linear system is not able to estimate the actual response accurately. Meanwhile, after short time the linear system will estimate the actual response accurately. Furthermore, as the input increased to q_c =110 l/min, the linear model cannot be able to estimate the actual plant response accurately. In other words, the linear model can only estimate an accurate response at the operating points of the actual system. Otherwise there will be a mismatch between the two responses.

Output comparison at q_c=85 l/min

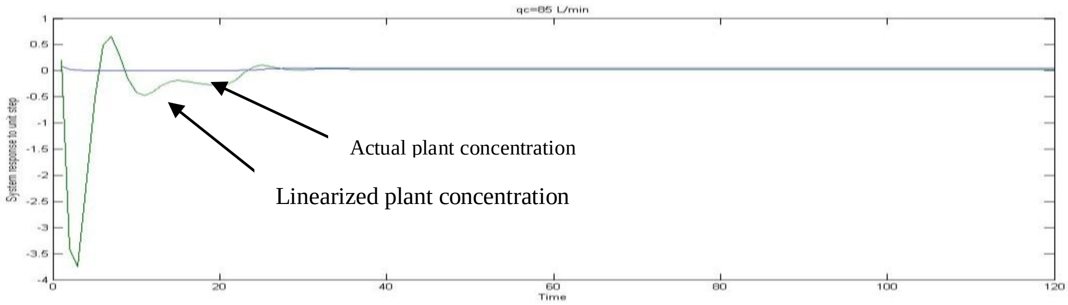


Figure 10: actual CSTR response vs. linearized model response

The estimating 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 Figure 10, 11 and 12. Figure 10 shows comparison between the plant output (CSTR) and the predicted output in a first order of ARX model.

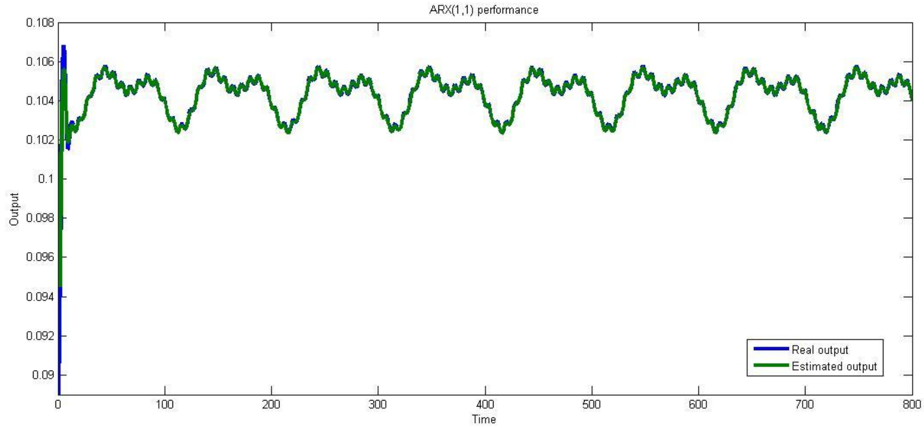


Figure 11: Comparison of the real output and the prediction by ARX (1, 1) model

In addition an ARX(2,2) has been implemented also for the prediction of the CSTR output as shown in figure 11. Figure 12 uses ARX(3,3) for the prediction.

