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Adaptive Control Design for a MIMO Chemical Reactor

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Table of Contents

Pages

List of Figures

Pages

List of Tables

Nomenclature

A:	Area of heat exchange [m^2]
C_A:	Concentration of reactor [mol/m^3]
C_{Af}:	Concentration of feed stream [mol/m^3]
Cp:	Heat capacity [J/kg.K]
F:	Volumetric flow rate [L/Hr]
T:	Reactor temperature [‘c]
T_f:	feed temperature [‘c]
U:	overall heat transfer coefficient[$kcal/m^2$.’c.hr]
V:	reactor volume [L]
ΔE:	activation energy [kcal/kmol]
$(-\Delta H)$:	heat of reaction[kcal/kmol]
ρ:	Density[kg/m^3]
Ko:	exponential factor
R:	ideal gas constant
r:	rate of reaction[mol/m^3.sec]
t:	time[s]
Kc:	controller gain []
$\tau_{I:}$	integral time[s]
τ_d	derivative time[s]
T:	Controller initial parameter []
S:	Controller initial parameter []

Abstract

The major disadvantage of non-adaptive control systems is that these control systems cannot cope with fluctuation in the parameters of the process. One solution to this problem is to use high levels of feedback gain to decrease the sensitivity of the control system. However high gain controllers have two major problems: large signal magnitude and closed loop instability. The solution to this problem is to develop a control system that adapts to changes in the process. This paper presents the design of adaptive controller to a MIMO chemical reactor. The proposed adaptive controller is tested by using Math lab Simulink program and its performance is compared to a conventional controller for a different situation. The paper demonstrated that while the adaptive controller exhibits superior performance in the presence of noise the convergence time is typically large and there is a large overshoot. To resolve these problems of adaptive controller, the proposed controller is redesigned by modifying the adaptation law. And the results show a significant improvement in the performance of the adaptive controller without excessive increase in the adaptation rate.
life of the low and middle income inner-city residents of Addis Ababa. Financial, institutional and legal problems are also seen as the major problems that hinder the implementation of LDPs in Addis Ababa.

Chapter One

1. Introduction

In common sense, ‘to adapt’ means to change a behavior to conform to new circumstances. Intuitively, an adaptive controller is thus a controller that can modify its behavior in response to the changing dynamics of the process and the character of the disturbances.

Adaptive control systems have been in existence for over thirty years, and a wide range of approaches have been developed. The core element of all the approaches is that they have the ability to adapt the controller to accommodate changes in the process. This permits the controller to maintain a required level of performance in spite of any noise or fluctuation in the process.

There are wide ranges of adaptive control methods currently in use but the objectives are the same that to provide an accurate representation of the process at all times. An adaptive system has maximum application when the plant undergoes transitions or exhibits non-linear behavior and when the structure of the plant is not known. Gain scheduling is one form of adaptive control but it requires knowledge about all the process to be effective. Another alternative is to adapt the controller’s parameters or when a model is available to use the model identification error to tune the controller’s parameters. Consequently, tuning of the controller is indirect and necessarily requires an accurate model of the process for satisfactory performance.

Adaptive control systems are currently used in many operations and one of these operations is chemical process. There are two main reasons why adaptive controller is needed in chemical processes. First, most chemical processes are non linear. Therefore, the linear zed models that are used to design linear controllers depend on the particular steady state (around which the process is linearized) .It is clear that as the desired steady state operation of a process changes, the ‘best’ values of the controller’s parameters change. This implies the need for controller adaptation. Second, most of the chemical processes are non stationary (i.e. their characteristics change with time). Typical examples are the decay of the catalyst activity in a reactor and the decrease of the overall heat transfer coefficient in a heat exchanger due to fouling. These change leads again to deterioration in the performance of linear controller which was designed using some nominal values for the process parameters, thus requiring adaptation of the controller parameters.

The purpose of this paper is to design and simulate a Model Reference Adaptive control (MRAC) for a multiple inputs multiple outputs chemical reactor. The paper includes the following parts: section 2 provides an overview of adaptive control and model reference adaptive control. In section 3 a multiple input and multiple output chemical reactor is mathematically modeled. Section 4 and section 5 describe in detail the design and simulation of both non-adaptive and adaptive controller and comparison of performance of adaptive controller and non-adaptive (conventional) controller.

Chapter two

2. Literature Review

2.1 Adaptive control

It is well known that conventional control theories are widely suited for applications where the processes can be reasonably described in advance. However, when the plant's dynamics are hard to characterize precisely or are subject to environmental uncertainties, one may encounter difficulties in applying the conventional design methodologies. Despite the difficulty in achieving high control performance, the fine-tuning of controller parameters is tedious task that always requires experts in both control theory and process information. Therefore, the control of systems with poorly known, nonlinear and uncertain dynamics has become a topics of considerable importance in the literature and presents great challenges for control engineers

In the past few decades, there has been considerable interest in the development of adaptive control systems that automatically adjust controller parameters to compensate for un anticipated changes in the process dynamics. The ability of dealing with time-varying characteristics, non-linearity and uncertainties enables adaptive control algorithms to have significant potential for the operation of chemical process whose dynamics are poorly known or subject to changes in unpredictable way.

Adaptive control systems have been in existence for over thirty years, and a wide range of approaches have been developed. The core element of all the approaches is that they have the ability to adapt the controller to accommodate changes in the process. This permits the controller to maintain a required level of performance in spite of any noise or fluctuation in the process.

An adaptive system has maximum application when the plant undergoes transitions or exhibits non-linear behavior and when the structure of the plant is not known. Gain scheduling is one form of adaptive control but it requires knowledge about all the process to be effective. Another alternative is to adapt the controller's parameters or when a model is available to use the model identification error to tune the controller's parameters. Consequently, tuning of the controller is indirect and necessarily requires an accurate model of the process for satisfactory performance.

Numerous references are available which treat the topic adaptive control and model reference adaptive control. These includes, the multiple model adaptive control design for a chemical reactor developed by R.Gundala and K.A.HOO [5]; adaptive temperature control of multi product jacketed reactor developed by Dwayne Tyner; Masoud Soroush [6] I; Direct adaptive control design for a chemical process system developed by Chyl-Tsong Chen Iain [4]; Adaptive control; A QUT Avionics project, Queens land University of Technology developed by Iain McManus. [7]

2.2 Adaptive control in chemical processes

Adaptive control systems have been applied in chemical process. The range of their applicability has expanded with the introduction of digital computer for process control. But why are adaptive controllers needed in chemical process?

There are two main reasons. First, most chemical processes are non-linear. Therefore the linearized models that are used to design linear controllers depend on the particular steady state (around which the process is linearized). It is clear, then, that as the desired steady-state operation of a process changes; the best values of the controller parameter change. This implies the need for controller adaptation.

Second, most of the chemical processes are non-stationary (i.e. their characteristics changes with time). Typical examples are the decay of the catalyst activity in a rector and the decrease of the overall heat transfer coefficients in a heat exchanger due to fouling. This changes lead again to deterioration in the performance of a controller, which was designed using some nominal values for the process parameters. Thus requires adaptation of the controller parameters.

2.3 Types of adaptive control

Generally there are two different mechanisms for the adaptation of the controller parameters. Programmed or scheduled adaptive control and self –adaptive control.

2.3.1 Programmed or scheduled adaptive control

Suppose that the process is well known and that an adequate mathematical model for it is available. If there is an auxiliary process variable, which correlates well with the changes in the process variables (dynamics), we can relate a head of time the ’best’ values of the controller parameters to the values of the auxiliary variable. Consequently, by measuring the value of the auxiliary variable, we can schedule or program the adaptation of the controller parameters.

Figure 2.1 shows the block diagram of a programmed adaptive control system. We notice that it is composed of two loops. The inner loop is an ordinary feedback control loop. The outer loop includes the parameters adjustment (adaptation) mechanism and it is comparable to feed forward compensation. A typical example is the gain scheduling adaptive control

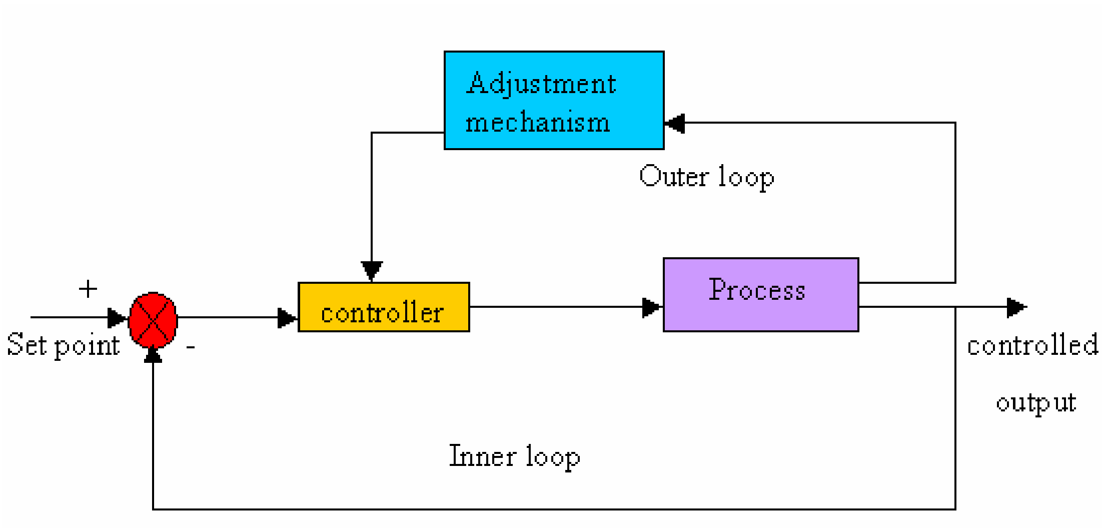


Figure 2.1 Programmed adaptive control system

2.3.2 Self –adaptive control

If the process is not well known, we need to evaluate the objective function on-line (while the process is operating) using the values of the controlled output. Then the adaptation mechanism will change the controller parameters in such away as to optimize (maximize or minimize) the values of the objective function (criterion). Typical examples of this type of control mechanism are ‘Model Reference Adaptive Control’ (MRAC) and self-tuning regulators (STR).

Self-tuning regulators (STR)

Figure 2.2 represents the structure of a self-tuning regulator, which constitutes another way of adjusting the parameters of a controller. It is composed again of two loops. The inner loop is consisting of the process and an ordinary linear feed back controller. The outer loop is used to adjust the parameters of the feedback controller and is composed of (1) a recursive parameter estimator and (2) an adjustment mechanism for the controller parameters.

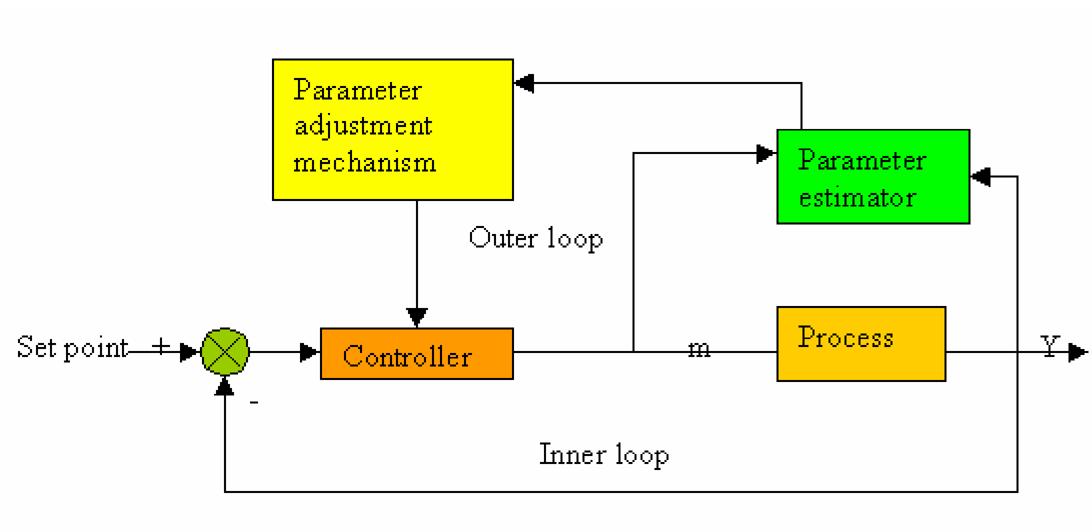


Figure 2.2 Self-tuning regulator (STR)

The parameter estimator assumes a simple linear model for the process:

$$\frac{Y(s)}{m(s)} = \frac{K_P e^{-t_d s}}{\tau s + 1} \qquad (2.1)$$

Then using measured values for the manipulated variable m and the controlled output Y, It estimates the values of the parameters Kp, τ and t_d, employing a least-squares estimation technique. Once the values of the process parameters Kp, ι and t_d are known, the adjustment mechanism can find the controller parameters using various design criteria, such as:

-Phase or gain margins

-Integral of the square error, etc.

The other typical example of self-adaptive control is model reference adaptive control (MRAC), which will be discussed in more details in the preceding sections.

2.4 MODEL REFERENCE ADAPTIVE CONTROL (MRAC)

2.4.1 Basic Definition

Model reference adaptive controller (MRAC) is a controller used to force the actual process to behave like idealized model process. MRAC systems adapt the parameters of a normal control system to achieve this match between model and process.

2.4.2 Core Elements of Model Reference Adaptive Control

The basic structure of a MRAC system is shown in figure 2.3.

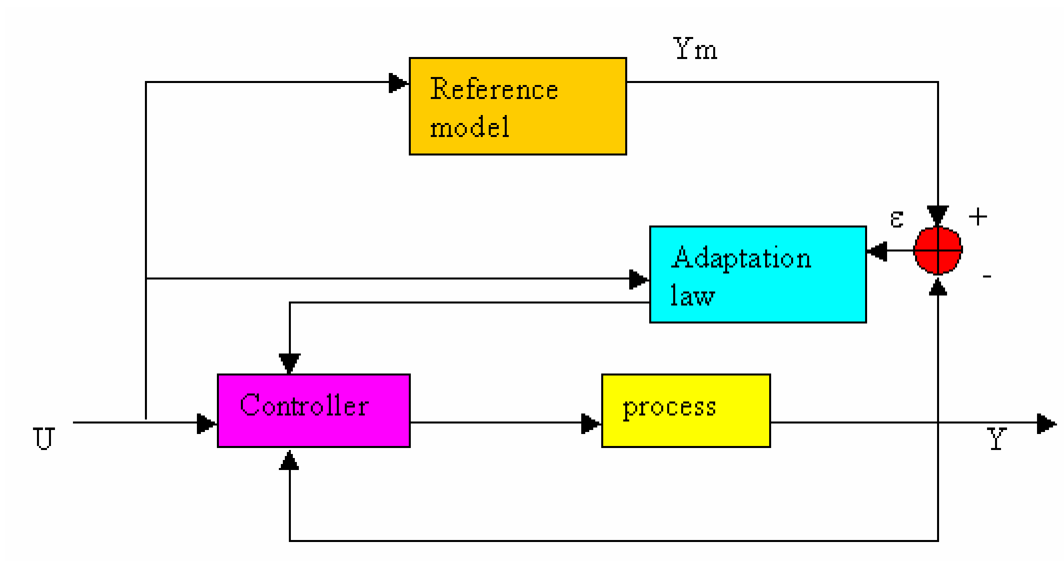


Figure 2.3 Basic model reference adaptive control structure

The standard implementation of MRAC based systems contains the four key blocks shown above. The reference model defines the desired performance characteristics of the process being controlled. The adaptation law uses the error between the process and the model output, the process output and input signal to vary the parameters of the control system. These parameters are varied so as to minimize the error between the process and the reference model.

The control system can be anything from a simple gain based controller to a more complicated parameter based transfer function or plant matrix. Whatever type of control system is used the parameters of the controller must be being varied by the adaptation law. The final element of the MRAC system is the process that is being controlled.

Controller

The typical controller structure used for adaptive control based solutions is shown in figure 2.4.

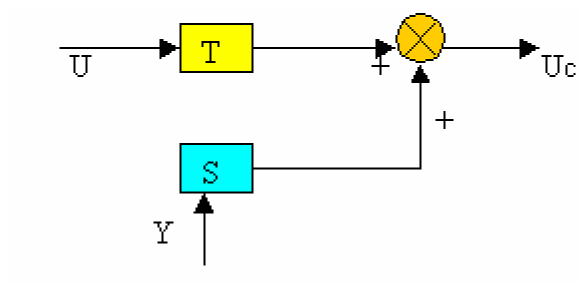


Figure 2.4 Standard controller's structure

This controller combines both feed forward and feedback control elements. These are typically just gain values however they can be complete transfer functions.

Irrespective of whether the control blocks are simple gain controllers or transfer functions they share one common property: they have parameters that can be modified by the adaptation law.

Adaptation law

The adaptation law shown in figure 2.2; uses the input signal, the output of the plant and the error between the plant and reference model outputs. These three signals are used to adapt the parameters of the selected controller. The adaptation law attempts to find a set of parameters that minimize the error between the plant and the model outputs. To do this, the parameters of the controller are incrementally adjusted until the error has reduced to zero.

A number of adaptation laws have been developed to date. The two main types are the gradient and the Lyapunov approach.

a) Gradient method

The gradient method, also known as the MIT rule, changes the parameters based upon the gradient of the error, with respect to that parameter. The parameters are changed in the direction of the negative gradient of the error. This means that if the error, with respect to a specified parameter, is increasing then by the MIT rule the value of that parameter will be decreased as shown by Equation 2.2 below.

$$d\theta/dt = - \gamma e \sigma e/\sigma t \qquad (2.2)$$

In this equation:

. $d\theta/dt$ is the incremental change to make to parameter θ

. γ is the adaptation rate from 0 to 1 (1=fastest adaptation)

. e is the error between the out puts of the plant and the model

. $\sigma e/\sigma t$ is the rate of change (gradient) of the error with respect to that parameter θ

This approach has one major disadvantage that it does not guarantee stability. The adaptation gain (rate) must be made small and the initial values of parameters must be stable for the adaptation law to operate correctly.

b) Lyapunov method

An alternative approach to the MIT rule is to use a Lyapunov based method, which avoids the stability problems present in the gradient approaches. A typical adaptation law for a Lyapunov based adaptive controller is shown in equation 3.2 below

$$d\theta/dt = - \gamma e \theta \qquad (2.3)$$

The major difference between the MIT rule and the Lyapunov method is that the sensitivity of the error to a specified parameter $\sigma e/\sigma t$, has been replaced by he actual value of the parameter, θ.

The adaptation law shown in equation 3.2 is commonly used for first or second system but it is proved that it can be applied for a much wider range of systems. A key result of this is that a different adaptation law need not be calculated when changing to a different plant or model, unless the performance of the adaptation law is proven to be insufficient.

It is possible to prove, using the adaptation law, that the adaptive controller is stable however the complexity of the proof precludes its inclusion in this document. It is also a relatively simple matter to test the stability of adaptive controller through simulation.

2.5 Constructing a Model Reference Adaptive Controller

Now that the individual elements of an adaptive controller have been identified and explained it is a simple matter to combine the various elements into a complete adaptive controller. These will be shown as simulink block diagrams.

