PERFORMANCE ANALYSIS OF MODEL PREDICTIVE CONTROL FOR DISTILLATION COLUMN

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PERFORMANCE ANALYSIS OF MODEL PREDICTIVE CONTROL FOR DISTILLATION COLUMN

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This is to certify that the work presented in this dissertation entitled *''Performance analysis model predictive control for distillation column*" by "Pratima Acharya", Roll Number 214EC3433, is a record of research project performed by her under my guidance and supervision in partial fulfillment of the degree of Master of Technology in Electronics and communication Engineering.

Tarun Kumar Dan

Declaration of originality

I, Pratima Acharya, Roll Number 214EC3433 hereby declare that this thesis entitled "Performance analysis of model predictive control for distillation column" contains my original work performed as a postgraduate student of NIT Rourkela and, to the best of my knowledge, it does not contain any contents which are written or published by other. It also does not contain material prepared for the award of any other Degree or diploma of other institution or NIT Rourkela. The works of other authors which are cited in this thesis have been properly acknowledged under the section "Reference".

I am well aware that if any objection detected in future, the Senate of NIT Rourkela may withdraw the degree awarded to me on the basis of the present thesis.

May 18, 2016 Pratima Acharya

NIT Rourkela

Dedicated

to

My parents

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.

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ABSTRACT

Model predictive control is an advanced process control method. It is a popular technique in chemical plants and oil refineries. Model predictive controller depends on dynamic model of the process and predicts the future output and so that the present input is optimized to avoid the future error. An optimization problem is solved over a prediction horizon P by regulating M control moves .Dynamic matrix control is a popular MPC method and it relies on the state space model of the plant.

In this work, first we represent the DMC as an LTI system. The effect of tuning parameter on both first order and second order system is observed by calculating transient parameters like settling time, rise time, peak over shoot. Then the close loop poles are calculated for a specific FOPDT by varying different tuning parameters using the DMC algorithm. From the observation, effect of tuning parameters like P, M, w, N are summarized and a design rule for the parameter adjustment of DMC is proposed.

Next a brief study on distillation column is provided and a mathematical model is also discussed. The design rule and control strategy of distillation column are discussed.

The control of a distillation column by PID controller is performed for different tuning methods. In order to get stable response decoupling technique is used. Two different techniques like inverted and simplified decoupling are performed and a comparison between them is given by calculating transient parameters.

The control of a distillation column by the MPC is also performed. A comparison between two controllers (PID and MPC) is discussed. The features of MPC like constraint handling, disturbance rejection, set point tracking is observed. Here different distillation process is taken and its response after using an MPC controller is observed.

MATLAB (matrix laboratory) provides a numerical environment and fourth generation programming language. It provides matrix manipulation, plotting of function, data and implementation of algorithms. It provides a different tool box and Simulink models for process control and design.

Model predictive control tool box provides functions, Simulink block for analysing, designing and simulating model predictive control. Here user can provide control and prediction horizon, weighting factor and model length. The toolbox can guide the user regarding tuning parameters and it also facilitates softening of constraints.

Key words: MPC; DMC; PID; Distillation column; Decoupler; Tuning parameters; control horizon; Prediction horizon

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LIST OF ABBREVIATIONS

MIMO	Multiple Input Multiple Output
SISO	Single Input Single Output
PID	Proportional Integral and Derivative
DMC	Dynamic Matrix Control
MPC	Model Predictive Control

CHAPTER 1

INTRODUCTION

Overview

Literature Review

Motivation

Objectives

Organisation of the Thesis

INTRODUCTION

This chapter provides the general overview of the work. This comprises of a brief description of MPC, PID controller and distillation column followed by literature survey. Next the objectives and organisation of thesis is described.

OVERVIEW

A wide family of predictive controllers is available, each member of which is defined by the choice of elements such as model, objective function and control law. MPC belongs to class of advanced control techniques and nowadays most widely used in process industries. The main benefit of using MPC is its capacity to handle constraints. Nowadays DMC algorithm is commercially more successful because of its capacity of model identification and global plant optimization. DMC has the ability to deal with multi input multi output process. Effect of tuning parameters is studied by calculating transient parameters like rise time, settling time and peak over shoot. Effect of tuning parameters also performed based on close loop analysis. Then a design rule is proposed for DMC [1].

The main work of the distillation column is to separate components of a mixture from each other. For separating mixture distillation column is more used techniques in the industry. Based on aspects of column and what assumptions are considered, distillation column can be represented by a number of models. The dynamics of distillation columns will be discussed in the next chapter. The response of vapor flow, as well as liquid flow will be discussed. First, a model will be defined, which specifies the model inputs and outputs of a continuous column. Next, a first-principles, behavioral model is presented consisting of mass, component and energy balances for each tray. The tray molar mass depends on the liquid and the vapor load, as well as on the tray composition. The energy balance is strongly simplified. Finally, dynamic models are derived to describe liquid, vapor and composition responses for a single tray and for an entire distillation column.[2]

The conventional PID controller is widely used for industrial control application. For a MIMO system one manipulated variable can be affected by more than one output variable. In order to reduce close loop interaction, we follow decoupling technique. The various techniques for decoupling like conventional decoupling, simplified decoupling and inverted decoupling are discussed. It also provides a comparison between simplified and inverted decoupling by taking Wood and Berry model of distillation column [3].

The Model predictive control controls MIMO system and provides better response than a conventional PID controller. It minimizes close loop interaction without using decouplers and handle constraint. Different models are taken to perform model predictive control.

MATLAB (matrix laboratory) provides a numerical environment and fourth generation programming language. It provides matrix manipulation, plotting of function, data and implementation of algorithms. It provides a different tool box and Simulink models for process control and design.

Model predictive control tool box provides functions, Simulink block for analyzing, designing and simulating model predictive control. Here user can provide control and prediction horizon, weighting factor and model length. The toolbox can guide the user regarding tuning parameters and it also facilitates softening of constraints.

1.2 LITERATURE REVIEW

The literature study of this starts with a study on the development of real time monitoring solution for distillation column [1]. The dynamics of distillation column are discussed. The process dealing with the real world is generally a MIMO system. The modelling of distillation system is necessary whenever one need to control the process. The fuzzy logic is used in MPC ant the controller controls the distillation column [2]. The conventional controller PID controller is also studied [3-5]. The effect of the PI controller based on Nyquist stability analysis is studied [6]. There are other controllers also available like IMC for controlling distillation column [8]. We can also handle MPC online [9-10]. In order to handle MIMO system decoupler is used to get stable response [11]. The mathematical model is analyzed and studied for distillation column [12-13].

The tuning design rule for DMC is necessary for controlling any process. A good tuning strategy is provided in [14-15] for SISO. The former one concludes tuning rule by finding close loop poles of the given system. The latter one gives the formula for different tuning parameters. A drum type boiler is controlled using a DMC algorithm [16]. A step response model is developed for boiler to implement DMC algorithm. Many plants have limitations on their process variable. For that reason we need to put limits on constraints. MPC is very good in handling constraint [17].

A noble method for auto tuning of predictive control is explained [18]. A noble method to find out tuning rule is explained in SISO [19]. Various method and techniques are explained [20-22]. The mathematical expression for inverted and simplified decoupler is described [22]. The advantages of inverted over simplified decoupler are explained using wood and berry model for distillation column.

1.3 MOTIVATION

Most of the process in the industry is MIMO system. A proper controller is used to handle it and provides desired response. The conventional PID controller requires decoupler to control MIMO system. The controllers are implemented by the microprocessor. So it is necessary to convert it into discrete before implementation. So MODEL PREDICTIVE CONTROLLER (control technique having discrete time application) is widely used in the industry for control action as it handles MIMO system effectively. MPC provides various algorithms for handling different control system and DMC one of the popular algorithm among them. It requires state space model and proper tuning parameters for implementation. The distillation column is widely used in industry to separate products. It bears 50% of plant cost for heating and cooling process. So a proper design rule and optimization technique are required for it. Hence we got a scope to work on MPC and provides a case study on distillation column.

1.4 OBJECTIVES

The objectives of the thesis are as follows.

- Analyze the effect of tuning parameters of DMC
- Design tuning rule for the DMC algorithm
- Find out mathematical modelling for distillation column
- To control the bottom purity of distillation column by the PID controller using decoupler technique
- To control the distillate purity of distillation column by the PID controller using decoupler technique
- To control the bottom purity of distillation column by MPC
- To control the bottom purity of distillation column by MPC
- To observe the response for different models of distillation columns

1.5 ORGANISATION OF THE THESIS

Including the introductory chapter, the thesis is divided into 6 chapters. The organization of the thesis is presented below.

Chapter – 2 DMC algorithm and tuning parameter effect

In this chapter, the MPC is introduced.The algorithm for DMC is explained and the effect of tuning parameters on both first order and second order system is described by calculating transient parameters of the output. Finally controller design rule is derived from observation.

Chapter – 3 A brief study on distillation column

In this chapter, a brief idea of the distillation column is given. It provides mathematical modelling for distillation column and describes about basic components of distillation columns.

Chapter – 4 Control of distillation column by PID controller

In this chapter, control of a distillation column by PID controller with and without using decoupler is described. Here we give a comparison between inverted and simplified decoupler technique using different tuning methods.

Chapter – 5 Control of distillation column by MPC

In this chapter, control of a distillation column by MPC controller for different distillation process is described. Here the disturbance rejection, set point tacking, constraint handling features of MPC are explained with examples.

Chapter – 6 Conclusion and future work

This chapter concludes the work and suggests the future work.

CHAPTER 2

DMC ALGORITHM AND TUNING PARAMETER EFFECT

Model predictive control

Dynamic matrix control

Tuning parameter effect

Design rule for DMC

DMC ALGORITHM AND PARAMETER EFFECT

This chapter introduces MPC and an overview of dynamic matrix control. It also gives an idea about tuning parameter effect.

A wide family of predictive controllers is available, each member of which is defined by the choice of elements such as model, objective function and control law.

2.1 Model predictive control

MPC belongs to class of advanced control techniques and nowadays most widely used in process industries. The main benefit of using MPC is its capacity to handle constraints.

Basic idea

At every step of time‘t’, controller solves an optimization problem. The objective function based on prediction horizon (P) and it should be minimized over a control horizon (M) control moves.

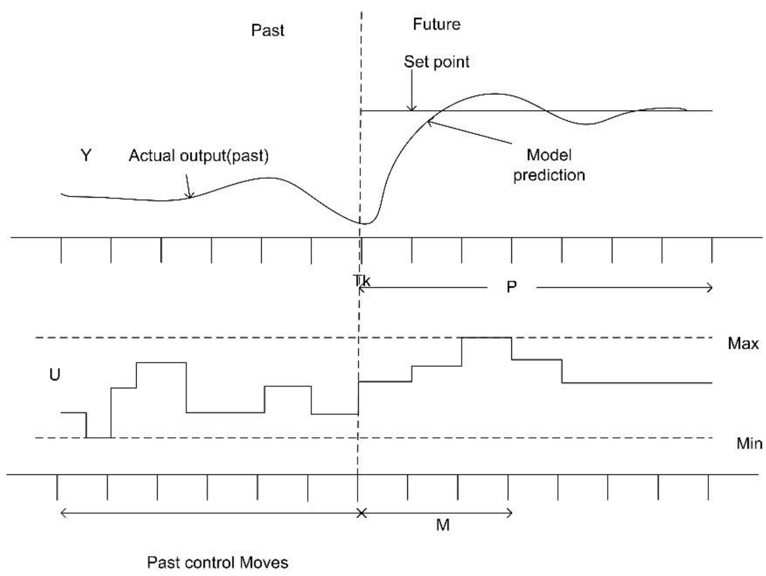

Figure1.1: Principle of MPC

2.2 Dynamic Matrix Control

At the end of the seventies, DMC was developed by Cutler and Remarker of Shell Oil Co. and since then it has been widely accepted in industrial world, mainly by petrochemical industries [2].

Nowadays DMC algorithm is commercially more successful because of its capacity of model identification and global plant optimization. DMC [1] has the ability to deal with multi input multi output process. In this chapter only single input case is discussed.

2.2.1 DMC algorithm

Plant step response model is considered in DMC algorithm

$$Y_P(t) = \sum_{i=1}^{\infty} s_i \Delta x(t-i) \tag{1}$$

Where s_i represents step response coefficients and Δx represents control instruments. Y_P Is the system response and $d(t)$ are the disturbances. So the predicted output will be

$$\hat{Y}_P(t+k) = \sum_{i=1}^{\infty} s_i \Delta x(t+k-i) + d(t+k)$$

$$= \sum_{i=1}^{k} s_i \Delta x(t+k-i) + \sum_{i=k+1}^{\infty} s_i \Delta x(t+k-i) + d(t+k) \tag{2}$$

Consider constant disturbance $\hat{Y}_m$ measured output

$$d(t+k) = d(t) = \hat{Y}_m(t) - Y_P(t) = \hat{Y}_m(t) - \sum_{i=1}^{\infty} s_i \Delta x(t-i) \tag{3}$$

Now the equation (2) can be written as

$$\hat{Y}_P(t+k) = \sum_{i=1}^{k} s_i \Delta x(t+k-i) + \sum_{i=k+1}^{\infty} s_i \Delta x(t+k-i) + \hat{Y}_m(t) - \sum_{i=1}^{\infty} s_i \Delta x(t-i)$$

$$= \sum_{i=1}^{k} s_i \Delta x(t+k-i) + F(t+k) \tag{4}$$

F is free response, this part does not depend on future control action

$$F(t+k) = \hat{Y}_m(t) + \sum_{i=1}^{\infty} (s_{i+k} - s_i) \Delta x(t-i) \tag{5}$$

If we take N no of samples coefficients of step response will tend to constant value after an N sample period.

$$s_{i+k} - s_i \to 0 \qquad i > N \tag{6}$$

So the equation (5) can be written as

$$F(t+k) = \hat{Y}_m(t) + \sum_{i=1}^{N} (s_{i+k} - s_i) \Delta x(t-i) \tag{7}$$

A system dynamic matrix can be defined as

$$\dot{s} = \begin{pmatrix} \dot{s}_1 & \cdots & 0 \\ \vdots & \ddots & \vdots \\ \dot{s}_P & \cdots & \dot{s}_{P-M+1} \end{pmatrix} \tag{8}$$

$$Y_P = \dot{s}\Delta x + F \tag{9}$$

The least square objective function

$$J = \sum_{i=1}^{P} (E_{k+i})^2 + w\sum_{i=0}^{M-1} (\Delta x_{k+i})^2$$

$$\frac{dJ}{d\Delta x} = 0$$
$$\Delta x = (\dot{s}^T \dot{s} + wI)^{-1} s^T E \tag{10}$$

DMC expressed as LTI model

$$\hat{Y}_P(t+k) = \sum_{i=1}^{k} s_i \Delta x(t+k-i) + F(t+k)$$

$$\Delta x = (\dot{s}^T \dot{s} + wI)^{-1} \dot{s}^T E$$

Here E is an error and measurable disturbances have not been taken into account

$$G = [\dot{s}_1 \dot{s}_2 \ldots . \dot{s}_P] = (\dot{s}^T \dot{s} + wI)^{-1} \dot{s}^T \tag{11}$$

$$F(t+k) = \hat{Y}_m(t) + \sum_{i=1}^{N} (s_{i+k} - s_i)\Delta x(t-i)$$

$$= \hat{Y}_m(t) + \sum_{i=1}^{N} g_n{}^k \Delta x(t-i) \tag{12}$$

$$g_n{}^k = g_1{}^k(z^{-1}) + g_2{}^k(z^{-2}) + g_3{}^k(z^{-3}) + \ldots\ldots\ldots + g_n{}^k(z^{-n}) \tag{13}$$

$$\Delta x(t) = \sum_{t=1}^{P} G_i \Delta r(t+i) - \sum_{t=1}^{P} G_i Y_P(t) - \sum_{t=1}^{p} G_i g_n{}^i \Delta x(t) \tag{14}$$

Compare above equation to figure

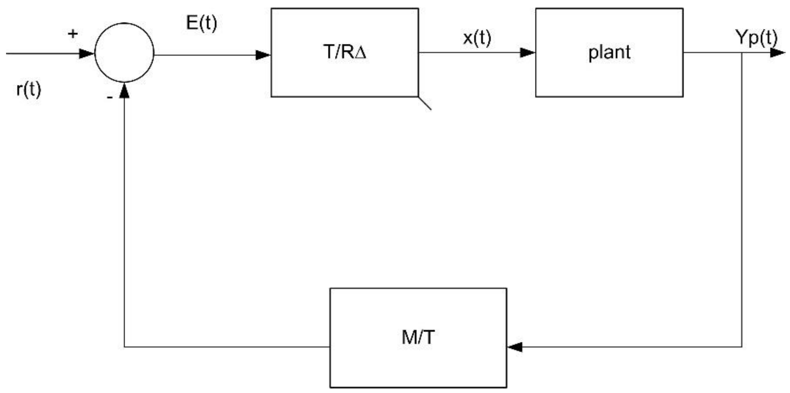

Figure1.2: DMC represented as LTI Model

$$R(z^{-1})\Delta x(t) = T(z^{-1})r(t) - M(z^{-1})Y_P(t)$$

$$R = 1 + \sum_{i=1}^{p} G_i g_n{}^i$$

$$T = \sum_{i=1}^{P} G_i z^i$$

$$M = \sum_{i=1}^{P} G_i$$

(15)

2.3 Observation

First, we considered a general first order and second order system to observe tuning parameters effect by calculating transient parameters like settling time, overshoot and rise time. Then we go for specific transfer function for calculation of design rule.