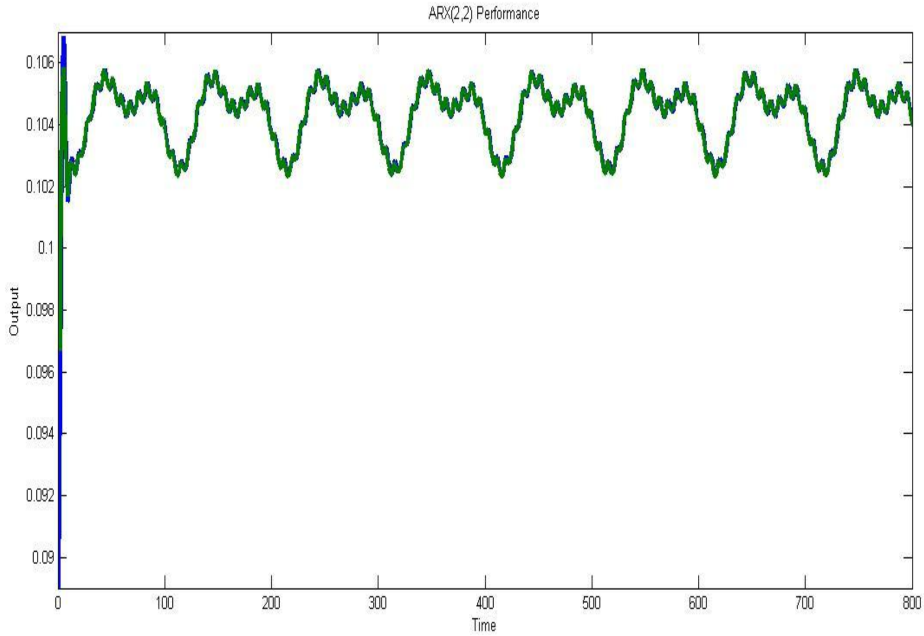


Figure 12: Comparison of the real output and the prediction by ARX (2, 2) model

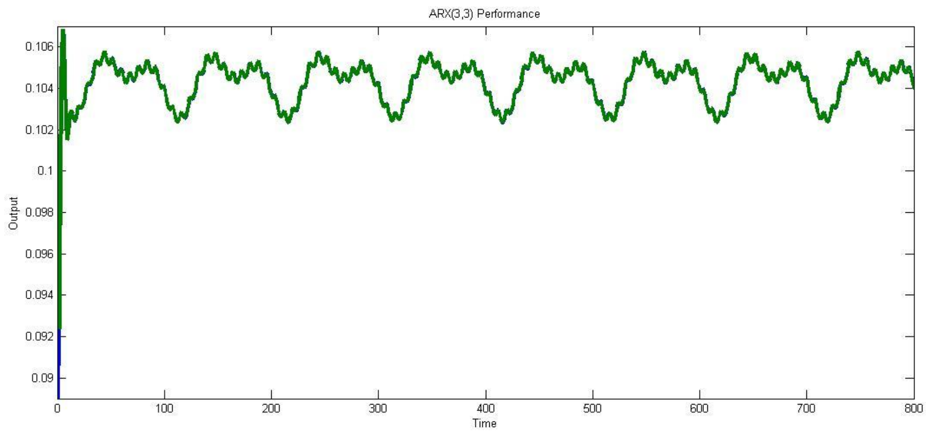


Figure 13: Comparison of the real output and the prediction by ARX (3, 3) model

Output Error (OE) model also has been implemented in the prediction using first order, second order and third order illustrated in figures 13,14 and 15.