First, we have the adaptation law based on the Lyapunov method, as shown in figure 2.5

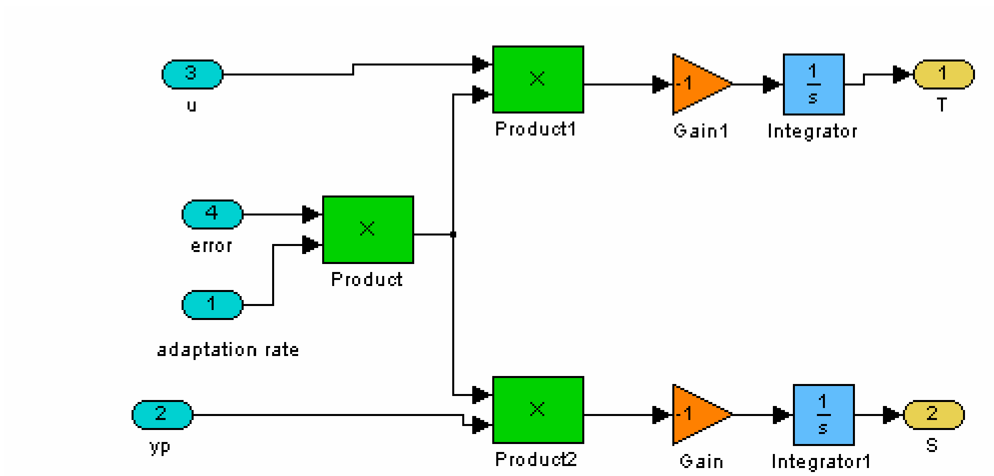


Figure 2.5 Simulink implementation of Lyapunov adaptation law

Next the actual controller is shown below in figure 2.6.

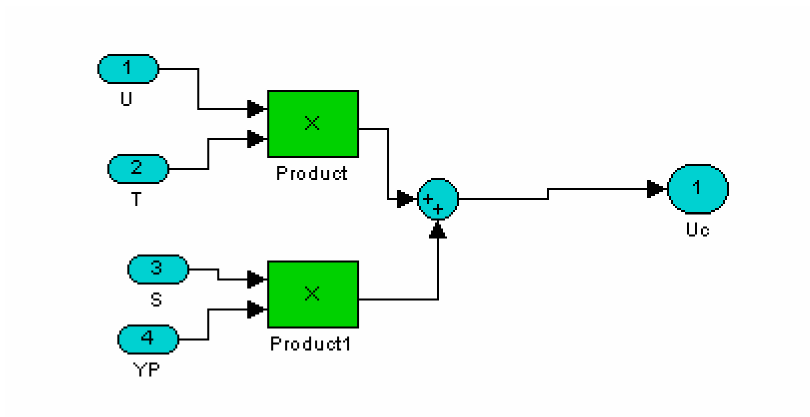


Figure 2.6 Simulink Implementation of Controller

The model and the plant will not be explicitly given here, as they will be chosen based upon the system that is being controlled and the response of the system. The final diagram, which is required to be shown, is therefore the completed diagram of the Model Reference Adaptive Controller, shown in figure 2.7.

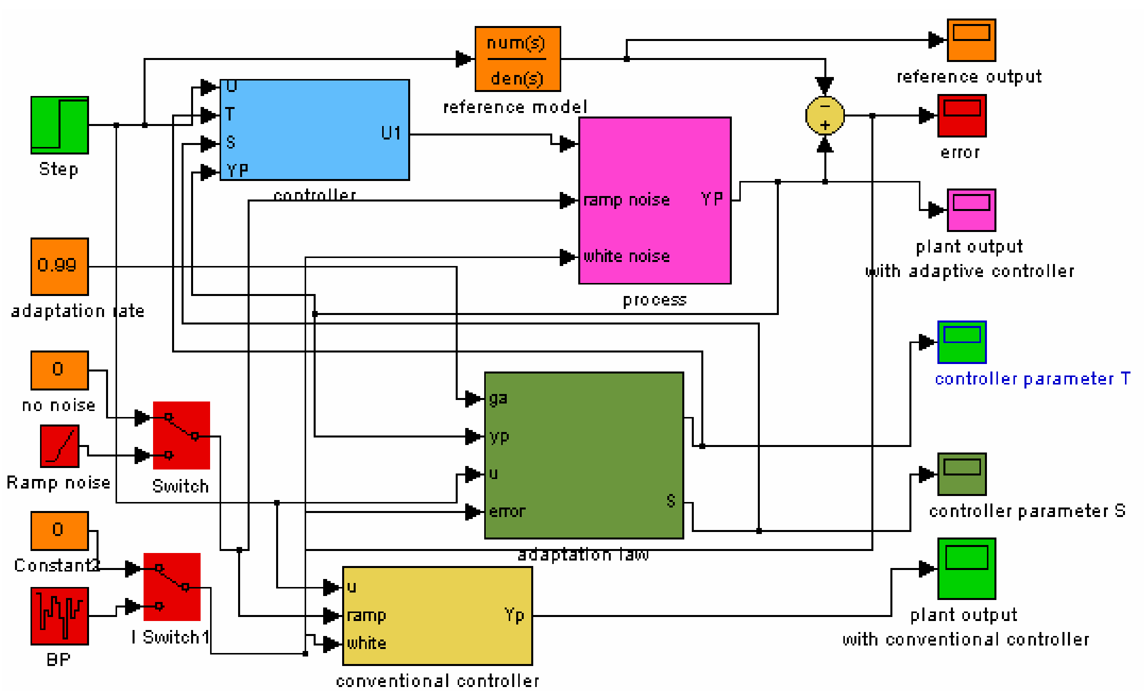


Figure 2. 7 Simulink Implementation of Model reference Adaptive Control

The diagram shows the controller and adaptation law systems given by figure 2.5 and figure 2.6. The plant and the model are also shown. Two blocks (Ap Noise and Bp Noise) are used to vary the parameters of the control system, forcing the adaptation law to continually adapt to the changes in the process parameters. A number of scopes are provided to monitor the output of the model, the output of the plant and the error between the two. The final element of the system is the adaptation rate (Gamma) which can be adjusted manually for instance to obtain rapid adaptation to changes in the system we have to set higher adaptation rate.

Chapter three

3. Mathematical Modeling

Diabetic continuous stirred tank reactor

The most important unit operation in a chemical process is generally a chemical reactor. Chemical reactions are either exothermic (release energy) or endothermic (require energy input) and therefore require that energy either be removed to the reactor for a constant temperature to be maintained. Exothermic reactions are the most interesting systems to study because of potential safety problems (rapid increases in temperature, sometimes called 'ignition' behavior) and the possibility of exotic behavior such as multiple steady states (for the same value of the input variable there may be several possible values of the outputs variable).

In this module we consider a perfect mixed continuously stirred tank reactor (CSTR) shown in figure 3.1.the case of a single, first-order exothermic irreversible reaction $A \rightarrow B$, will be studied. In figure 3.1 we see that a fluid stream is continuously fed to the reactor and other fluid stream is continuously removed from the reactor. Since the reactor is perfectly mixed, the exit stream has the same concentration and temperature as the reactor fluid. Notice that: a jacket surrounding the reactor also has feed and exit streams. The jacket is assumed to be perfectly mixed and at lower temperature than the reactor. Energy passes through the reactor walls into jacket, removing the heat generated by reaction.

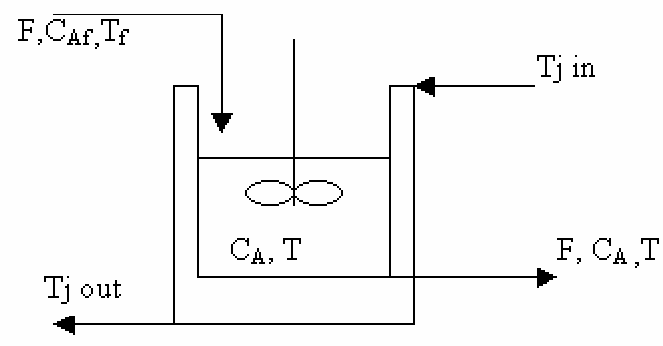


Figure 3. 1 Continues stirred tank reactor with cooling jacket

3.1 Modeling Equation

Overall material balance

Rate of material accumulation = rate of material in – rate of material out

$$\frac{dV\rho}{dt} = F_{in}\rho_{in} - F_{out}\rho_{out}$$

Assuming constant volume and constant density:

$$F_{in}\rho_{in} = F_{out}\rho_{out}$$

$$F_{in} = F_{out} \quad \text{and} \quad \frac{dV}{dt} = 0 \qquad (3.1)$$

Balance on component A

$$V \, {dC_A}/{dt} = FC_{Af} - FC_A - rV \qquad (3.2)$$

Energy balance

Assuming constant Cp

$$V\rho Cp \, {dT}/{dt} = F\rho Cp(T_f - T) + (-\Delta H)Vr - UA(T - T_j) \qquad (3.3)$$

3.2 State variable form of dynamic equation

We can write equation (3.2) and equation (3.3) as:

$$f_1(C_A, T) = {dC_A}/{dt} = {F}/{V}\left(C_{Af} - C_A\right) - r$$

$$f_2(C_A, T) = {dT}/{dt} = {F}/{V}\left(T_f - T\right) + \left(-\Delta H/\rho Cp\right)r - {UA}/{V\rho Cp}\left(T - T_j\right)$$

And $r = KC_A$,

$r = K_o \exp(-E/RT)\, CA$

$$f_1(C_A, T) = {dC_A}/{dt} = {F}/{V}\left(C_{Af} - C_A\right) - Ko\exp\left(-E/RT\right)C_A$$

$$f_2(C_A, T) = {dT}/{dt} = {F}/{V}\left(T_f - T\right) + \left(-\Delta H/\rho Cp\right)Ko\exp\left(-E/RT\right)C_A - {UA}/{V\rho Cp}\left(T - T_j\right)$$

3.3 Steady State Solution

The steady state solution is obtained when $dC_A/dt = 0$ and $dT/dt = 0$, that is

$$f_1(C_A,T)=\frac{dC_A}{dt}=0=\frac{F}{V}\left(C_{Af}-C_A\right)-Ko\exp\left(-\frac{E}{RT}\right)C_A$$

$$f_2(C_A,T)=\frac{dT}{dt}=0=\frac{F}{V}\left(T_f-T\right)+\left(\frac{-\Delta H}{\rho Cp}\right)Ko\exp\left(-\frac{E}{RT}\right)C_A-\frac{UA}{V\rho Cp}\left(T-T_j\right)$$

To solve these two equations, all parameters and variables except for two (C_A and T) must be specified. Given numerical values for all of the parameters and variables, we can use Newton's method to solve for the steady state values of C_A and T. By writing a program in mat lab which is shown in Appendix 1:

The command to run this file is

X= fsolve ('cstr_ss', x0);

Where x0 is a vector of the initial guesses and x is the solution. Before using this command the reactor parameters must be entered in the global parameter vector CSTR_PAR.

When choosing initial guesses for numerical algorithm, it is important to use physical insight about the possible range of solutions. For example, since the feed concentration of A is 10 kgmol/m3 and the only reaction consumes A; the possible range for the concentration of A is 0<CA<10. Also it is to show that a lower bound for temperature is 298 K, which would occur if there was no reaction at all. For reactor parameters below [1]:

Table 3. 1 Reactor Parameter's value

Reactor parameters	Values
F/V,hr-1	1
Ko,hr-1	9703 x 3600
(-ΔH),kcal/kmol	5960
E,kcal/kmol	11843
ρCp,kcal/m3'c	500
Tf,'c	25
Caf,kmol/m3	10

UA/V,kcal/m3'c.hr	150
Tj,'c	25

GUESS 1

High concentration (low conversion) and low temperature. We consider an initial guess of CA=9 and T=300K.

```
X= fsolve ('cstr_ss', [9; 300]);

X =
     8.5636
    311.17
```

So the steady-state solution for guess 1 is C_{As}=8.5636 and T_s=311.2.

The result for different guess are summarized in table 3.2

Table 3. 2 Guesses and Solutions

Guesses and Solutions	**Guess 1**	**Guess 2**	**Guess 3**
Ca guessed	9	5	1
T guessed	300	350	450
CA solution	8.564	5.518	2.359
T solution	311.2	339.1	368.1

3.4 Linearization of Dynamic Equation

The stability of the non-linear equation can be determined by finding the following state space form:

$$X' = AX + BU$$

And determine the eigenvalues of the A (state space) matrix.

The non-linear dynamic equation (3.4) and (3.5) are

$$F_1\ (CA, T) = dC_A/dt = F/\ V\ (C_{Af} - CA) - koexp\ (-E/RT)\ C_A$$

$$F_2\ (VA, T) = dT/dt = F\ /V\ (T_f - T) + (-\Delta H/\rho Cp)\ koexp\ (-E/RT)\ C_A$$

$UA/V\rho Cp\ (T - Tj)$

Let the state and input variables be defined in deviation variable form:

$$X= \begin{bmatrix} C_A - C_{AS} \\ T - T_S \end{bmatrix}$$

$$U= \begin{bmatrix} F\ - F_S \\ T_J - T_{JS} \end{bmatrix}$$

Stability Analysis

Performing the linearization, we obtain elements for A

$$A_{11}=\partial f1/\partial x1 \mid xs, us = \partial f1/\partial CA \mid xs, us = -F/V - Ks$$

$$A_{12}=\partial f1/\partial x2 \mid xs, us =\partial f1/\partial T \mid xs, us = -CasKs\ (\Delta E/RTs^2)$$

A_{21}=∂f2/∂x1 | xs, us=∂f2/∂CA | xs, us= (-ΔH/ρCp) Ks

A_{22}=∂f2/∂x1 | xs, us=∂f2/∂T | xs, us= -F/V –UA/VρCp + (-ΔH/ρCp) Ks ($\Delta E/RTs^2$)

The stability characteristics are determined by the eigenvalues of A, which are obtained by solving

$$\mathrm{Det}(\lambda I - A) = 0$$

The stability of particular operating point is determined by finding the A-matrix for that particular operating point and finding the eigenvalues of the A-matrix

The A matrix is obtained as:

$$A = \begin{bmatrix} -F/V - K_S & -C_{AS}K_S\left(\Delta E/RT_S{}^2\right) \\ \left(-\Delta H/\rho C_P\right)K_S & -F/V - UA/V\rho C_P + \left(-\Delta H/\rho C_P\right)K_S\left(\Delta E/RT_S{}^2\right) \end{bmatrix}$$

-Substituting the values for the lower temperature steady state point, we have

$$A = \begin{bmatrix} -1.1567 & -0.0829 \\ 1.868 & -0.3115 \end{bmatrix}$$

Then to find the eigenvalues, In Mat lab command we write

```
>>

A= [-1.1567,-0.0829; 1.868,-0.3115];
```

$$\begin{bmatrix} -1.1567 & -0.0829 \\ & \end{bmatrix}$$

A = 1.868 -0.3115

```
>>Lambda = eig(A);
>>Lambda=
          -0.8882
          -0.5800
>>
```

Both of the eigenvalues are negative, indicating that the point is stable.

3.5 Input output Relation

To find the input-output relation, first we have to find the A, B, C and D matrix.

A Matrix

We already obtain the A matrix as:

$$A = \begin{bmatrix} -1.1567 & -0.0829 \\ 1.868 & -0.3115 \end{bmatrix}$$

B Matrix

Similarly performing linearization,

$$B_{11} = \partial f1/\partial u1 \,|\, xs, us = \partial f1/\partial F \,|\, xs, us = (Caf\text{-}CAs)/\ V$$

$$B_{12} = \partial f1/\partial u2 \,|\, xs, us = \partial f1/\partial Tj \,|\, xs, us = 0$$

$B_{21}=\partial f2/\partial u1\,|\,xs, us=\partial f2/\partial F\,|\,xs, us= (Tf- Ts)/V$

$B_{22}=\partial f2/\partial u1\,|\,xs, us=\partial f2/\partial Tj\,|\,xs, us= UA/V\rho Cp$

$$B = \begin{bmatrix} (C_{Af} - C_{AS})/V & 0 \\ (T_f - T_S)/V & UA/V\rho C_P \end{bmatrix}$$

$$B = \begin{bmatrix} 1.4364 & 0 \\ -13.171 & 0.3 \end{bmatrix}$$

C-Matrix

The output Y in deviation variable form is:

$$Y = \begin{bmatrix} C_A - C_{AS} \\ T - T_S \end{bmatrix}$$

Where $Y_1= C_A-C_{As}$,

$Y_2= T-Ts$

$C_{11}=\partial Y1/\partial X1\,|\,xs, us = 1$

$C_{12}=\partial Y1/\partial X2\,|\,xs, us =0$

$C_{21}=\partial Y2/\partial X1\,|\,xs, us=0$

$C_{22}=\partial f2/\partial X1\,|\,xs, us=1$

$$C = \begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix}$$

D Matrix

$$D_{11}=\partial Y1/\partial U1 \,|\, xs,\, us = 0$$

$$D_{12}=\partial Y1/\partial U2 \,|\, xs,\, us = 0$$

$$D_{21}=\partial Y2/\partial U1 \,|\, xs,us = 0$$

$$D_{22}=\partial Y2/\partial U2 \,|\, xs,us = 0$$

$$D = \begin{bmatrix} 0 & 0 \\ 0 & 0 \end{bmatrix}$$

Once we found the A, B, C and D matrix, the transfer function that relate the input to output is obtained by using the Mat lab command

[num, den] = ss2tf (A, B, C, D, m)

Where m = the input number.

Transfer function relating CA to F:

$$g_{11} = \frac{1.4364s + 1.5393}{s^2 + 1.4682s + 0.5152}$$

Transfer function relating CA to Tj:

$$g_{12} = \frac{-0.0249}{s^2 + 1.4682s + 0.5152}$$

Transfer function relating T to F:

$$g_{21} = \frac{-13.171 -12.5517}{s^2 + 1.4682s + 0.5152}$$

Transfer function relating T to Tj:

$$g_{22} = \frac{0.3s + 0.347}{s^2 + 1.4682s + 0.5152}$$

3.6 COUPLING

Let

$Y_1 = C_{A,}$

$Y_2 = T,$

$m_1=F,$

$m_2=T_j$

Then we can write the input output relation as:

$$Y_1 = \frac{1.4364s + 1.5393}{s^2 + 1.4682s + 0.5152} m_1 + \frac{-0.0249}{s^2 + 1.4682s + 0.5152} m_2$$

$$Y_2 = \frac{-13.171s - 12.5517}{s^2 + 1.4682s + 0.5152} m_1 + \frac{0.3s + 0.347}{s^2 + 1.4682s + 0.5152} m_2$$

Coupling requires finding of the Relative Gain Array matrix:

$$\lambda_{11} = \frac{(\Delta y_1/\Delta m_1)|m_2 = \text{const}}{(\Delta y_1/\Delta m_1)|y_2 = \text{const}} = \frac{3.0635}{1.3314} = 2.3$$

RGA:

$$\lambda = \begin{bmatrix} 2.3 & -1.3 \\ -1.3 & 2.3 \end{bmatrix}$$

From the relative gain array matrix, it can be seen that the diagonal elements are negative. This indicates that the system is unstable for any feed back control system. In order to eliminate the interaction a decoupler must be designed for the two systems.