2.3.1 Effect of P on first order and second order system

Y(s)/U(s) =5/5s+1

Table 1
Transient parameters for different values of P and M

Parameters	M=2			M=3			M=4		
	P=10	P=15	P=20	P=10	P=15	P=20	P=10	P=15	P=20
Settling time(sec)	61.98	61.98	61.98	61.98	61.98	61.98	61.98	61.98	61.98
Overshoot	0	0	0	0	0	0	0	0	0
Rise time(sec)	4.132	4.132	4.132	4.132	4.132	4.132	4.132	4.132	4.132

To observe the effect of tuning parameters on first system, systems with constant gain k=5 but different time constant like 10,20, 30, 40 and so on are taken.
Y(s)/U(s) =5/Ts+1 for
T=10, 20, 30,40,50,60,70,80,90,100

Table 2
Settling time for different values of P

Time Constant(sec)	P=5	P=10	P=15	P=20
Settling time (Sec)				
10	61.9764	61.9791	61.9687	61.9571
20	61.9765	61.9789	61.9714	61.9619
30	61.9765	61.9788	61.9724	61.9637
40	61.9765	61.9788	61.9728	61.9645
50	61.9766	61.9787	61.9731	61.9650
60	61.9766	61.9787	61.9733	61.9554
70	61.9766	61.9787	61.9735	61.9656
80	61.9766	61.9787	61.9736	61.9558
90	61.9766	61.9787	61.9736	61.9560
100	61.9766	61.9787	61.9737	61.9661

2.3.2 Result Analysis

For higher value of M (more than 1) system response remain constant for P=10 to20.Simulations show that there is no need for a very long prediction horizon. We can assure stability and feasibility of system for short prediction horizon. Hence, short horizons are preferred in this project as the computational time is less.

Second order system

Y (s) /U (s) =$\omega_n{}^2 / (s^2 + 2 * \varepsilon * \omega_n s + \omega_n{}^2)$

ε =0.1, 0.2, 0.3, 0.4….
ω_n=10

Table 3
Settling time for different values of P

Damping Ratio	P=5	P=10	P=15	P=20
Settling time (Sec)				
0.1	60.2798	61.8679	61.9582	61.9696
0.2	60.5944	61.9472	61.9693	61.9643
0.3	61.7124	61.9617	61.9661	61.9635
0.4	61.8852	61.9643	61.9632	61.9629
0.5	61.9294	61.9643	61.9612	61.9612
0.6	61.9470	61.9626	61.9596	61.9592
0.7	61.9562	61.9616	61.9580	61.9671
0.8	61.9616	61.9609	61.9564	61.9549
0.9	61.9652	61.9652	61.9549	61.9528

Y(s)/U(s) =$\omega_n{}^2 / (s^2 + 2 * \varepsilon * \omega_n s + \omega_n{}^2)$

ε =0.1, 0.2, 0.3, 0.4…
.ω_n=100

Table 4
Settling time for different values of P

Damping Ratio	P=5	P=10	P=15	P=20
Settling time (Sec)				
0.1	41.98	41.9767	41.9729	41.9705
0.2	41.98	41.98	41.98	41.98
0.3	41.98	41.98	41.98	41.98
0.4	41.98	41.98	41.98	41.98
0.5	41.98	41.98	41.98	41.98
0.6	41.98	41.98	41.98	41.98
0.7	41.98	41.98	41.98	41.98
0.8	41.98	41.98	41.98	41.98
0.9	41.98	41.98	41.98	41.98

Y (s) /U (s) =$\omega_n{}^2 / (s^2 + 2 * \varepsilon * \omega_n s + \omega_n{}^2)$

ε =0.1, 0.2, 0.3, 0.4...
ω_n=1

Table 5
Settling time for different values of P

Damping Ratio	P=5	P=10	P=15	P=20
Settling time (Sec)				
0.1	32.6543	32.6543	32.6543	32.6543
0.2	30.6683	30.6683	30.6683	30.6683
0.3	29.8818	29.8818	29.8818	29.8818
0.4	29.7545	29.7545	29.7545	29.7545
0.5	29.4463	29.4463	29.4463	29.4463
0.6	30.3519	30.3519	30.3519	30.3519
0.7	30.8070	30.8070	30.8070	30.8070
0.8	31.2813	31.2813	31.2813	31.2813
0.9	31.7213	31.7213	31.7213	31.7213

2.3.3 Result Analysis

1. For second order system ($\omega_n = 10$), for the values P=5, 10, 20, 15 settling time varies slightly for all values of ε.
2. For second order system ($\omega_n = 100$), settling times remain constant for $\varepsilon \geq 0.2$ irrespective of P value, but varies slightly with respect to P for $\varepsilon = 0.1$.

3. For second order system ($\omega_n = 1$), settling times remain constant for the same value of ε irrespective of change in P value.

2.3.4 Effect of M on different order systems

First order system

Y(s)/U(s) =5/10s+1

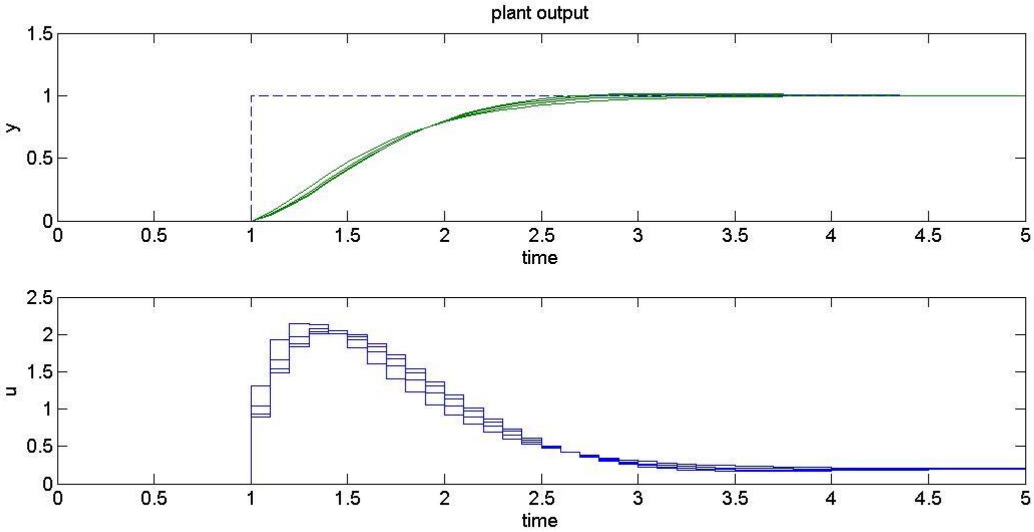

Figure1.3: System Response for M=1:1:4, P=10

Second order system

Y(s)/U(s) $= \omega_n^2 / (s^2 + 2 * \varepsilon * \omega_n s + \omega_n^2)$

ε =0.1
ω_n=10

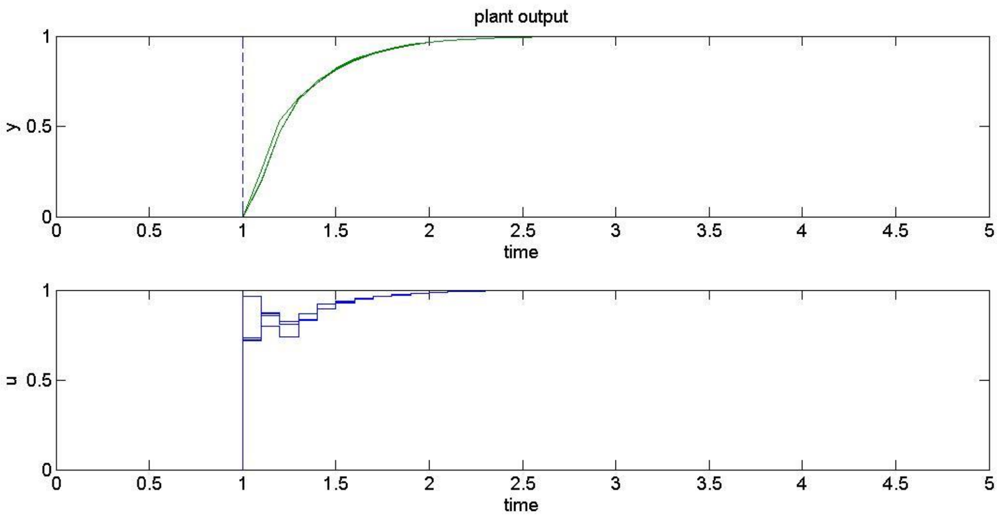

Figure1.4: System Response for M=1:1:4

2.3.5 Result Analysis

1. For a first order system as the M value increases the input decreases for a system having same time constant.

2 For first order system at the time constant increases the input to the system increases in the same value of M.

3. For a second order system as the M value increase the input decreases for the same value of ω_n and ε.

2.3.6 Effect of DMC parameters on system response (consider a specific system)

$$\frac{Y(s)}{U(s)} = \frac{1e^{-0.3s}}{10s+1}$$

Table 6

For sampling time=1 Sec

	P=4	P=8	P=12	P=20
Closed loop pole value	0.9048	0.9048	0.9048	0.9048
	0.6776+0.2572i	0.7482	0.8142	0.8585
	0.6776-0.2572i	0.2349	0.0952	0.0329

Table 7

For sampling time=0. 5 Sec

	P=4	P=8	P=12	P=20
Closed loop pole value	0.9512	0.9512	0.9512	0.9512
	0.8772+0.2109i	0.6678	0.8385	0.8923
	0.8772-0.2109i	0.6385	0.2425	0.0746

Table 8

For sampling time=1 Sec

parameters	P=4	P=8	P=12	P=20
Settling time	13.7659	13.6822	13.6893	13.7026
Rise time	8.7003	9.246	9.477	9.6061

Table 9

For sampling time=0. 5 Sec

parameters	P=4	P=8	P=12	P=20
Settling time	41.1028	39.2693	29.3515	41.8978
Rise time	25.925	11.7301	14.7615	6.817

Table 10

For P=10, w=0.5

	M=1	M=2	M=3	M=4	M=5
Closed loop pole value	0.9704	0.9704	0.9704	0.9704	0.9704
	0.725+0.0607i	0.7882+0.1293i	0.8146+0.1435i	0.8267+0.1493i	0.8321+0.1522i
	0.725-0.0607i	0.7882-0.1293i	0.8146-0.1435i	0.8267-0.1493i	0.8321-0.1522i

Table 11

For P=40, w=0.5

	M=1	M=2	M=3	M=4	M=5
Closed loop pole value	0.9704	0.9704	0.9704	0.9704	0.9704
	0.9419	0.9134	0.8384	0.8060+0.1094i	0.8135+0.1394i
	0.03	0.5172	0.726	0.8060-0.1094i	0.8135-0.1394i

Table 12

For P=120, w=0.5

	M=1	M=2	M=3	M=4	M=5
Closed loop pole value	0.9704	0.9704	0.9704	0.9704	0.9704
	0.7888+0.1682i	0.9159	0.7735+0.06i	0.7877+0.1468i	0.9636
	0.7888-0.1682i	0.5150	0.7735-0.06i	0.7877-0.1468i	0.0035

Table 13

For sampling time=0.3

parameters	M=1	M=2	M=3	M=4	M=5
Settling time	6.2565	8.0437	8.7892	8.7703	8.4672
Rise time	41.8956	41.8927	41.8788	41.8743	41.8763

Table 14

For M=1, w=0

	P=4	P=6	P=10
Closed loop pole value	0.9704	0.7128	0.9704
	0.5598	0.9704	0.8255

Table 15

For M=1, w=0.25

	P=4	P=6	P=10
Closed loop pole value	0.9704	0.7259+0.2081i	0.9704
	0.8742+0.2312i	0.9704	0.8144
	0.8742-0.2312i	0.7259-0.2081i	0.2748

Table 16

For M=1, w=0.75

	P=4	P=6	P=10
Closed loop pole value	0.9704	0.9704	0.9704
	0.9709+0.09i	0.9397+0.1309i	0.8305+0.1358i
	0.9709-0.09i	0.9397-0.1309i	0.8305-0.1358i

Table 17

For M=1, w=1

	P=4	P=6	P=10
Closed loop pole value	0.9704	0.9704	0.9704
	0.9771+0.0675i	0.9588+0.1018i	0.8865+0.1312i
	0.9771-0.0675i	0.9588-0.1018i	0.8865-0.1312i

Table 18

For P=4

parameters	W=0	W=0.25	W=0.5	W=0.75	W=1.0
Settling time	6.4917	17.4823	25	25.9246	26.0311
Rise time	24.20	40.2824	40.4419	41.1022	41.2421

Table 19

For P=6

parameters	W=0	W=0.25	W=0.5	W=0.75	W=1.0
Settling time	10.5621	8.8408	12.4454	17.1826	21.0652
Rise time	22.961	36.494	40.6886	40.0205	35.3945

Table 20

For P=10

parameters	W=0	W=0.25	W=0.5	W=0.75	W=1.0
Settling time	15.1616	13.5319	12.3358	12.1652	12.5759
Rise time	30.0127	27.9579	24.2612	22.0178	35.48