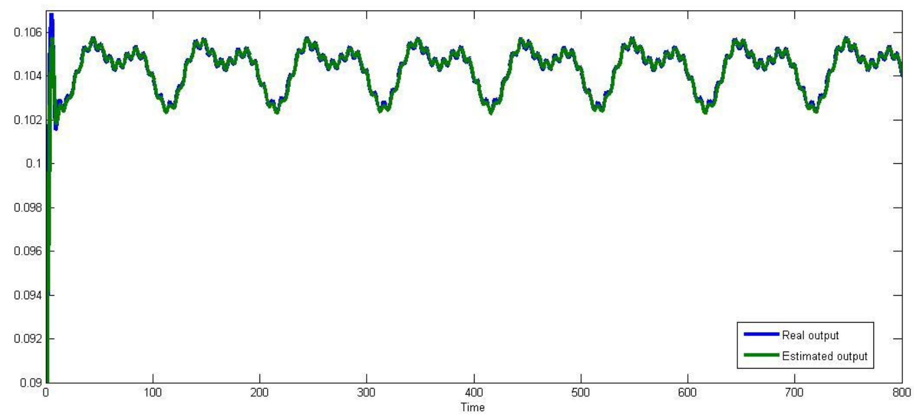


Figure 14: Comparison of the real output and the prediction by OE (1, 1) model

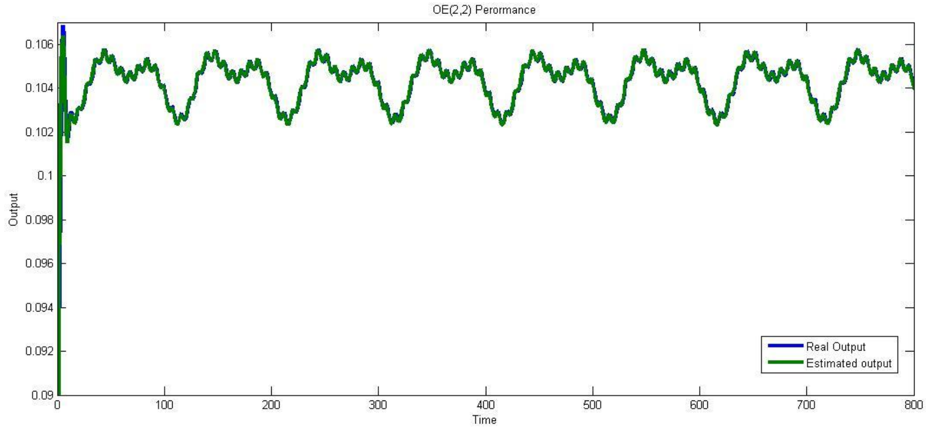


Figure 15: Comparison of the real output and the prediction by OE (2, 2) model

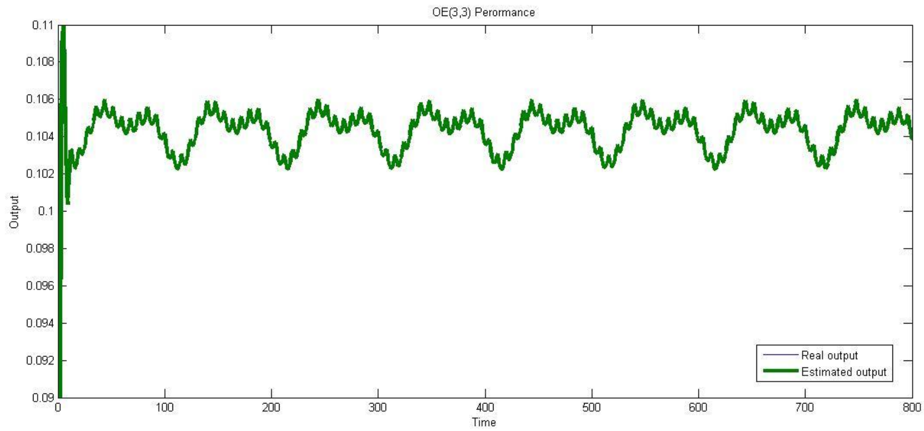


Figure 16: Comparison of the real output and the prediction by OE (3, 3) model

We notice in both cases using ARX and OE the third order model has better prediction. However, theoretically the probability of the noise is higher because we are depending on three past measurements for the delayed input and output.

OE model has been utilized in the fault diagnosis of the plant. Figure 16 illustrate the plant when there is no fault detected.

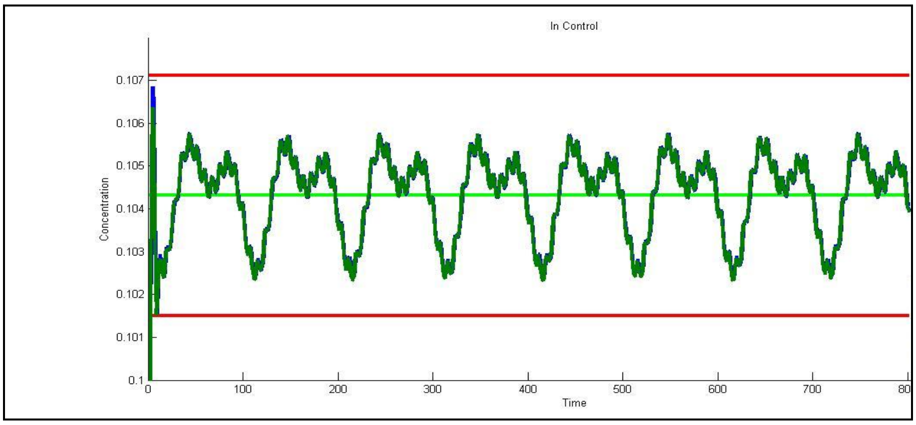


Figure 17: fault free plant concentration

Figure 17 shows fault detection as result in a variation in the CSRT plant. These variations are accrued due to input leakage.

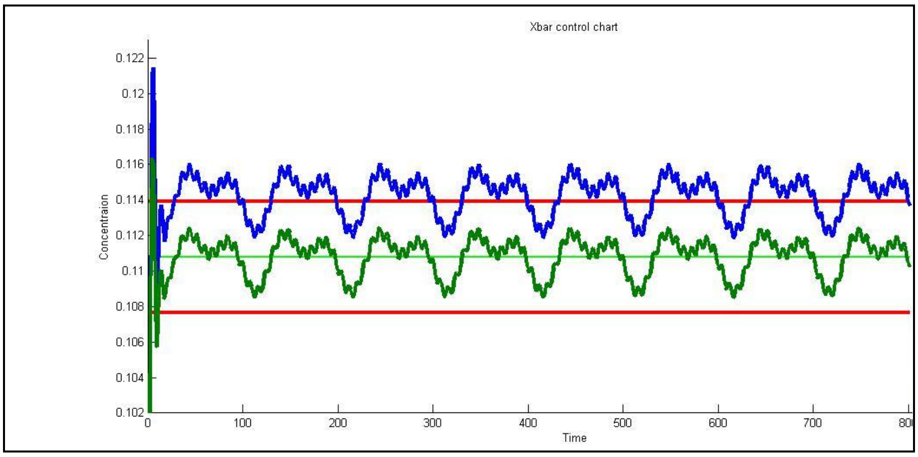


Figure 18: fault occurred in the concentration due to input leakage

Figure 18 shows fault detection due to an internal changed in the plant which was simulated by changing some of the internal parameters in the SIMULINK block diagram. Figure 19 shows another possible fault due to a different variation in the internal parameter of the plant.