3.7 Design of Decouplers

The input output relation is obtained as:

$$Y_1 = \frac{1.4364s + 1.5393}{s^2 + 1.4682s + 0.5152} m_1 + \frac{-0.0249}{s^2 + 1.4682s + 0.5152} m_2$$

$$Y_2 = \frac{-13.171s - 12.5517}{s^2 + 1.4682s + 0.5152} m_1 + \frac{0.3s + 0.347}{s^2 + 1.4682s + 0.5152} m_2$$

Thus $H_{11} = \dfrac{1.4364s + 1.5393}{s^2 + 1.4682s + 0.5152}$, $H_{12} = \dfrac{-0.0249}{s^2 + 1.4682s + 0.5152}$

$H_{21} = \dfrac{-13.171s - 12.5517}{s^2 + 1.4682s + 0.5152}$ and $H_{22} = \dfrac{0.3s + 0.347}{s^2 + 1.4682s + 0.5152}$

-To cancel the effect of jacket temperature (m_2) on the outlet concentration (Y_1):

$$D_1(s) = -\frac{H_{12}}{H_{11}} = \frac{-0.0249}{1.4364s + 1.5393}$$

-To cancel the effect of feed flow rate (m_1) on the reactor temperature (Y_2):

$$D_2(s) = \frac{-H_{21}}{H_{22}} = \frac{13.171s + 12.5517}{0.3s + 0.347}$$

The complete block diagram of the process with two decouplers is shown in figure 3.2 and the equivalent representation of the process is shown in figure 3.3

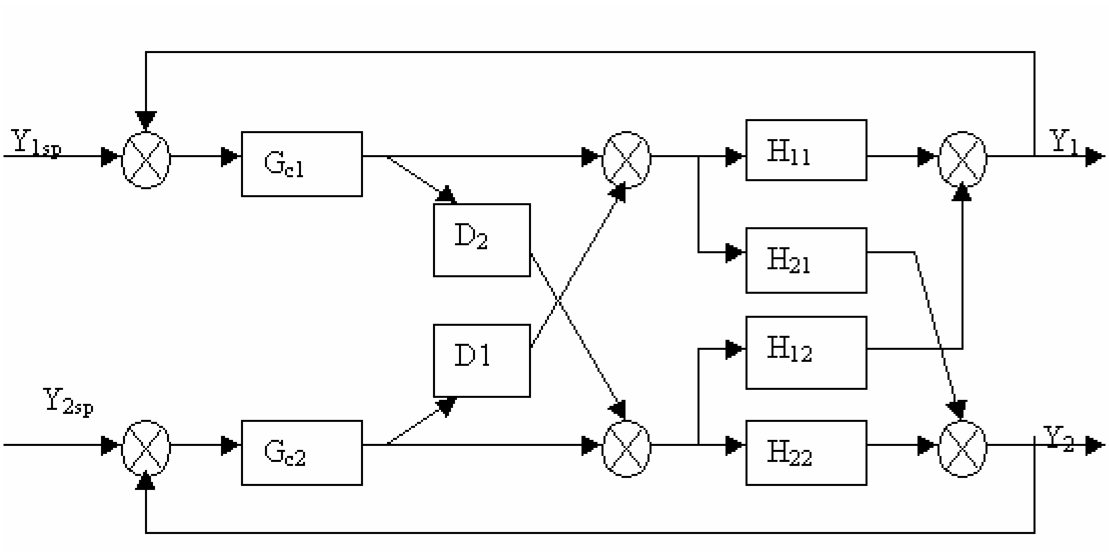


Figure 3. 2Complete block diagram with two decouplers

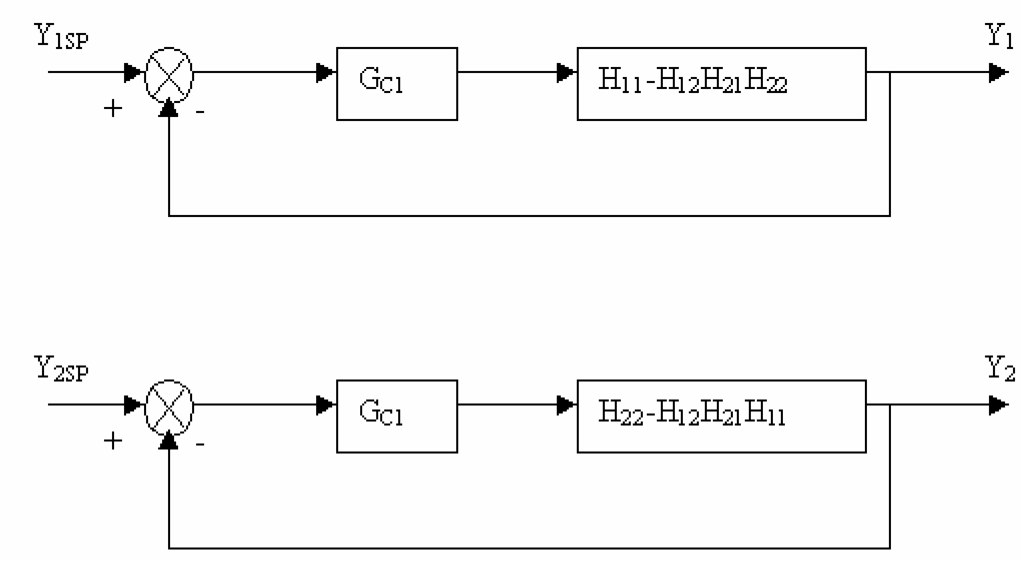


Figure 3. 3Equivalent representation of the process

Chapter four

4. NON-ADAPTIVE CONTROL ANALYSIS

This section presents the effect of different non-adaptive controllers on a feedback system. To analyze this first, simulink model of the feed back systems are designed then the simulation of the feed back systems were run with different combination of the parameters of the PID controller,

4.1 Concentration control system

The simplified transfer function model of the process is given as:

$$Gp1(s) = \frac{1.44s^5+5.78s^4+9s^3+6.88s^2+2.53s+0.31}{S^6+4.41s^5+7.94s^4+8.42s^3+4.1s^2+1.19s+0.14}$$

The closed loop control system and its simulink representation are shown below in figure 4.1 and 4.2.

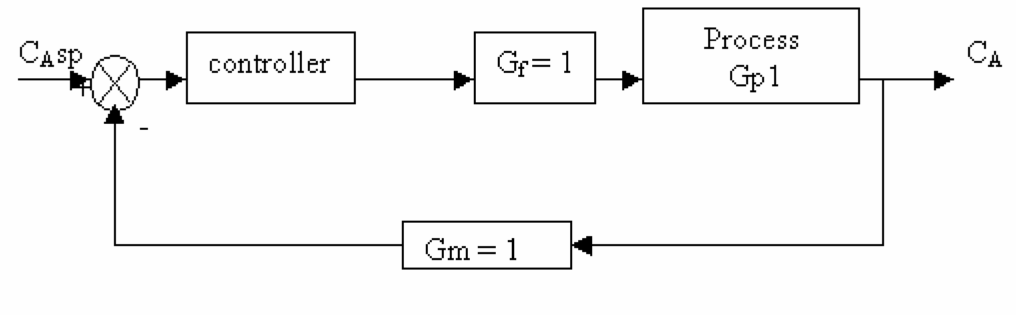


Figure 4. 1 Closed loop concentration control system

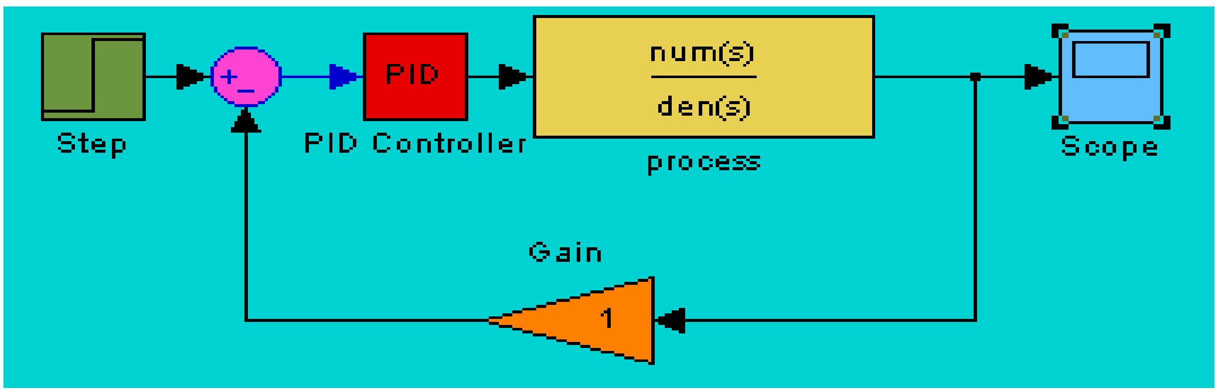


Figure 4. 2 Simulink representation of the control system

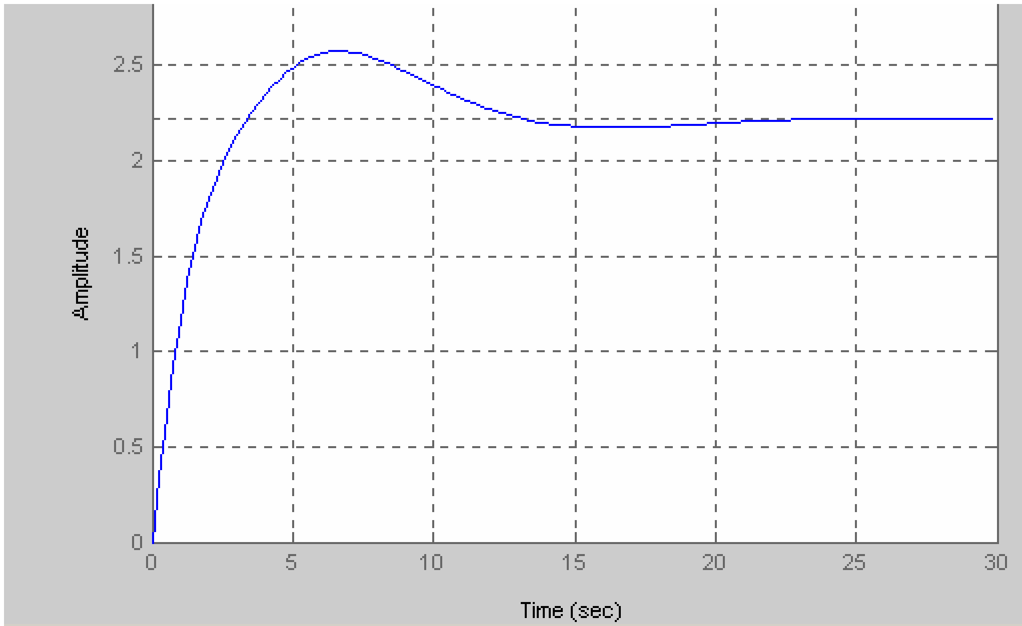


Figure 4. 3. Response for step input(concentration control)

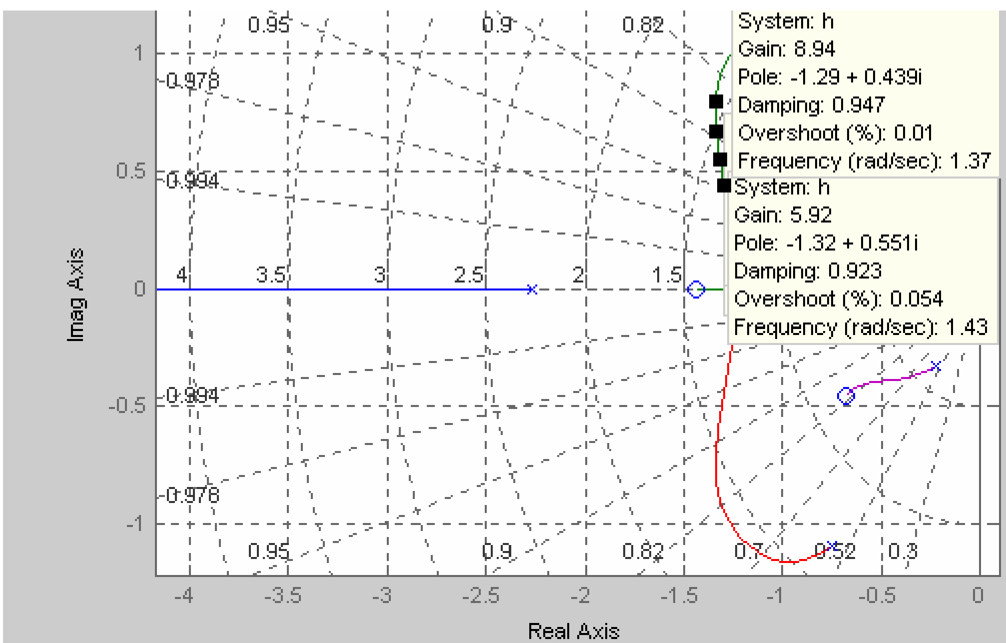


Figure 4. 4 Root locus analysis (concentration control)

4.2 Temperature control system

The simplified transfer function model of the process is given as:

$$Gp2(s) = \frac{0.3s^5+1.18s^4+ 1.96s^3+1.54s^2+0.62s+0.095}{S^6+4.41s^5+7.94s^4+8.42s^3+4.1s^2+1.19s+0.14}$$

The closed loop control system and its simulink representation are similar to the concentration control except G_{P1} is replaced by G_{P2} as they are shown below in figure 4.3 and 4.4.

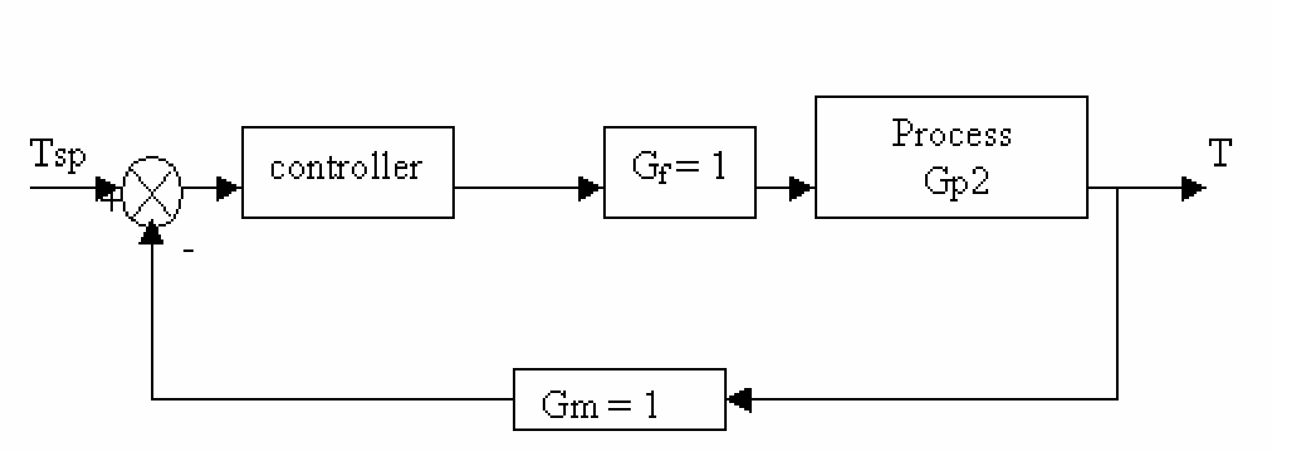


Figure 4. 5. Closed loop temperature control system

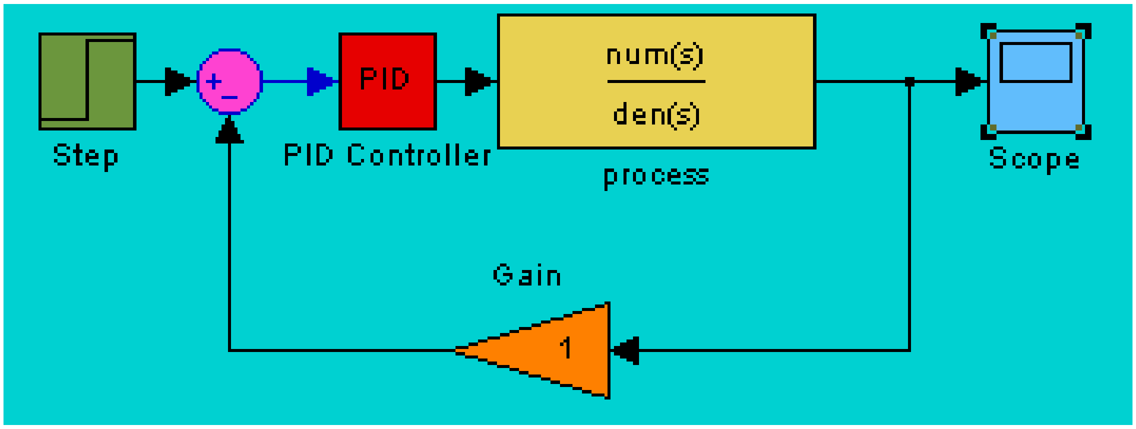


Figure 4. 6 Simulink representation of the control system

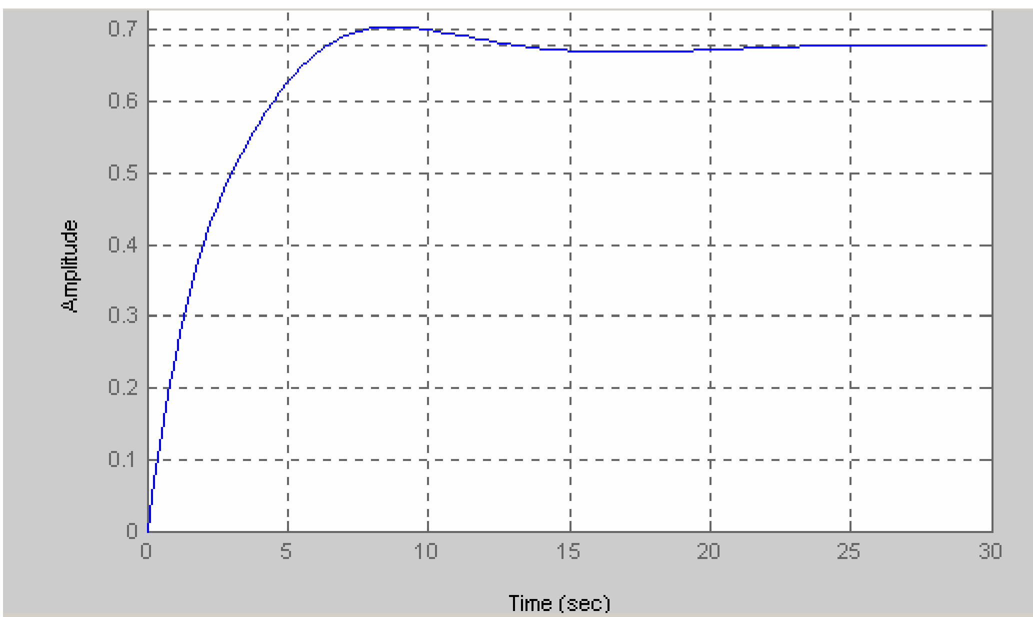


Figure 4. 7 Response for step input (temperature control)

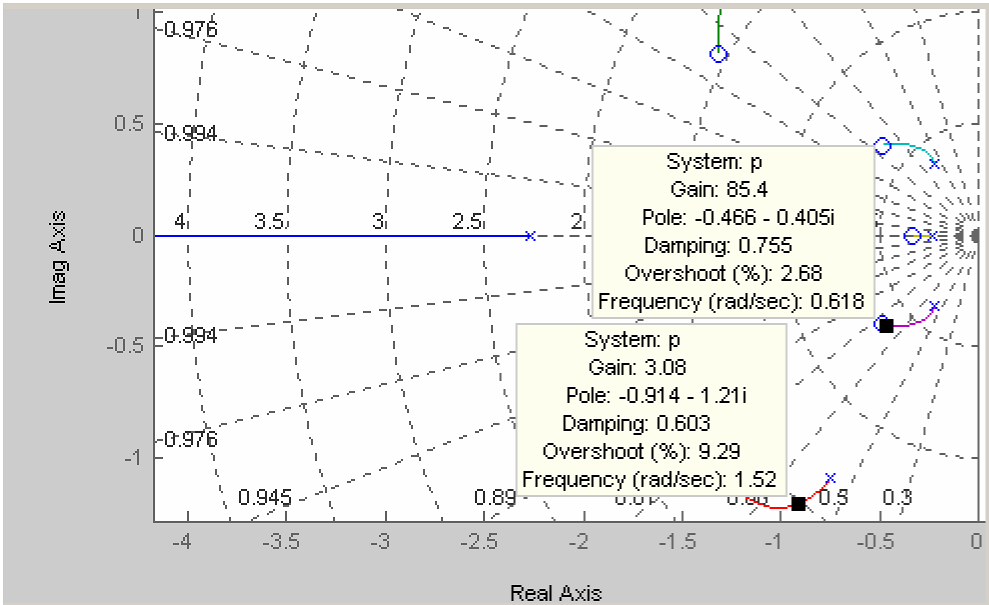


Figure 4. 8 Root locus analysis (temperature control)

4.3 Analysis of Result

The simulink models of the closed loop control system were run with different combination of the PID controller. The resulting outputted graphs for the P, PI and PID controllers are included in table 4A, 4B and 4C respectively.

