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‘MASTER’

In Control Engineering

Option: Control

Title:

Study And Simulation Of Predictive Control Applied To Binary Distillation Column

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you given us the guidance and the power to believe in ourselves, and the help to complete this work successfully.

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Finally, our deep thanks to all people who have supported us to complete this work among them our friends and IAP formers.

DEDICATION

I dedicate this work to my ***Parents***

To ***family****,* ***friends,*** *and* ***classmates***

Adel

*"****To family and friends****"*

Islem

ABSTRACT

Despite the advanced reach of multivariable control theory, multiloop control remains the most widely used control technique in the chemical process industry. This project aims to apply a multivariable control technique on the field, most precisely on the distillation column, this was done by proposing a new Technique Model Predictive Control (MPC), and comparing its results with the ones obtained from the conventional controller, furthermore, because it is a new technique, although many companies deal with it, it remains a new technique for the engineers, we proposed several procedures to tune the Model Predictive Control (MPC) controller.

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NOMENCLATURES

PID	Proportional-Integral-Derivative
FOPDT	First Order Plus Dead time
RGA	Relative Gain Array
MIMO	Multiple Input Multiple Output
SISO	Single Input Single Output
MPC	Model Predictive Control
DMC	Dynamic Matrix Control
IMC	Internal Model Control
QDMC	Quadratic Dynamic Matrix Control
GPC	Generalized Predictive Control
PFC	Predictive Functional Control

General Introduction

Our country is rich in natural resources especially oil and gas. Hydrocarbon production has a large portion of our economic revenue that make it a strategic field, so the state-owned company SONATRACH, the major company in Africa, focus on applying the leading technologies in the industrial market to cope with the market demands for product quality specifications.

The distillation is an essential operation in product purification and separation, the main process in the distillation is the Distillation column, since it provides high purity products and low cost of energy. Operating these columns efficiently necessitates a high level of automated control, due to its multi-input and multi-output representation, constraints caused by equipment, and the nonlinear behaviour. Practically the methods used are sufficient but has some drawbacks that leads to low performance in the distillation process.

In this report we are going to investigate the PID controller and feedforward control, furthermore, many other methods used in the distillation process control, including, cascade control, override control and on-off control. Using conventional methods engineers may encounter many problems such as interaction between the loops that makes the tuning challenging. Predictive control, has proven its benefit in the fields related to oil and gas industry, due to its ability to cater the problems of the conventional methods. This project is devoted to represent the leading control approach which is Model Predictive Control (MPC) that is based on the process model to predict the future behaviour of the controller system and can handle multivariable inputs, which can reduce the problems that encounter the conventional methods. The control of distillation column is carried out using simulation in HYSYS software.

This report is divided into 4 chapters organized as follow:

Chapter 1: a brief study on distillation column with presenting the basic control structures.

Chapter 2: gives some methods used in distillation column control, and deals with loops interaction by quantifying the interaction and the proposed solution using decouplers.

Chapter 3: this chapter introduces predictive control and explains DMC algorithm and its tuning parameters.

Chapter 4: demonstrates the model used in the HYSYS simulation and the application of MPC

Chapter 1: A brief study on distillation column

Chapter 1: A brief study on distillation column

1.1 Introduction

Distillation columns are key unit operations in chemical engineering, especially in the oil and gas industry, it is one of the most important and most commonly used methods of separation and is based on the distribution of components between two liquid and gas phases. This chapter aims to provide a general overview of the columns and the different strategies to control them.

1.2 Principle operation of distillation

Distillation is a crucial and most common separation unit operation in chemical engineering. Distillation is illustrated as a process that removes heat to separate a liquid or vapour mixture of two or more elements into its component fractions of desired purity, by the application and removal of heat. Distillation is based on the difference in the volatility of the components. The vapour of a boiling mixture will be richer in the components that have lower boiling points. Therefore, when this vapour is cooled and condensed, the condensate will contain more volatile and light components. At the same the time, the original mixture will contain more of the less volatile material, for example, water boils at 100°c and ethanol boils at around 83°C, at atmospheric pressure. If we heat the mixture to 92°c, the ethanol will boil and be transformed into vapour (which will be collected and condensed) while the water will remain as a liquid. This phenomenon is usually quantified by the relative volatility of the two components.

1.3 Distillation Column

1.3.1 Main Components of Distillation Column

Distillation columns (distillation towers) are made up of several components, each of which is used either to transfer heat energy or enhance material transfer. A typical distillation column consists of several major parts:

- A vertical shell where separation of the components is carried out.
- Column internals such as trays, plates, or packings are used to enhance component separation.
- A reboiler to provide the necessary vapourization for the distillation process.

- A condenser to cool and condense the vapour leaving the top of the column.
- A reflux drum to hold the condensed vapour from the top of the column so that liquid (reflux) can be recycled back to the column [1].

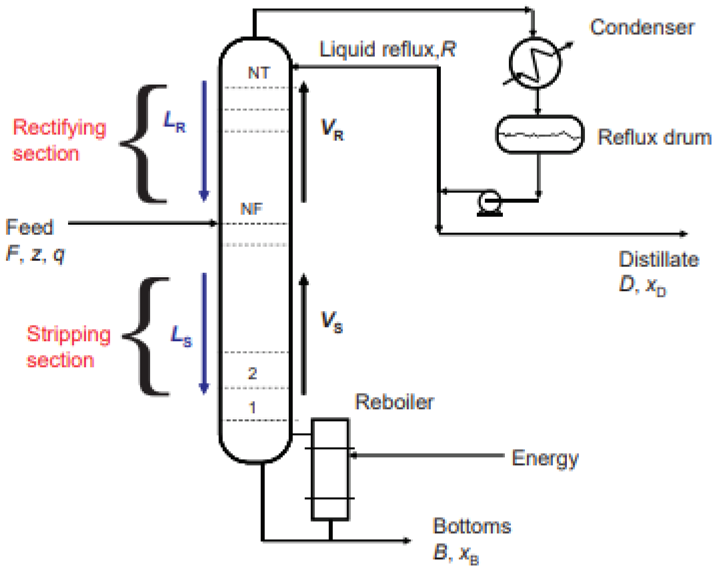


Figure 1-1.Representation of a distillation column plant [2]

- **Tower** [3]

A distillation column is a tube that provides surfaces on which condensations and vaporizations can occur before the gas enters the condenser to concentrate the more volatile liquid in the first fractions and the less volatile components in the later fractions.

- **Reboiler** [3]

The reboiler, which is usually placed at the ends of the tower and next to it, is responsible for providing heat or energy for distillation. reboiler is generally considered to be a distillation equilibrium.

- **Condenser** [3]

The role of the condenser is actually to convert the vapours from the combined heat treatment to the liquid. Generally, the condensers are divided into two basic categories:

Total Condenser

Partial condenser

If all the steam above the tower turns into a liquid and part of it enters the tower, and the other part enters the collecting tank, total condensation is carried out. But if part of the vapour is liquid and the other part is removed from the condenser in the form of steam, it is called a partial condenser.

- **Feed** [3]

A mixture of the inlet into the tower, which may be liquid, gas, or a mixture of liquid and gas, is a feed. Usually, the place of feed is at a specified point in the tower, which is predetermined.

1.3.2 Types of Distillation Column [4]

There are many types of distillation columns, each designed to perform specific types of separations, and each design differs in terms of complexity. One of classifying distillation column types is to look at how they are operated. Thus, we have:

- **Batch Columns**

In batch operation, the feed to the column is introduced batch-wise. That is, the column is charged with a 'batch', and then the distillation process is carried out. When the desired task is achieved, the next batch of feed is introduced.

- **Continuous Columns**

In contrast, continuous columns process a continuous feed stream, no interruptions occur unless there is a problem with the column or surrounding process units. They are capable of handling high throughputs and are the most common of the two types.

1.3.3 Basic operation and terminology [3]

The liquid mixture that is to be processed is known as the feed and this is introduced usually somewhere near the middle of the column to a tray known as the feed tray. The feed tray divides the column into a top (enriching or rectification) section figure (1-3) and a bottom (stripping) section figure (1-2). The feed flows down the column where it is collected at the bottom in the reboiler.

Heat is supplied to the reboiler to generate vapour. The source of heat input can be any suitable fluid, although in most chemical plants this is normally steam. In refineries, the heating source may be the output streams of other columns. The vapour raised in the reboiler is re-introduced into the unit at the bottom of the column. The liquid removed from the reboiler is known as the Bottoms product or simply, bottoms.