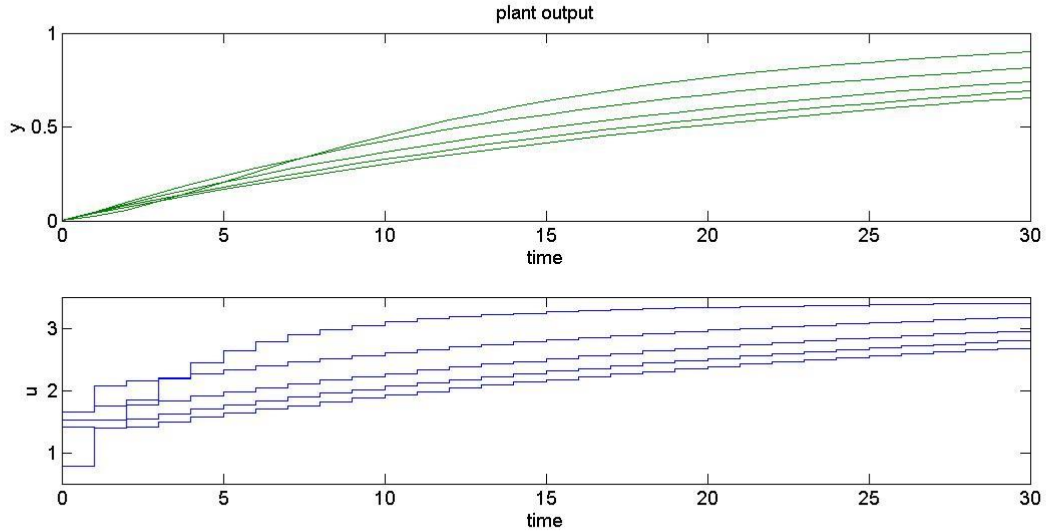

Figure1.5: System response for sampling time=1sec and P=4:4:20

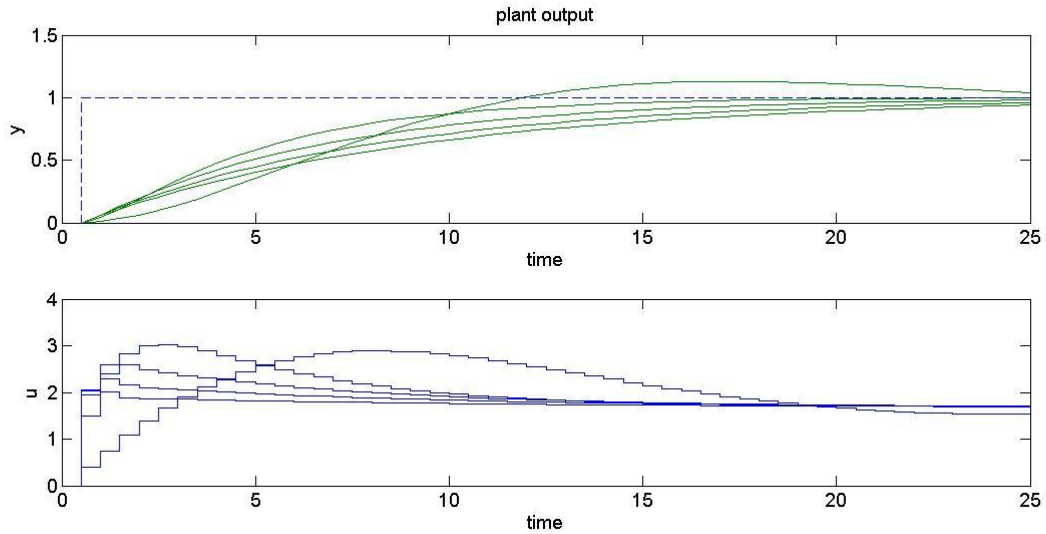

Figure1.6: System response for sampling time=0.5sec and P=4:4:20

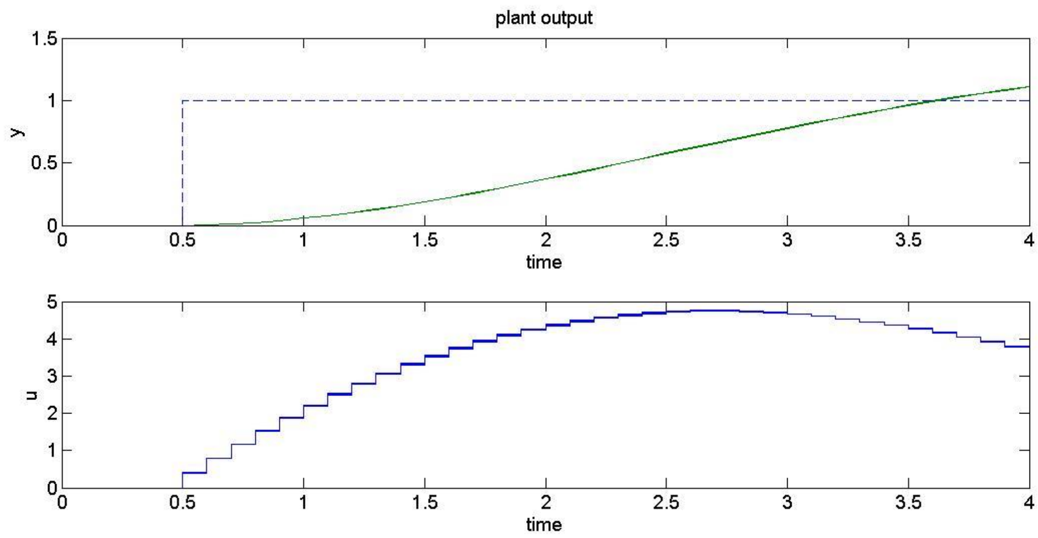

Figure1.7: System response for w=0.5, P=10 and M=1:1:5

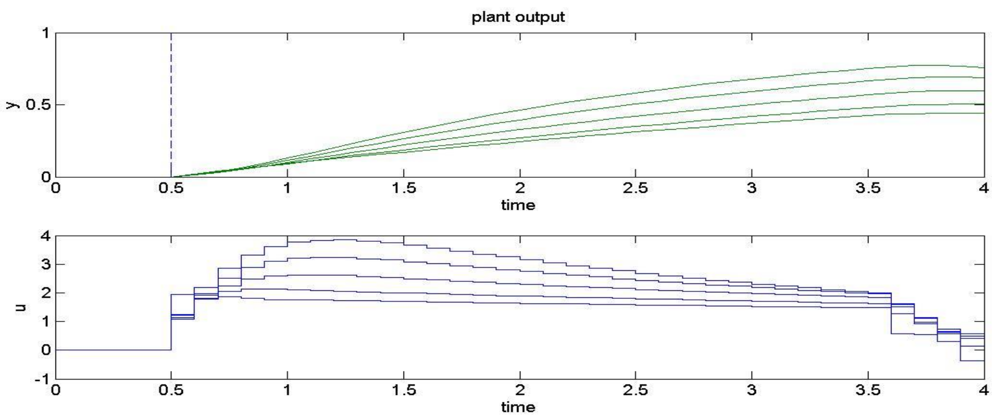

Figure1.8: System response for w=0.5, P=40 and M=1:1:5

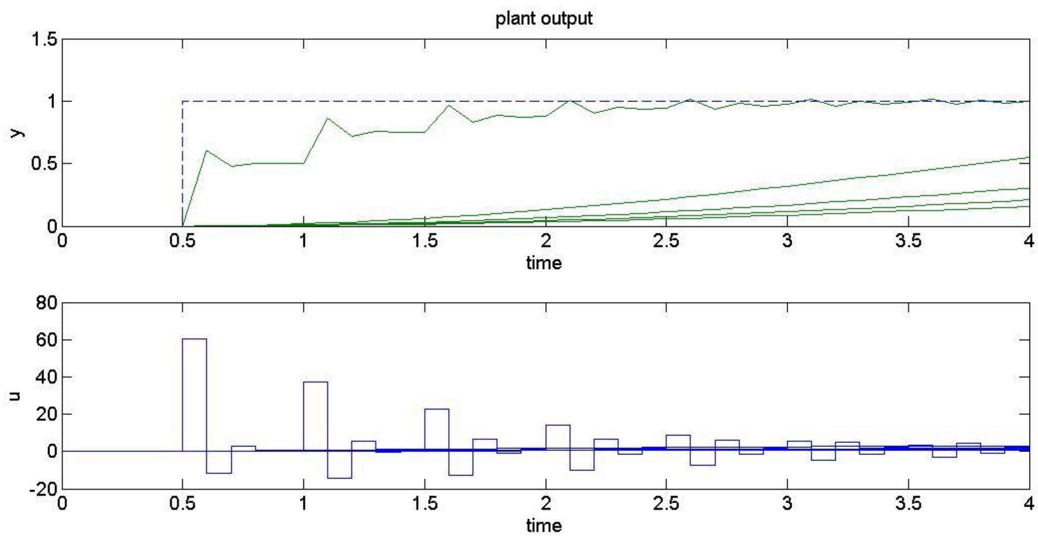

Figure1.9: System response for w=0.5, P=120 and M=1:1:5

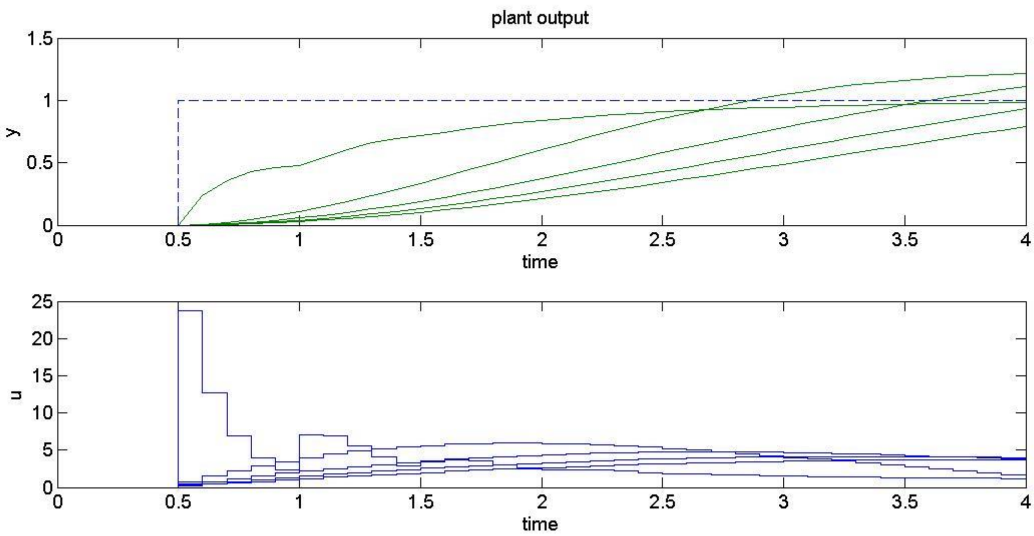

Figure1.10: System response for P=6, M=1 and w=0:0.25:1

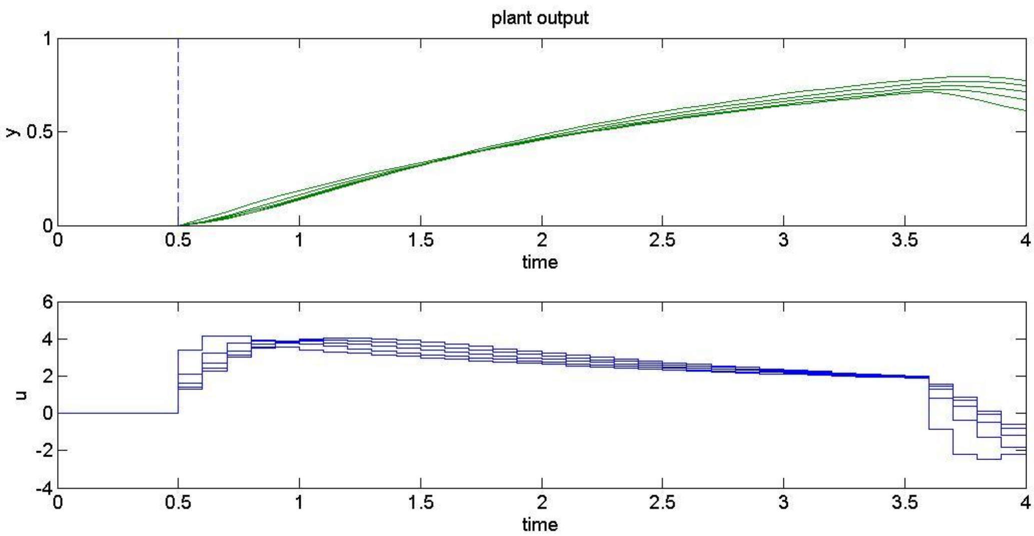

Figure1.11: System response for P=10, M=1 and w=0:0.25:1

2.3.7 Result analysis

Effect of prediction horizon and sampling time in the process

As explained above, the given SISO system is analysed for sampling time 1sec and 0.5sec.Table 6 and Table 7 provide the closed loop poles for these sampling times for different values of the prediction horizon (P). (Refer figure1.5 and 1.6)

Table 6 and 7 provide first conclusion is that with the increase in prediction horizon value the real pole value increases and modulus of complex poles decreases. So the real positive poles become the dominant one and decides the behaviour of the system. The complex pole causes oscillation, but the real pole produces an oscillation free response. As we further increase the

P value there is a slight variation in the pole value. It means its effect on pole decreases and the system behaves like open loop system.

For lower sampling time maximum pole is closer to the unit circle. In high sampling time settling time less. For a particular sampling time, as the P value increases settling time increases, but up to a certain value beyond that settling time increases. So there is limitation on increasing on P value.

Effect of control horizon on the process

Literature work shows that M has less effect on the process. Various simulations have been performed by keeping w=0. 25 and for different values of P. Table 10, 11, 12 show close loop poles.

Let us discuss the effect of M for given FOPDT. Actually the effect of M depends on P and w value. As an M value increased for small P value, there is a small change in close loop value. But for high P value there is a marginal change in dominant pole value for change in M value. In complex pole the real part increases gradually. So it may deteriorate the response.

Table 13 gives settling time and rise time for different value of M. It shows that there is a very slight variation in those parameters for change in M value. But high M value increases computational complexity. And small M value gives aggressive behaviour of manipulating value. So we have to choose an M value very wisely.). (Refer figure 1.7, 1.8 and 1.9)

Weighting factor effect

The softening of system response depends on weighting factor. On lightly effect of w opposite to effect of P. As w value increases in the same value of P the real positive pole and imaginary part of complex pole decreases, but real part of complex pole increases. Imaginary part causes oscillation. Value of imaginary part decreases, it means real part is approaching towards real axis. It results oscillation free response.

Table 18, 19, 20 give rise time and settling time values for different weighting factor. To increase in w value there is a small change in settling time, but there is a large variation in rise time.). (Refer figure1.10 and 1.11)

Model length effect

Model length (N) gives no of step response coefficient is used in the model. It has less effect on DMC algorithm. We have to just keep in mind that the system must reach steady state value for the given model length and must be greater than the prediction horizon value (P). Model length and settling time depend on each other. The model length should be nearly equal to settling time of the process, i.e. time required to reach steady state after a step input change. Sampling time is roughly one tenth of dominant time constant.

System stability

Effect of weighting factor, prediction horizon and control horizon is studied for system stability analysis.

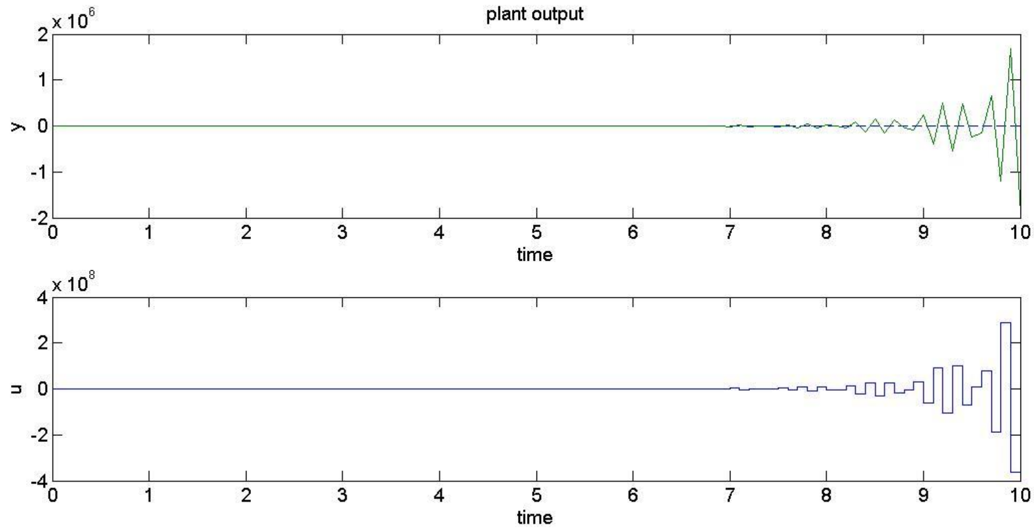

Figure1.12: Unstable response of the transfer function for P=100, M=2:1:5, w=0

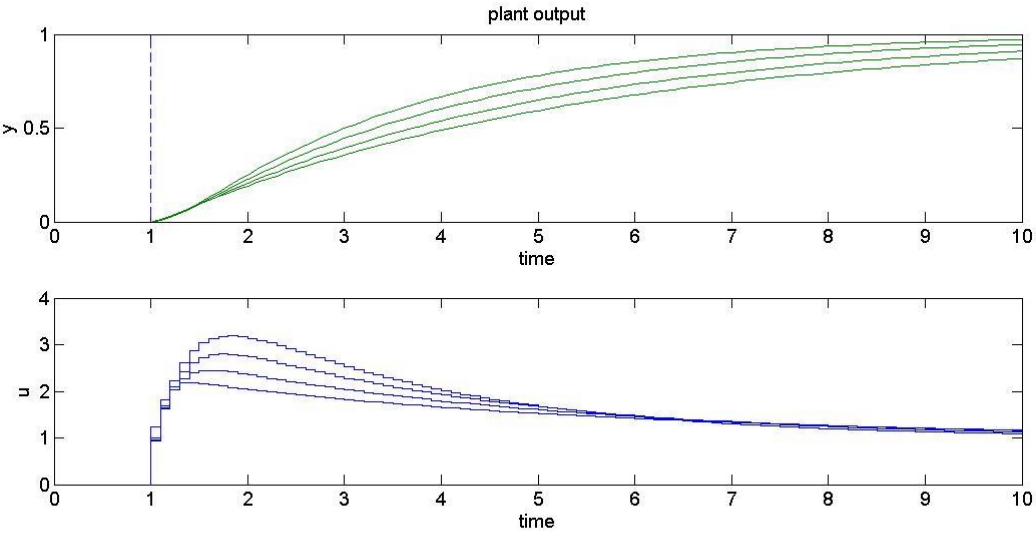

Figure1.13: stable response of transfer function for P= 100, M=2:1:5, w=0.75

As from the previous discussion, it is found that high values of prediction horizon (P) and control horizon (M) have an effect on system stability. The large values of prediction horizon lead to large control increment and it unstabilizes the system. (Refer figure1.12) this effect can be compensated by using a weighting factor (w). (Refer figure1.13)

2.4 Proposed Design rule for DMC

1. Model length nearly equal to settling time
2. Prediction horizon equal to the time constant of FOPDT

3. M has less influence. But for large value of P (when P>> time constant), M value corrects system response.
4. Sampling time 0.1T (T=dominant time constant)
5. Contribution of w is to soften the response. But its effect disappears for high P value. To compensate this we have to increase the M value.

Table 21
Tuning the parameters of proposed, Shridhar–Cooper and Iglesias et al. Methods.

Method	Time constant	Settling time	Sampling time	P	M	N	W
Proposed	10	60	1	10	1	60	0.5
Shridhar–Cooper	10	60	0.5	101	5	101	0.7
Iglesias et al.	10	60	0.5	101	5	101	0.3881

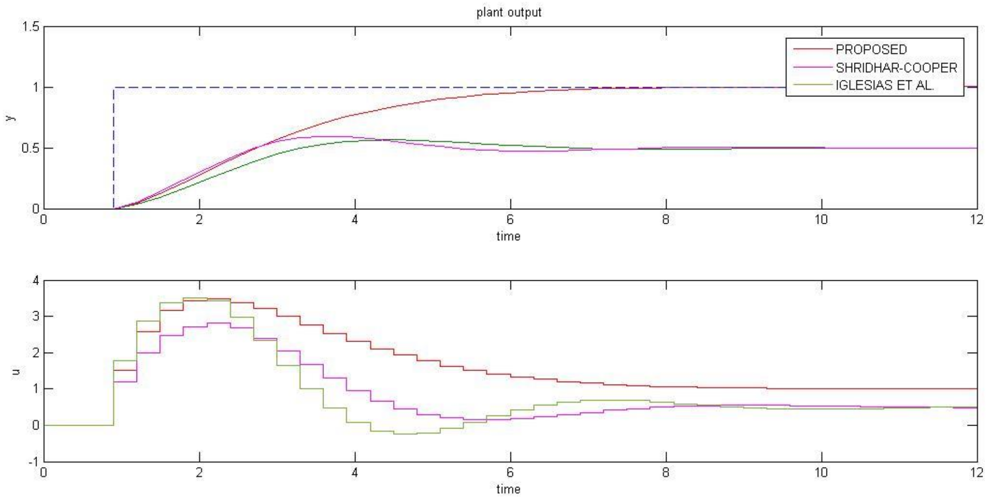

Figure1.14: Response of the transfer function for different methods

CHAPTER 3

A BRIEF STUDY ON DISTILLATION COLUMN

Introduction

Mathematical modelling

Basic component

Design principle

Control strategy

A BRIEF STUDY ON DISTILLATION COLUMN

This chapter introduces distillation column, then presents its mathematical modelling. The basic operating principle of the distillation column is discussed here.

The dynamics of distillation columns will be discussed in this chapter. The response of vapor flow, as well as liquid flow will be discussed. First, a model will be defined, which specifies the model inputs and outputs of a continuous column. Next, a first-principles, behavioral model is presented consisting of mass, component and energy balances for each tray. The tray molar mass depends on the liquid and the vapor load, as well as on the tray composition. The energy balance is strongly simplified. Finally, dynamic models are derived to describe liquid, vapor and composition responses for a single tray and for an entire distillation column.

3.1 Introduction

The main work of distillation column is separation of components from a mixture. For separating mixture distillation column is more used techniques in industry. Based on aspects of column and what assumptions are considered, distillation column can be represented by a number of models.

The distillation column comprises of a column and trays. These trays are used to improve component separation. x_F Represents mole fraction of component posse by feed. x_D Represents mole fraction of component posse by top producers. x_B .Represents mole fraction of component posse by bottom product. The schematic diagram of the distillation column is illustrated in Fig. 1.