PID controller operating in P mode

Table 4.1A illustrates the effect of a P controller on the closed loop response of the concentration control system. The simulation start with Kc=1. As the graph indicates there is a big offset (=0.2) and also the response is very slow. Increasing the value of Kc (Kc=10) decreases the offset and increases the speed of the response. But as the gain increases the system will goes toward instability. This is also shown in the root locus analysis. So if it is desired to use proportional controller Kc=10 is suggested.

In Table 4.1B, the effect on the closed response of the temperature control system is illustrated. With Kc=1, there is a biggere offset(=0.5) and the reponse is very slow. Increasing the value of Kc has the same effect as the previous case but a higher gain(Kc=50) is required to eliminate the offset.

PID controller operating in PI mode

In Table 4.2A and 4.2B the characteristic of the PI controller on the two systems have been analyzed. Increasing the value of (from 0.5 to 2) while keeping the proportional gain(Kc=10) decrease the overshoot of the systems but the rise time of the systems increase. For both systems τ_I=1 with Kc = 10 is suggested for both system

PID controller operating in PID mode

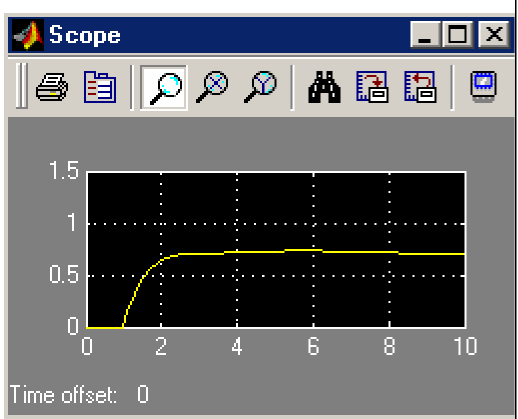
At last we have the PID controller operating in a PIS mode, as illustrated in table C. The effect of PID controller on the response of the concentration control system is shown in table 4.3A. Increasing the value of τd decrease the overshoot of the system but doesn't change the rise time (remain 1.3s).

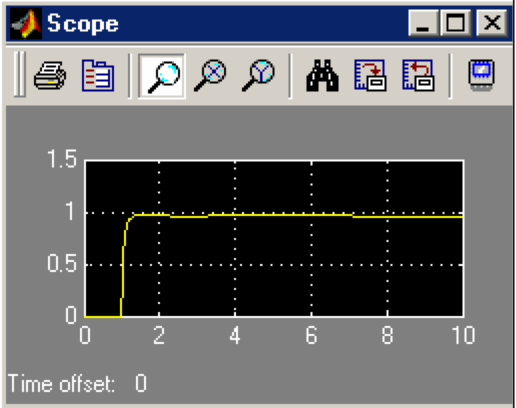
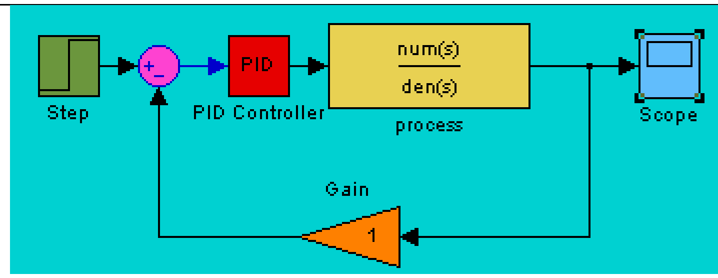
Table 4.3B illustrated the effect on the response of the temperature control system. The value of on this case has a significant effect on the response. Increasing the value of τd increases the overshoot and decreases the speed of the response.

As it is known the main advantage of PID controller is that it allows to use a higher gain without affecting the stability of the system. Thus for both feedback system, If it is desired to use a PID with a higher proportional gain τi = 1, τd=0.01 is suggested.

Table 4. 1 Plots of system response for P controller

Table 4.1A: Concentration control

Plots for various values of Kc	System
Kc=1 	System under P Control

<table>
<tr><td>Kc=10

</td>
<td rowspan="2">

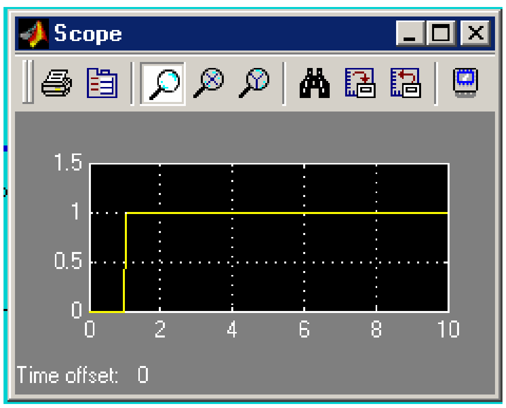
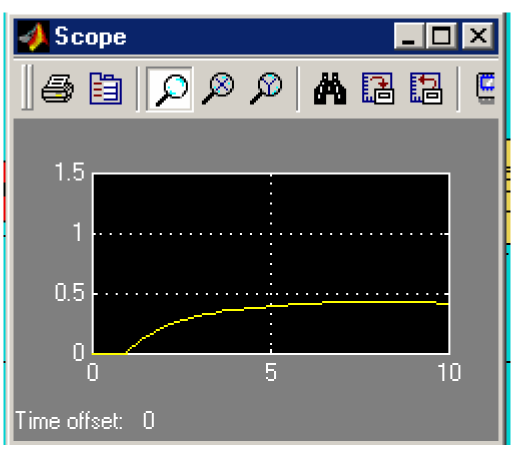
Note:Kc= parameter, τi = 0, ,τd=0</td></tr>
<tr><td>Kc=50

</td></tr>
</table>

Table 4.1B: Temperature control

<table>
<tr><td>Plots for various values of Kc</td><td>System</td></tr>
<tr><td>Kc=1

</td><td></td></tr>
</table>

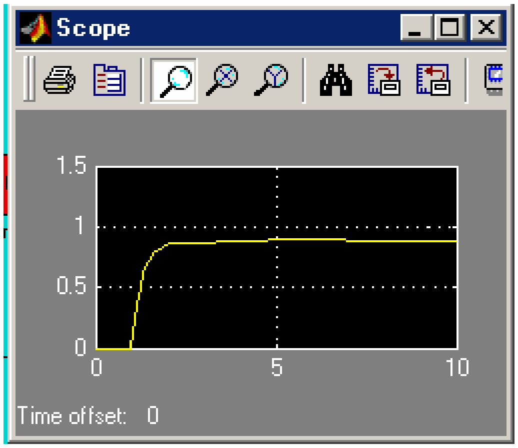
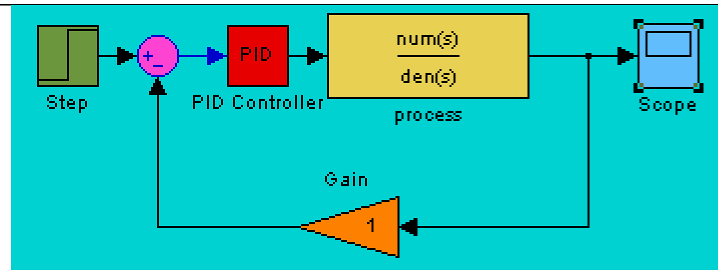
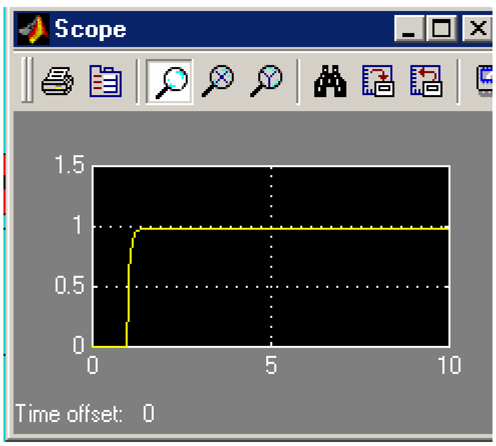
<table>
<tr>
<td>Kc=10

</td>
<td rowspan="2">
</td>
</tr>
<tr>
<td>Kc=50

</td>
</tr>
</table>

Table 4. 2: Plot of system response for PI controller

Table 4.2A: concentration control

Plots for varios values of τi	System

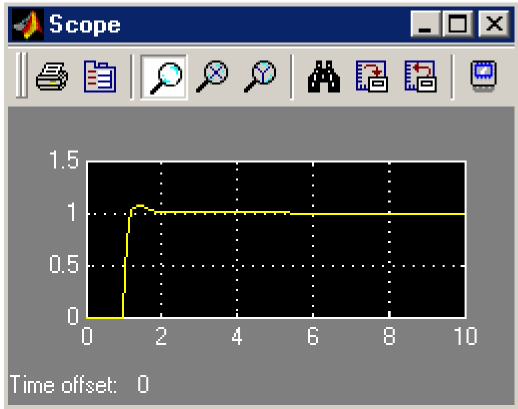
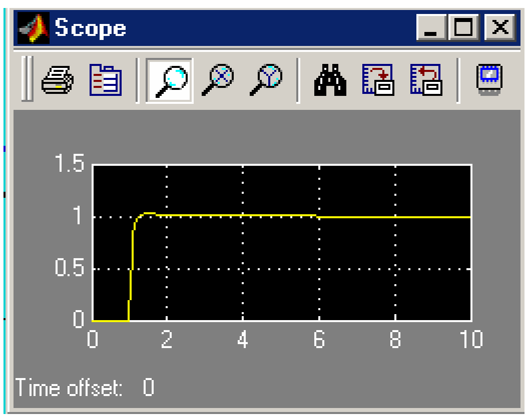
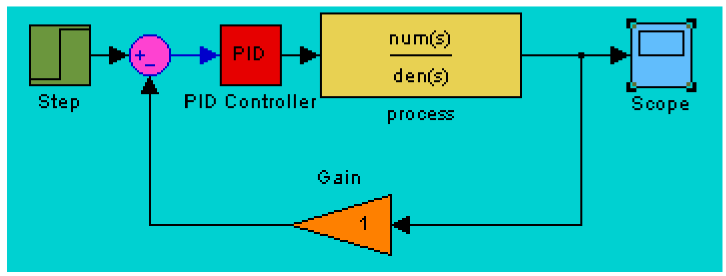
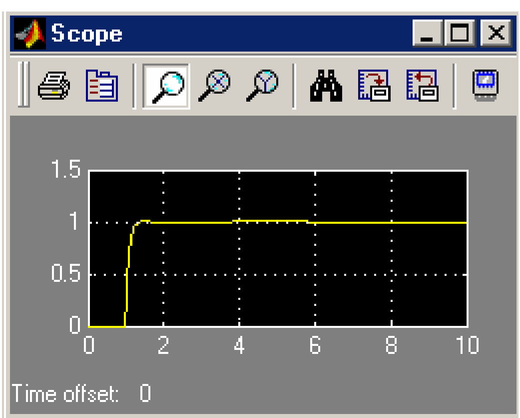
Kc=10,τi = 0.5  	System under PI Control
Kc=10,τi = 1,  	 Note: τi=parameter, Kc=10, τd=0
Kc=10,τi = 2,  	

Table 4.2B: Temperature control

Plots for various τi	System

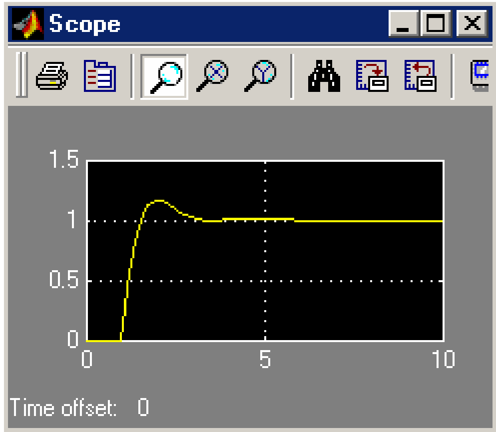
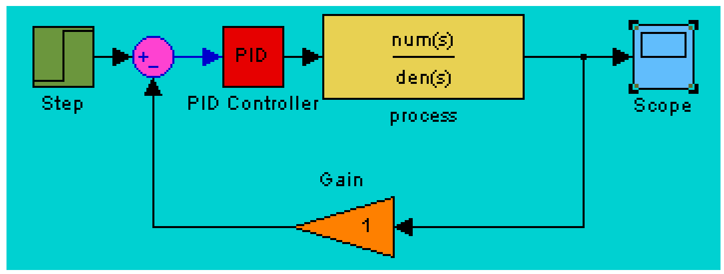
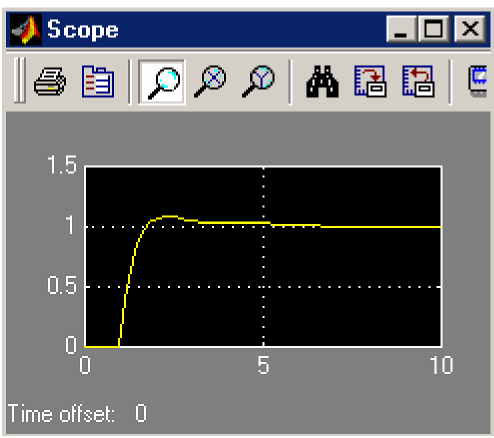
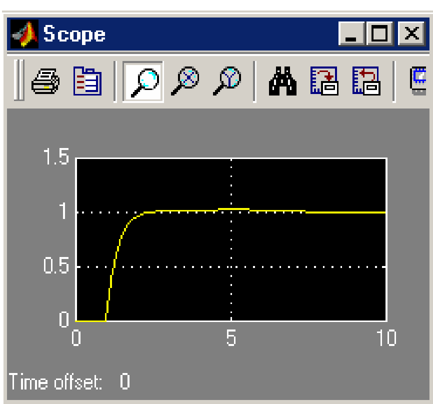
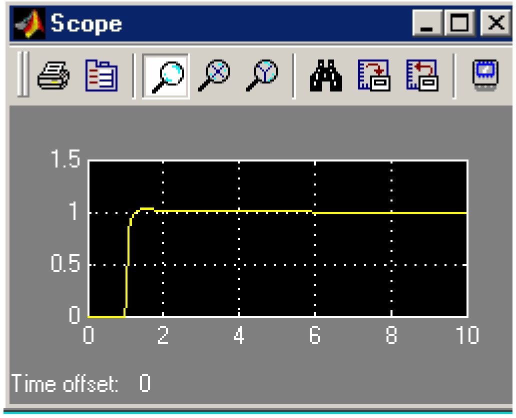
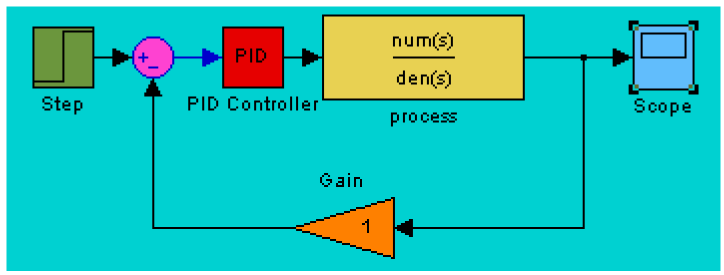
<table>
<tr>
<td>Kc=10,τi = 0.5

</td>
<td rowspan="3">
</td>
</tr>
<tr>
<td>Kc=10,τi = 1

</td>
</tr>
<tr>
<td>Kc=10,τi = 2

</td>
</tr>
</table>

Table 4. 3 : Plots of system response for PID controller

Table 4.3A: Concentration control

<table>
<tr><th>Plots for various values of τd</th><th>System</th></tr>
<tr><td>Kc=10,τi = 1, τd=0.001

</td>
<td rowspan="3">System under PID Controller


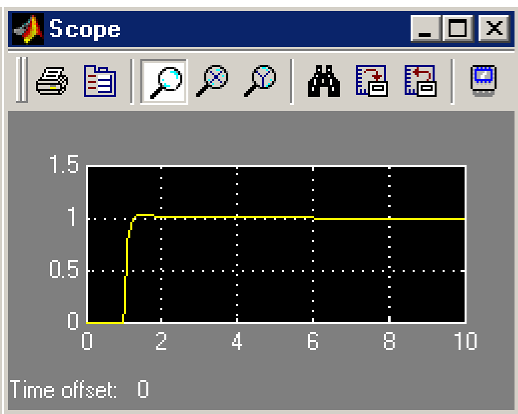
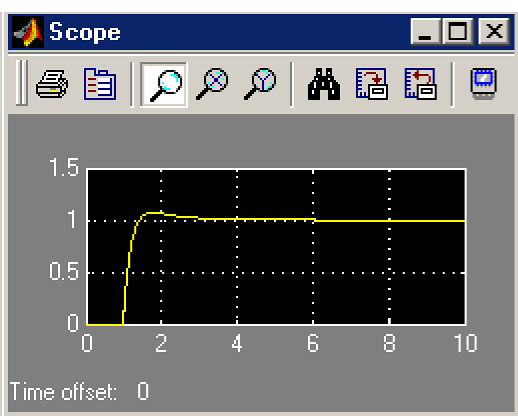
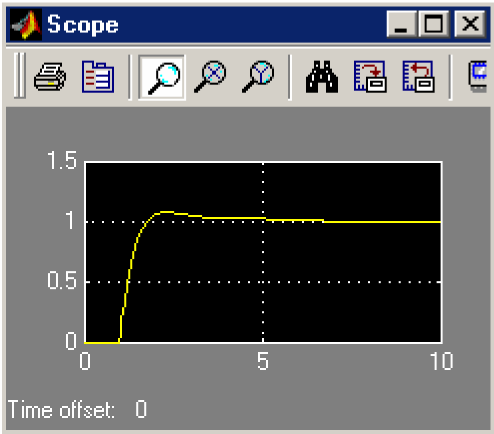
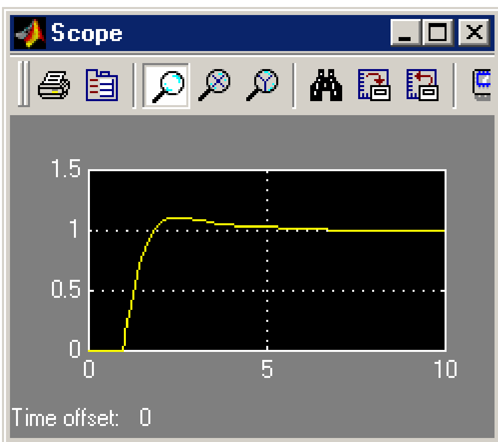
Note: Kc=10,τi = 1, τd=parameter</td></tr>
<tr><td>Kc=10,τi = 1, τd=0.01

</td></tr>
<tr><td>Kc=10,τi = 1, τd=0.1

</td></tr>
</table>

Table 4.3B:Temperature control

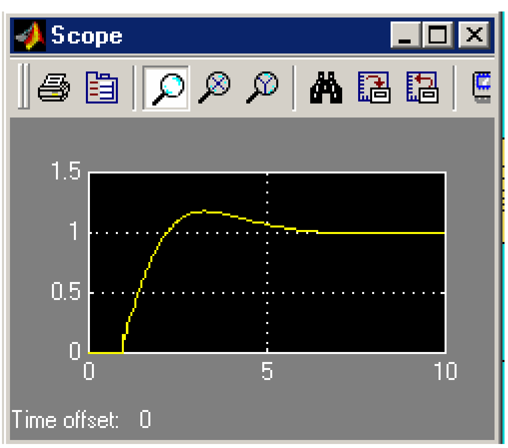
Kc=10,τi=1,τd=0.01

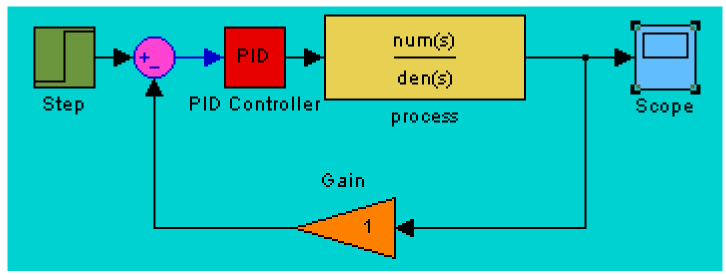


Kc=10,τi=1,τd=0.1



Kc=10,τi=1, ,τd=0.5





Chapter five

5. Adaptive control design and simulation

This section provide five sets: the first covers the design of model reference adaptive control and its implementation in simulink. The second and the third compare the performance of an adaptive control to a conventional controller without noise and with noise respectively. In the fourth set a case study which considered the control of Van de Vausee reactor will be demonstrated. The final set discusses the expansion of model reference adaptive controller to adapt faster and better accommodate variations in the parameters.