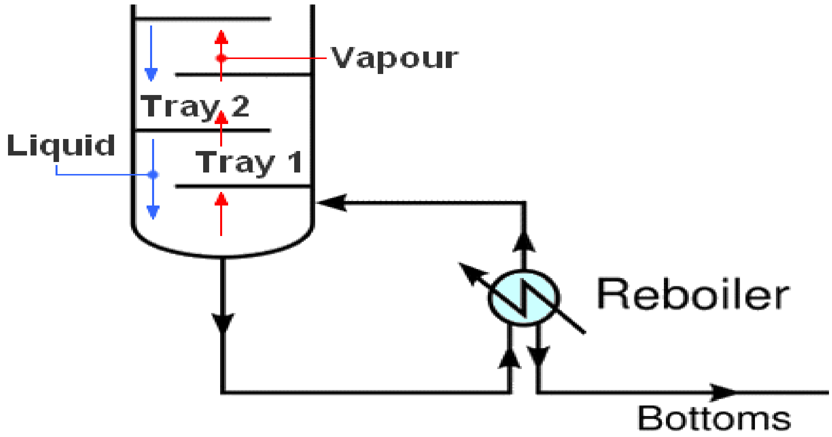


Figure 1-2: stripping section [2]

The vapour moves up the column, and as it exits the top of the unit, it is cooled by a condenser. The condensed liquid is stored in a holding vessel known as the reflux drum. Some of this liquid is recycled back to the top of the column and this is called the reflux. The condensed liquid that is removed from the system is known as the distillate or top product.

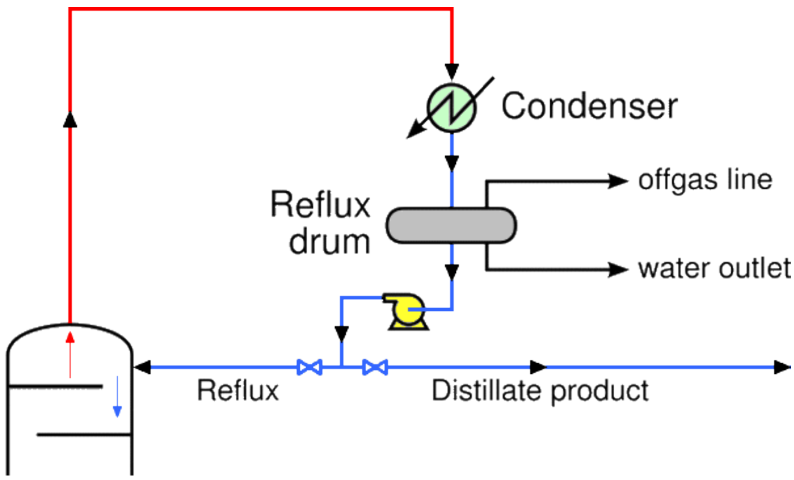


Figure 1-3: Rectification section [2]

Thus, there are internal flows of vapour and liquid within the column as well as external flows of feeds and product streams, into and out of the column.

1.4 Control Strategies [5]

In every process, the choice of control structures for distillation columns is important to get the desired product. There is no specific structure for all columns, so each column should be controlled differently.

A simple distillation column with a total condenser has a total of six valves as in Figure.(1-4). Of these six valves, the feed valve is usually set by an upstream unit in the process. Also, two valves must be used to control the reflux drum level and the reboiler level as liquid levels are non-self-regulating. Another valve must be used to regulate the column pressure which represents the vapour inventory in the column. Typically, the cooling duty valve in the condenser is used for pressure control. After implementing the three inventory loops, the position of the remaining two control valves can be set by an operator or a controller to regulate the separation. This gives an operation degree of freedom of two for a simple distillation column.

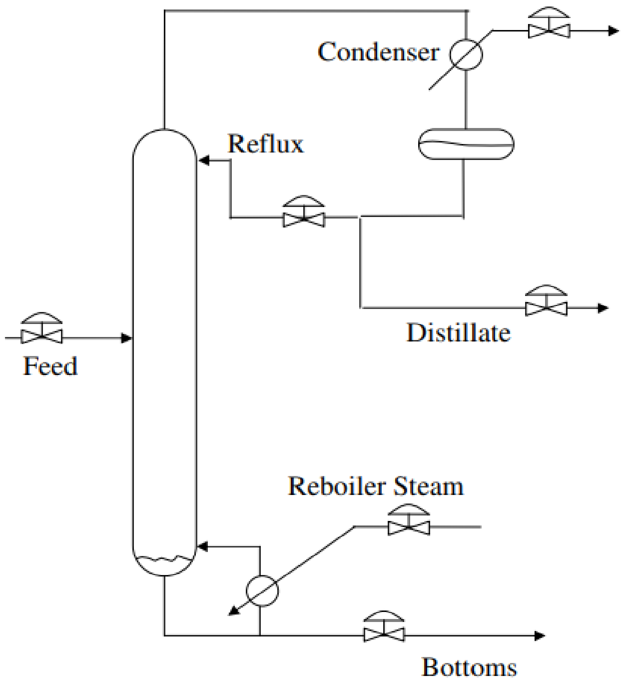


Figure 1-4: Schematic of a simple distillation column along with the control valves [5]

1.4.1 Basic control strategies [5]

Finding a structure that will control the columns is crucial. Four control structure types result in a distillation column corresponding to the choice of valve used for reflux drum and reboiler level control. These are the LQ, DQ, LB, and DB structures and are illustrated in Figure (1-5). The designation corresponds to the two control degrees of freedom (valves) that remain to regulate the separation. The LQ control structure corresponds to the distillate (D) controlling the reflux drum level and the bottoms (B) controlling the reboiler level. This leaves the reflux (L) and reboiler duty (Q) as the two valves for regulating the separation achieved, hence the label LQ. In the DQ structure, the condenser level is controlled using the reflux while in the LB structure, the bottoms level is controlled using the reboiler duty. Lastly, in the DB control structure, the reboiler duty and reflux are used for controlling the reboiler and condenser levels

respectively.