3.2 Mathematical Modelling

The mathematical model of the distillation column is provided below. For linearization Francis-Weir formula is used. It is

$$l_n = l_{no} + \frac{m_n - m_{no}}{\beta} \tag{16}$$

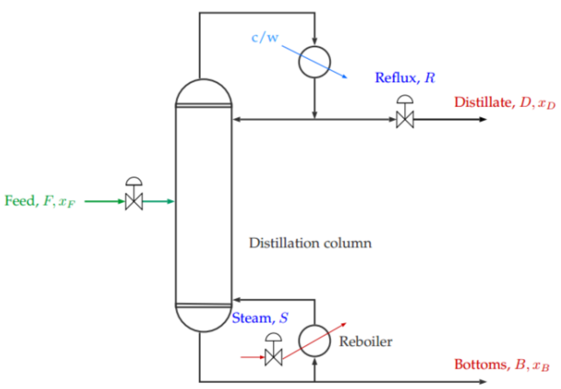

Figure 2.1: Schematic diagram of distillation column

The mathematical model for condenser and reflux drum can be represented as

$$\frac{dm_d}{dt} = v_{nT} - (r + d_L + d_V)$$

(17)

$$\frac{dm_d x_D}{dt} = v_{NT} y_{NT} - (r + d_L) x_D - d_V y_D \tag{18}$$

The mathematical model for top tray can be represented as

$$\frac{dm_{NT}}{dt} = r + v_{NT-1} - l_{NT} - v_{NT} \tag{19}$$

$$\frac{dm_{NT} x_{NT}}{dt} = r x_D + v_{NT-1} y_{NT-1} - l_{NT} x_{NT} - v_{NT} y_{NT} \tag{20}$$

For nth tray the mathematical model is

$$\frac{dm_n}{dt} = l_{n+1} - l_n + v_{n-1} - v_n \tag{21}$$

$$\frac{dm_n x_n}{dt} = l_{n+1} x_{n+1} - l_n x_n + v_{n-1} y_{n-1} - v_n y_n \tag{22}$$

For feed tray the mathematical model is

$$\frac{dm_{NF}}{dt} = l_{NF+1} - l_{NF} + v_{NF-1} - v_{NF} + f_L \tag{23}$$

$$\frac{dm_{NF} x_{NF}}{dt} = l_{NF+1} x_{NF+1} - l_{NF} x_{NF} + v_{NF-1} y_{NF-1} - v_{NF} y_{NF} + f_L z_L \tag{24}$$

The mathematical model for bottom tray is

$$\frac{dm_1}{dt} = l_2 - l_1 + v_B - v_1 \tag{25}$$

$$\frac{dm_1 x_1}{dt} = l_2 x_2 - l_1 x_1 + v_B y_B - v_1 y_1 \tag{26}$$

For reboiler the mathematical model is

$$\frac{dm_B}{dt} = l_1 - v_B - b \tag{27}$$

$$\frac{dm_B x_B}{dt} = l_1 x_1 - v_B y_B - b\, x_B \tag{28}$$

Table 22. Nomenclature

Symbol	Description	Unit
d_L	Flow rate of liquid distillate	lbmol/h
d_V	Flow rate of vapor distillate	lbmol/h
y_D	Composition of vapor distillate	Mole fraction
x_D	Composition of liquid distillate	Mole fraction
m_d	Liquid holdup on stage in the reflux drum	lbmol
r	Reflux flow rate	lbmol/h
l_n	Internal liquid flow rate	
l_{no}	Reference value of internal flow rate	
m_{no}	Reference molar holdup for nth tray	

3.3 The basics of a distillation column

The distillation column is widely used in industry to separate various chemicals, mostly petroleum products.

The working of distillation column can be explained by examples. Let the mixture contains two products such as A to boiling point to and component B with higher boiling point at Tb. Equilibrium is achieved between the temperature Ta and Tb where the % of A in vapor is comparably high than % of A in the liquid.

The primary component in distillation column is column, whose target is to get separation more efficiently. It consumes more energy both in term of cooling and heating. 50% of plant cost is due to this. In order to reduce the cost one has to increase its efficiency and operation by this process optimization and control. We need to understand distillation principles and its design rule to achieve this improvement. In the distillation column, it heats the liquid until some of its ingredients converts into vapour phase and cools the vapour to get it in liquid form using the condensation method. If the boiling point difference between the two substances is great, complete separation may be possible in single stage distillation. If there is a slight difference in boiling point many redistillation is required.

The vessel in which the liquids are boiled is called still. But sometimes this term applied all the parts including the condenser, the receiver and the column. When we are trying to separate water and alcohol; the mixture returns from the condenser through several plates and makes bubbles at each plate. There is an interaction between vapour and liquid the water in the vapour starts to condense and alcohol starts to vaporize. Interaction is equivalent to redistillation. This process, in industry well known as fractional distillation.

3.4 Basic components of distillation columns

Different varieties of configuration of distillation column perform specific types of separations. According to way of the operation distillation column is divided into two major types (1) continuous, (2) batch column. During batch operation, batch wise the feed is provided in column and in the continuous operation flow of feed is continuous to the column. Continuous column can be further divided into binary column (there are two components present in the feed), multicomponent component (more than two components are in the feed).

To improve the transfer of heat energy or mass, there are several important components. Those are shells which are vertically oriented and where liquid component separation is happened. Column internals such as tray, plates which effects component separation. The reboiler is required for providing necessary steam to distillation column; a condenser to cool and the vapour is condensed at the top of the columns. The liquid (reflux) is recycled back to the column.

The mixture which is to be processed is named as feed and it is applied at column's middle. The feed tray divides column into two sections, the top section is called enriching or rectification section. And the bottom section is called stripping section. The feed flow down the column and it is called at the bottom in the reboiler. The vapor is generated at retailer because heat is provided to it do so. The liquid removed at the reboiler is called bottom product.

The vapour moves upward in column and at the top of the column. Then condenser condense it. The condensed liquid is stored in the huddling vessel known as reflux drum. The condensed liquid that is removed from the system is known as the distillate or top product.

The most commonly used trays are cap tray, valve tray and sieve tray. A riser or chimney is fitted over each hole of a bubble cap tray. There is a space between the cap and riser for allowing passage of vapour. Through the chimney vapour rises and moves downward by the cap and discharges through the slots. There are bubbling though the liquid on the tray. Typically bubble tray or plate tower has a no of shallow plates over which liquid flows downward. The gas enters at the bottom of the tower and forms no of bubble caps on each plate. There are various shapes caps. Usually inverted cup form caps are used.

The lifetable caps cover the perforation in valve trays. The caps are lifted by vapour flow and thus it creates a flow area for vapour passage by itself. The sieve trays are simply metal plates with holes in them. Vapour moves upward in the column through the plate. Sieve and valve trays have replaced the bubble caps trays in many application because of efficiency, wide operating range

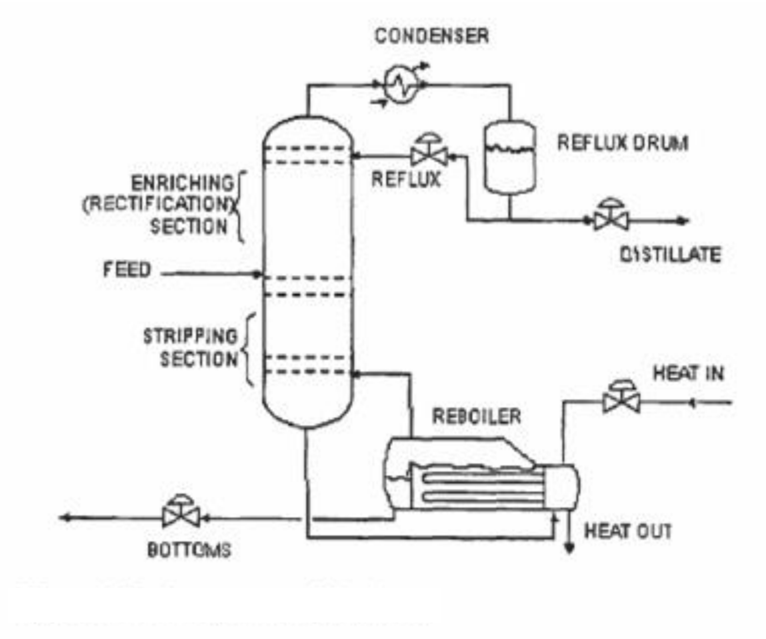

Figure2.2: Basic component of Distillation column

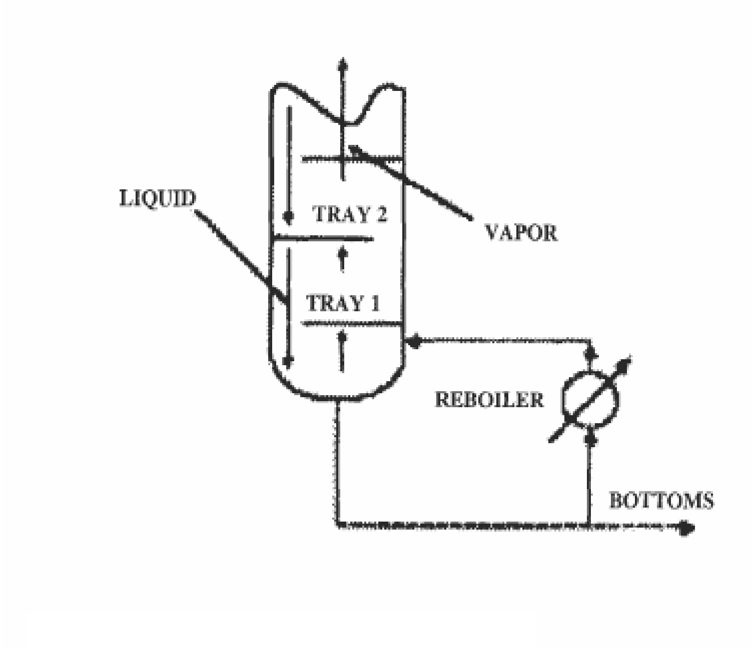

Figure2.3: Role of reboiler of Distillation column

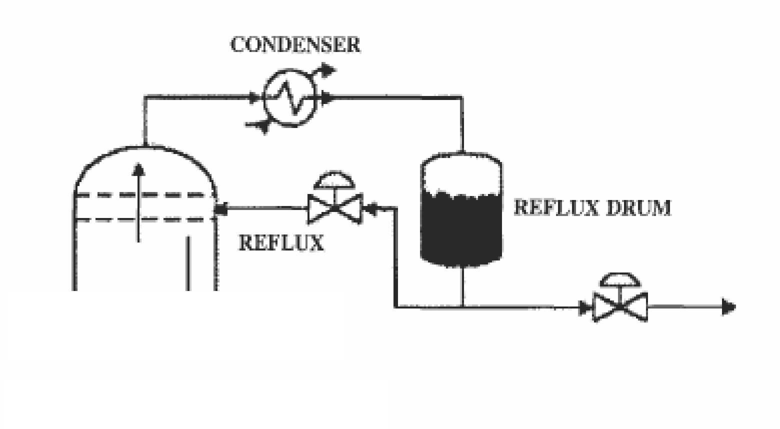

Figure2.4: Role of reflux of Distillation column

3.5 Design principles

Basic principle of the distillation column is that it depends on boiling points of the components of the mixture. Thus the distillation process depends on vapour pressure characteristics of liquid mixtures.

The equilibrium pressure exerted by molecules entering and leaving the liquid surface is called the vapour pressure of the liquid at a particular temperature. The vapour pressure also relates to the boiling. When the vapour pressure of the liquid equals the surrounding pressure then the liquid boils. The liquid having higher vapour pressure will boil at a lower temperature (i.e. Volatile liquid).

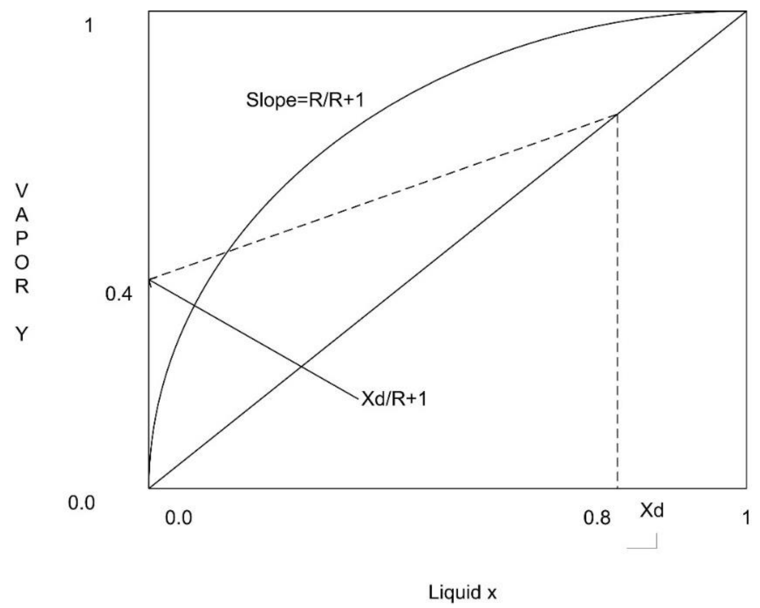

Figure2.5: Application of McCabe-Thiele to VLE diagram

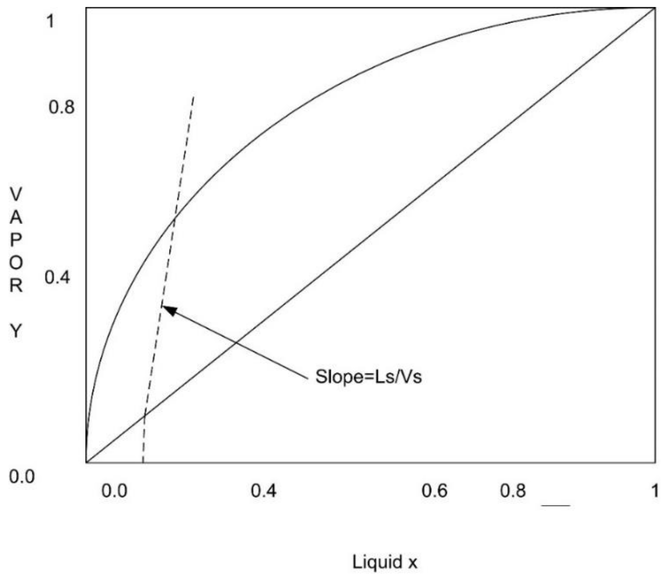

Figure2.6: Construction of operating line for stripping section

The description of the process is provided by the boiling point diagram. At a fixed pressure the diagram shows how the composition of components in a liquid mixture varies with respect to temperature. Let consider one mixture contains two components A and B. The boiling point of A, at which mole fraction of A is unity. The mole fraction of A is zero at the boiling point of B. So in this example, A is a more volatile component and has a lower boiling point than B. The curve is called dew point curve and the lower one is called bubble point curve. The equilibrium composition of superheated vapour is represented by the region above the dew point and equilibrium composition of super cooled liquid is represented by region below the bubble point curve. For example, liquid with mole fraction 0.4 at point A possess a constant mole fraction until it reaches point B. Then vapour generates during boiling has 0.8 mole fraction A.

The difference in volatility between two components is called relative volatility. It decides how easy or difficult a particular separation process will be[4].

The relative volatility of component P with respect to q is defined by

$$\alpha_{pq} = \frac{y_p / x_p}{y_q / x_q} \tag{29}$$

y_q Is the mole fraction of component q in the vapour and x_q is the mole fraction of component q in the liquid. If α_{pq} =1 then they have similar boiling point and hence difficult to separate by the distillation process.

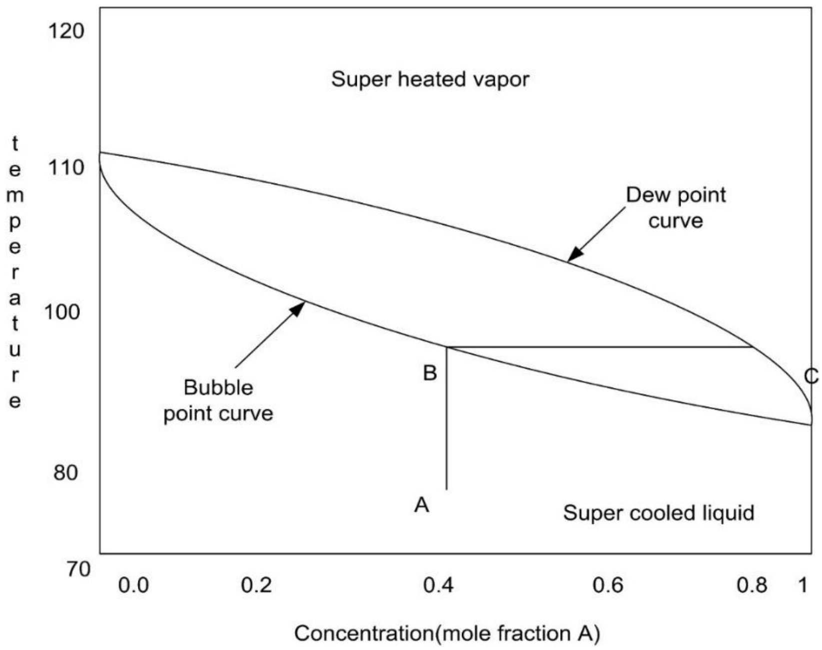

Figure2.7: Boiling point diagram of binary mixture

McCabe-Thiele determine the theoretical number of stages for effective separation in distillation column using VLE plot. Molar overflow is assumed to be constant and heat effect is constant. The mass balance relationship between vapour and liquid phases can be made by operating lines. There is an operating [5] line for both bottom section and top section. First the molar concentration of the desired product is located on VLE diagram and then a vertical line produced until it interacts with the diagonal line that splits the VLE plate in half. The slope of the line is R/(R+1). R is defined as the ratio of reflux flow (L) to distillate flow (D) is called reflux ratio. Similarly line obtained for bottom product and its slope is L_s / V_s. Where L_s represents liquid rate and V_s represents vapour rate.