5.1 Basic adaptive controller

This set provides the implementation of a basic adaptive controller using simulink. The first item that must be defined is the plant that is to be controlled. We have got the transfer function for the two SISO systems (concentration and temperature of reaction control) as

a) Concentration control

The simplified transfer function model of the process is given as:

$$Gp1(s) = \frac{1.44s^5+5.78s^4+ 9s^3+6.88s^2+2.53s+0.31}{S^6+4.41s^5+7.94s^4+8.42s^3+4.1s^2+1.19s+0.14}$$

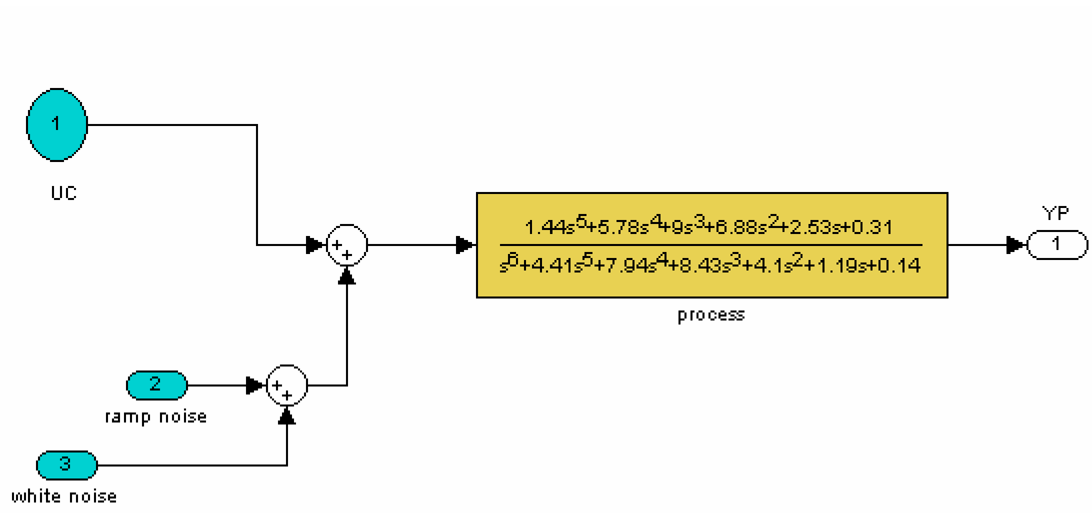


Figure 5. 1 Simulink plant implementation

The plant output for step change (without noise) is shown in figure 5.2

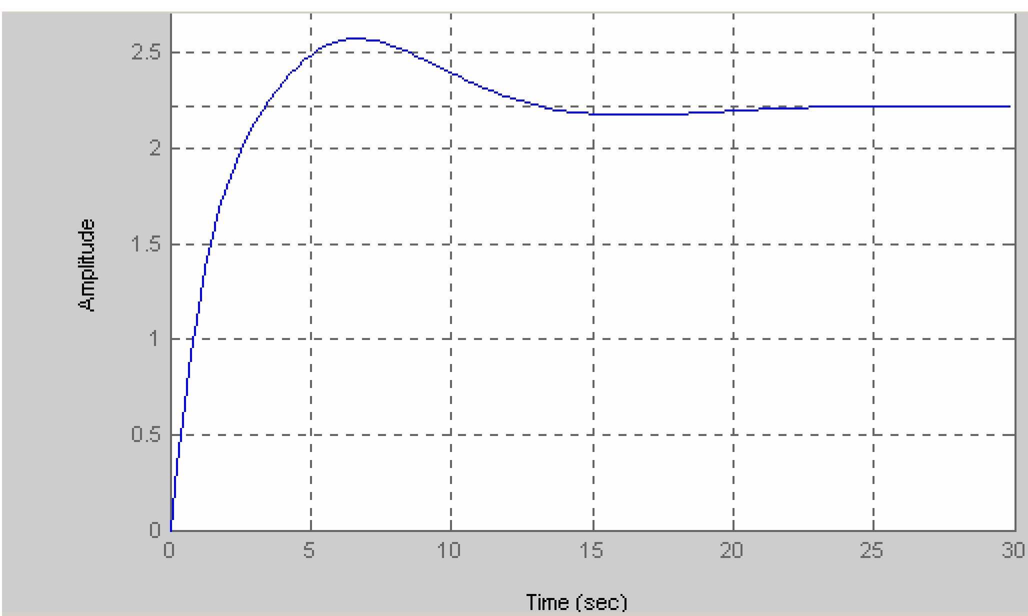


Figure 5.2 Plant Step Response

The next step is to define the model that the plant must be matched to. To determine this model we must first define the characteristics that we want the system to have. Firstly we will arbitrary select the model to be a second order model of the form:

$$Gm(s) = \frac{\omega_n^{\ 2}}{s^2 + 2\omega_n \xi s + \omega_n^{\ 2}} \qquad (5.2)$$

We must then determine the damping ratio ξ and the natural frequency ωn to give the required performance characteristics.

For the concentration control a maximum overshoot (Mp) of 5% and a settling time (Ts) of less than 2 seconds are selected. We can use the equation below to determine the required damping ratio and natural frequency of the system.

$$\xi = \frac{\ln Mp/100}{-\pi} \sqrt{\frac{1}{1+\left[\frac{\ln Mp/100}{-\pi}\right]^2}} \qquad (5.3)$$

Equation 5.3.Damping ratio from Maximum Overshoot

$$\omega_n = \frac{3}{T_S \xi} \qquad (5.4)$$

Equation 5.4.Natural frequency from settling time and damping ratio

Based upon these formulae we get ξ=0.68 and ωn=2.1986 rad/s. The transfer function for the model is therefore

$$\text{Gm(s)} = \frac{4.834}{s^2 + 3s + 4.834} \qquad (5.5)$$

Equation 5.5.Model transfer function

Note that we have defined the plant we need to develop a standard controller to compare with the adaptive controller. Controller setting is done using Ziegler-Nicholas technique and the best controller parameters are found to be Kc=10, τ_I=1 and τd=1.The simulink diagram for this controller (and the plant) is shown in figure 5.3.

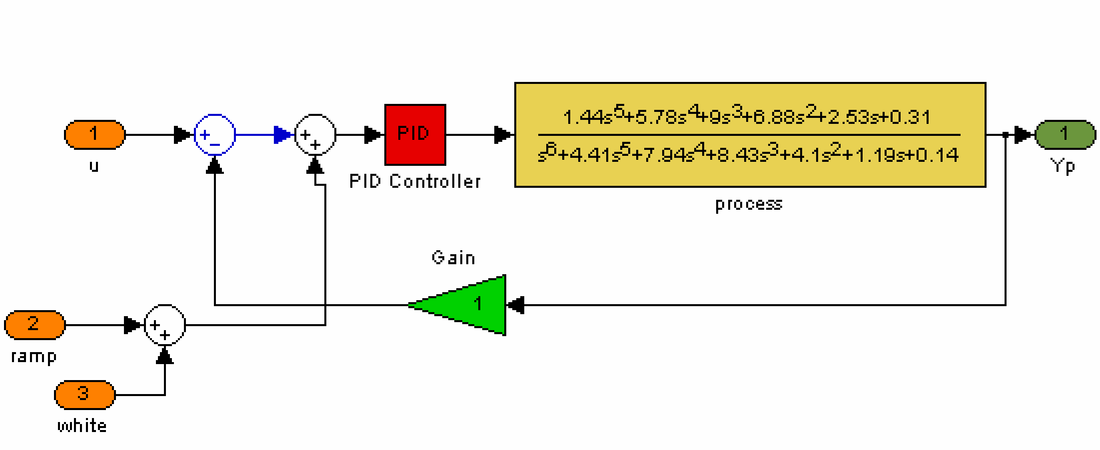


Figure 5. 3 Simulink conventional controller

The final steps are then to implement the controller, the adaptation law and the link between the systems. All of these items are identical to the simulink diagrams already shown in chapter 2, however these diagrams are repeated here for simplicity.

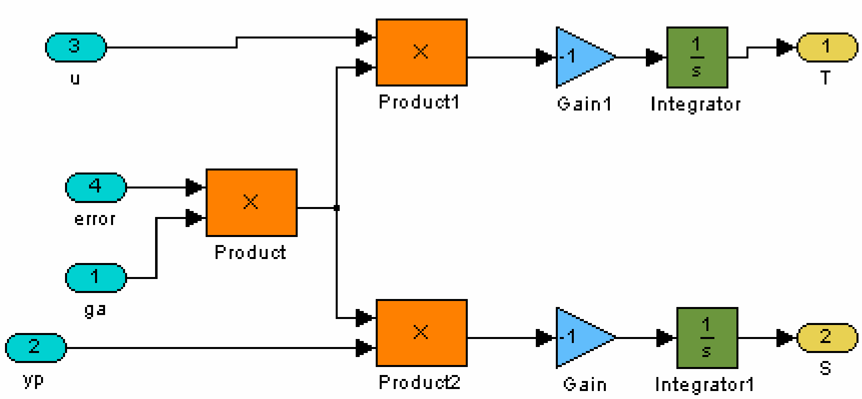


Figure 5. 4 Simulink implementation of Lyapunov Adaptation Law

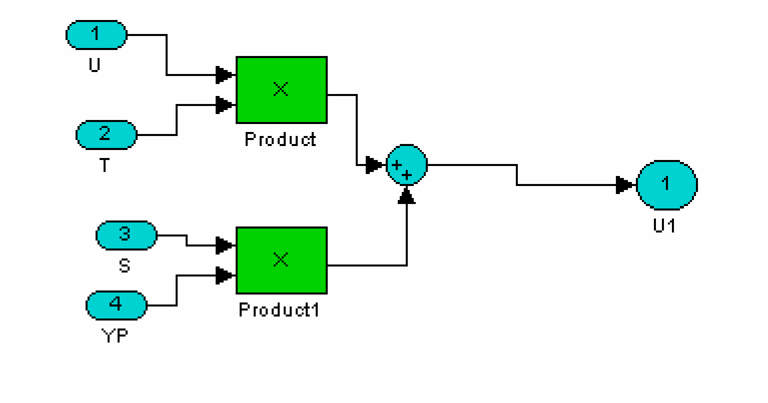


Figure 5. 5 Simulink implementation of Controller

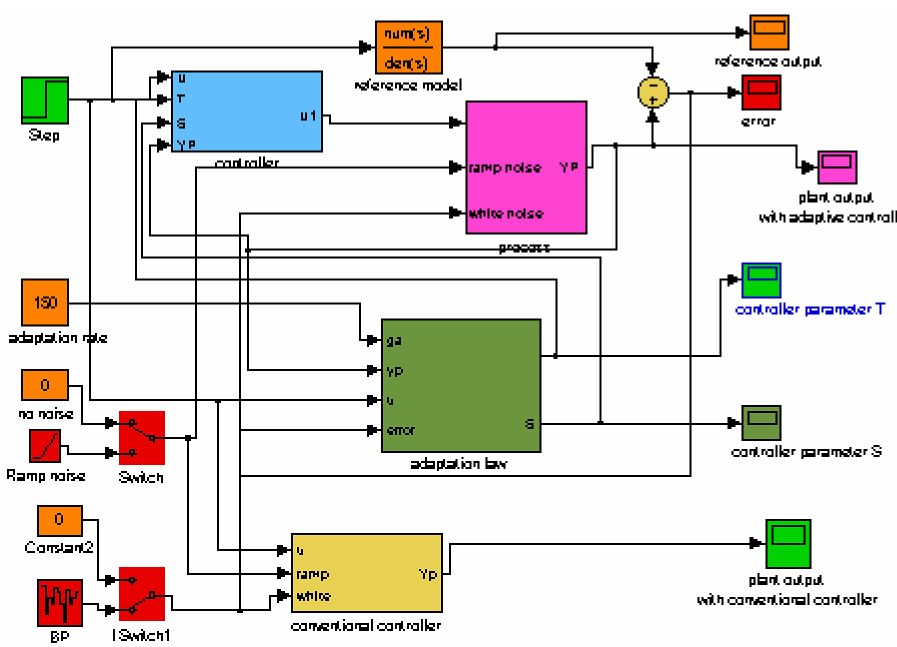


Figure 5. 6. Simulink implementation of a Model Reference Adaptive Controller

b) Temperature control

The simplified transfer function model of the process is obtained as:

$$Gp2(s) = \frac{0.3s^5+1.18s^4+1.96s^3+1.54s^2+0.62s+0.095}{S^6+4.41s^5+7.94s^4+8.42s^3+4.1s^2+1.19s+0.14} \qquad (5.6)$$

A reference model (second order) with a maximum overshot (Mp) of 2.5% and settling time(Ts) of 1 second is chosen. And the transfer function for the model is:

$$Gm(s) = \frac{15.54}{s^2 + 6s + 15.54} \tag{5.7}$$

The implementation of the complete model reference adaptive control is identical to the previous case except Gp1 and Gm1 are replaced by Gp2 and Gm2 respectively.

The completed model permits the noise to be disabled, ramp function only, white noise only or a combination of ramp and white noise. The following parameters are plotted on graph: plant output with adaptive and with conventional control, model output, error between plant and model outputs and the controller parameters.

5.2. Comparison without noise

Note that the model is complete, the first task we must perform is to compare the performance of the two controllers for a step input and no noise

a)concentration

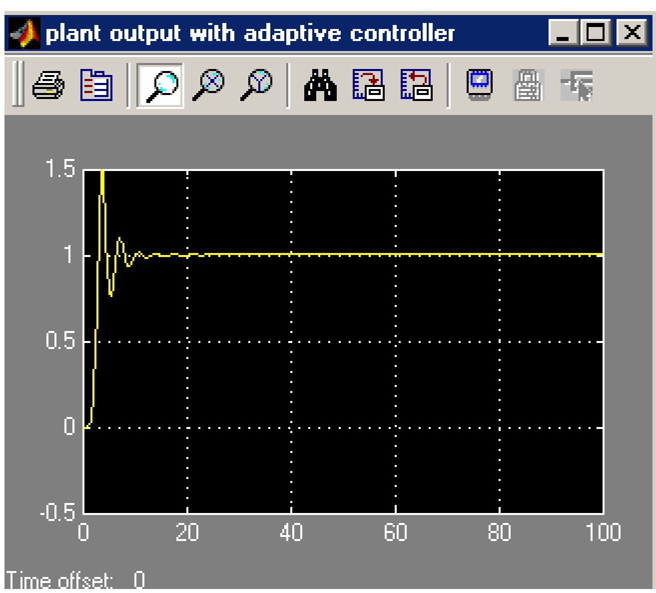


Figure 5. 7 Plant output{concentration) with adaptive control (step input, no noise, Gamma=0.99)

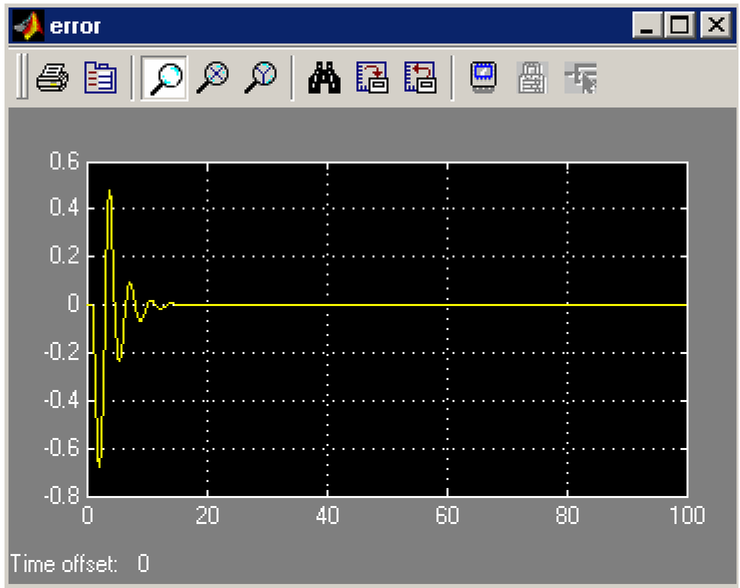


Figure 5. 8 Error (step input, no noise, Gamma=0.99)

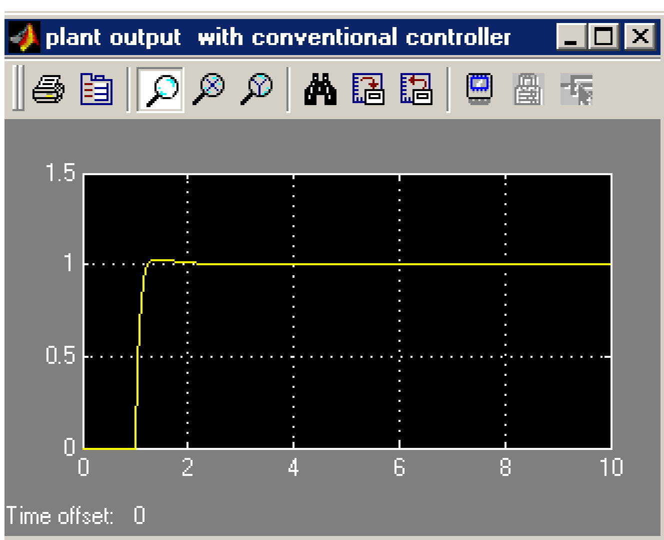


Figure 5. 9 Plant output with conventional control (step input, no noise, Gamma=0.99)

b)Temperature

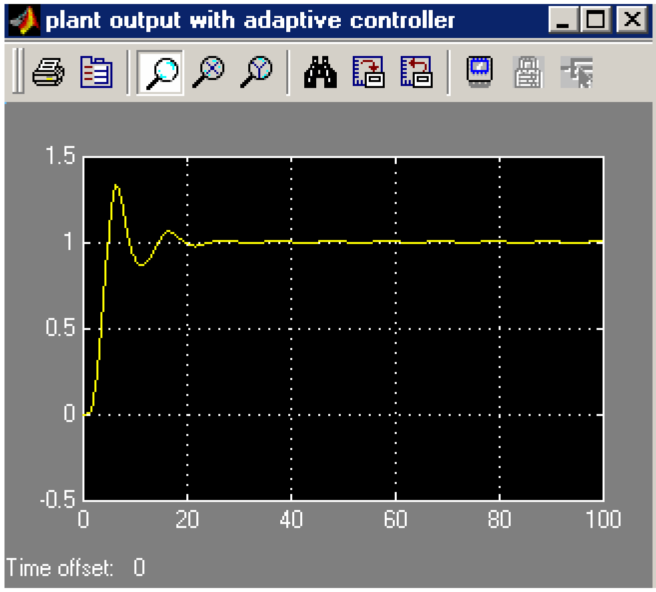


Figure 5. 10 Plant output{temperature) with adaptive control (step input, no noise, Gamma=0.99)

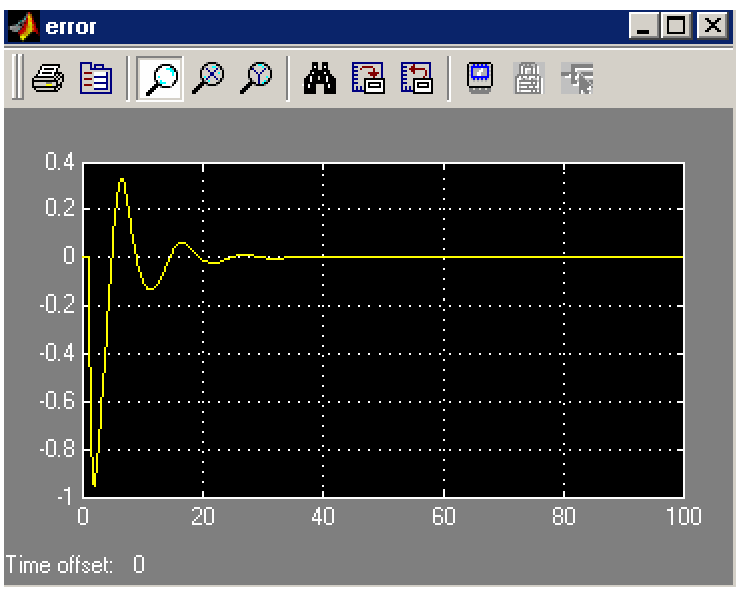


Figure 5. 11 Error temperature) (step input, no noise, Gamma=0.99)

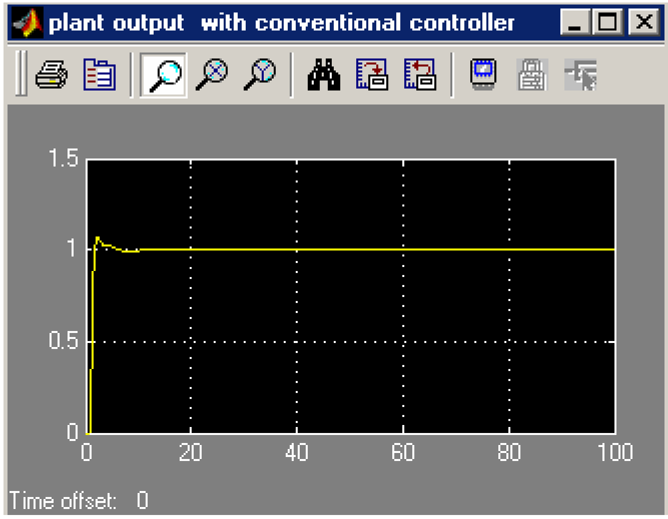


Figure 5. 12 Plant output temperature) with conventional control (step input, no noise, Gamma=0.99)

Looking at figure 5.7 and figure 5.9, one of the major disadvantages of adaptive control is immediately apparent. It takes the adaptive controller nearly 20 seconds to match perfectly the output of the reference model. However the conventional controller is matched within 2 seconds. The overshoot of the adaptive controller is also excessive (of the order of 50%) while the conventional controller has an overshoot of below 3%.