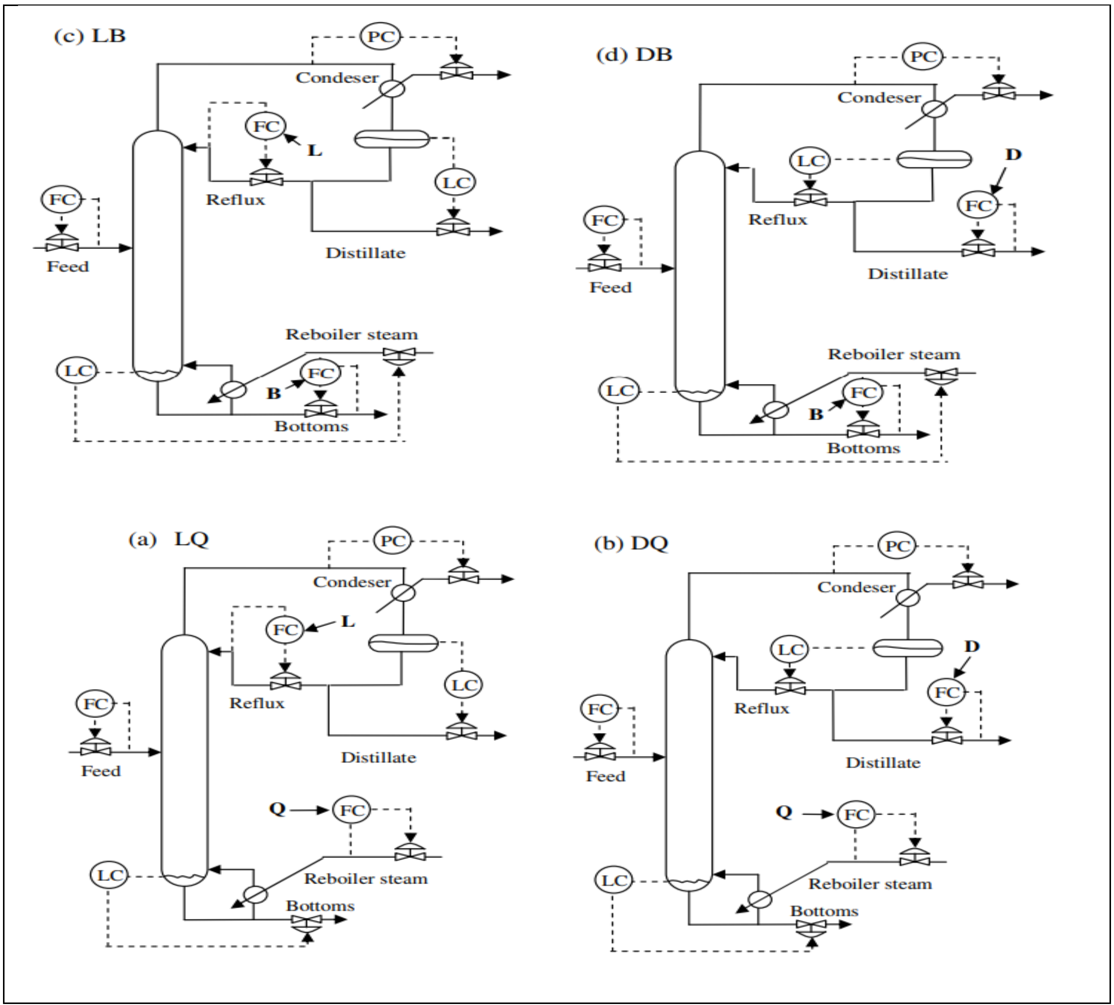


Figure 1-5: Schematics of (a)LQ, (b)DQ, (c)LB, and (d)DB control structures [5]

1.4.1.1 The Energy balance LQ strategy [5]

The LQ control structure is the simplest control strategy to control a column, this is because the separation in a distillation column occurs due to successive condensation and vaporization of the counter-current vapour and liquid streams flowing through the column, by adjusting the cold reflux, which is the source of condensation, and the reboiler duty, which is the source of vaporization. As a result, the LQ control structure is the most widely used in distillation. Changing L (cold reflux) or Q (vaporization) affects the energy balance across the column, which leads to a product split.

1.4.1.2 Material Balance Structures [5]

The other control structures are referred to as material balance structures as the product split is directly adjusted by changing the distillate or bottoms stream flow rate. When a level loop for the LQ structure would be inefficient due to a very low product stream (D or B) flow rate, material balancing structures are used. The distillate streamflow is then a fraction of the reflux stream so that the reflux drum level cannot be maintained using the distillate, The reflux must then be used to control the level.

1.4.2 Temperature Based Inferential Control [5]

The distillation column performs a separation between the light and the heavy components, so that heavy component and light component impurity levels respectively in the distillate and bottoms are below design specifications. The primary control objective then is to ensure these impurity levels remain below specifications for load changes. A change in the flow rate and composition of the feed into the column are the two major load disturbances that must be rejected by the control system.

Control of the impurity levels in the product streams is usually based on the control of the temperature of the trays. Considering that the column consists of an array of trays, the trays would respond to a load disturbance much before the effect of the disturbance reaches the product streams. It therefore makes sense to control an appropriate tray process variable so that the disturbance is compensated for before the product purities are affected. This would lead to tighter product purity control.

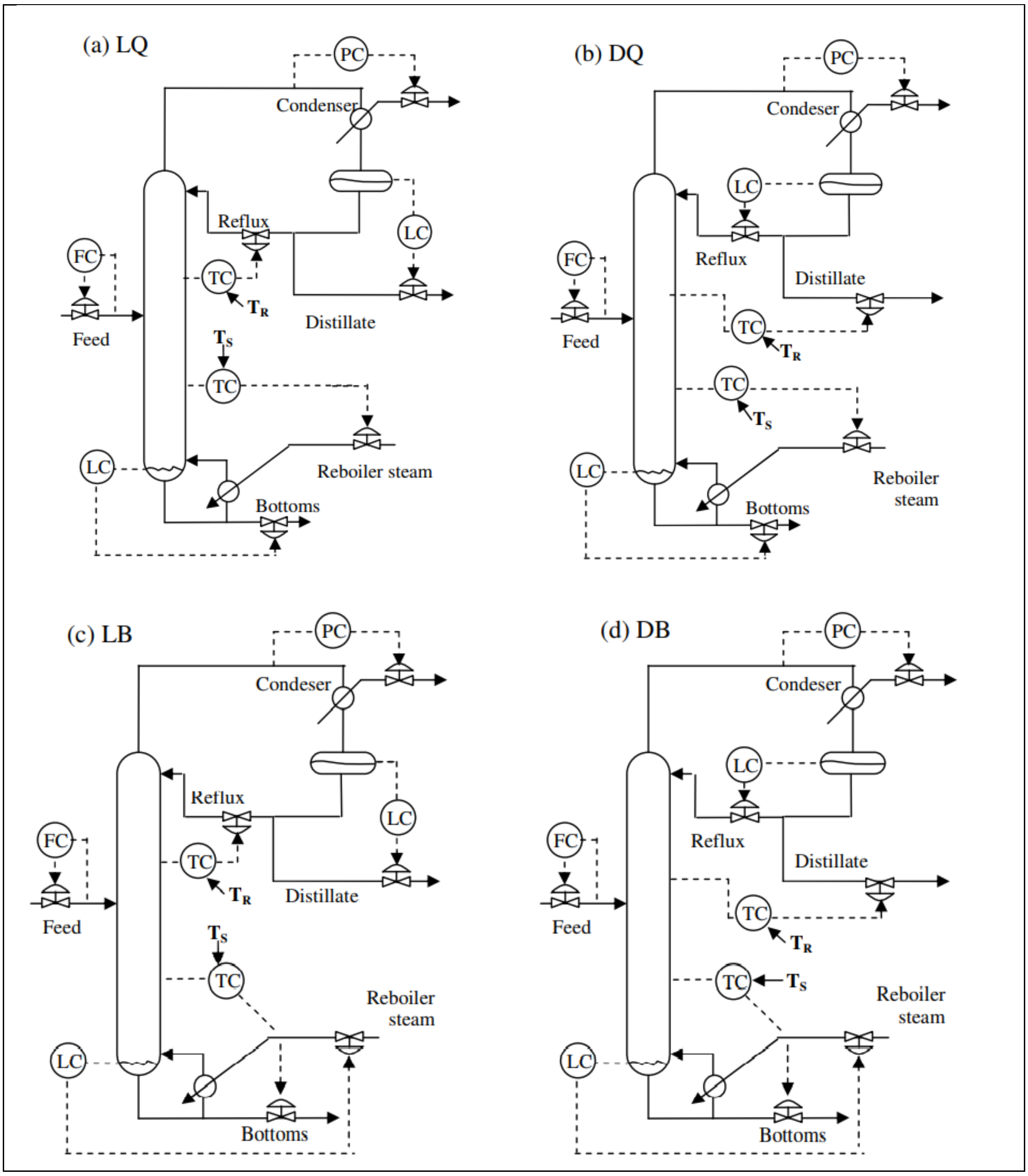


Figure 1-6: Dual-ended temperature control structures using (a)LQ, (b)DQ, (c)LB, and (d)DB schemes [5]

1.4.2.1 Dual-Ended Temperature Control [5]

Theoretically speaking, since the column degree of freedom is two, two tray temperatures can be controlled in a column. This is referred to as dual-ended temperature control. For example, in the LQ control structure, the reflux rate can be used for controlling a rectifying tray temperature and the reboiler duty can be used to control a stripping tray temperature as in Figure (1-6).

1.4.2.2 Temperature Sensor Location Selection [5]

Various criteria have evolved for the selection of the most appropriate tray location(s) for temperature control. Prominent among these are selection of tray with the maximum slope in the temperature profile, sensitivity analysis and SVD analysis. Therefore, the maximum slope criterion is the simplest to use and requires only the steady state temperature profile. From the temperature profile, the tray location where the temperature changes the most from one tray to the other is chosen as the control tray. The temperature profile usually also shows a large change / break at the feed tray location. The feed tray should however not be chosen for control as the changes in temperature would be due to changes in the feed composition / temperature and not due to a change in the separation.

1.5 Conclusion

this chapter introduces the backgrounds of distillation column starting from its components and the control structure in this project the structure used is the Dual-ended temperature control using the energy balance strategy.

Chapter 2: Conventional Control methods.

Chapter 2: Conventional Control methods

2.1 Introduction

In developing the control configuration for the distillation column, the technology used is widely available, the subject of this chapter is not to delve into every specified technique but to provide a demonstrative overview. Moreover, introduce the notation, terminology, and structure for each method used.