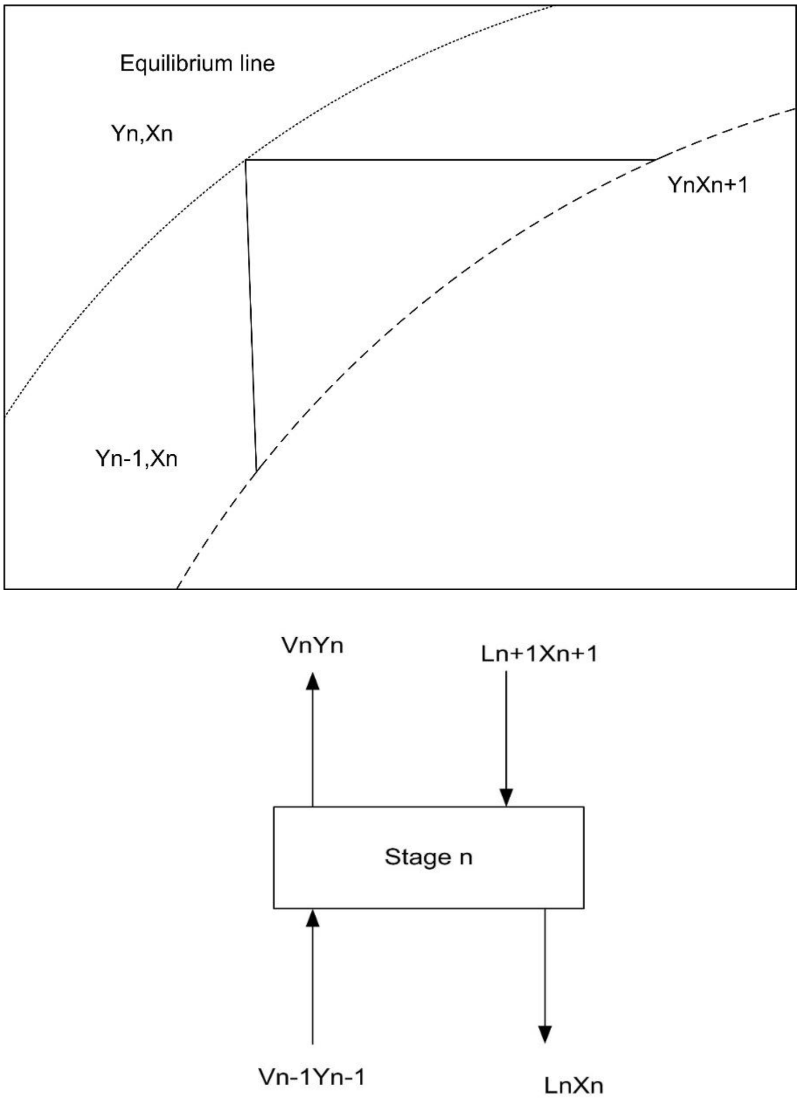

Figure2.8: construction of an operating line

In the above figure n-1 denotes material from the stage below n while n+1 refers to material from the stage above n. The term ‘L’ is liquid flow while V represents the vapor flow.

Using operation lines for both stripping and rectification section theoretical stages can be calculated. The required number of trays can be calculated as the ratio of the number of theoretical trays to the tray efficiency [7]. Typical values for tray efficiency ranges from 0.5 to 0.7.

3.6 Control strategy

Here the control strategy of the distillation column is described. Fig 2.9 provides a complete list of the manipulated and control variables. Fig.2.10 shows control structure of the distillation column. A typical distillation column has five input variables such as feed rate, feed composition, reflux rate and reboil heat. It has also five process variables to be controlled such as distillate composition, distillate rate, tray5 temperature, tray 15 temperature, bottom flow rate, bottom composition

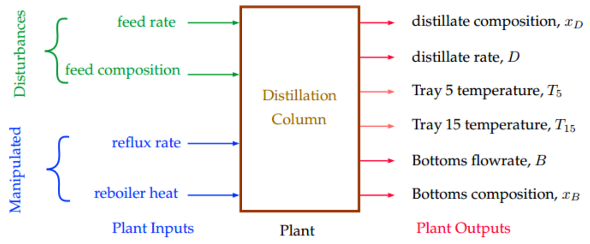

Figure 2.9: Block diagram of control structure for distillation column.

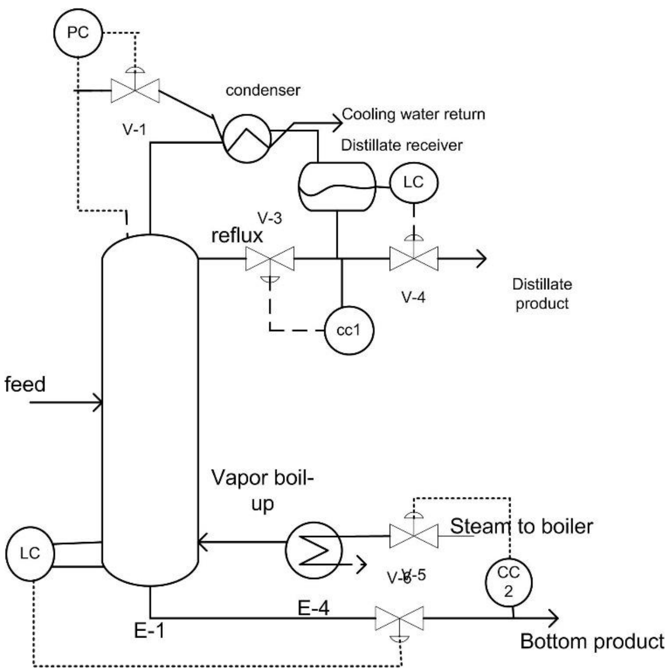

Figure2.10: control structure for distillation column

In the distillation column, the pressure can be controlled by handling the flow of water to the condenser. By controlling bottom product flow rate, base level can be handled. The bottom and top product purity can be controlled by manipulating temperature of tray. In a distillation column minimum four control loops to control distillate and bottom product, reboiler level and reflux rate level. So the distillation column comes under the MIMO control problem.

CHAPTER 4

CONTROL OF DISTILLATION COLUMN BY PID CONTROLLER

Conventional Decoupling

Simplified Decoupling

Inverted Decoupling

CONTROL OF DISTILLATION COLUMN BY PID CONTROLLER

This chapter describes about conventional decoupling, simplified decoupling and inverted decoupling. It also provides a comparison between simplified and inverted decoupling by taking Wood and Berry model of distillation columns.

The conventional PID controller is widely used for industrial control application. For a MIMO system one manipulated variable can be affected by more than one output variable. In order to reduce close loop interaction, we follow decoupling technique.

4.1 Conventional Decoupling

First, consider conventional decoupling and we will discuss two input and two output process. This technique can be implemented on more number of input and output but the complexity of implementation increases.

Here we assume the process transfer function G_{Pij} can be represented by gain, time constant and dead time. Following equations relate process output y_i to process input x_j

$$\begin{aligned} y_1 &= m_1 G_{P11} + m_2 G_{P12} \\ y_2 &= m_1 G_{P21} + m_2 G_{P22} \end{aligned} \tag{30}$$

While the following equations relate process inputs m_j to controller outputs c_k through decoupling elements T_{ij}

$$\begin{aligned} m_1 &= c_1 T_{11} + c_2 T_{12} \\ m_2 &= c_1 T_{21} + c_2 T_{22} \end{aligned} \tag{31}$$

Put value of m_j from equation (31) into equation (30)

$$\begin{aligned} y_1 &= (c_1 T_{11} + c_2 T_{12}) G_{P11} + (c_1 T_{21} + c_2 T_{22}) G_{P12} \\ y_2 &= (c_1 T_{11} + c_2 T_{12}) G_{P21} + (c_1 T_{21} + c_2 T_{22}) G_{P22} \end{aligned} \tag{32}$$

Equation (32) can be simplified by two approaches. The first approach gives complicated transfer function for decoupling elements, but results desirable "apparent" process control loop. The second one gives the simple transfer function, but it does not match to desirable output of process. These approaches are termed as "ideal" and "simplified" respectively.

We want the apparent process equation to be:

$$\begin{aligned} y_1 &= c_1 G_{P11} \\ y_2 &= c_1 G_{P22} \end{aligned} \tag{33}$$

Equation (32) and (33) provides below four equations

$$
\begin{aligned}
T_{11} &= \frac{G_{P22}G_{P11}}{G_{P22}G_{P11} - G_{P12}G_{P21}} \\
T_{12} &= \frac{-G_{P12}G_{P22}}{G_{P22}G_{P11} - G_{P12}G_{P21}} \\
T_{21} &= \frac{-G_{P21}G_{P11}}{G_{P22}G_{P11} - G_{P12}G_{P21}} \\
T_{22} &= \frac{G_{P22}G_{P11}}{G_{P22}G_{P11} - G_{P12}G_{P21}}
\end{aligned}
\tag{34}
$$

4.2 Simplified decoupling

In equation (3), if we arbitrarily assign $T_{11} = T_{22} = 1$, we can solve for T_{21} and T_{12}.

$$
\begin{aligned}
T_{12} &= -G_{P12} / G_{P11} \\
T_{21} &= -G_{P21} / G_{P22}
\end{aligned}
\tag{35}
$$

It results in a structure shown in figure. Now put the value of decoupling elements from the equation (35) into equation (32) which yields apparent process equations given below

$$
\begin{aligned}
y_1 &= \frac{G_{P22}G_{P11} - G_{P12}G_{P21}}{G_{P22}} c_1 \\
y_2 &= \frac{G_{P22}G_{P11} - G_{P12}G_{P21}}{G_{P11}} c_2
\end{aligned}
\tag{36}
$$

Here it is simple to implement decoupling elements; if process is modelled by first order lag plus dead time elements.

$$
G_{Pij} = -K_{ij} e^{T_{dij} s} / T_{ij} s + 1 \tag{37}
$$

Then each decoupling element has steady state gain and dead time elements. However the apparent process differs from process when no decoupling elements are applied and only one controller at a time.

Disadvantage of conventional decoupling is common to both ideal and simplified approaches. It assumes all computed process input signals retain their integrity.

4.3 Inverted decoupling

For inverted decoupling, decoupling circuits are represented by the equations

$$
\begin{aligned}
m_1 &= c_1 + m_2 T_{12} \\
m_2 &= c_2 + m_1 T_{21}
\end{aligned}
\tag{38}
$$

If we put m_j the value of equation 9 in equation 1, we get the same representation of decoupling elements as for simplified decouplers given by equation (35).

The advantage of using inverted decoupler is the apparent process calculated, when decoupling is implemented is same as when there is no decouplers. Any abnormalities cannot hamper the control loop.

Before using inverted decoupler, there are certain things must be considered. These are

1. Realizability
2. Stability
3. Robustness

1. Realizability

As it is given in the literature, if $T_{d11} \le T_{d12}$ and $T_{d22} \le T_{d21}$, then both $\frac{G_{P12}}{G_{P11}}$ and $\frac{G_{P21}}{G_{P22}}$ are realizable.

$$T_{d12} = \frac{G_{P12}}{G_{P11}}$$

$$T_{d21} = \frac{G_{P21}}{G_{P22}}$$

2. Stability

Figure 3.1: Equivalent feedback loop created by inverted decoupler

The loop equation is given by

$$\frac{m_i(s)}{c_i(s)} = \frac{1}{1 - \frac{G_{P21}G_{P12}}{G_{P22}G_{P11}}}$$

If G_{Pij} represented as first order lag plus dead time, then the loop equation is:

$$\frac{m_i(s)}{c_i(s)} = \frac{1}{1 - K\dfrac{(T_{d11}s+1)(T_{d22}s+1)e^{-T_d s}}{(T_{d12}s+1)(T_{d21}s+1)}}$$

$$T_d = T_{d12} - T_{d11} + T_{d21} - T_{d22}$$

There are limitations on T_d and K value, which are must be satisfied for decoupling to be feasible i.e. stable.

3 .Robustness

It is found from the literature that ideal decoupling is sensitive to modelling errors. Steady state gain value depends on model parameters. So we have to choose model parameters so wisely to get the K value which makes sure that inverted decoupling meets robustness. From the literature, it is also found that inverted decoupling is only applicable to dual composition, material balance distillation control strategies.

4.4 Models of distillation column

The Wood and Berry model is based on a 9 inch diameter, 8-tray binary distillation column which separates methanol from water. It can be represented as

$$\begin{bmatrix} y_1 \\ y_2 \end{bmatrix} = \begin{bmatrix} \dfrac{12.8e^{-s}}{16.7s+1} & \dfrac{-18.6e^{-3s}}{21s+1} \\ \dfrac{6.6e^{-7s}}{10.9s+1} & \dfrac{-19.4e^{-3s}}{14.4s+1} \end{bmatrix} \begin{bmatrix} u_1 \\ u_2 \end{bmatrix} + \begin{bmatrix} \dfrac{3.8e^{-8s}}{14.9s+1} \\ \dfrac{4.9e^{-3.4s}}{13.2s+1} \end{bmatrix} d$$

Here y_1 is the mole fraction of methanol in distillate [mol%], y_2 is mole fraction of methanol in bottom [mol%], u_1 represents reflux flow rate [lb/ min], u_2 represents steam flow rate [lb/ min], and d is unmeasured feed flow rate [lb / min].

We use two PID controller. One controller controls distillate product purity and other control bottom product purity.

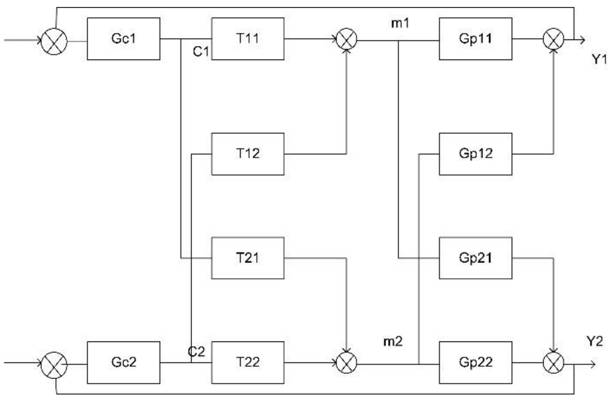

Figure 3.2: PID control using conventional decoupling

Different tuning methods are given for PID controller in table 23.

Table 23

Tuning parameters for PID controller

Tuning methods	K_{c1}	T_{i1}	K_{c2}	T_{i2}
Astrom et.al	0.8219	3.2	-0.158	9.6
BLT method	0.375	8.2	-0.07	23.6
Fruehauf et.al	0.7248	5	-0.1374	15
Z-N	0.6	16.37	-0.124	16.12

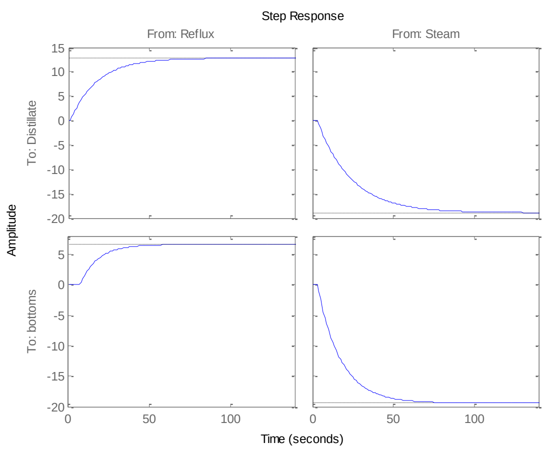

Figure 3.3: Open loop step response analysis

4.5 Simulation result and analysis

Fig.3.3 shows the open loop step response of distillation column. PID controller using Ziegler-Nichold tuning method is used to control Distillation Column. (Refer figure3. 6) It can be seen from the graph the top and bottom product are unstable and overshoot needed to be removed. So the decoupler is used. Here we used to simplify and inverted decoupler for different tuning parameters given in the table. To have a comparison between[9-10] the two methods different transient parameters such as maximum overshoot M_p and settling time t_s as IAE and ISE are evaluated. Table II summarizes the performance of PID controller with simplified decoupler to control the bottom product of the binary distillation column.

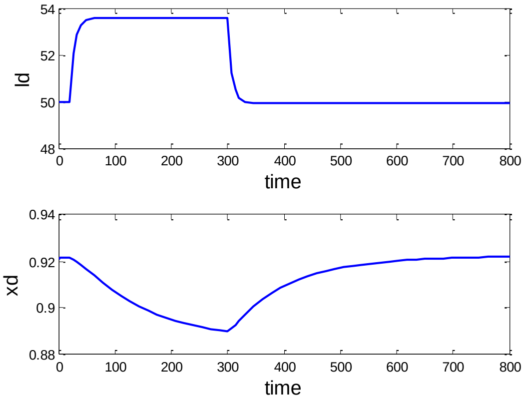

Figure 3.4: Change in flow rate of distillation column

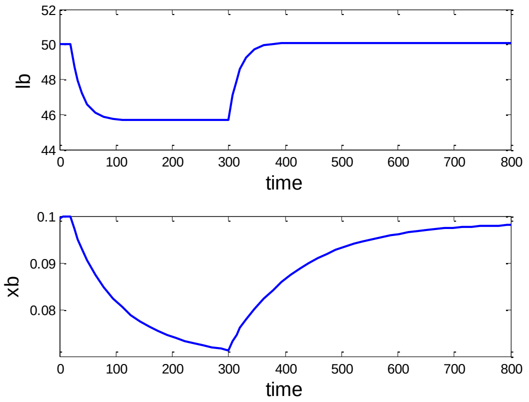

Figure 3.5: Change in flow rate of distilaltion column

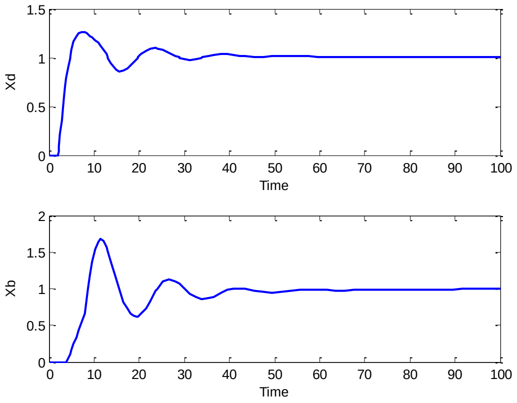

Figure 3.6: Response of PID controller without decoupler

4.5.1 Control of distillation column using PID control (simplified decoupled)

Figure 3.7 is the block diagram of control of distillation column using PID control with simplified decoupler.