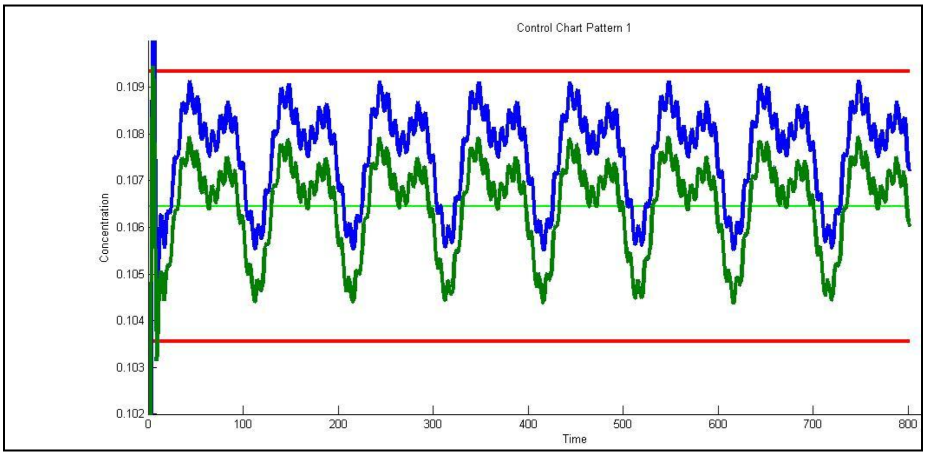


Figure 19: Possible Fault Pattern

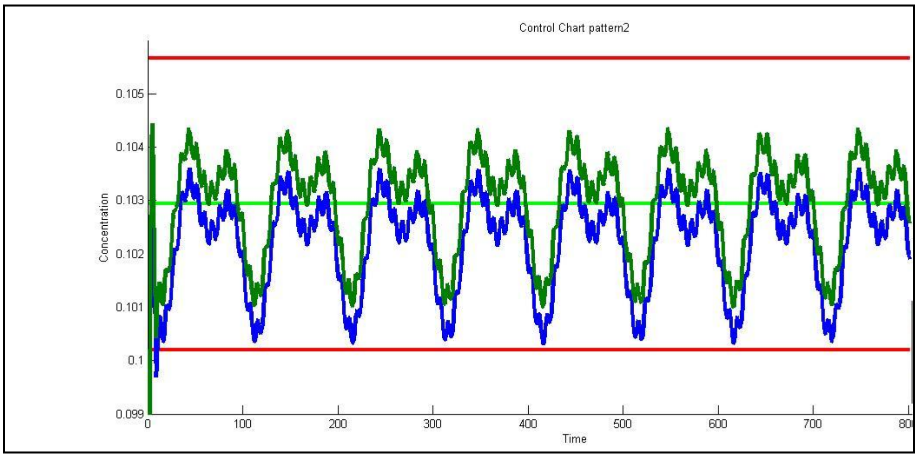


Figure 20: Another Possible Fault Pattern

Chapter 5
CONCLUSION AND RECOMMENDAITON

5.1 Conclusion

The main aim of this project was to develop an efficient fault diagnosis approach that is able to detect, isolate, and identify fault in CSTR plant.

The proposed model-based fault diagnosis scheme consists of two stages. The first part of this project focused on developing a different prediction models to the real system. Moreover, a linearized model using Taylor Series Expansion approach and ARX (Autoregressive with external input) model of the real system have been designed. In addition, the most accurate identification model which describes the dynamic behavior of the monitored system has been selected.

Furthermore, a technique Statistical Process Control (SPC) used in fault diagnosis. This method depends on central limit theorem and used to detect faults by the analysis of the mismatch between the ARX model estimation and the process plant output.

Finally, the proposed aproach for fault diagnosis has been applied in numerical simulations to a non-isothermal CSTR (continuous stirred tank reactor) and the results have been reported and showed excellent estimation of ARX model and good fault diagnosis performance of SPC.

5.2 Recommendation

This work can be extended where multiple statistical process control can be implemented for the purpose of fault diagnosis. Neural network architecture can be also implemented as a prediction methodology for the diagnosis scheme. A piratical test of the model will enhance the performance and will give a chance to correct any errors.

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APPENDICES

Appendix A: SIMULINK blocks Diagram.

Appendix B: M-files codes used for the project

APPENDIX A:

SIMULINK BLOCKS DIAGRAM

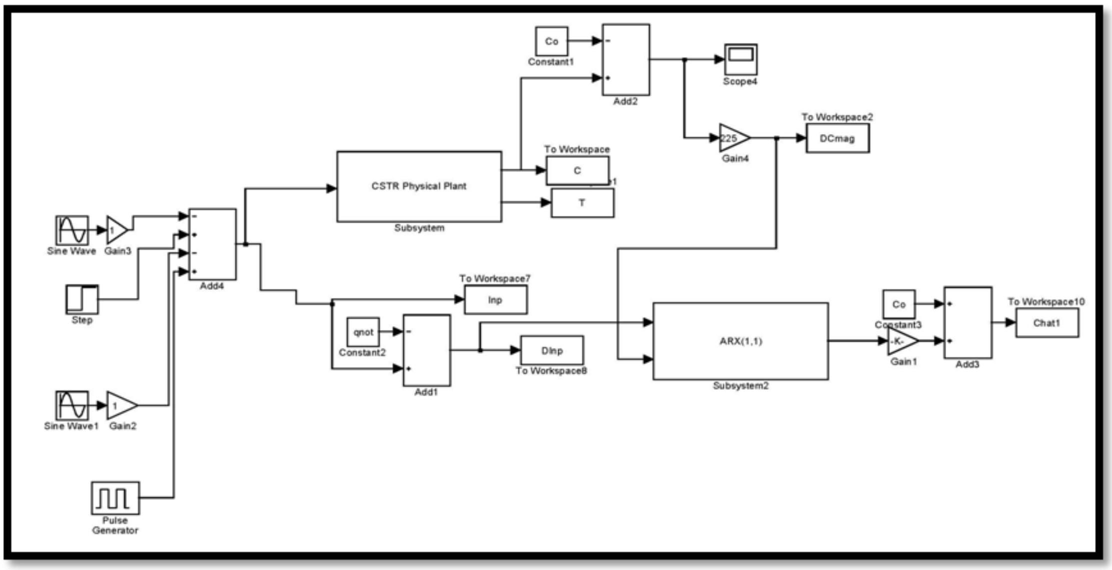

Figure 21: ARX (1, 1) model Identification scheme

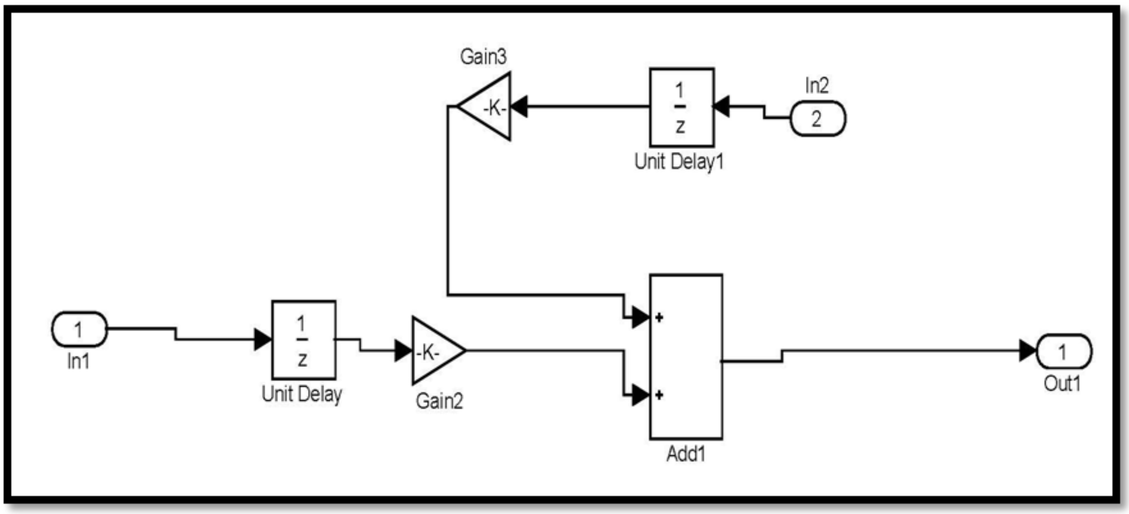

Figure 22: ARX (1, 1) model simulation

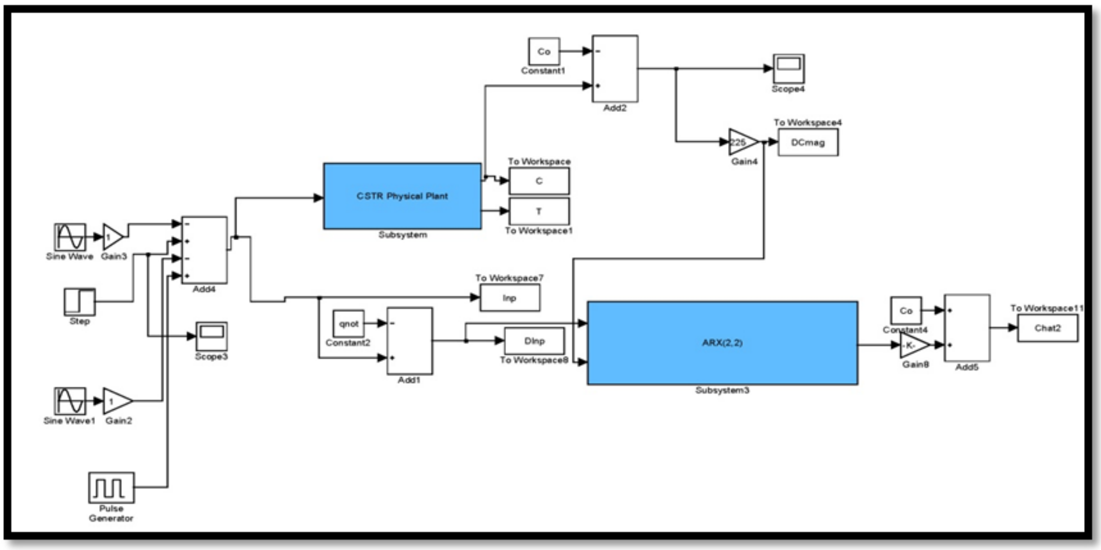

Figure 23: ARX (2, 2) model Identification scheme

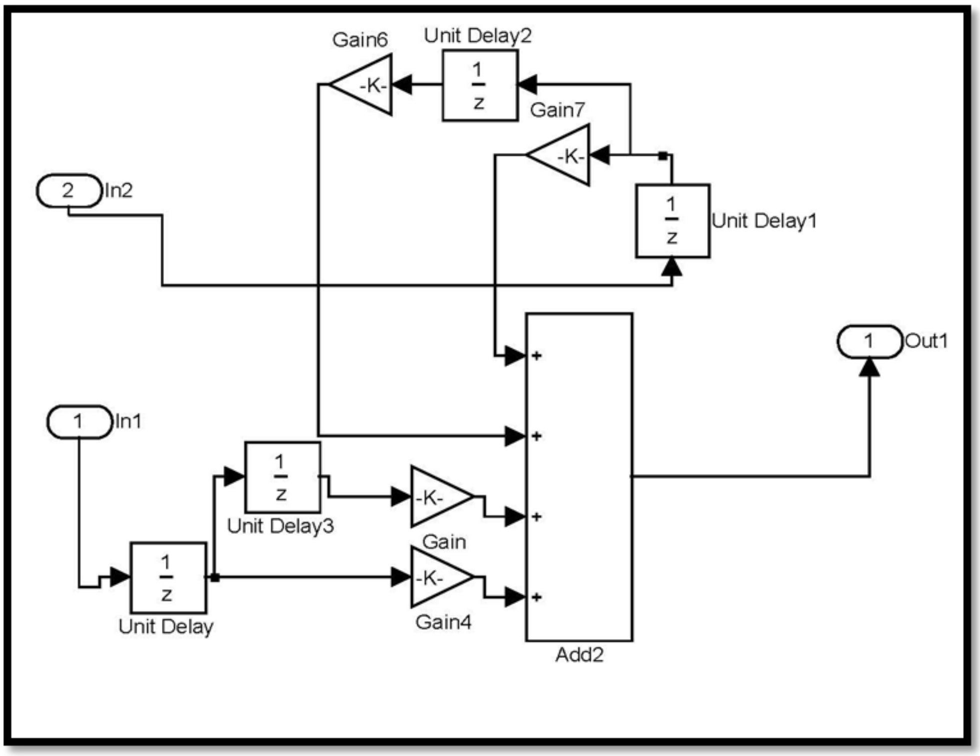

Figure 24: ARX (2, 2) model simulation

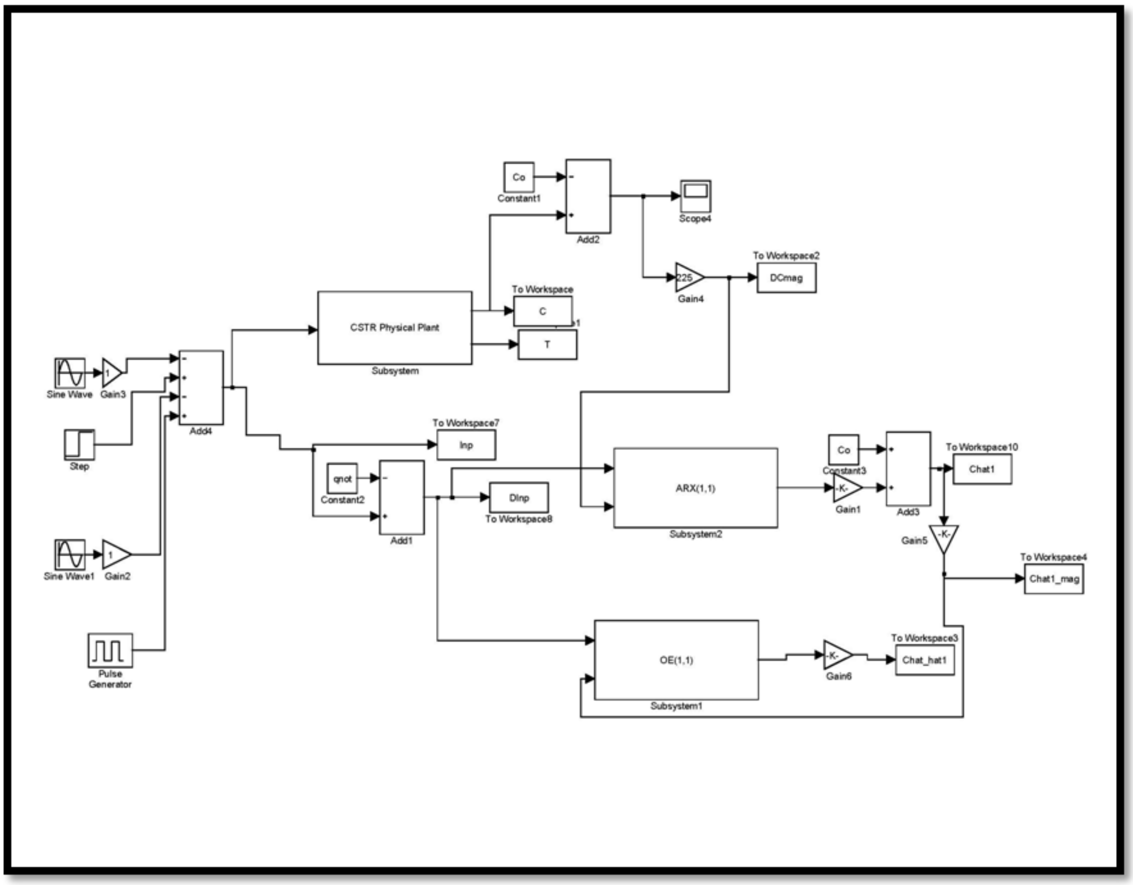

Figure 25: OE (1, 1) model Identification scheme

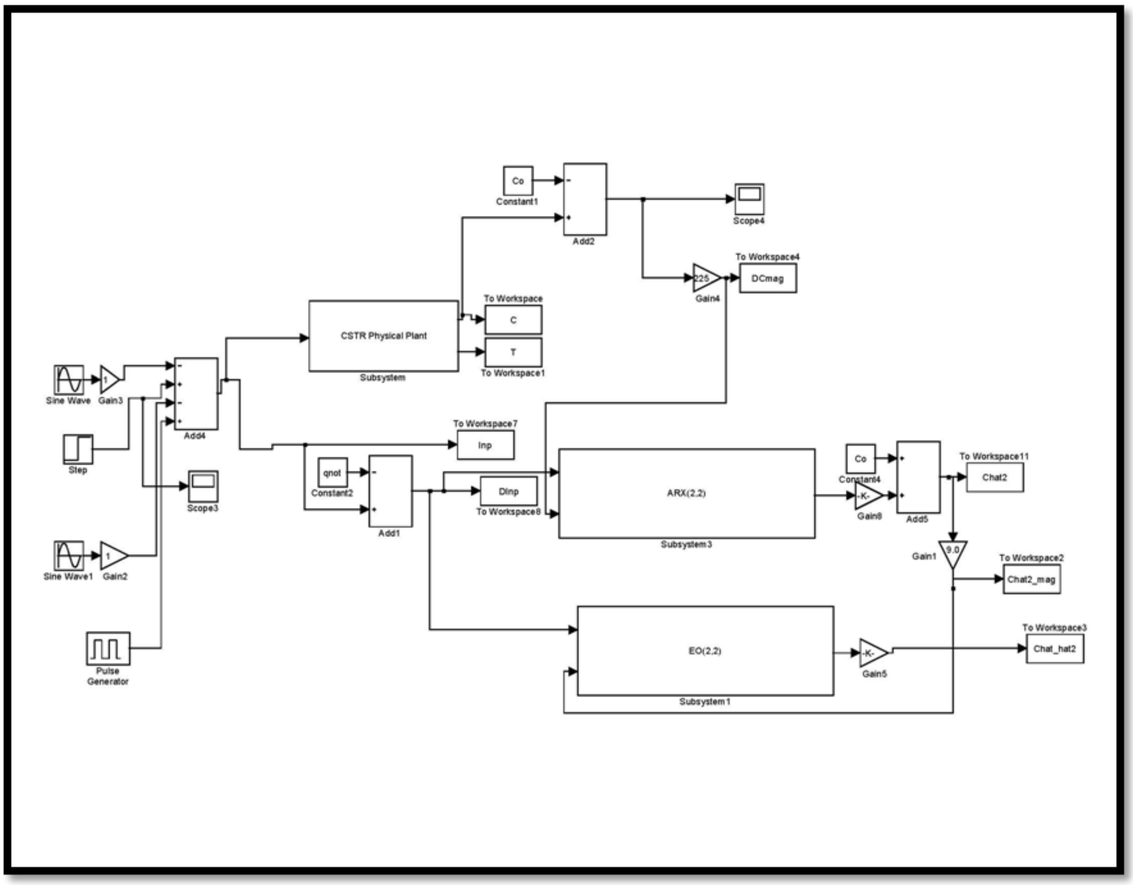

Figure 26: OE (2, 2) model Identification scheme

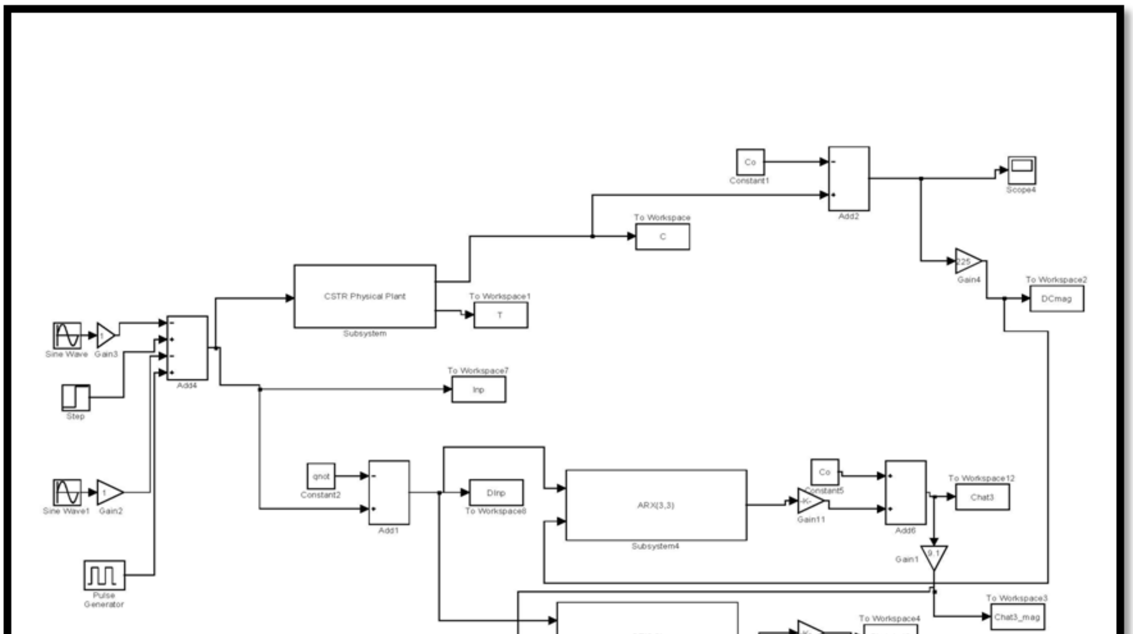

Figure 27: OE (3, 3) model Identification scheme

APPENDIX B:

M-FILES CODES USED FOR THE PROJECT

```
function pa1= paramest1(DInp,DCmag)
n_inp=size(DInp);
n_outp=size(DCmag);
Yt=DCmag(100:6:n_outp);
Yt_1=DCmag(99:6:n_outp-1);
Xt_1=DInp(99:6:n_inp-1);
U1=[Yt_1 Xt_1];
pa1=pinv(U1)*Yt;
return
```

```
function pa2= paramest2(DInp,DCmag)
n_inp=size(DInp);
n_outp=size(DCmag);
Yt=DCmag(100:6:n_outp);
Yt_1=DCmag(99:6:n_outp-1);
Yt_2=DCmag(98:6:n_outp-2);
Xt_1=DInp(99:6:n_inp-1);
Xt_2=DInp(98:6:n_inp-2);
U2=[Yt_1 Yt_2 Xt_1 Xt_2];
pa2=pinv(U2)*Yt;
return
```

```
function pa3= paramest3(DInp,DCmag)
n_inp=size(DInp);
n_outp=size(DCmag);
Yt=DCmag(100:6:n_outp);
Yt_1=DCmag(99:6:n_outp-1);
Yt_2=DCmag(98:6:n_outp-2);
Yt_3=DCmag(97:6:n_outp-3);
Xt_1=DInp(99:6:n_inp-1);
Xt_2=DInp(98:6:n_inp-2);
Xt_3=DInp(97:6:n_inp-3);
U3=[Yt_1 Yt_2 Yt_3 Xt_1 Xt_2 Xt_3];
pa3=pinv(U3)*Yt;
return
```

```
function pa_1= paramest_1(DInp,Chat1_mag)
m_inp=size(DInp);
m_outp=size(Chat1_mag);
Yt=Chat1_mag(100:6:m_outp);
Yt_1=Chat1_mag(99:6:m_outp-1);
Xt_1=DInp(99:6:m_inp-1);
Q1=[Yt_1 Xt_1];
pa_1=pinv(Q1)*Yt;
return
```

```
function pa_2= paramest_2(DInp,Chat2_mag)
m_inp=size(DInp);
m_outp=size(Chat2_mag);
Yt=Chat2_mag(100:6:m_outp);
Yt_1=Chat2_mag(99:6:m_outp-1);
Yt_2=Chat2_mag(98:6:m_outp-2);
Xt_1=DInp(99:6:m_inp-1);
Xt_2=DInp(98:6:m_inp-2);
Q2=[Yt_1 Yt_2 Xt_1 Xt_2];
pa_2=pinv(Q2)*Yt;
return
```

```
function pa_3= paramest_3(DInp,Chat3_mag)