There are numerous concepts in dynamic system control. A good starting point is a Proportional-Integral-Derivative control (PID) and the requirement to tune the PID controller, due to the different control strategies in a distillation column, furthermore, feedforward is added to cancel the effect of the disturbance that shows the ability to improve and expand the application by interconnecting, redirecting, and even rearranging the elements of the control system. It is crucial to cope with loop interaction and pairing problems using Decoupler which leads to a multivariable control strategy.

2.2 Proportional-Integral-Derivative PID controller [6]

The PID controller is a simple application of feedback, it is the most common algorithm used in industry and still withstanding the advent of technology, on account of its simplicity, efficiency, and low cost. known as a three-term controller: the P-term (which is proportional to the error), the I-term (which is proportional to the integral of the error), and the D-term (which is proportional to the derivative of the error). Its equation is given by:

$$u(t) = Kp\left(e(t) + \frac{1}{T_i}\int_0^t e(\tau)d\tau + T_d\frac{de(t)}{dt}\right) \quad \textbf{(2.1)}$$

Where:

u: is the control variable.

e: is the control error.

Kp: is the gain.

T_i: is the integral time

T_d: is the derivative time

2.2.1 Proportional action

The proportional controller has a great influence on the value of the controlling process, especially when it is far from the desired amount and the output is linearly proportional to the input.

2.2.2 Integral action

Due to the limitation of the proportional controller where there always exists an offset between the process variable and the desired value which is called steady-state error, the Integral controller provides the necessary action to eliminate the steady-state error. It integrates the error over some time until the error value reaches zero. It holds the value to the final control device at which error becomes zero. So is an accumulation of past errors.

2.2.3 Derivative action

The integral controller cannot predict the future behavior of error. It reacts normally once the reference input is changed. D-controller overcomes this problem by anticipating the future behavior of the error. Its output depends on the rate of change of error concerning time, multiplied by the derivative constant. It gives the kick start for the output thereby increasing system response.

2.3 Implementation of the PID controller

It is a matter of fact that selecting the design of the PID controller and its parameters is not done arbitrarily, therefore, it is necessary to be acquainted with the process dynamics and the adequate controller mode for each. After that choosing tunning method.

2.3.1 Process dynamics

The three major classifications of process response are self-regulating, integrating, and runaway. Each of these process types is defined by its response to a step-change in the manipulated variable. A "self-regulating" process responds to a step-change in the final control element's status by settling to a new, stable value. An "integrating" process responds by ramping either up or down at a rate proportional to the magnitude of the final control element's step-change. Finally, a "runaway" process responds by ramping either up or down at a rate that increases over time, headed toward complete instability without some form of corrective action from the controller [7].

The table below shows the characteristic of each process:

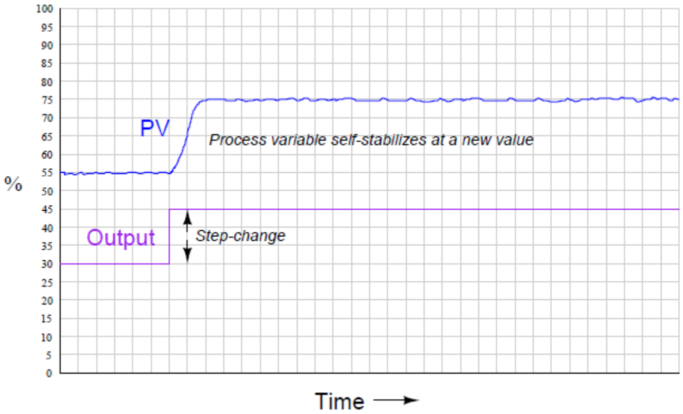
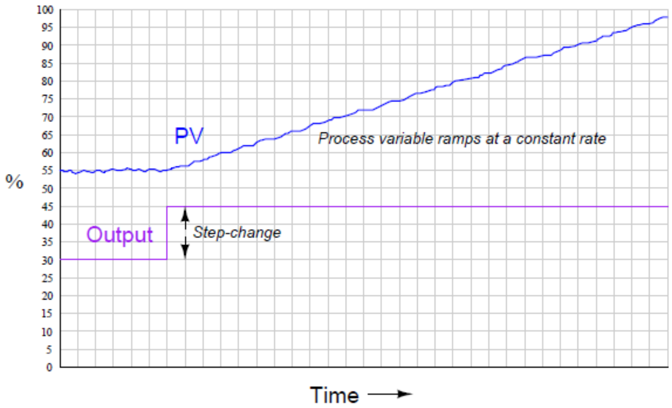
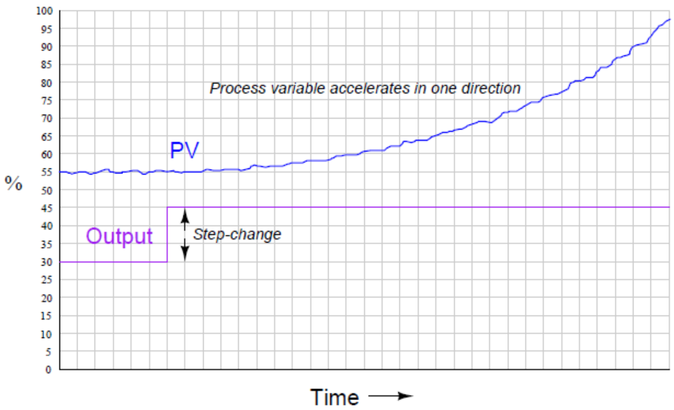
<table>
<tr><th>Process type</th><th>Response to a step-change</th><th>Controller mode</th><th>example</th></tr>
<tr><td>self-regulating</td><td>
</td><td>liquid flow PI, require more integral action and less proportional action (I is necessary and P is recommended), as well as I-only control, which can be used</td><td>liquid flow</td></tr>
<tr><td>Integrating</td><td>
</td><td>PI require more proportional action and less integral action (P is necessary and I is recommended) as well as P-only control can be used.</td><td>Mass balance (Liquid level control, Gas pressure control, Storage bin level control)</td></tr>
<tr><td>Runaway</td><td>
</td><td>PID</td><td>water-moderated fission reactors, inverted pendulum</td></tr>
</table>

Table 2-1: Process dynamics

2.3.2 Additional PID Concepts: Interactive and Noninteractive Modes

PID controllers arrange the Proportional, Integral, and Derivative modes into one of three different controller algorithms or forms. These are called the Interactive, Noninteractive, and Parallel forms.

Interactive (series PID)

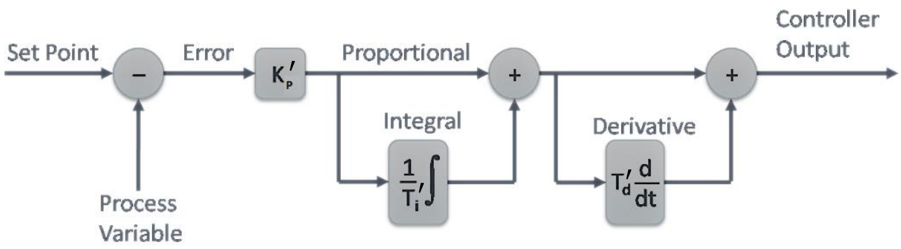


Figure 2-1: Interactive PID diagram [8]

$$u(t) = K'_P \left[e + \frac{1}{T'_i} \int e(t) \cdot dt \right] \times \left[1 + T'_d \frac{d}{dt} \right] \tag{2.2}$$

Noninteractive (Ideal PID)

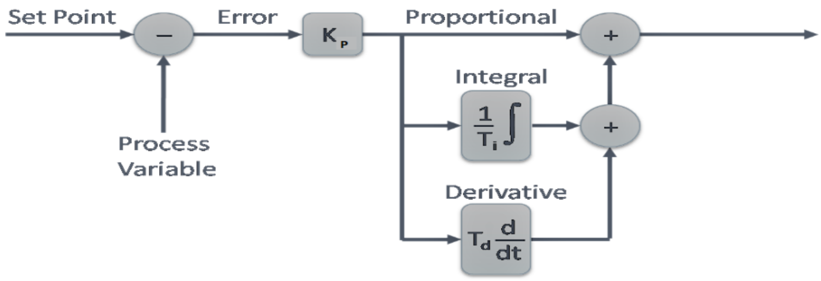


Figure 2-2: Noninteractive PID diagram [8]

$$u(t) = K_p \left[e(t) + \frac{1}{T_i} \int e(t) \cdot dt + T_d \frac{de(t)}{dt} \right] \tag{2.3}$$