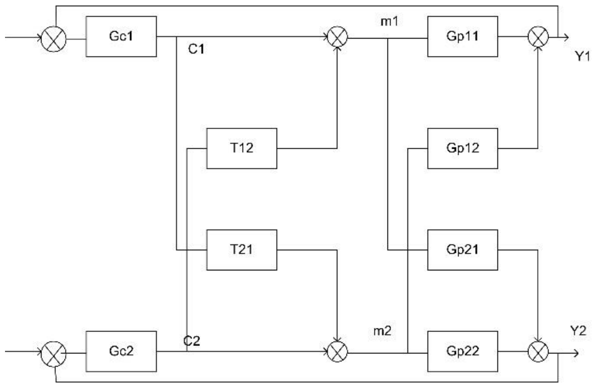

Figure 3.7:. Control of MIMO plant with simplified decoupler

Table 23, 24 summarizes the performance of PID controller with simplified decoupler to control the bottom product and distillate product of the binary distillation column respectively.

Table 24

Transient Parameters of response (Bottom product) for simplified decoupler

Tuning methods	M_p	t_s	ISE	IAE
Astrom et.al	16.94	31.45	5.011	8.397
BLT method	2.128	27.72	12.76	28.55
Fruehauf et.al	6.77	15.23	4.85	6.35
Z-N	-0.715	48.44	6.346	13.26

Table 25

Transient Parameters of response (Distillate product) for simplified decoupler

Tuning methods	M_p	t_s	ISE	IAE
Astrom et.al	56.96	100	12.12	30.14
BLT method	3.969	14.31	2.346	4.395
Fruehauf et.al	50.94	51.53	3.253	9.169
Z-N	2.128	27.72	2.137	4.441

4.5.2 Control of distillation column using PID control (inverted decoupler)

Table 25, 26 provides the performance of PID controller with inverted decoupler to control the distillate product and bottom product of the binary distillation column respectively.

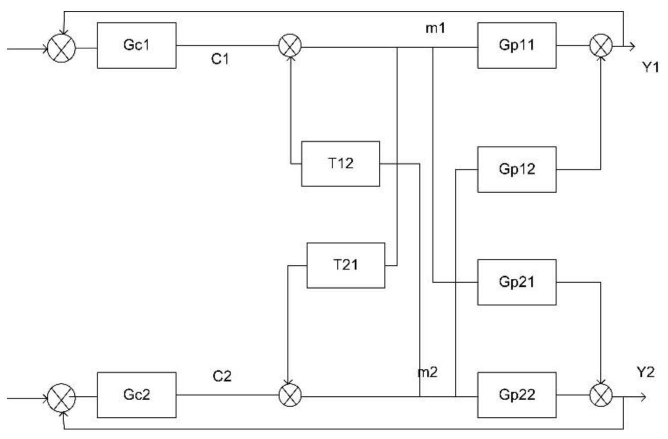

Figure 3.8:. Control of MIMO plant with inverted decoupler

Table 26

Transient Parameters of response (Distillate product) for inverted decoupler

Tuning methods	M_p	t_s	ISE	IAE
Astrom et.al	54.42	10.299	2.1232	3.466
BLT method	10.43	19.03	2.293	4.21
Fruehauf et.al	50.84	47.45	3.243	8.987
Z-N	2.12	4.6088	1.754	2.301

Table 27

Transient Parameters of response (Bottom product) for inverted decoupler

Tuning methods	M_p	t_s	ISE	IAE
Astrom et.al	88.1	91.87	13.25	25.89
BLT method	-1.45	60.39	7.181	15.76
Fruehauf et.al	6.81	15.44	4.85	8.987
Z-N	1.177	11.31	1.754	2.301

Fig. 3.7 shows the response of simplified decoupler to control bottom product of distillation columns. Fig. 3.8 shows the response of simplified decoupler to control distillate product of distillation columns. Fig.3.9 and Fig. 3.10 show the response of inverted decoupler to control bottom product and distillation product of distillation column respectively.

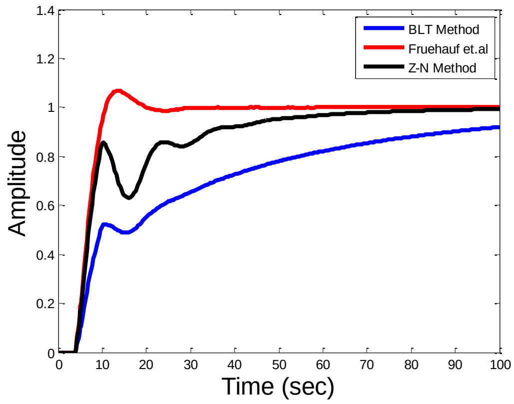

Figure 3.9: Response of simplified de-coupler to control bottom product

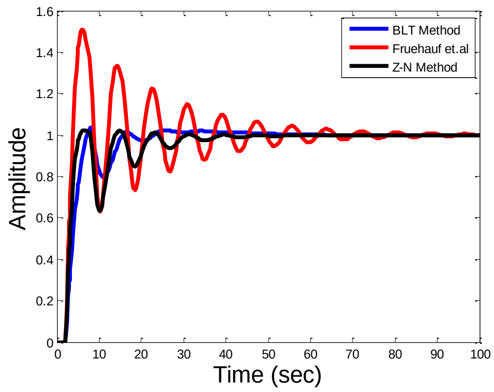

Figure 3.10: Response of simplified de-coupler to control distillate product

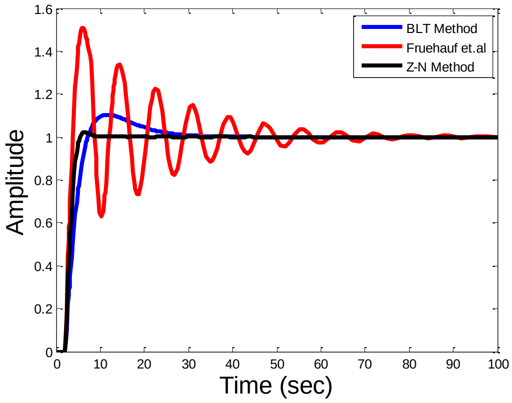

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Figure 3.11: Response of inverted decoupler to control the bottom product

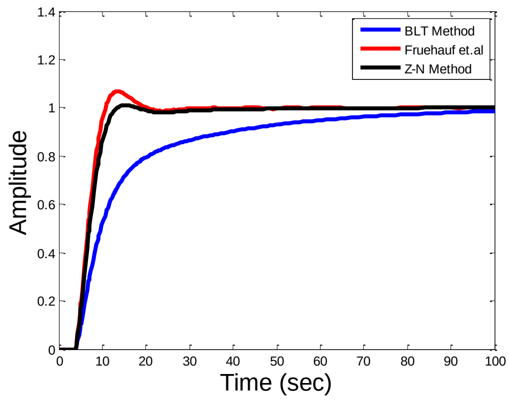


Figure 3.12: Response of inverted decoupler to contol the distillate product

CHAPTER 5

CONTROL OF DISTILLATION COLUMN BY MPC

Wood and Berry Model

Ogunnaike and ray Model

Comparison between PID and MPC

CONTROL OF DISTILLATION COLUMN BY MPC

In this chapter different models for distillation column is taken and distillation column is controlled by the model predictive controller

5.1 Model Predictive Control

The output vector can be represented in a MIMO control $O = \left[O_1 O_2 --O_m \right]^T$ and input vector can be represented as

$I = \left[I_1 I_2 --I_r \right]^T$

The MIMO model for the corrected prediction can be represented as

$$\hat{o}(k+1) = s\Delta i(k) + \hat{o}^0(k+1) + \phi[o(k) - \hat{o}(k)] \tag{39}$$

$$\hat{o}(k+1) = \begin{bmatrix} \hat{o}(k+1) \\ \hat{o}(k+2) \\ : \\ \hat{o}(k+P) \end{bmatrix}$$

$$\Delta i(k) = \begin{bmatrix} \Delta i(k) \\ \Delta i(k+1) \\ : \\ \Delta i(k+m-1) \end{bmatrix}$$

We can defined the dynamic matrix as

$$s = \begin{pmatrix} s_1 & \cdots & 0 \\ \vdots & \ddots & \vdots \\ s_P & \cdots & s_{P-M+1} \end{pmatrix}$$

Fig. 5.1 shows the block diagram of model predictive control for distillation column

The quadratic performance index used for model predictive controller is expressed as

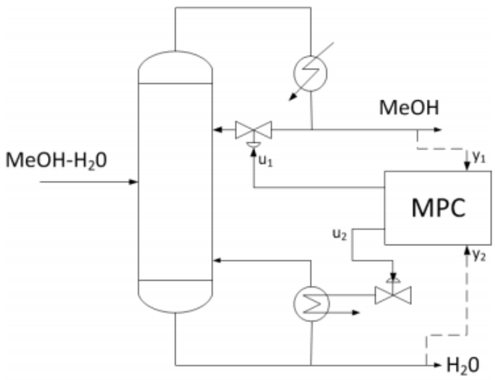
$$\overset{\min}{\Delta i(k)}\ j = \widehat{e}(k+1)^T q \widehat{e}(k+1) + \Delta i(k)^T r \Delta i(k) \tag{40}$$

Where q is a positive-definite weighting matrix and r is a positive semi-definite matrix. Both q and r are positive diagonal matrix. The control law for MPC can be derived by solving equation 40.

Now we can write control law as

$$\Delta i(k) = K_c \hat{e}^{\circ}(k+1) \tag{41}$$

Here $k_c = (s^T q s + r)^{-1} s^T q$



. Fig. 4.1: Block diagram representing control of distillation column by MPC

5.2 Models of distillation column

The wood and berry model that separate methanol from water can be represented as

$$\begin{bmatrix} y_1 \\ y_2 \end{bmatrix} = \begin{bmatrix} \dfrac{12.8e^{-s}}{16.7s+1} & \dfrac{-18.6e^{-3s}}{21s+1} \\ \dfrac{6.6e^{-7s}}{10.9s+1} & \dfrac{-19.4e^{-3s}}{14.4s+1} \end{bmatrix} \begin{bmatrix} u_1 \\ u_2 \end{bmatrix} + \begin{bmatrix} \dfrac{3.8e^{-8s}}{14.9s+1} \\ \dfrac{4.9e^{-3.4s}}{13.2s+1} \end{bmatrix} d$$

Here y_1 is mole fraction of methanol in distillate [mol%], y_2 is mole fraction of methanol in bottom [mol%], u_1 represents reflux flow rate [lb/ min], u_2 represents steam flow rate [lb/ min], and d is unmeasured feed flow rate [lb / min].

5.3 Set point tracking

In the first scenario, the wood and berry model is used to observe set point tracking using model predictive controller. The set point change in output Y1 and Y2 is applied at t=0 Sec.

We select P=10, M=2, w=0. 25, N=50 for MPC tool box to get a response.

Here no constraints were applied on MVs. Again, the controller is capable tracking the set point and taking products purity back to their set point.(refer figure 4.2)

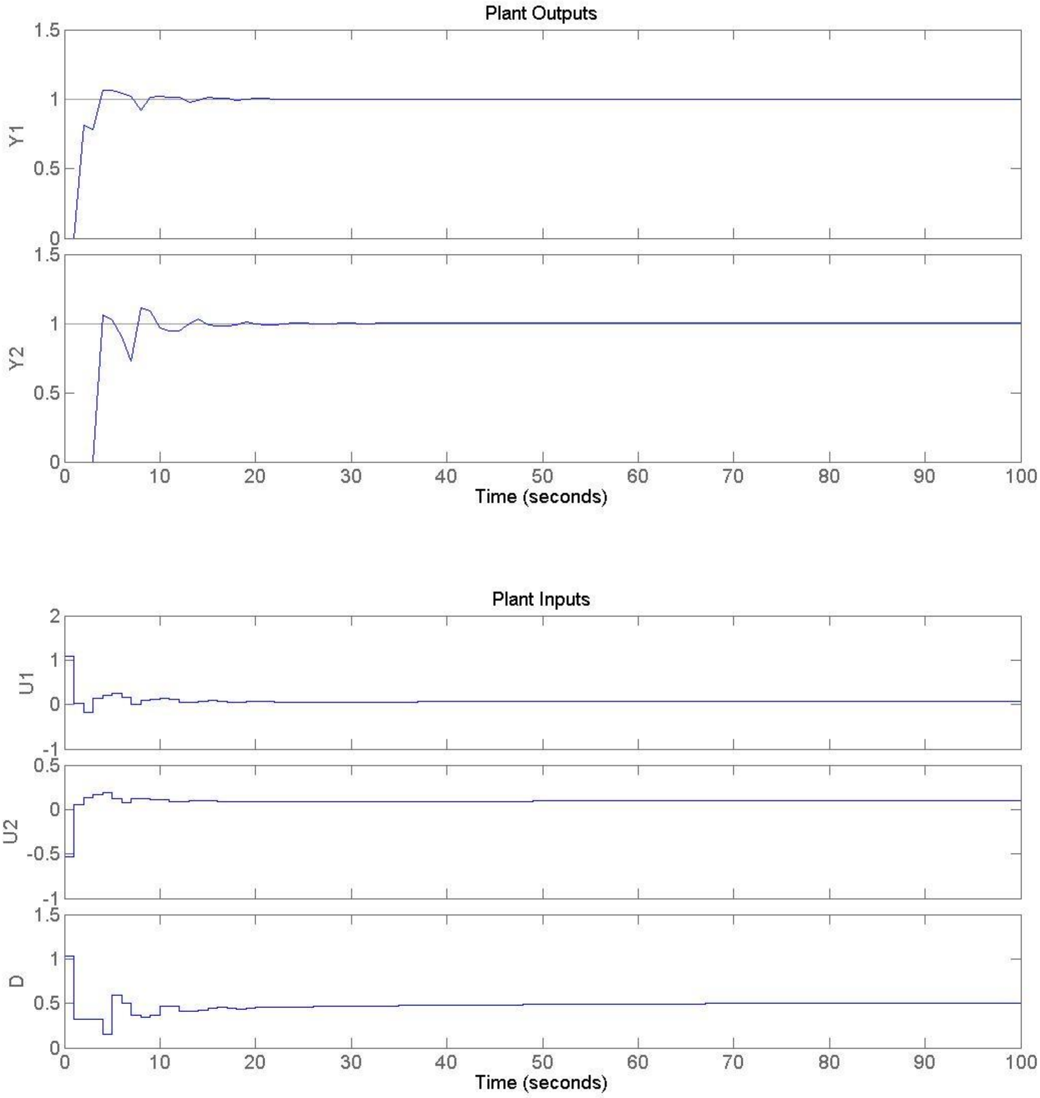


Figure 4.2: Response of MPC controller for wood and berry model

5.4 Disturbance rejection

In the second scenario, the wood and berry model is used to observe disturbance rejection using model predictive controller. A pulse change in feed flow rate is applied at t=10 sec. Prediction and a control horizons were equal to P=10, M=2 respectively. Here no constraints were applied on MVs. Again, the controller is capable of rejecting his disturbance in feed composition and taking products purity back to their set point. (Refer figure 4.3)

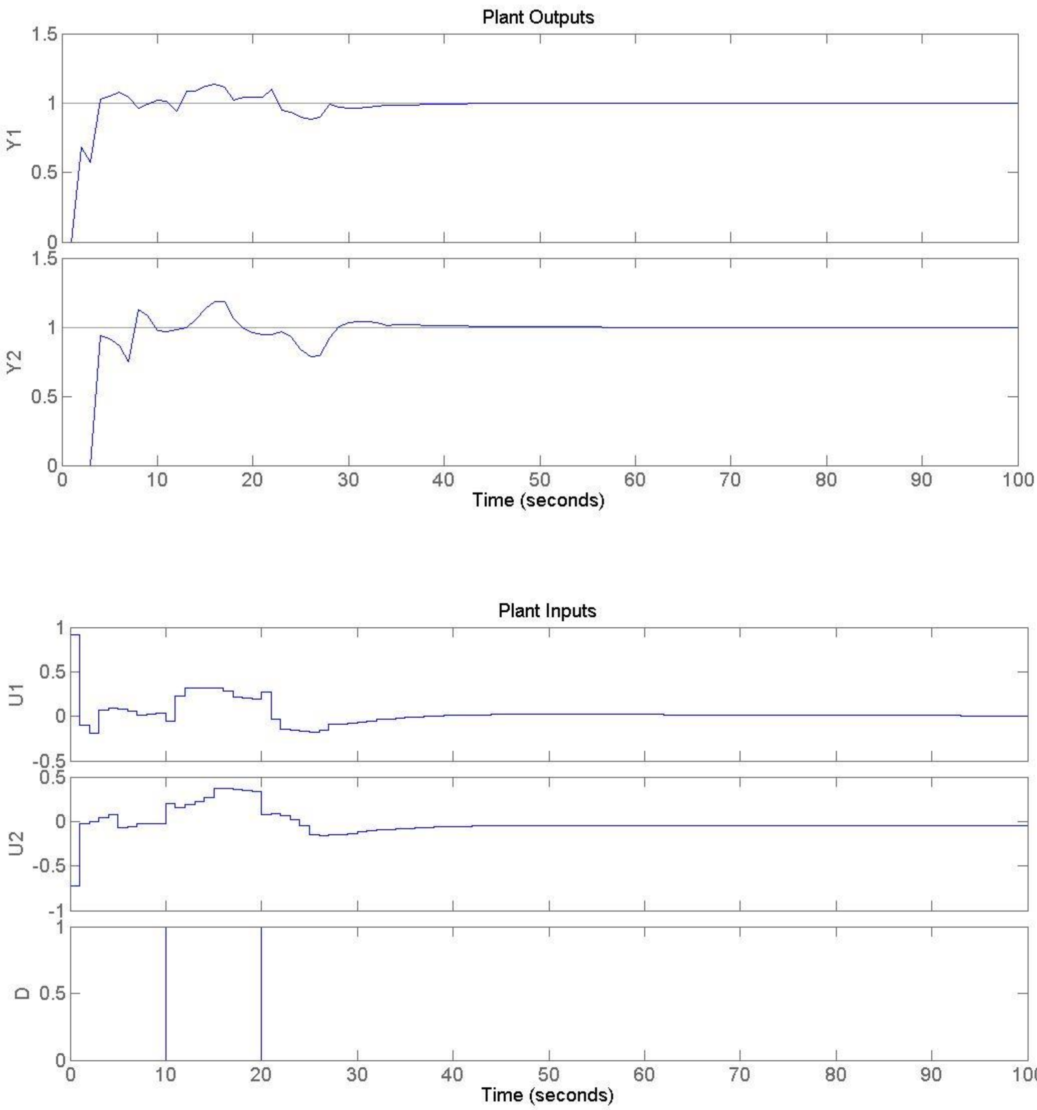


Figure4.3: Response of MPC controller for wood and berry model

In the third scenario, we increased the control horizon value to 5 keeping other tuning parameters constant. Here we got a better result than previous one in terms of disturbance rejection but the changes in manipulated variables increased. (Refer figure 4.4)