One method of addressing this problem is to increase the adaptation gain (Gamma). For example, increasing the adaptation gain to 100 gives the response shown in figure 5.13 & 5.14.

a)concentration

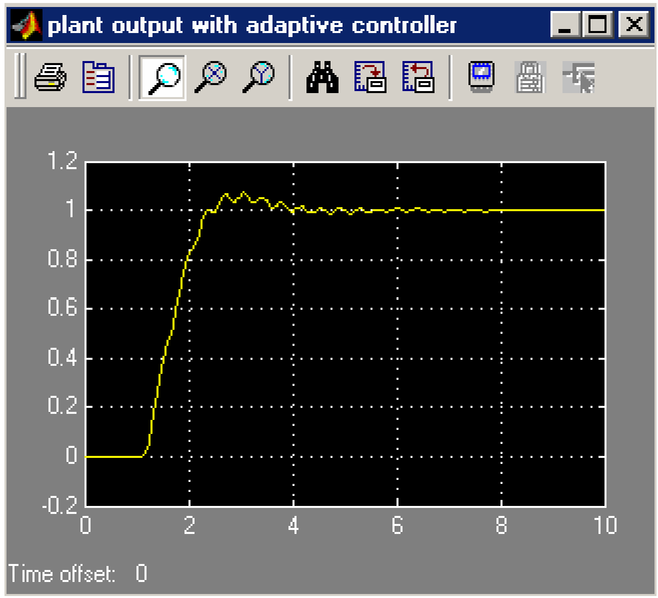


Figure 5. 13 Plant output with adaptive control (step input, no noise, Gamma=100)

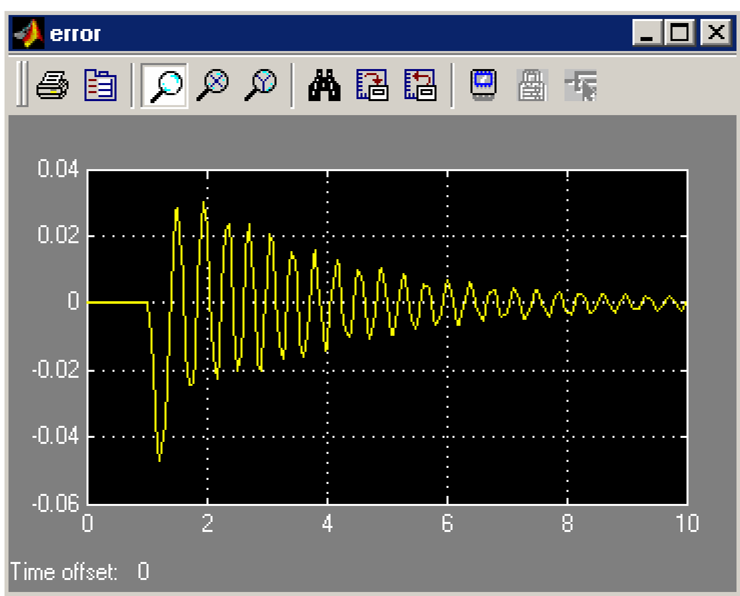


Figure 5. 14 Error (step input, no noise, Gamma=100)

b)Temperature

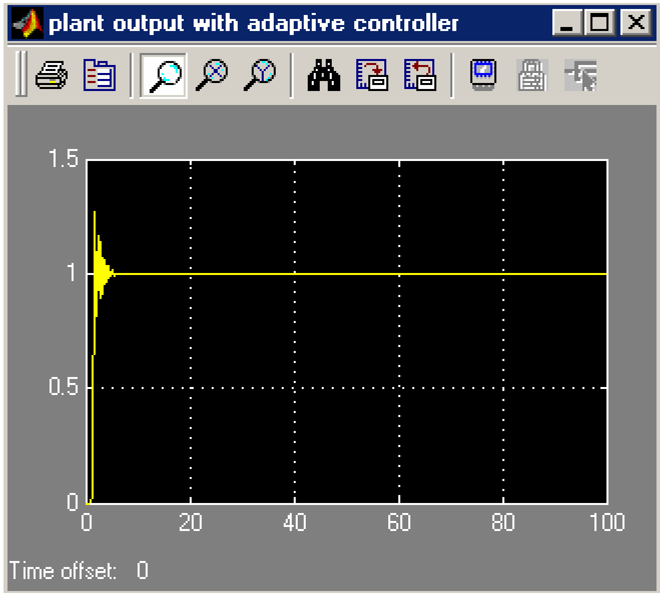


Figure 5. 15 Plant output with adaptive control (step input, no noise, Gamma=100)

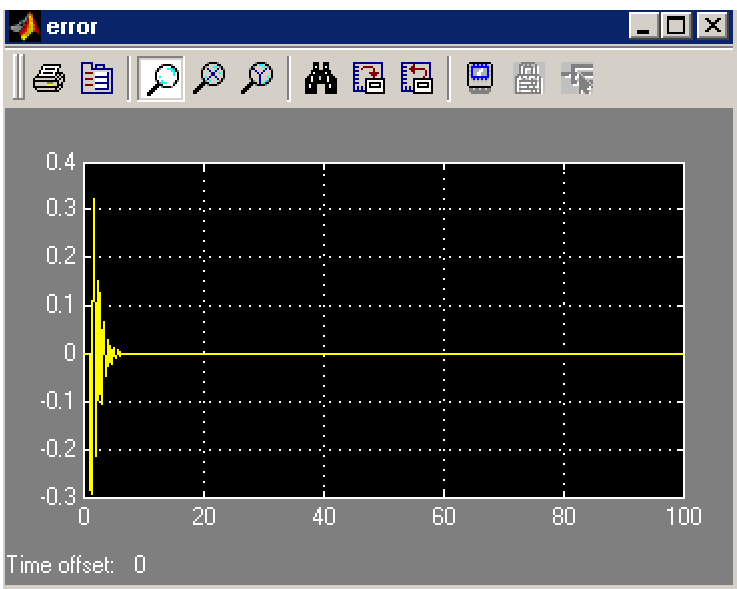


Figure 5. 16 Error (step input, no noise, Gamma=100)

This has improved the overshoot to below 10% and the settling time is now less than 10 seconds. While not perfect this is a significant improvement. Further increase in the adaptation gain does not result in an improvement of the system.

5.3. Comparison with noise

5.3.1. Comparison with ramp noise

The next logical step is to compare the performance of the two controllers in the presence of noise in the form of ramp signal, (slope=1). The adaptation gain has bee restored to 0.99.

a)concentration

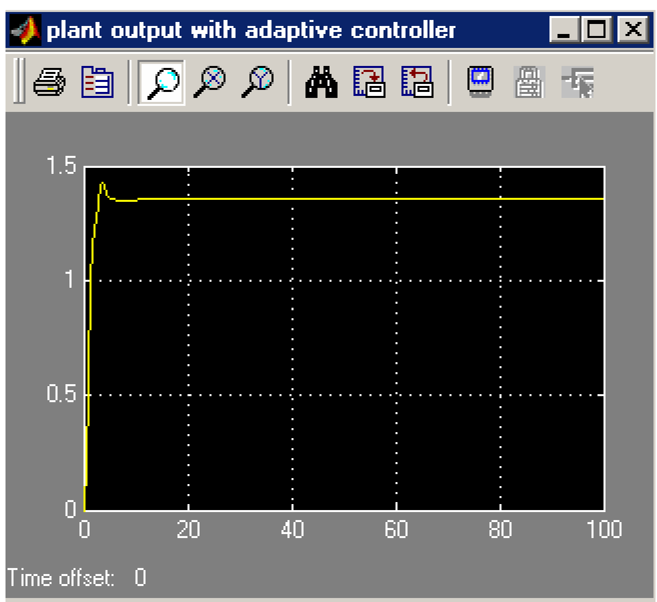


Figure 5. 17 Plant output (concentration) with adaptive control (step input, ramp noise, Gamma=0.99)

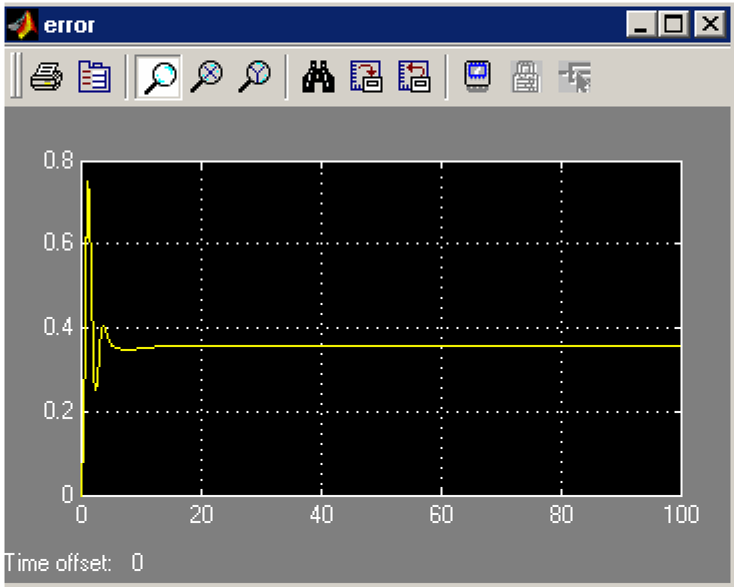


Figure 5. 18 Error (concentration)(step input, ramp noise, Gamma=0.99)

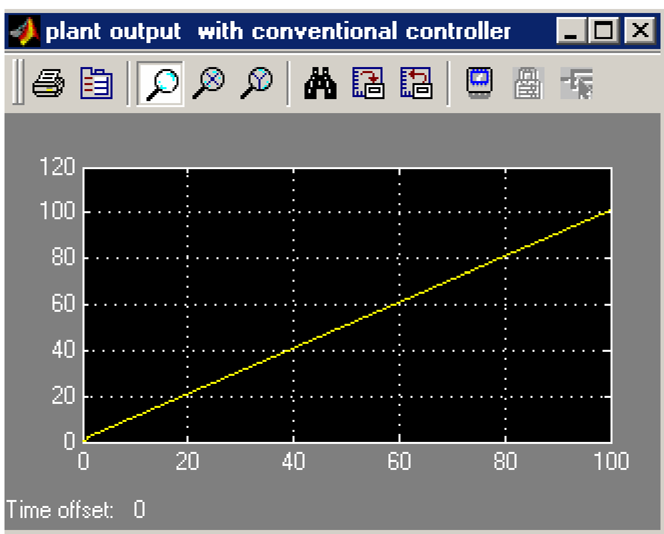


Figure 5. 19 Plant output (concentration)with conventional control (step input, ramp noise, Gamma=0.99)

b)temperature

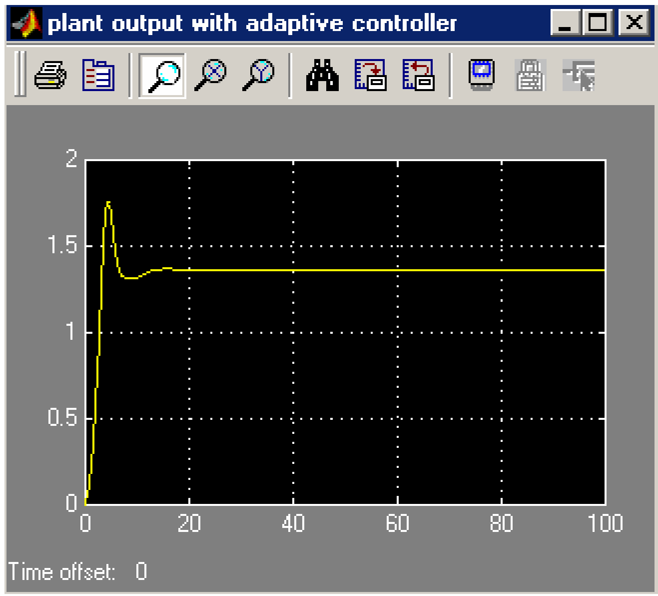


Figure 5. 20 Plant output (temperature) with adaptive control (step input, ramp noise, Gamma=0.99)

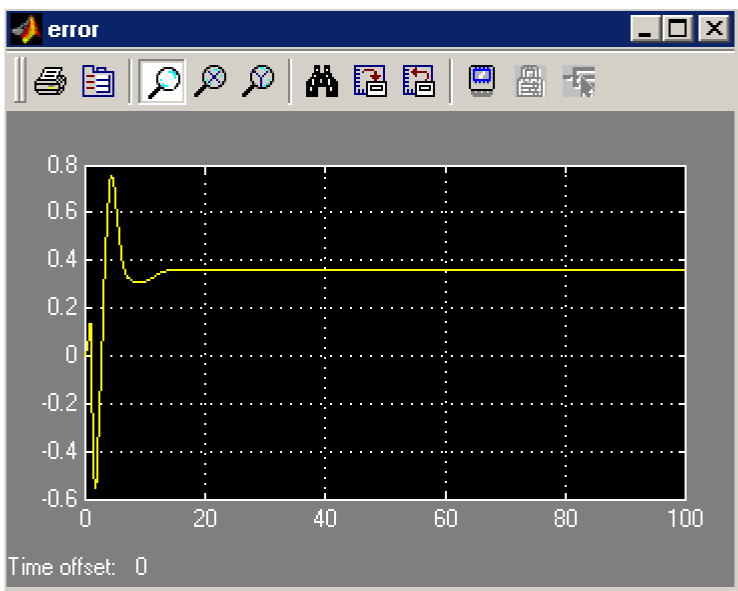


Figure 5. 21 Error (temperature)(step input, ramp noise, Gamma=0.99)

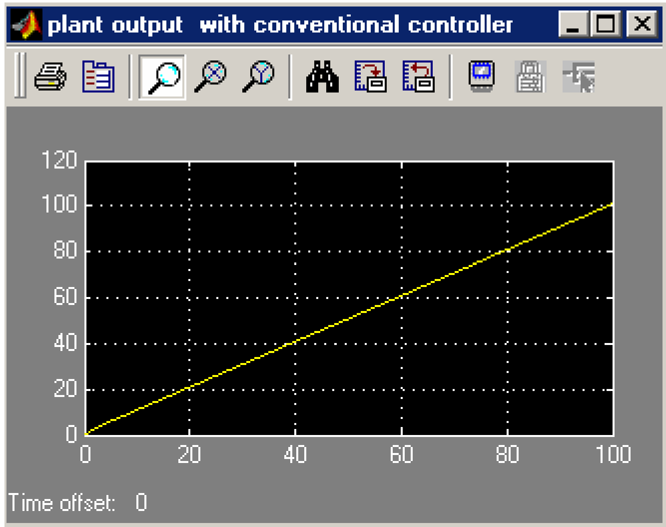


Figure 5. 22 Plant output(temperature) with conventional control (step input, ramp noise, Gamma=0.99)

The situation begins to show the actual advantages of adaptive control. In this case the conventional controller is incapable of maintaining even a stable system. On the other hand the adaptive control manages to maintain stability. However large overshoot and offset and long settling time are present. There is also a large steady state error present. As before increasing the adaptation gain to 100 reduces the overshoot to below 10%, the settling time to below 5 seconds and the steady state error to zero. This is shown below in figure 5.23.

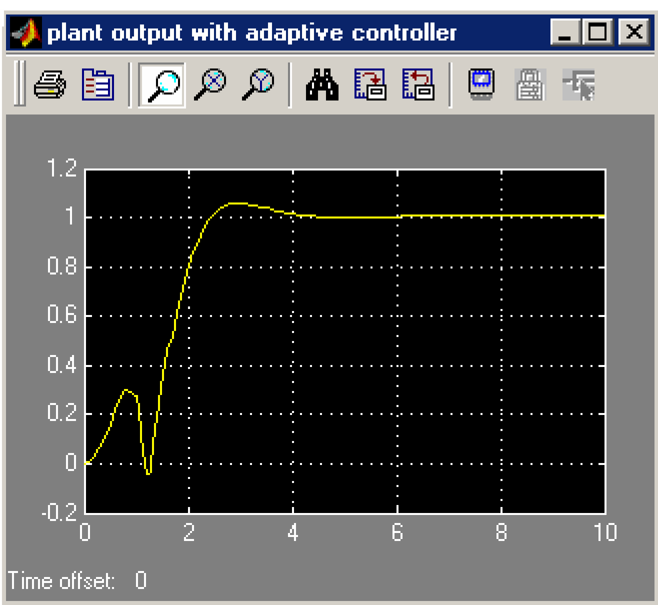


Figure 5. 23 Plant output(concentration) with adaptive control (step input, ramp noise, Gamma=100)

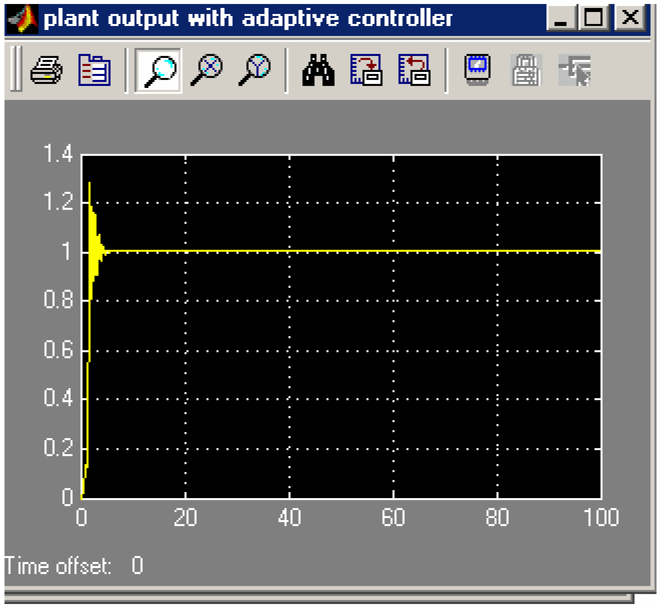


Figure 5. 24 Error (concentration)(step input, ramp noise, Gamma=100)

5.3.2.Comparison with white noise

The final comparison that must be performed is for white noise input. The white noise input is shown below in figure 5.25

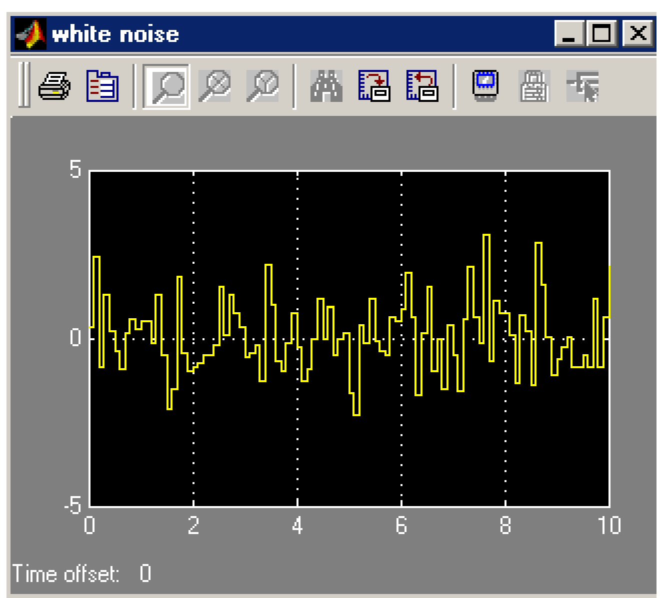


Figure 5. 25 White Noise Input Signal

The output of the plants with adaptive control and conventional control are shown in the preceding figures. The adaptation gain has been restored to 0.99.