Parallel PID

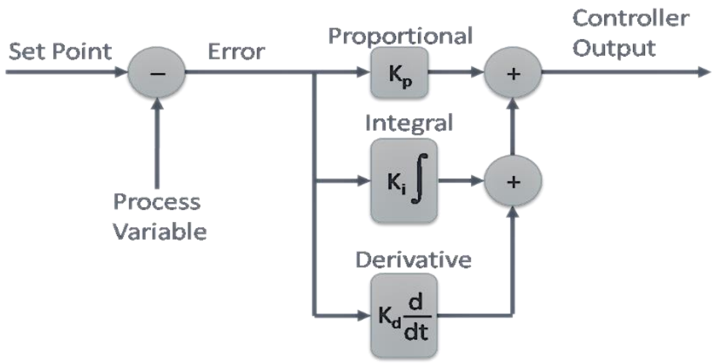


Figure 2-3: Parallel PID diagram [8]

$$u(t) = K_p \times e(t) + K_i \int e(t) \cdot dt + K_d \frac{de(t)}{dt} \quad (2.4)$$

The biggest difference between the different forms is that Controller Gain affects all three modes (Proportional, Integral, and Derivative) of the Series and Ideal forms, while Proportional Gain affects only the Proportional mode of a Parallel controller. Equations have been developed for converting tuning settings between Ideal and Series controller algorithms. [9]

If one has an interactive controller, the equivalent parameters for a noninteracting controllers are given by:

$$\begin{cases} K_p = K'_P \left(\dfrac{T'_i + T'_d}{T'_i}\right) \\ T_i = T'_i + T'_d \\ T_d = \dfrac{T'_i T'_d}{T'_i + T'_d} \end{cases} \quad (2.5)$$

If one has a noninteractive controller, the equivalent parameters for an interacting controller are given by [9] :

$$\begin{cases} K'_p = \lambda K_p \\ T'_i = \lambda T_i \\ T'_d = \dfrac{T_d}{\lambda} \end{cases} \quad (2.6)$$

Where: $\lambda = \frac{1}{2} + \sqrt{\frac{1}{4} - \frac{T_d}{T_i}}$

2.3.3 Tuning methods

There are lots of tuning methods to tune the PID controller, in this study, the model is approximated to the first-order system with dead time and time constant. FOPDT

$$G(s) = \frac{K.e^{-\tau s}}{1 + Ts} \quad (2.7)$$

K: Process Gain.

T : Process time constant.

τ: process Dead time.

2.3.3.1 Open-loop Ziegler-Nichols method

The Ziegler-Nichols open-loop method is also referred to as a process reaction method because it tests the open-loop reaction of the process to a change in the control variable output. To use the Ziegler-Nichols open-loop tuning method, you must perform the following steps given by BROIDA method [10]:

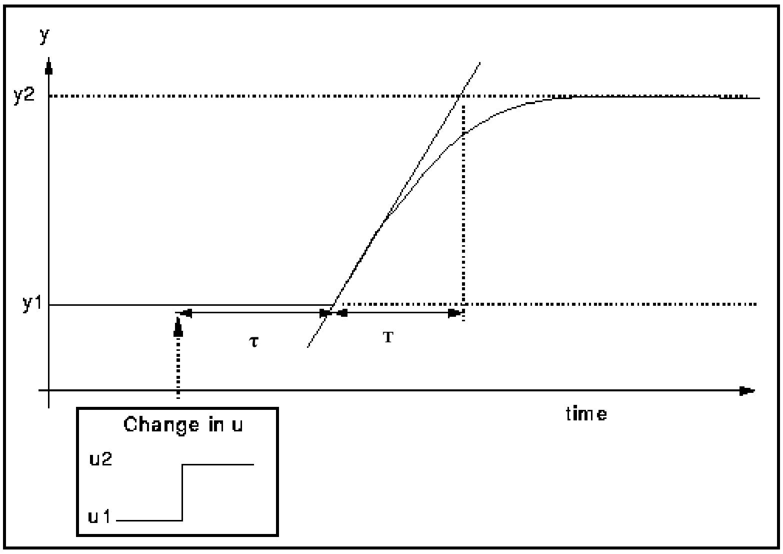


Figure 2-4 BROIDA method

- Look at the open-loop response of the process to a step-change in the manipulated variable.
- Evaluate
    - The steady-state gain ,K = (y2 - y1) / (u2 - u1)
    - The time delay, τ
    - The time constant, **T**
- Finally, substitute these values into the table below to obtain the relevant controller parameters:

Control mode	K_p	T_i	T_d
PI	0.9 τ/KT	3.33T	-
PID series	1.2 τ/KT	2T	0.5T
PID ideal	1.5 τ/KT	2.5T	0.4T

Table 2-2: Open-loop Ziegler-Nichols tuning parameters

2.3.3.2 Closed-loop Ziegler-Nichols method

The Zeigler Nichols Closed-Loop Tuning Method looks at the response of the system under proportional only control to obtain PID controller settings. The method is outlined below.

- Set up the system with proportional only control and add a disturbance.
- Alter the gain of the process until you obtain the smallest gain which gives constant amplitude oscillations. This gain is called the Ultimate Gain, $\mathbf{K_U}$.
- Now evaluate the period of these constant oscillations. This is known as the Ultimate Period, $\mathbf{P}_{\boldsymbol{U}}$.

Finally, substitute these values into the table below to obtain the relevant controller parameters:

Control mode	K_p	T_i	T_d
PI	$0.45K_U$	$P_U/1.2$	-
PID series	$0.6K_U$	$0.5P_U$	$P_U/8$
PID ideal	$0.75K_U$	$0.625P_U$	$P_U/10$

Table 2-3:Closed-loop Ziegler-Nichols tuning parameters

2.3.3.3 Internal model control IMC method

The IMC tuning method was developed for use in self-regulating processes. Most control loops, e.g., flow, temperature, pressure, speed, and composition, contain self-regulating processes. One obvious exception is a level control loop, which contains an integrating process.

The table below shows how to obtain the relevant controller parameters:

Control mode	K_p	T_i	T_d
PI	$\frac{T}{K(\lambda+\tau)}$	T	-
PID series	$\frac{2T}{K(2\lambda+\tau)}$	T	$\tau/2$
PID ideal	$\frac{2T+\tau}{K(2\lambda+\tau)}$	$T+\tau/2$	$\frac{T\tau}{2T+\tau}$

Table 2-4: IMC tuning parameters

Such that: $T<\lambda<\tau$

2.4 Feedforward control

Feedforward control is a strategy that involves measuring major disturbances to the controlled process variable and calculating the change in output variable required to compensate for it. Feedback control, on the other hand, cannot prevent large deviations of the process variable from its set point caused by disturbances. Before the controller can react, disturbances cause the process variable to vary from its set point, also the delays between the process and sensor can cause the process variable to oscillate about its set point, which can be on the scale of hours, these issues are crucial. Feedforward control is one solution to these issues

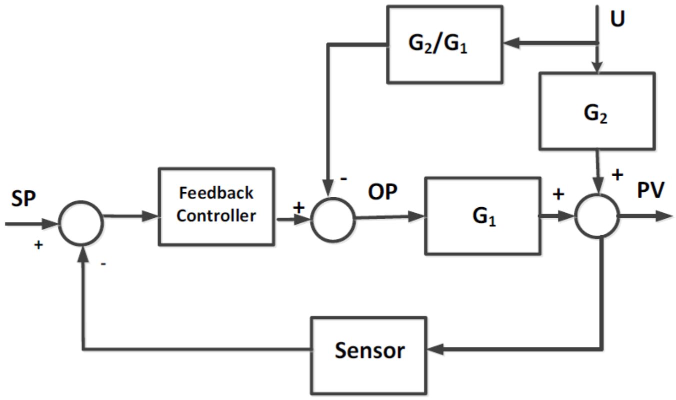


Figure 2-5: block diagram for feedforward control [11]

PV: Process Variable

OP: Output Target

SP: Setpoint

2.5 Pairing Problem and loop interaction

Control loops are said to interact when the movement of the final control element of one loop affects not only its process variable but the process variable of one or more additional control loops as well. This problem will be solved by introducing a new element called Decouplers. and the amount of interaction can be computed by using the Relative Gain Array (RGA).