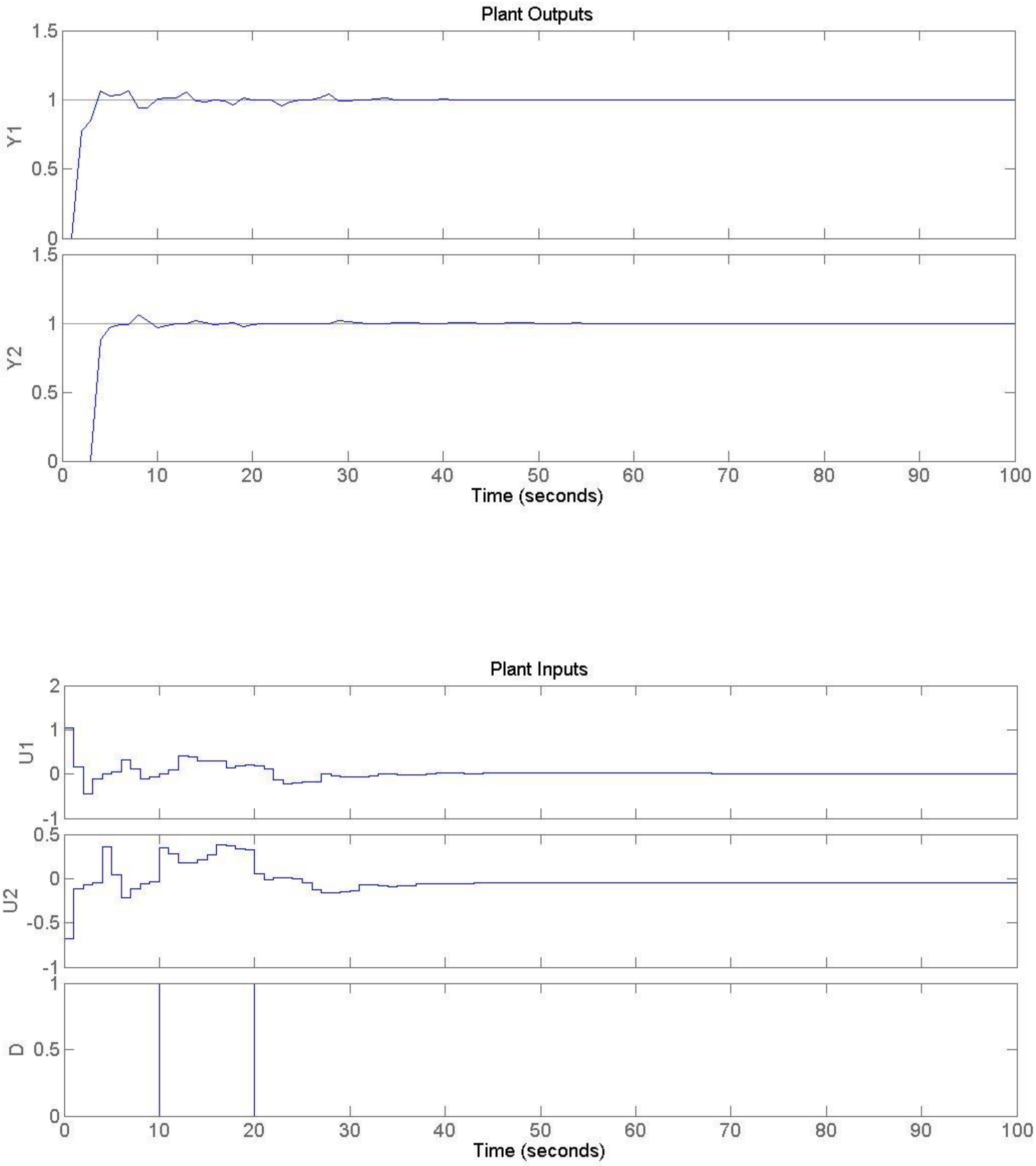


Figure4.4: Response of MPC controller for wood and berry model

5.5 Distillation Process

$$\begin{bmatrix} y_1 \\ y_2 \end{bmatrix} = \begin{bmatrix} \dfrac{0.013e^{-0.1s}}{s+0.125} & \dfrac{-0.016e^{-0.3s}}{s+0.097} \\ \dfrac{-0.013e^{-0.4s}}{s+0.093} & \dfrac{-0.014e^{-0.1s}}{s+0.117} \end{bmatrix} \begin{bmatrix} u_1 \\ u_2 \end{bmatrix} + \begin{bmatrix} \dfrac{0.031e^{-0.4s}}{s+0.131} \\ \dfrac{0.057e^{-0.5s}}{s+0.095} \end{bmatrix} d$$

y_1 =mole fraction of product in distillate (mol%)

y_2 = mole fraction of product in bottom (mol%)

u_1 =Reflux ratio

u_2 =Reboil/steam ratio

d =Light component mole fraction in feed stream (mol%)

The above model is given by Abdallah Al-Samaria, Naim Faqir of the department of chemical engineering, king Fahd University of petroleum and mineral. The form of the transfer function is similar to Wood and Berry model. The major difference is that here unmeasured disturbance is light component mole fraction in feed stream where as in Wood and Berry model feed flow rate is disturbance variable. Indeed, because of lack of composition analysis in a chemical plant, one must consider feed composition as an unmeasured disturbance. On the other hand, feed flow rate is easily determined using a flow meter. It is easier to set bounds (constraints) on reflux ratio and reboil ratio than on its flow rates [14].

In the first scenario, a pulse change in feed composition was applied at t=10 Sec. Prediction and a control horizons were equal to P=35, M=5 respectively. Here no constraints were applied on MVs. Again, the controller is capable of rejecting his disturbance in feed composition and taking products purity back to their set point. (Refer figure 4.5)

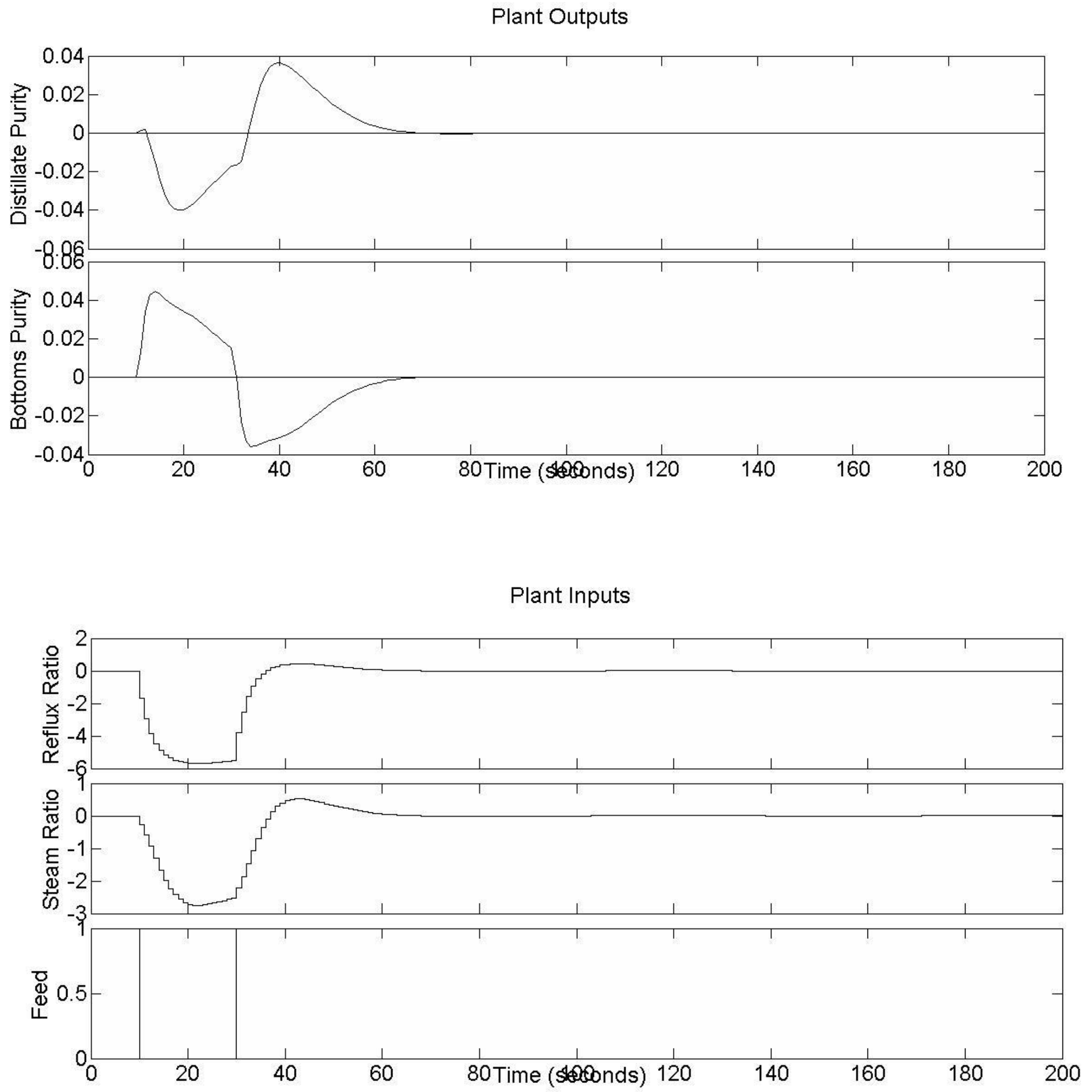


Figure 4.5: Control of MIMO plant by MPC

In the second scenario a step change in set points of distillate purity and bottom purity without any change in feed composition was performed [17-18]. Here we select prediction and control horizons such that P=35, M=5 respectively. Constraints on MVs have been applied as follows -0.25<=R,S<=0.25.Although there are restriction movement of MVS, controller achieved new set point by increasing both reflux ratio and steam ratio(both reached saturation) . (Refer figure 4.6)

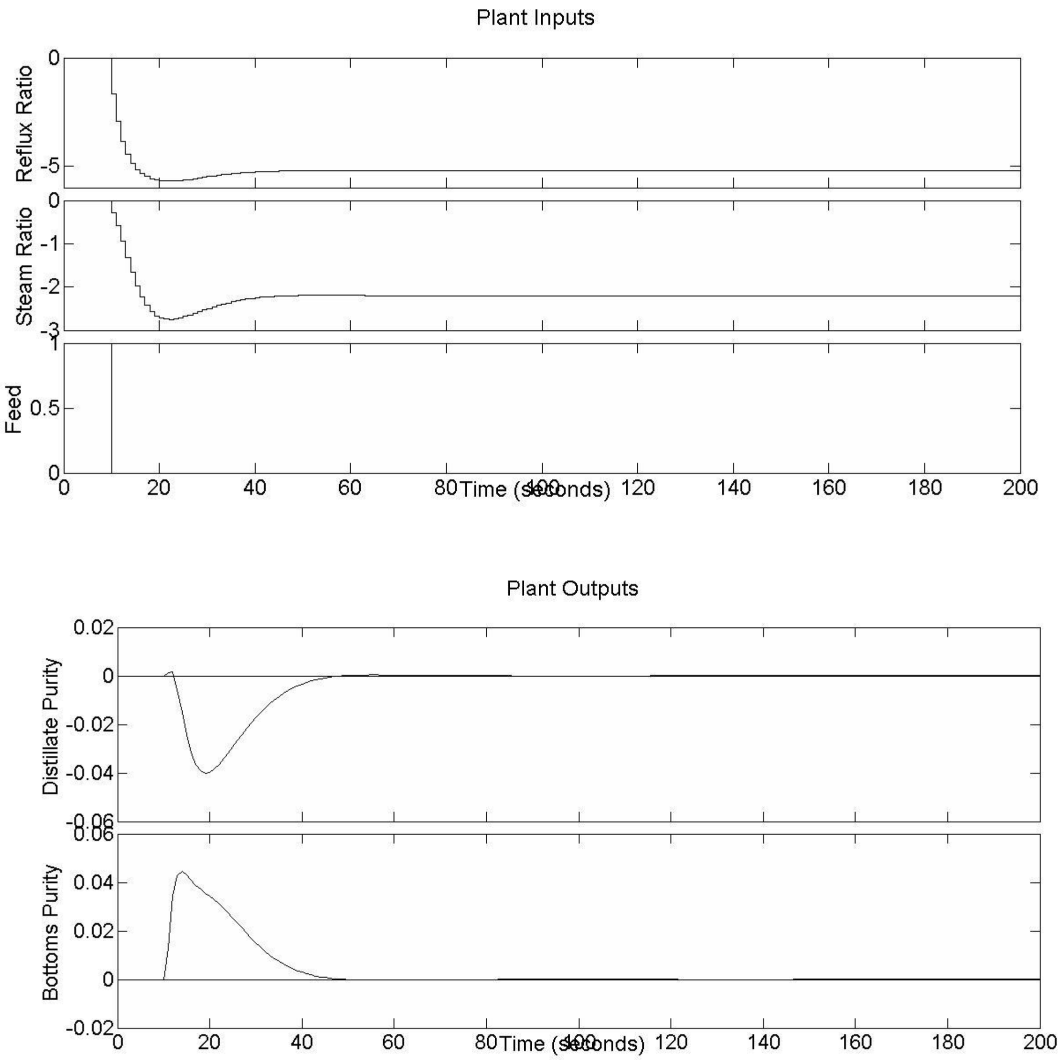


Figure 4.6: Control of MIMO plant by MPC

In the third scenario, it is observed that if we apply constraints on MVs (-1<R, S<=2.5).Controller is able to reject the disturbance by reaching the saturation limit. . (Refer figure 4.7)