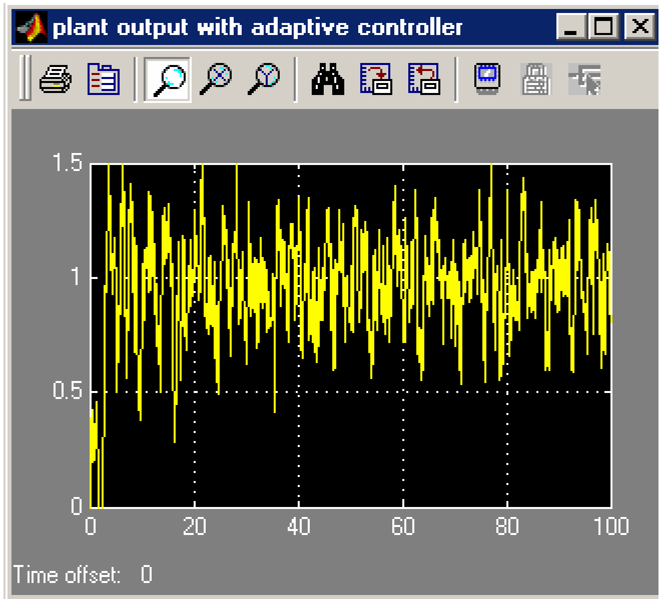


Figure 5. 26 Plant output(concentration) with adaptive control (step input, white noise, Gamma=0.99)

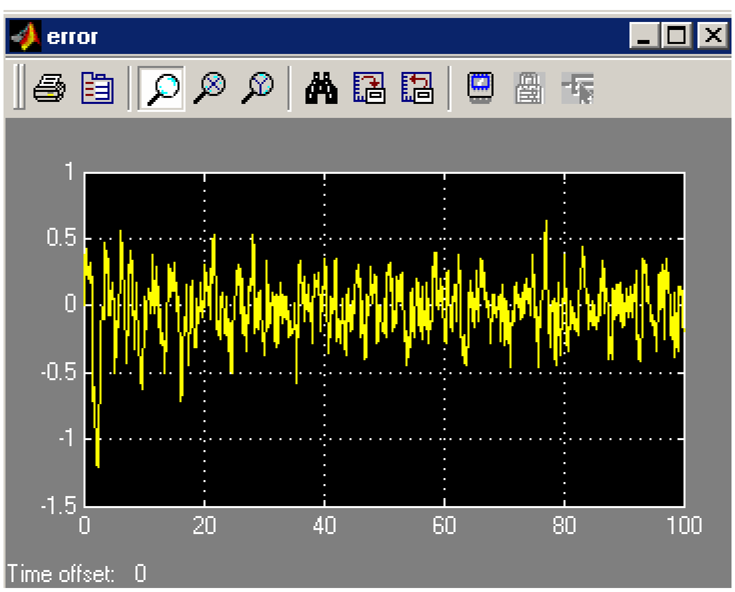


Figure 5. 27 Error(concentration) (step input, white noise, Gamma=0.99)

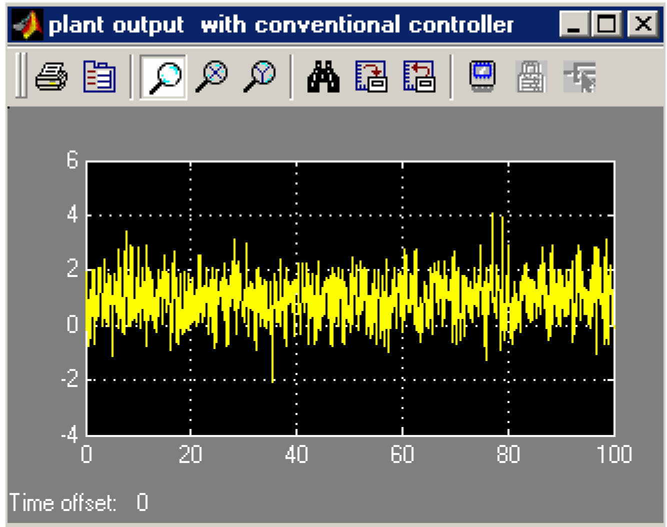


Figure 5. 28 Plant output(concentration) with conventional control (step input, white noise, Gamma=0.99)

b)Temperature

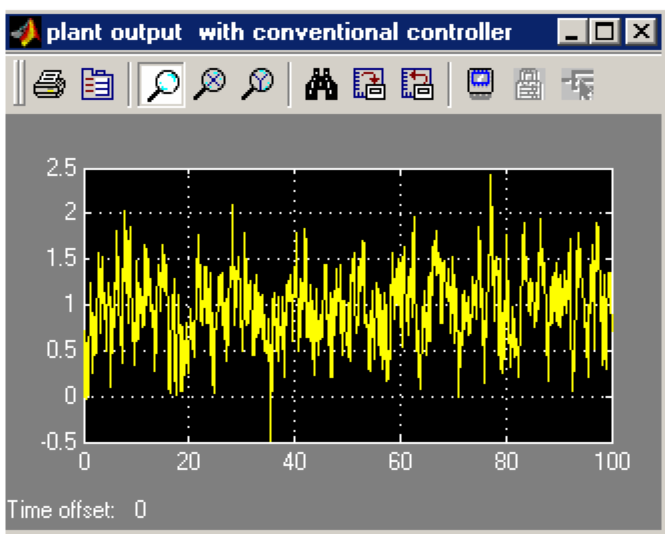


Figure 5. 29 Plant output(concentration) with conventional control (step input, white noise,G amma=0.99)

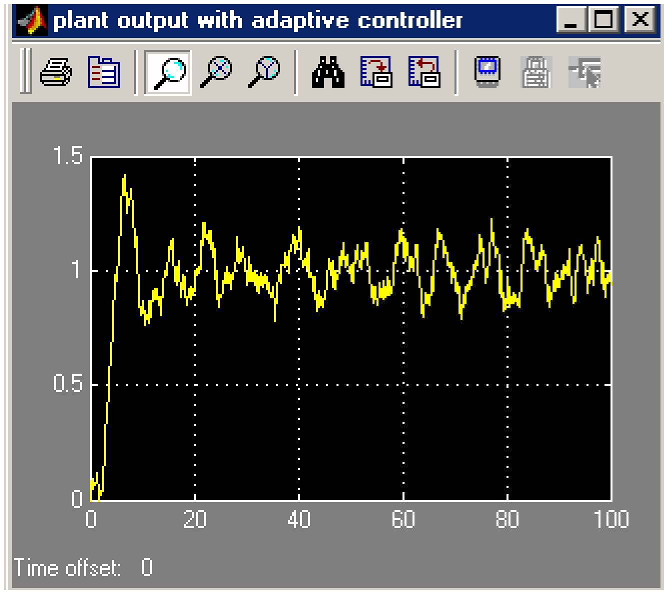


Figure 5. 30 Plant output(concentration) with adaptive control (step input, white noise, Gamma=0.99)

Again the advantages of the adaptive controller are clear with the adaptive controller managing to achieve reasonably matching with the model. The conventional controller is incapable of maintaining the required performance characteristics. The adaptive controller has still retained its excessive overshoot and long settling time. As before increasing the adaptation gain to 100 improves the performance of the adaptive controller, at the cost of initial oscillations.

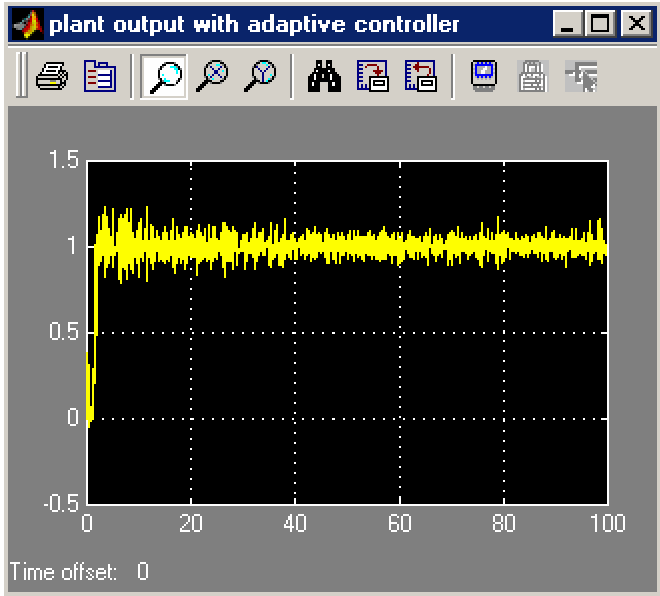


Figure 5. 31 Plant output(concentration) with adaptive control (step input, White noise, Gamma=100)

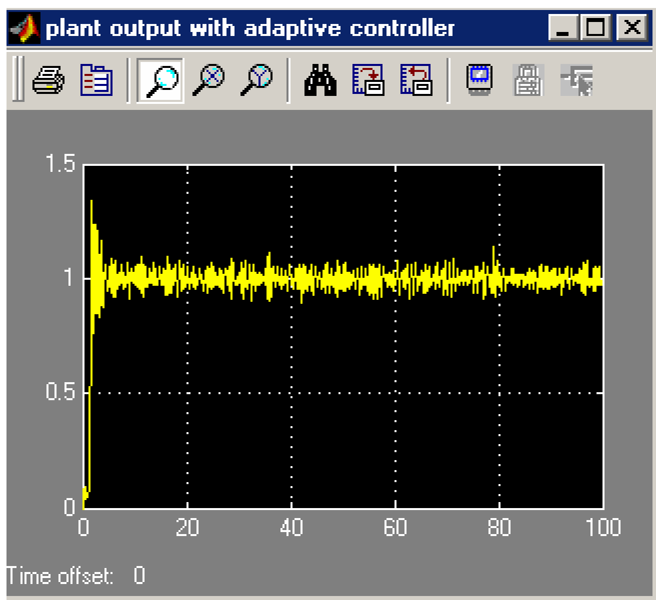


Figure 5. 32 Plant output (temperature) with adaptive control (step input, White noise, Gamma=100)

5.4. Case study

Up to now, we have taken a general reaction A→B. So it is essential to consider a specific reaction to demonstrate the proposed adaptive control scheme to a great existent.

This case study considers the control of the Van de Vusse reactor, the reaction scheme consisting of the following reactions:

$$A \rightarrow B \rightarrow C$$

$$2A \rightarrow D$$

Where

A = Cyclopentaddiene

B = Cyclopentenol

C = Cyclopentanediol

D = dicyclopentandiene

The actual process dynamics are described by

$$dx_1 / dt = u(C_{Af} - C_{AS} - x_1) - (u_s + k_1 + 2k_3 C_{As})x_1 - k_3 x_1^2 \qquad (5.8)$$

$$dx_2 / dt = -u(x_2 + C_{BS}) + k_1 x_1 - (u_s + k_2)x_2 \qquad (5.9)$$

Where C_{AS} and C_{BS} denote the effluent concentration of component A and B at steady state, respectively. The state variables x_1 and x_2 are deviation variables defined by x_1=C_A-C_{AS} and x_2= C_B-

C_{BS}; u is the manipulated variable given by u=F/V – us, where u_s=Fs/V. the concentration of A in the feed stream, denoted by C_{Af} and is equal to 10mol/L. The reactor volume, V, is 7L and the rate constants are k_1= 0.8333min-s, k_2 =1.6667min-s and k3=0.1667 L.mol-1.min-1. It is known that the process is at steady state with Fs=4 L/min, C_{AS}=3mol/L and C_{BS}=1.117 mol/L initially. The control objective is to regulate the concentration of B, x_2, by manipulating the dilution rate, u.

Here, it is assumed that the original nonlinear characteristics are unknown and only the process nominal transfer function

$$G_p(s) = \frac{0.5848(-0.3549s+1)}{0.1858s^2+0.8627s+1} \qquad (5.10)$$

Is known and is available for design. The response for step change in the input is shown in figure 5.33.

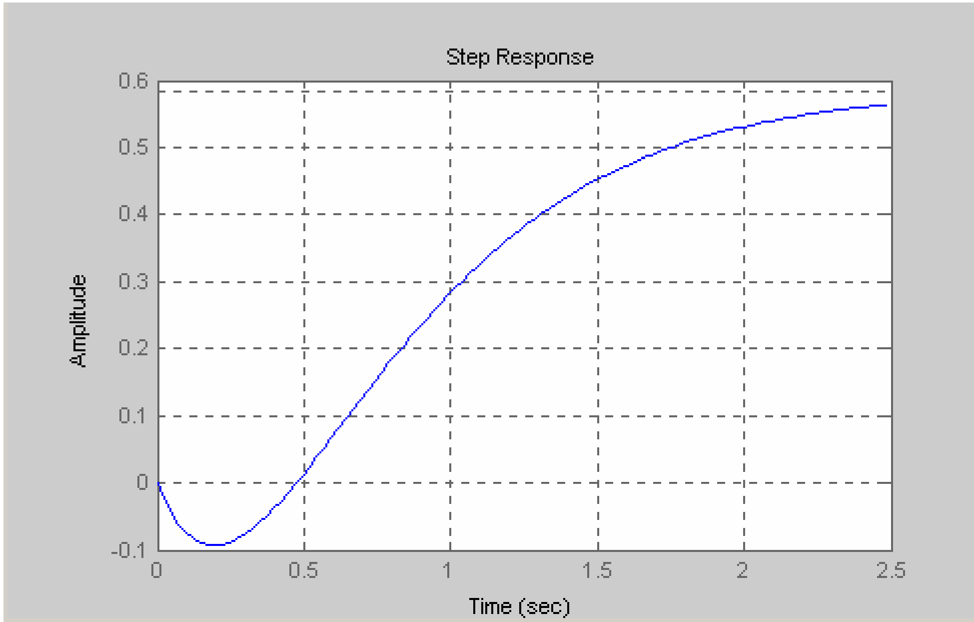


Figure 5. 33 Response for a step change in the input(Van de Vausee reactor)

For the adaptive control system, a reference model (second order) with maximum overshoot (5%) and settling time of 2 second is chosen and the transfer function for the model is:

$$G_P(s) = \frac{4.834}{s^2 + 3s + 4.834} \tag{5.11}$$

Controller setting for the non-adaptive controller is done using Ziegler-Nicholas technique and the best controller parameters are found to be Kc=3, τ_I=1 and τd=0.167.

Using the above information the performances of the two controllers are compared for different situation.

5.4.1 Comparison without noise

First, the performances of the two controllers without noise are compared. The responses for a step change (0.1) in the input are shown in figure 5.36 and figure 5.37.

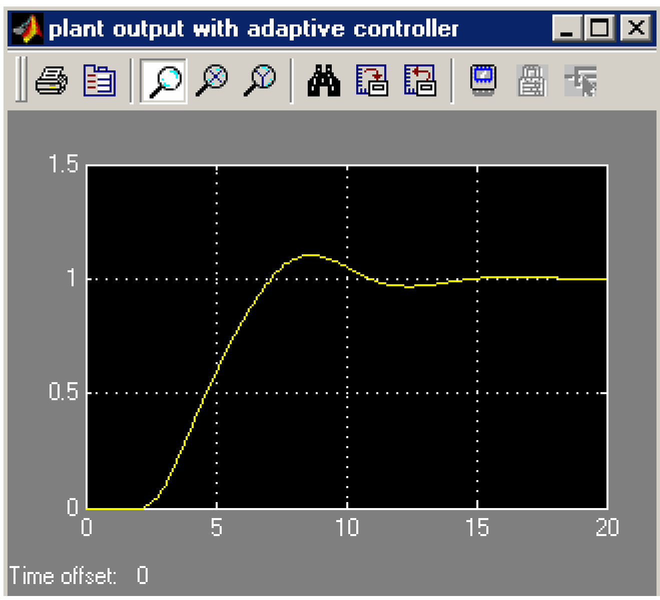


Figure 5. 34. Plan(Van de Vausee reactor) t output with adaptive controller (step input, no noise,γ=0.5)

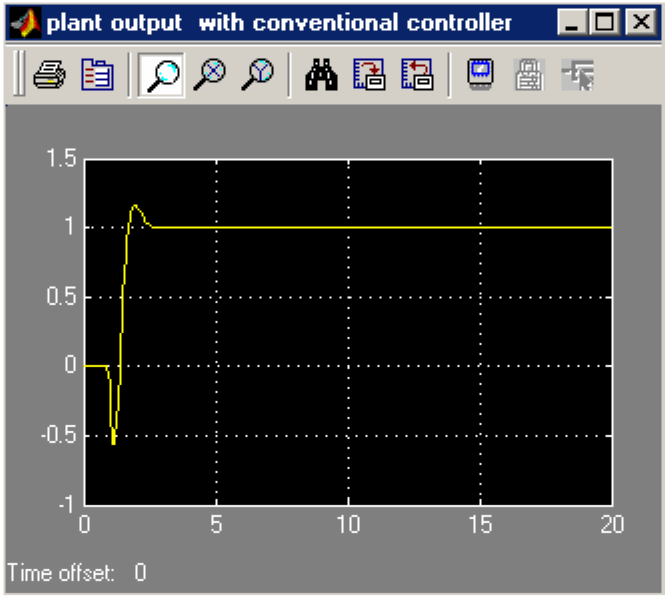


Figure 5. 35. plant outpu(Van de Vausee reactor) t with conventional controller (step input, no noise)

Looking at these two graphs, the advantage of adaptive controller can be seen as it eliminates the inverse response. Although the conventional controller has the smaller response time (2 second) compared to the adaptive controller (7 second), it is incapable of eliminating the inverse response. The response time for the adaptive controller can be decreased at a cost of initial oscillation. Figure 5.38 shows the effect of increasing the adaptation rate to 0.75.