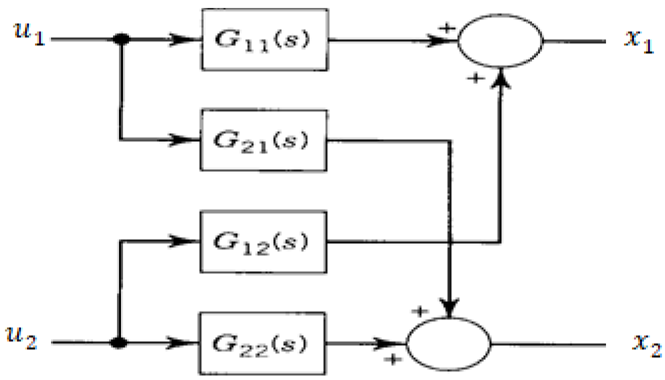


Figure 2-6:Block diagram for loop interaction

2.5.1 Relative Gain Array (RGA)

In the study of an interaction system, the main problem is whether this interaction is negligible, whether it is important, and in what amount. It is a way of quantifying this interaction in order to determine how to link the process variables to the control variables of the system. To solve this problem, we use a method called the Relative Gains Array method. We will work on a two-variable system. It is generally represented by:

$$\begin{bmatrix} x_1 \\ x_2 \end{bmatrix} = \begin{bmatrix} G_{11} & G_{12} \\ G_{21} & G_{22} \end{bmatrix} \times \begin{bmatrix} u_1 \\ u_2 \end{bmatrix} \tag{2.8}$$

Where G_{ij} is the steady-state gain of the process transfer function matrix.

$$X = G.U \tag{2.9}$$

The RGA is

$$RGA = \Lambda = G \otimes (G^{-1})^T \tag{2.10}$$

Where $\otimes$ denotes the element-by-element product.

This leads to

$$\Lambda = \begin{bmatrix} \lambda_{11} & \lambda_{12} \\ \lambda_{21} & \lambda_{22} \end{bmatrix} \tag{2.11}$$

Λ is a symmetric square matrix , based on this, the RGA matrix can be represented by.

$$\Lambda = \begin{bmatrix} \lambda_{11} & 1 - \lambda_{11} \\ 1 - \lambda_{11} & \lambda_{11} \end{bmatrix} \tag{2.12}$$

In a 2×2 system, it is sufficient to compute λ_{11} to give pairing selection which can be stated as

- $\boldsymbol{\lambda_{11}}$ **= 0** u_1 should not be used to pair x_1 because u_1 has no effect in $x_1$and the same case for u_2 and x_2
- $\boldsymbol{\lambda_{11}}$ **= 1** u_2 does not affect x_1. In this case, we can say that we have a perfectly decoupled system, so there is no interaction between the loops.
- **0<** $\boldsymbol{\lambda_{11}}$ **<1** there is a u_2 interaction that affects x_1 and the smaller the value of λ_{11} the greater the interaction.
- $\boldsymbol{\lambda_{11}}$ **< 0 or** $\boldsymbol{\lambda_{11}}$ **> 1** the interaction becomes large as u_2 affects x_1 and in the opposite direction, thus the decouplers are more than necessary.

2.5.2 Decoupling the system

Decoupling refers to the insertion of a signal processor between the primary controllers and the final control elements to make the loops appear to be independent, in other words, decouplers are used to remove the interaction between the loops. In general, there are three forms of decoupling: ideal, simplified, and inverted decoupling, but in our project, we will focus on and use the simplified (forward) decoupling.

forward decoupling

Forward Decoupling is based on the approach used for feed-forward control; it is mainly composed of the inverse of the mathematical model of the controlled process. figure (2-7) shows the basic structure of a system containing a decoupler

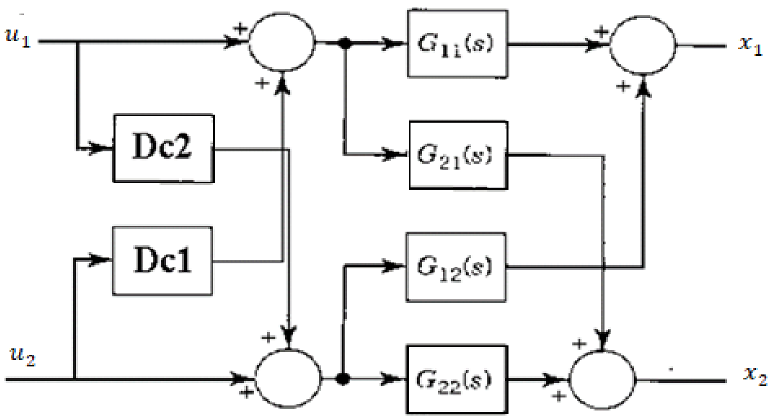


Figure 2-7: Block diagram for forward decoupling

Dc_1,Dc_2 are the Decoupler gains

from the figure, the transfer function of x_1 and $x_2$is:

$$x_1 = (G_{11} + Dc_2.G_{12})u_1 + (G_{12} + Dc_1.G_{11})u_2 \tag{2.13}$$

$$x_2 = (G_{21} + Dc_2.G_{22})u_1 + (G_{22} + Dc_1.G_{21})u_2 \tag{2.14}$$

To eliminate the effect of u_2 on x_1 the decoupler term Dc_1 should be:

$$Dc_1 = -\frac{G_{12}}{G_{11}} \tag{2.15}$$

And the effect of u_1 on x_2

$$Dc_2 = -\frac{G_{21}}{G_{22}} \tag{2.16}$$

2.6 conclusion

this chapter is included in the project due to the wide application of the methods mention in the oil and gas industry .in addition, the reason for changing these methods.

Chapter3: Model Predictive Control

Chapter 3: Model Predictive Control

3.1 Introduction

As time pass by, the process control engineers have to deal with more challenging and difficult problems. In need of that, advanced hardware and control algorithms have been produced for better controller performance. This chapter introduces MPC as a type of modern controller and provides a compact and accessible overview of its essential elements. And demonstrates the underpinning theory of predictive control.

3.2 Overview

There are many successful applications of predictive control in use today, not just in the process industry but also in the control of other processes ranging from robots to clinical anaesthesia. Cement industry applications, drying towers, and robot arms are among the advancements, as are distillation columns, steam generators, and so on. The MPC's ability to develop extremely efficient control systems capable of operating for long periods with little intervention is demonstrated by the good performance of these applications. The good performance of these applications shows the capacity of the MPC to achieve highly efficient control systems able to operate during long periods with hardly any intervention.

MPC presents a series of advantages over other methods, amongst which the following stand out:

- Because the concepts are quite clear and the tuning is reasonably easy, it is particularly appealing to staff with only a basic understanding of control.
- maybe be used to regulate a wide range of processes, from those with simple dynamics to those with more complex dynamics, such as systems with extended delay times, nonminimum phase, or unstable dynamics.
- The multivariable case can easily be dealt with.
- Constraints can be handled easily.
- The resulting controller is an easy-to-implement linear control law.

3.3 History of Predictive control [12]

Predictive control, later also called Model Predictive Control (MPC), is a kind of control algorithm originally rising from industrial processes in the 1970s. Unlike many other control methods driven by theoretical research, the generation of predictive control was mainly driven by the requirements of industrial practice. For quite a long time the industrial process control mainly focused on regulation using the feedback control principle. The well-known PID (Proportional–Integral–Differential) controller can be used for linear or nonlinear processes, even without model information, has few tuning parameters, and is easy to use. However, the advantage of the PID controller is mainly embodied in the loop control. When the control turns from a loop to the whole system, it is difficult to achieve good control performance by using such a single-loop controller without considering the couplings between the loops. Furthermore, a PID controller can handle input constraints but is incapable of handling various real constraints on outputs and intermediate variables. With the development of industrial production from a single machine or a single loop to mass production, the optimization control for constrained multivariable complex industrial processes became a new challenging problem.

During this period, modern control theory was rapidly developed and went to mature with brilliant achievements in aerospace, aviation, and many other fields. Simultaneously, advances in computer technology created a powerful tool for real-time computing. Both were undoubtedly attractive for the industrial process control engineers when pursuing higher control quality and economic benefits. They began to explore the applications of the mature modern control theory, such as optimal control, pole placement, and so on, in optimization control of the complex industrial processes. However, through practice they found that a big gap existed between the perfect theory and the real industrial processes, mainly manifested in the following:

- Modern control theory is based on an accurate mathematical model of the plant, while for a high-dimensional multivariable complex industrial process, it is hard to get its accurate mathematical model.
- The structure, parameters, and environment of an industrial plant are often uncertain. Due to the existence of uncertainty, the optimal control designed based on an ideal model would never remain optimal in real applications.