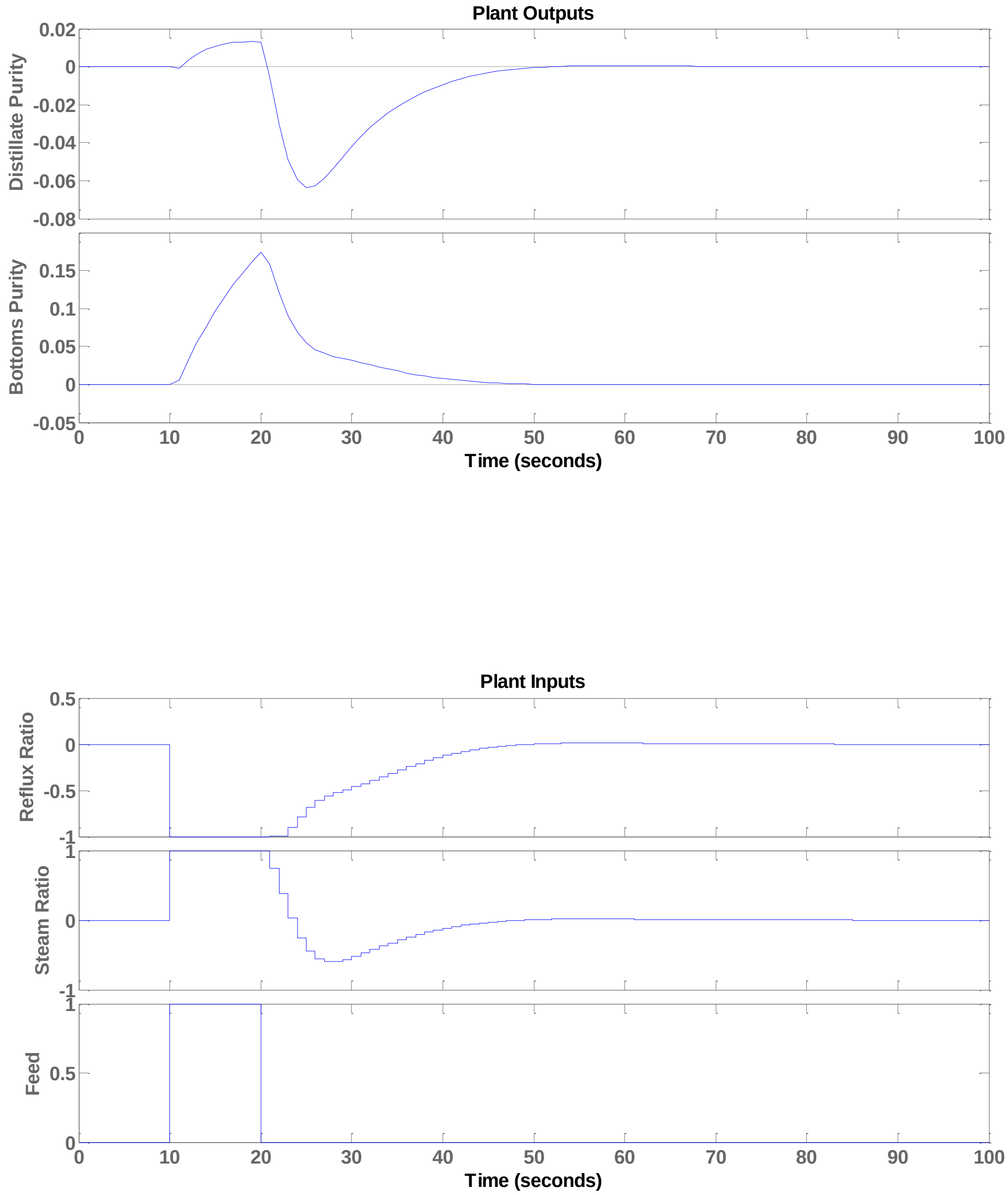
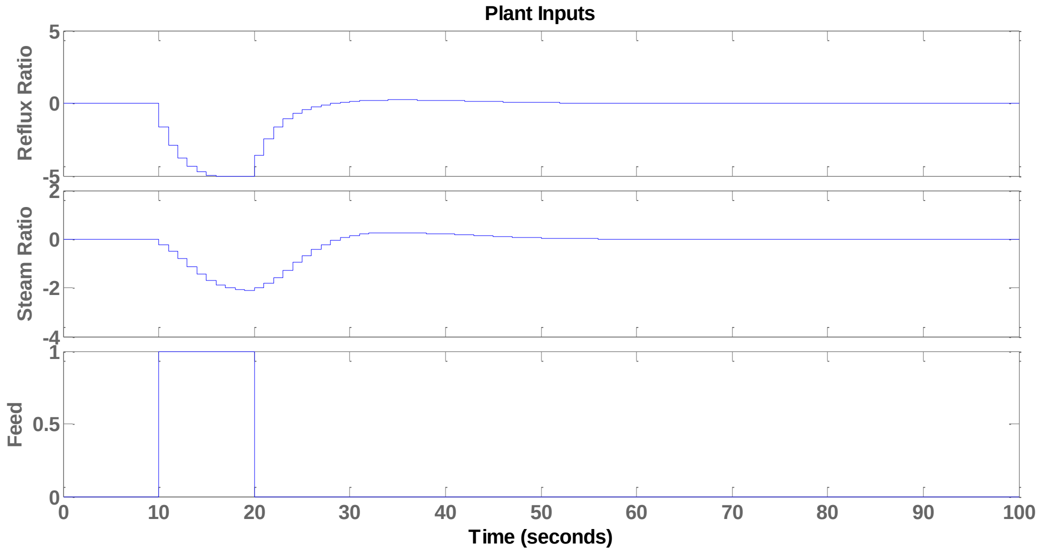


Figure 4.7: Control of MIMO plant by MPC

However, when constraints on MVs were more relaxed (-5<=R, S<=5) controller was able to reject the disturbance only reaching saturation level in reflux ratio but not in steam ratio. But it will take more time to reject the disturbance. (Refer figure 4.8)



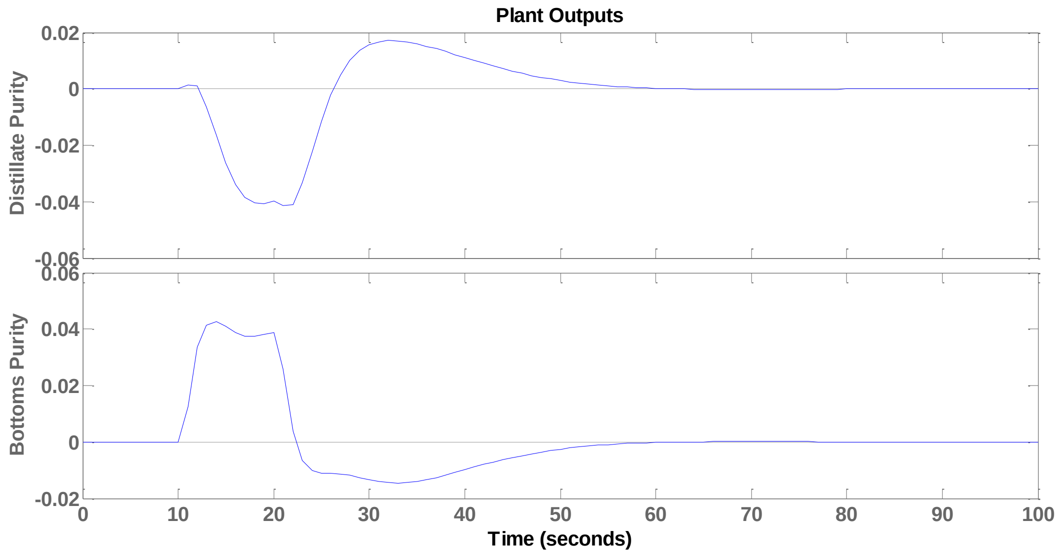


Figure 4.8: Control of MIMO plant by MPC

5.6 Ogunnaike and ray Model

$$\begin{bmatrix} y_1 \\ y_2 \\ y_3 \end{bmatrix} = \begin{bmatrix} \dfrac{0.66e^{-2.6s}}{6.7s+1} & \dfrac{-0.61e^{-3.5s}}{8.64s+0.097} & \dfrac{-0.0049e^{-0.1s}}{9.06s+1} \\ \dfrac{-1.11e^{-6.5s}}{3.25s+1} & \dfrac{-2.3e^{-0.1s}}{5s+1} & \dfrac{-0.012e^{-0.4s}}{s+0.093} \\ \dfrac{-34.68e^{-9.2s}}{8.15s+1} & \dfrac{-46.2e^{-9.4s}}{10.9s+1} & \dfrac{-0.0032(19.32s+1)e^{-2.6s}}{(8.94s+1)(7.29s+1)} \end{bmatrix} \begin{bmatrix} u_1 \\ u_2 \\ u_3 \end{bmatrix}$$

$$+ \begin{bmatrix} \dfrac{0.1e^{-12s}}{6.2s+1} & \dfrac{-0.0011(26.32s+1)e^{-2.6s}}{(7.85s+1)(14.63s+1)} \\ \dfrac{0.53e^{-10.5s}}{6.9s+1} & \dfrac{-0.0032(19.62s+1)e^{-3.44s}}{(7.29s+1)(8.94s+1)} \end{bmatrix} \begin{bmatrix} d_1 \\ d_2 \end{bmatrix}$$

y_1 =Ethanol purity (mole fraction) for over head

y_2 = Ethanol purity (mole fraction) for side stream

y_3 =Temperature at tray (#19) (‘c)

u_1 =Overhead reflux flow (L/sec)

u_2 =Side stream draw off flow rate (L/sec)

u_3 =Reboiler Stream pressure (KPa)

d_1 = Feed flow rate (L/sec)

d_2 = Feed temperature (‘c)

By considering above model, we describe constraint and unconstrained behaviour.

In the first scenario, value of prediction horizon and control horizon are P=15, M=3 respectively. N=100, sampling time=1. (refer figure 4.9)

$-0.06 \le u1 \le 0.06$ $\quad$ $-0.06 \le \Delta u1 \le 0.06$

$-15 \le u2 \le 15$ $\quad$ $-1.5 \le \Delta u2 \le 1.5$

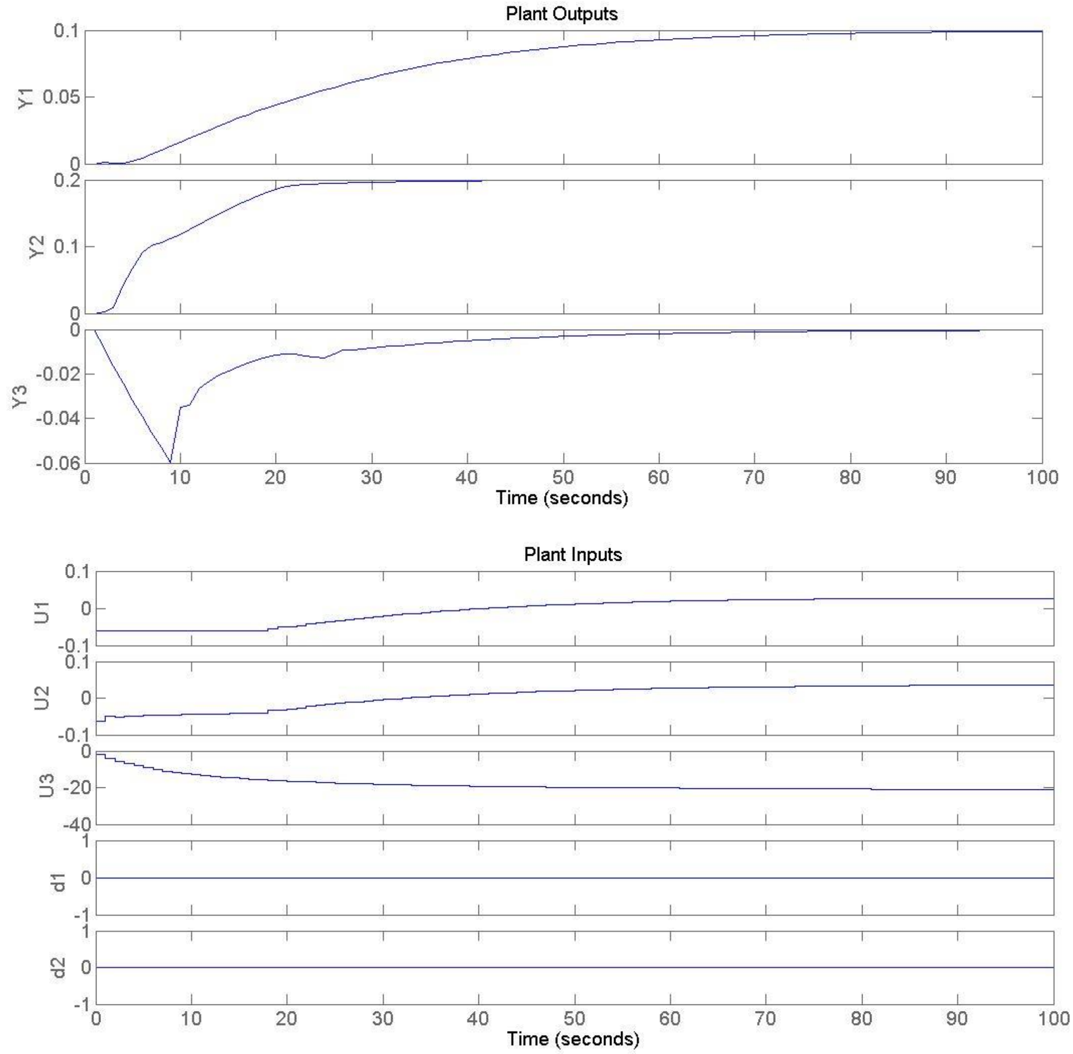


Figure 4.9: Control of MIMO plant b MPC

From the second scenario, it is found that when the MPC is the unconstrained close loop response of all variable showed [15] good performance. In case of constrained MPC, Y1 response still shows improvement, while Y2 response degrades substantially. This is because of high interaction and input saturation.

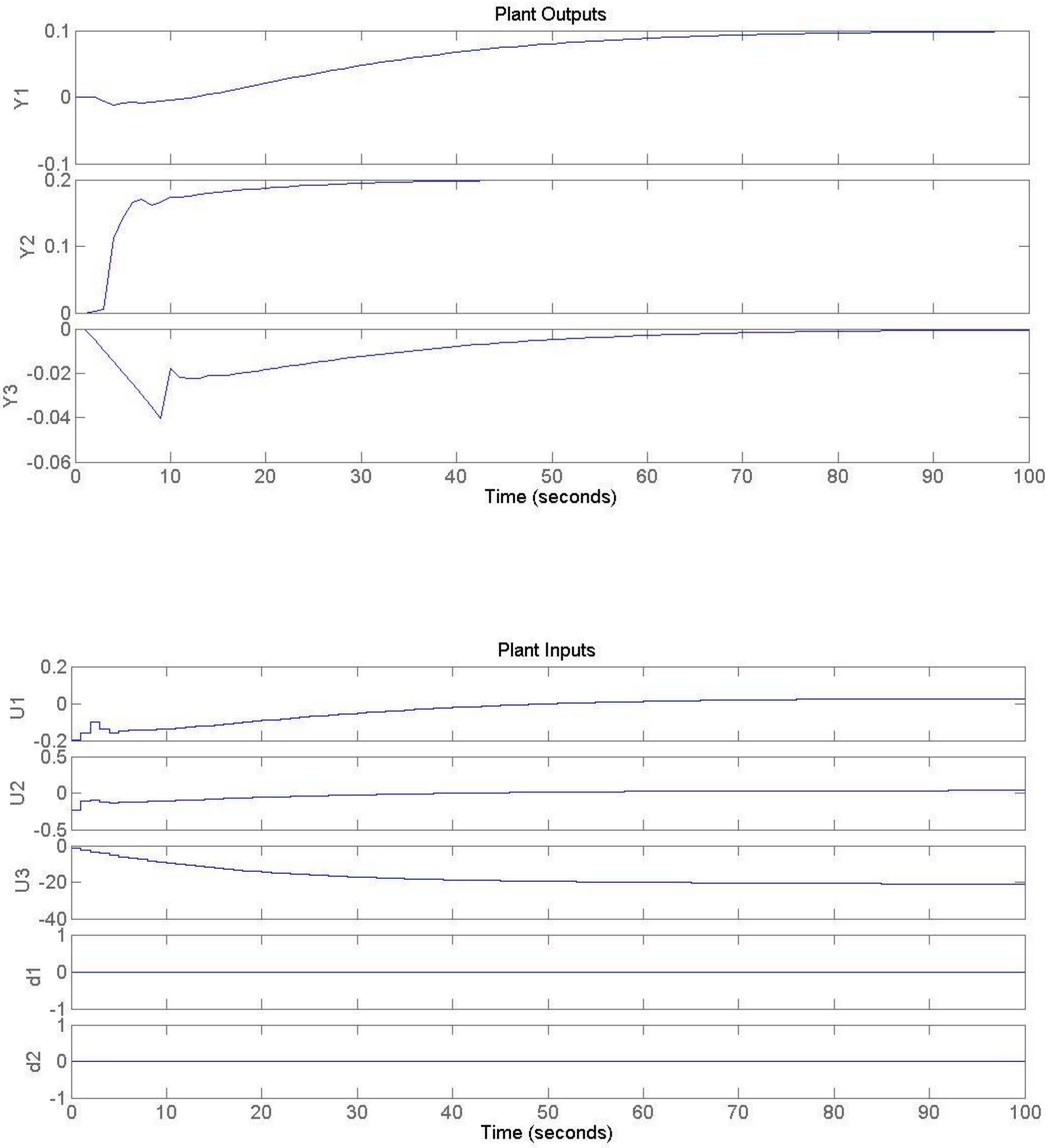


Figure 4.10: Control of MIMO plant by MPC

5.7 Comparison between PID and MPC

MPC handles MIMO system effectively, but for PID controller it is difficult to get response to a complex system (large time delay and high dynamics) [21].

Set point tracking

If we observe the response of PID controller, it varies its control after the change in set point, but for MPC, it begins changing control before the change in set point.

Disturbance Rejection

For both MPC and PID, the disturbance is not predicted in advance. So there is not much difference between the responses of the two controllers.

Robustness

As MPC is highly based on the model, so if model mismatch occurs, then set point tracking is not possible for the MPC.

Constraint handling

MPC able to handle constraint and this feature is not available to PID.

CHAPTER 6

CONCLUSION AND FUTURE WORK

Conclusion

Future Work

CONCLUSION AND FUTURE SCOPE

This chapter concludes the work and provides idea about future work.

5.1 Conclusion

DMC is most preferable algorithm in the chemical industry. So first we have developed an LTI model for DMC algorithm. First tuning parameters effect is observed on first order and second order systems by calculating transient parameters like rise time, peak overshoot and settling time. Then for a specific FOPDT [23], closed loop poles are calculated by varying tuning parameters. From all the above result a conclusion is made regarding tuning parameters effect on the response of the system. A design rule for DMC is derived for quick start of the process.

Distillation column is considered for the case study. First distillation column's output such as distillate product and bottom product are controlled by using PID controller. The decouplers are used for reducing close loop interaction. It is concluded from the chapter that inverted decoupler gives better performance than simplified decoupler. PID controller alone cannot handle MIMO system. It requires decouplers [22].

Various models are taken for distillation column to observe the response by using MPC. A comparison between PID and MPC is also provided. Following key points are concluded from the observation

1. MPC can compensate for dead time
2. In order to compensate measurable disturbance, MPC provides feed forward control
3. In a very easy way, MPC can handle constraints
4. In order to implement MPC, knowledge about model is necessary
5. When we are considering the constraints, then the computational complexity is more.

5.2 Future scope

Due to restriction of time, some jobs are still there to be done in this project work. Especially the controller must be implemented on the real plant. MPC can only be used for the system having slow dynamics. This is the main disadvantage of this controller. So the algorithm must be improved for handling system having complex dynamics. When we put constraints on input and output, then in the MIMO system amount of computation becomes very high. So optimal work must be performed to reduce computation complexity. The generic neural network based technique can be used to represent the nonlinear model.

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