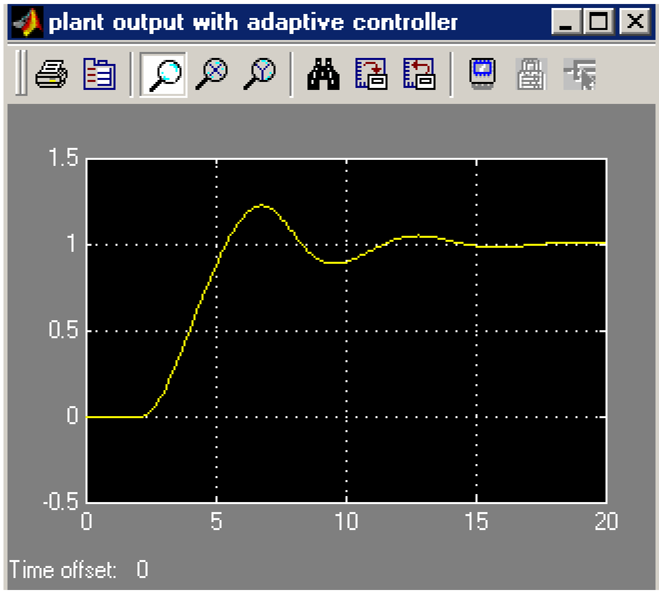


Figure 5. 36. Plant output (Van de Vausee reactor) with adaptive controller (step input, no noise,γ=0.75)

5.4.2. Comparison with ramp noise

The next task to be done is to compare the performances when there is a disturbances or a change in the process parameters. The responses for a step change in the input with a ramp noise (slope=0.1) are shown in the next two figures.

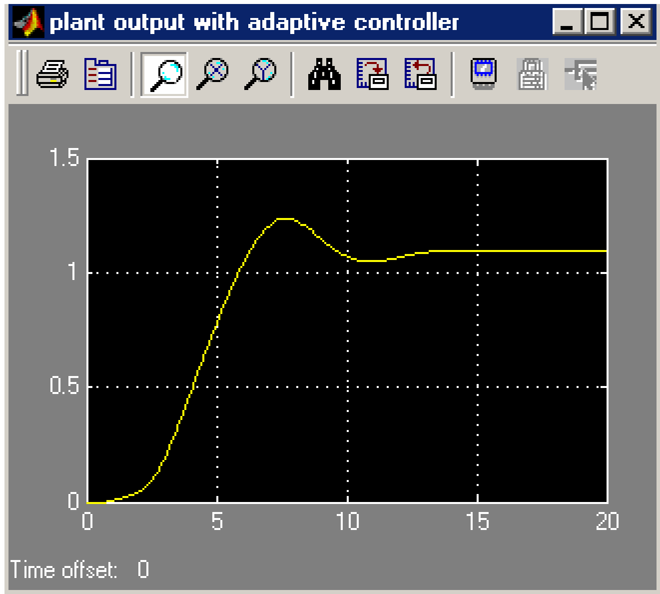


Figure 5. 37. Plant output(Van de Vausee reactor) with adaptive controller (step input, ramp noise, γ=0.5)

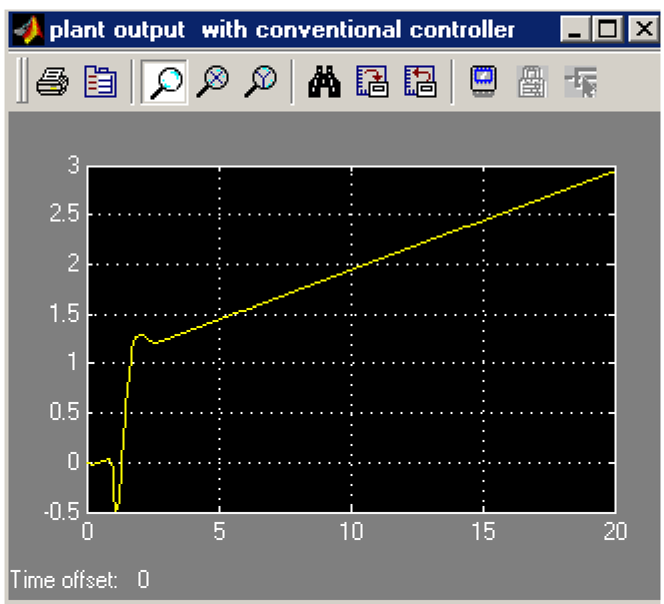


Figure 5. 38. Plan(Van de Vausee reactor) t output with conventional controller (step input, ramp noise)

From the above two figures it can be seen that the conventional controller is incapable of maintain even stability. Although there is a large steady state error, the adaptive controller gives a better plant response. But the steady state error can be eliminated by increasing the adaptation rate. This is shown in the next figure.

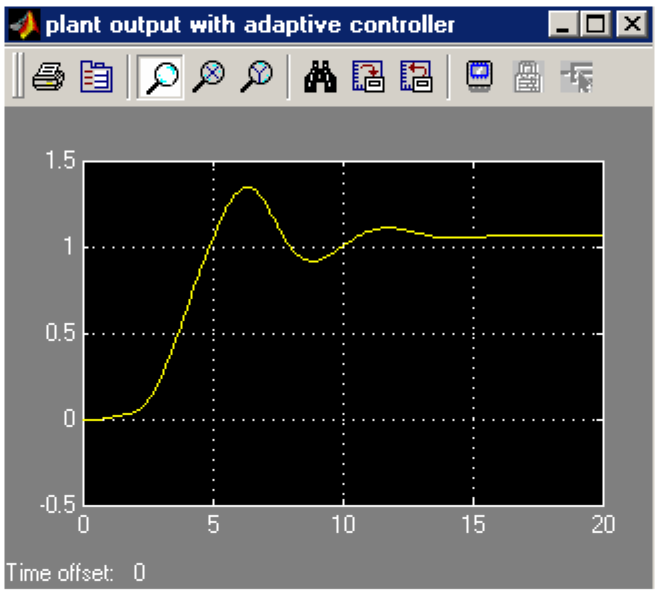


Figure 5. 39 Plant(Van de Vausee reactor) output with adaptive controller (step input, ramp noise, γ=0.75)

In general; it is noted that while the adaptive controller exhibits superior performance in the presence of noise, the convergence time is typically large and there is a large overshoot. These two problems are due to the adaptive controller failing to adapt fast enough to force the plant to match the model. Increasing the adaptation rate improves the performance of the adaptive controller at the cost of initial oscillations. The next set will look at ways to improve the performance of the adaptive controller.

5.5. Expanding Adaptive Controller Capabilities

The previous section identified some of the major problems with adaptive control. These problems were excessive overshoot and long settling time. The previous approach to resolving these problems was to increase the adaptation gain. The disadvantage of this approach is the increase in the initial oscillation. The purpose of this section is to discuss some of the ways in which the performance of the adaptive controller can be improved without excessive increase in the gain.

Up to now we initialized the controller parameters (S and T) to zero. It is therefore logical to assume that if we initialize the controller parameters to a value closer to their final value we can improve the performance of the adaptive controller. Another action that can be taken is to limit the adaptation based upon the error. That is if the error is below a given value to stop the action of the adaptation law.

In both cases modifications are only made to the adaptation law of the controller. The modified adaptation law is shown below in figure 5.26.

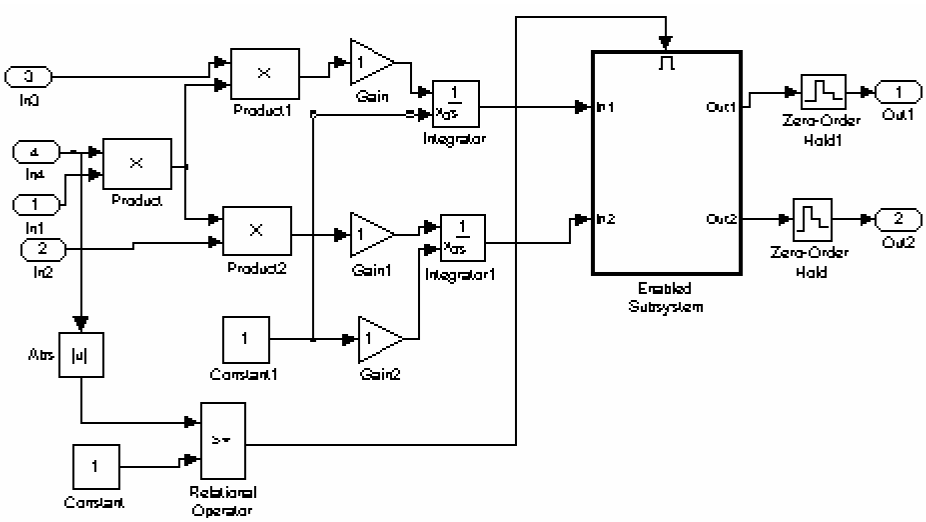


Figure 5. 40 Modified Adaptation Law

The first modification that we make is to the blocks that integrate the controller parameters (T and S) corrections. In the previous section these integrators were initialized to zero, initially placing the system far away from the desired value. The solution to this is to give an initial value to both of this integrator to speed up the learning process. This can be determined experimentally by gradually varying the initial value of the integrators to achieve the best performance. A good estimate of the starting points is provided by running the simulation and looking at the final values of the T and S parameters.

5.5.1 Expanded adaptive control without noise

After progressively varying the initial conditions for the two integrators, the ideal values were found to be 1.84 for the T' integrator and –1.4 for the S' integrator. Using these initial conditions the performance of the adaptive controller can be significantly improved as shown by figure.

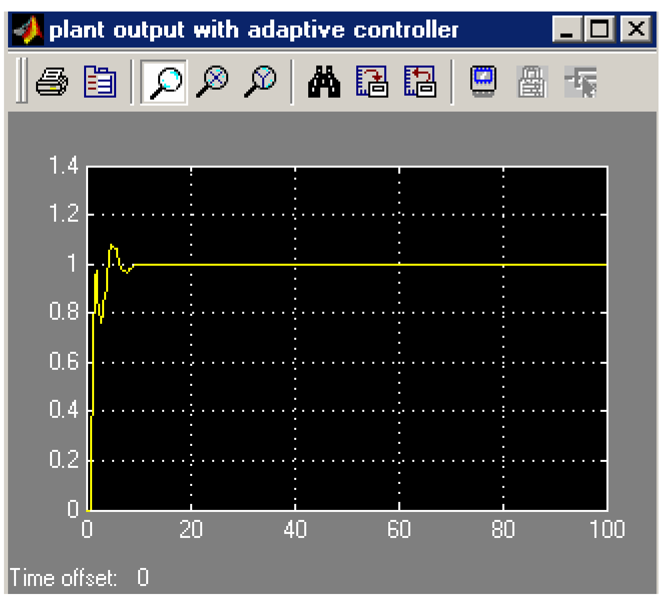


Figure 5. 41 Plant output(concentration) with adaptive controller(step input, no noise,γ=20, T=1.84 ,S=-1.4)

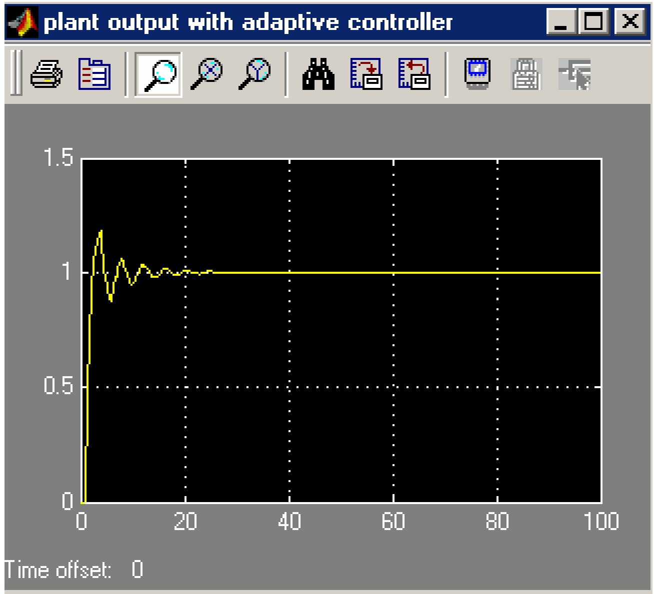


Figure 5. 42 Plant output(temperature)with adaptive controllere (step input, no noise,γ=20, T=1.84 ,S=-1.4)

From this diagram the performance increase, through non-zero initial controller parameters, is immediately evident. The overshoot has been reduced by 90% and the settling time has been significantly reduced without the introduction of a high adaptation gain.

5.5.2. Expanded Adaptive Controller with Noise

We have examined the performance of the modified adaptive controller to the situation where there is no noise; however we must compare its performance in the presence of noise to determine if the improvement is retained.

The first case is for the situation where ramp noise is present. The initial controller's parameter found to be 10 for the T' integrator and –105 for the S' integrator. The results are shown in the preceding two figures.

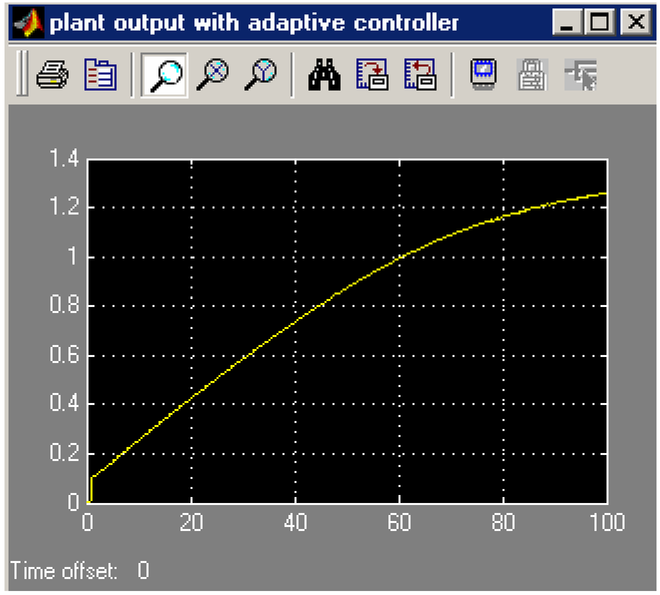


Figure 5. 43 Plant output(concentration)with adaptive controller (step input, ramp noise,γ=20, T=10 ,S=-105)

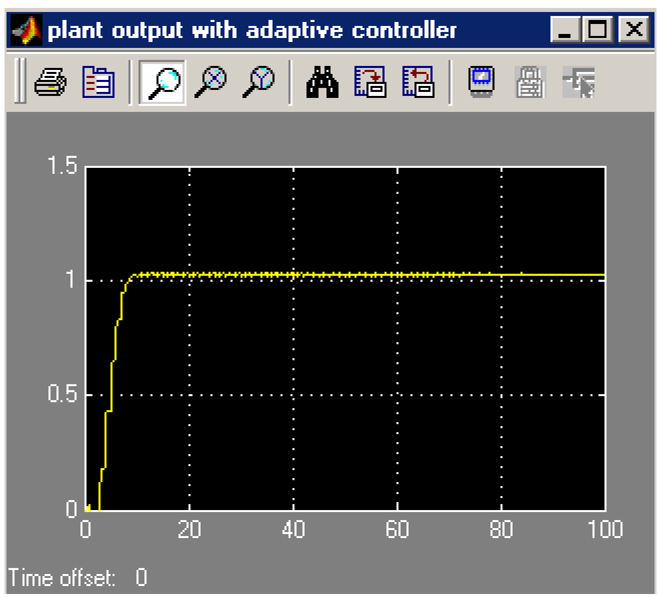


Figure 5. 44 Plant output(temperature)with adaptive controller (step input, no noise,γ=20, T=10 ,S=-105)

Both cases show that the presence of noise has not remained ideal. However even without adjusting the adaptation rate (gamma) the performance is good with the exception of the large steady state error. The second graph shows that unlike the previous case a very high adaptation rate (gamma) is not required and a rate of 20 is sufficient to eliminate the steady state error and the settling time below 15 seconds.

The final test to perform is to apply the modified adaptation law to the Van de Vausee reactor which was taken as a case study. After progressively varying the initial control parameters, the best value found to be 1.5 for the S' integrator and 0.2 for the S' integrator. The results is shown below in figure 5.45.

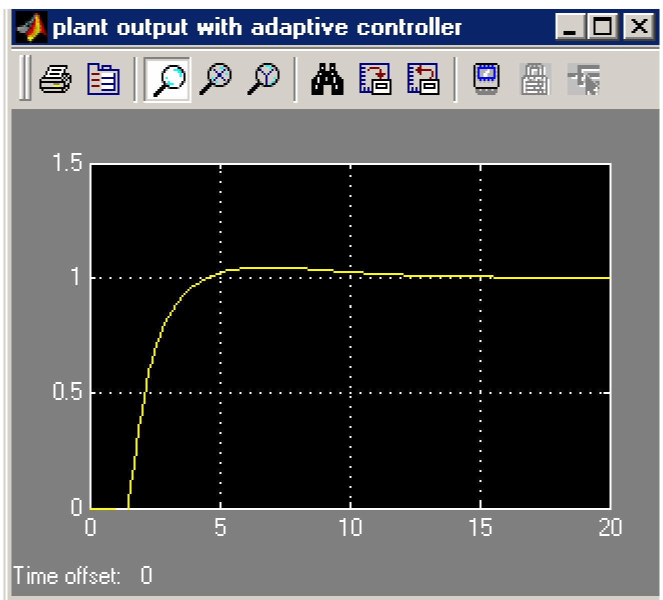


Figure 5. 45 Plant output(Van de Vausee reactor) with adaptive controller (step input, no noise,γ=0.15, T=1.5 ,S=0.2)

The graph shows the increased performance of the modified adaptive controller. Within 5 seconds the adaptive controller parameter matches the model up to 95% and also the overshoot is eliminated. Overall the modified adaptive controller has been proven to exhibit superior performance. However this performance gain requires that the system be run a number of times to establish good values for the controller parameters. This may not always be practical or possible.

Chapter six

6. Conclusion

The use of multiple model and adaptive controller are attractive especially when the process is known to transition to unknown operating states. it is also intuitive that a fixed parameter controller(conventional controller) may not provide satisfactory closed loop control. The non-adaptive model can provide speed whenever its parameters are close to those of the process while the adaptive model can provide accuracy because its parameters are permitted to adapt.

The paper has aimed to provide an understanding of how to implement an adaptive controller and to compare an adaptive controller with a conventionally designed controller in various situation. The paper demonstrated that while the adaptive controller exhibits superior performance in the presence of noise the convergence time is typically large (greater than 10 seconds) and there is large overshoot. These two problems are due to the adaptive controller failing to adapt fast enough to force the plant to match the model. Increasing the adaptation rate improves the performance of the adaptive controller at the cost of increased oscillation. One interesting observation is that the presence of noise increase the time required for the adaptive controller to converge. The probable reason for this is that the presence of the noise provides the adaptive controller with more of signals to process.
The results from the case study indicate that the use of adaptive controller can be extended to process with inverse response. For such process the adaptive controller will be superior to the conventional controller even without parameters change in the process. Although the conventional controller has the smaller response time, it is incapable of eliminating the inverse response.

The paper has also shown that it is possible to significantly improve the performance of an adaptive controller simply by initializing the controller parameters to a value close to their final value. In a real world situation, these parameters could be estimated by using simulations or real execution of the system. It may possible to improve the performance of the adaptive controller by further modifying the adaptation law or by incorporating parameter identification in to the control

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Appendix

```
>>
            Function        f = Cstr_ss(x)
                            F=zeros (2, 1);
                            Global     CSTR_PAR;

                                        CA= X(1);
                                  Temp=X(2);
                            Ko=  Cstr_par(1);
                            Eact= Cstr_par (2);
                            H_rxn= Cstr_par(3);
                            Rhocp== Cstr_par(4);
                            UA= Cstr_par(5);
                            R= Cstr_par(6);
                            R= Cstr_par(7);
                            V = Cstr_par(8);

                  FOV=F/V;

                  Tj=UA/V;

            RATE=KO*exp(-E_act/(R*Temp)*Ca

        DCA/dt=FOV*(Caf-CA)- rate;

DT/dt=fov*(Tf – Temp)+(H_rxn)*rate – (UAOV/rhocp)*(Temp – Tj);

F(1)=dcadt;
F(2)=dTdt;>>
```