- The industrial control must take the economics of the control tools into account.

Due to the above issues coming from practice, it is hard to directly use modern control theory for complex industrial processes. To overcome the gap between theory and practice, in addition to investigating system identification, robust control, adaptive control, and so on., people began to break the constraints of traditional control methods and tried to seek new optimization control algorithms by the characteristics of the industrial processes such as Dynamic Matrix Control (DMC) developed 1980 ,Quadratic Dynamic Matrix Control (QDMC) developed in 1986 ,Generalized Predictive Control (GPC) that developed in 1987, Predictive Functional Control (PFC) was developed in 1993 and the newest one was the Global predictive control (Glob-PC) appeared in 2000. These predictive control techniques that have had a significant impact on the industrial world and are commercially available cover several topics. Although some companies use technologies developed in-house but not externally provided, the following can be considered representative of current model predictive control technologies. Their product names and acronyms are:

- **AspenTech:** Dynamic Matrix Control (DMC)
- **Adersa:** Identification and Command (IDCOM) , Hierarchical Constraint Control (HIECON), and Predictive Functional Control (PFC)
- **Honeywell Profimatics:** Robust Model Predictive Control Technology (RMPCT) and Predictive Control Technology (PCT)
- **Setpoint Inc.:** Setpoint Multivariable Control Architecture (SMCA) and IDCOM-M (multivariable)
- **Treiber Controls:** Optimum Predictive Control (OPC)
- **ABB:** 3dMPC
- **Pavillion Technologies Inc.:** Process Perfecter
- **Simulation Sciences:** Connoisseur

3.4 MPC Strategy

Model predictive control (MPC) is an approach represented in variety control methods based on optimal control theory. its aim is to provide solutions to problems of many types of complex systems, such as. unstable open-loop systems, systems with non-minimum phase, large delay systems, the solutions involve optimizing the cost function for the prediction horizon, where the predictions are based on a mathematical model of the dynamical system to be controlled. The differences between those methods reside in the cost function and the model used, nevertheless, they have the same strategy as shown in the figure below:

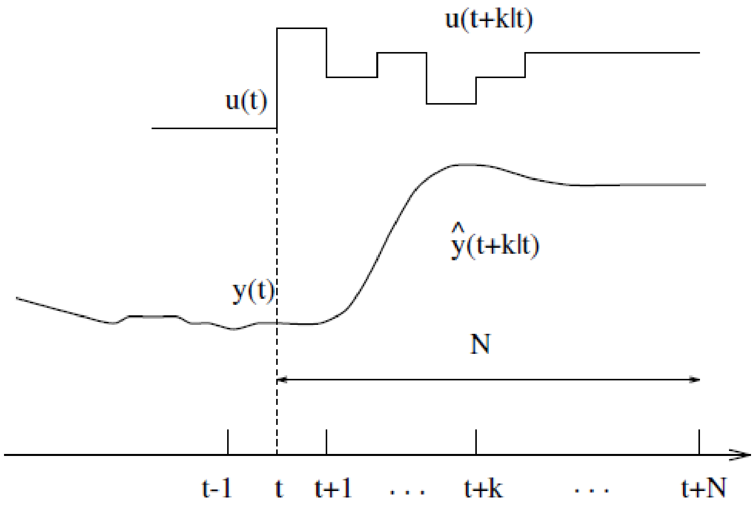


Figure 3-1 : MPC strategy

3.5 The main components of MPC

3.5.1 Prediction horizon

The prediction horizon, that is, how far ahead does one anticipate and the time horizon during which the output must follow the setpoint.

3.5.2 Control horizon

Indicates the future time steps for which control increments are calculated.

3.5.3 The model

Predictive control is model sensitive control; the essence part of prediction is the accurate and the simple model beside of that accurate model may leads to a high order model which implies sophisticated and expensive procedure [13]. To avoid contradiction the model used captures the key dynamics during the transients, so FOPDT is used .

3.6 Dynamic Matrix Control (DMC) Based on the Step Response Model

Dynamic Matrix Control (DMC)is the most popular and preferable algorithm in the chemical industry. DMC is based on the step response of the plant, and thus is suitable for asymptotically stable linear systems. For a smooth nonlinear system, step response can be tested at its operating point and then DMC can be adopted. For an unstable system, the DMC algorithm can be used after stabilizing the system by a conventional PID controller.

3.6.1 DMC Algorithm and Implementation

DMC algorithm is mainly implemented in three steps: prediction model, optimization, and feedback correction.

3.6.1.1 Prediction model [14]

Unit step model is common model utilised in commercial MPC packages. This part explains how to make predictions using a unit step-based model. The response was approximated with three parameters representation process gain, dead time, and time constant then all the sampled data collected through the step testing is retained in a series sequence of values ($a_{1,}a_2 \dots a_N$) that results from a step-input change of one unit would be retained as the step-response model. The dimension N of this vector is called the response horizon. Usually, the value of N equals 30 but values of 60, 90 or 120 can also be used This data vector is called “**a”** the vector a is defined as follows:

$$a = \left[a_{1,}a_2 \dots a_N\right]^T \tag{3.1}$$

We can get the element of A by discretization the transfer function as shown in equation:

$$G(z) = \sum_{i=1}^{N} a_i z^{-i} \tag{3.2}$$

For the control horizon, the predicted values of *y*, after the *M* control moves, are given by:

$$\tilde{y}_M(k+i|k) = \tilde{y}_0(k+i|k) + \sum a_{i-j+1}\Delta u(k+j-1) \ ; \quad i = 1,2, \dots N \ ; \ j = 1,2, \dots i \qquad \textbf{(3.3)}$$

Where:

$\tilde{y}_0(k+i|k)$:is the initial prediction from k to N

$\Delta u(k)$: change in controller output at sampling instant *k*

The equation (3) shows that in any time k the value of y after M control samples can be predicted if the initial prediction of y after N samples and controller moves are known.

3.6.1.2 Optimization

Since DMC algorithm is based on the optimization of the control moves M also called control horizon of the controller input $\Delta u(k)$,…, $\Delta u(k+M-1)$, using the predicted output of the process $\tilde{y}_M$ for the next P prediction samples where P is called the prediction horizon to reach the desired value $w(k+i); i = 1,2, \dots, p$, obviously it is assumed that $M \leq P$.which is shown in figure (3-2)

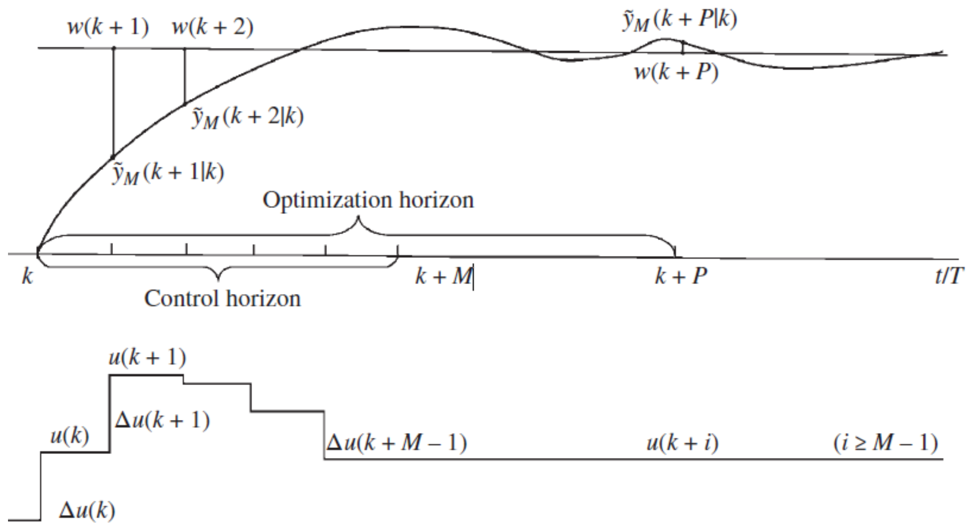


Figure 3-2: DMC optimization strategy

The performance index is given by

$$\min_{\Delta u} J(K) = \sum_{i=1}^{P} q_i[w(k+i) - \tilde{y}_M(k+i|k)]^2 + \sum_{j=1}^{M} r_j \Delta u^2(k+j-1) \qquad \textbf{(3.4)}$$