m_inp=size(DInp);
m_outp=size(Chat3_mag);
Yt=Chat3_mag(100:6:m_outp);
Yt_1=Chat3_mag(99:6:m_outp-1);
Yt_2=Chat3_mag(98:6:m_outp-2);
Yt_3=Chat3_mag(97:6:m_outp-3);
Xt_1=DInp(99:6:m_inp-1);
Xt_2=DInp(98:6:m_inp-2);
Xt_3=DInp(97:6:m_inp-3);
Q3=[Yt_1 Yt_2 Yt_3 Xt_1 Xt_2 Xt_3];
pa_3=pinv(Q3)*Yt;
return
```

```
function pa_3= paramest_3(DInp,Chat3_mag)
m_inp=size(DInp);
m_outp=size(Chat3_mag);
Yt=Chat3_mag(100:6:m_outp);
Yt_1=Chat3_mag(99:6:m_outp-1);
Yt_2=Chat3_mag(98:6:m_outp-2);
Yt_3=Chat3_mag(97:6:m_outp-3);
Xt_1=DInp(99:6:m_inp-1);
Xt_2=DInp(98:6:m_inp-2);
Xt_3=DInp(97:6:m_inp-3);
Q3=[Yt_1 Yt_2 Yt_3 Xt_1 Xt_2 Xt_3];
pa_3=pinv(Q3)*Yt;
return
```