Where q_i and r_j are the weighting coefficients

The optimization is aiming to minimize the deviation of the predicted output and the control effort which lies under tracking problems, adding soft penalties represented as weighting coefficients to deal with excessive control increment

To obtain the control law we will use the matrix notation so the prediction model is denoted:

$$\tilde{y}_{PM}(k) = \tilde{y}_{P0}(k) + A\Delta u_M(k) \tag{3.5}$$

Where:

$$\tilde{y}_{PM}(k) = \begin{bmatrix} \tilde{y}_M(k+1|k) \\ \tilde{y}_M(k+2|k) \\ \tilde{y}_M(k+3|k) \\ \vdots \\ \tilde{y}_M(k+M|k) \\ \vdots \\ \tilde{y}_M(k+P|k) \end{bmatrix} \qquad ; \tilde{y}_{P0}(k) = \begin{bmatrix} \tilde{y}_0(k+1|k) \\ \tilde{y}_0(k+2|k) \\ \tilde{y}_0(k+3|k) \\ \vdots \\ \tilde{y}_0(k+M|k) \\ \vdots \\ \tilde{y}_0(k+P|k) \end{bmatrix}$$

$$A = \begin{bmatrix} a_1 & 0 & 0 & \dots & 0 \\ a_2 & a_1 & 0 & \dots & 0 \\ a_3 & a_2 & a_1 & & \vdots \\ \vdots & \vdots & & \ddots & \vdots \\ a_M & a_{M-1} & & a_2 & a_1 \\ \vdots & \vdots & & & \vdots \\ a_N & a_{N-1} & \cdots & \cdots & a_{N-M+1} \end{bmatrix} \qquad ; \Delta u_M(k) = \begin{bmatrix} \Delta u(k) \\ \Delta u(k+1) \\ \Delta u(k+2) \\ \vdots \\ \Delta u(k+M-1) \end{bmatrix}$$

And the performance index is given by:

$$\min_{\Delta u_M(k)} J(k) = [w(k) - \tilde{y}_M(k)]^T Q [w(k) - \tilde{y}_M(k)] + [\Delta u_M(k)]^T R [\Delta u_M(k)] \tag{3.6}$$

Also, can be written

$$\min_{\Delta u_M(k)} J(k) = \|w_P(k) - \tilde{y}_{PM}(k)\|_Q^2 + \|\Delta u_M(k)\|_R^2 \tag{3.7}$$

Where:

$\boldsymbol{w}_P(k) = [w(k+1) \cdots w(k+P)]^{\mathrm{T}}$

$\boldsymbol{Q}$ = diag $(q_1, \dots, q_P)$ is the error weighting matrix composed of weighting coefficients qi,

$\boldsymbol{R} = \text{diag}\ (r_1, \dots, r_M)$ is the control weighting matrix composed of weighting coefficients rj

By putting (3.5) into (3.7) gives:

$$\min_{\Delta u_M(k)} J(k) = \|w_P(k) - \tilde{y}_{P0}(k) - A\Delta u_M(k)\|_Q^2 + \|\Delta u_M(k)\|_R^2 \qquad (3.8)$$

To obtain the minimum of J, the derivative is set to zero $\frac{\partial j(k)}{\partial \Delta u_M(k)} = 0$, hence:

$$\Delta u_M(k) = (A^T QA + R)^{-1} A^T Q[w_P(k) - \tilde{y}_{P0}(k)] \qquad (3.9)$$

This equation gives the calculation of $\Delta u_M$for the current period and M-1 future periods, this is for each execution of the algorithm. But it will only take the value of Δu_M for the present period. Only the first row in the matrix has to be calculated.

$$\boldsymbol{d}^{\mathrm{T}} = \boldsymbol{c}^{\mathrm{T}}(\boldsymbol{A}^{\mathrm{T}}\boldsymbol{Q}\boldsymbol{A} + \boldsymbol{R})^{-1} A^{\mathrm{T}}\boldsymbol{Q} \triangleq [d_1 \cdots d_P] \qquad (3.10)$$

Where:

$\boldsymbol{c}^{\mathbf{T}} = [1, 0 \dots 0]$represents the operation of selecting the first row for a matrix,

3.6.1.3 Feedback correction [14]

Due to the uncertainty of the model and the disturbance acting on the system the prediction becomes inaccurate which leads to a deficient optimization; thus, the prediction must be corrected. the correction is done by calculating the difference between the actual output $y(k+1)$ and the predicted output $\tilde{y}(k+1|k)$ which generates the error:

$$e(k+1) = y(k+1) - \tilde{y}(k+1|k) \qquad (3.11)$$

And the corrected output is formulated by adding the error to the predicted error for the next control move as shown:

$$\tilde{y}_{cor}(k+1) = \tilde{y}_{N1}(k) + he(k+1) \qquad (3.12)$$

Where h is the weighing vector for the error coefficients also called the correction vector

the elements of $\tilde{y}_{cor}(k+1)$ should be shifted to construct the initial predicted outputs at time k+1 hence:

$$\tilde{y}_0(k+1+i \mid k+1) = \tilde{y}_{\mathrm{cor}}\,(k+1+i \mid k+1), i = 1, \dots, N-1 \qquad (3.13)$$

This can be formulated:

$$\tilde{y}_{N0}(k+1) = S\tilde{y}_{\mathrm{cor}}(k+1) \tag{3.14}$$

Where: S is the shift matrix

$$S = \begin{bmatrix} 0 & 1 & & 0 \\ \vdots & \ddots & \ddots & \\ \vdots & & 0 & 1 \\ 0 & \cdots & 0 & 1 \end{bmatrix} \tag{3.15}$$

The algorithm of DMC is briefly shown in figure

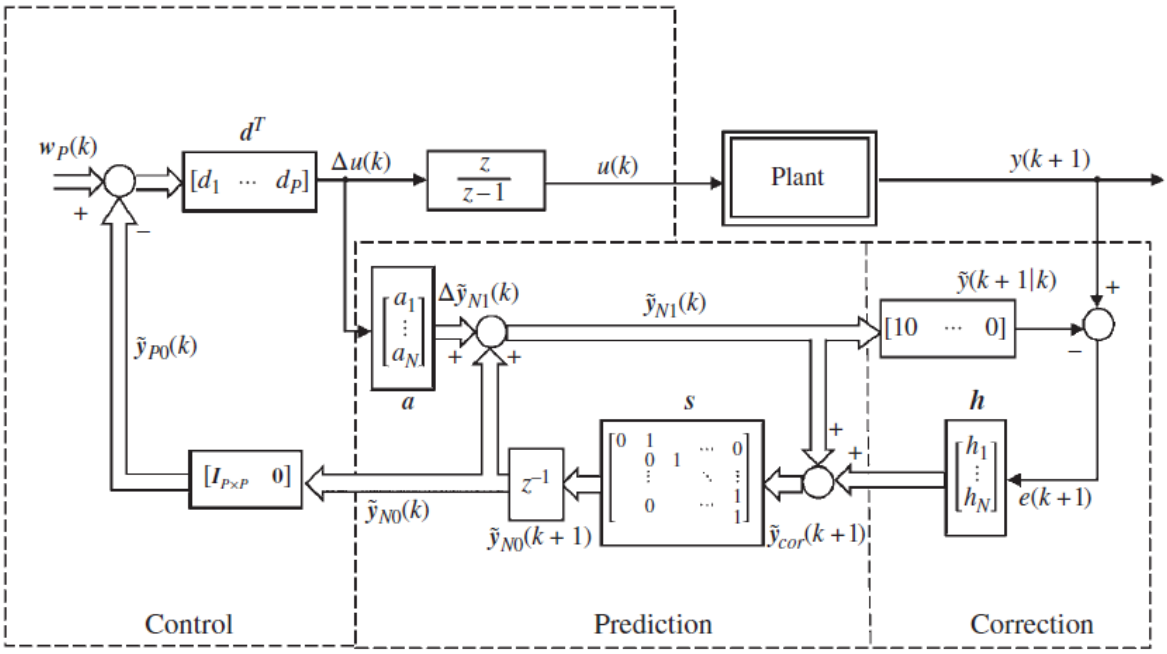


Figure 3-3: DMC Algorithm structure

3.7 DMC applied to binary distillation column

the system in this project is a multi-input multi-output, hence, based on the previous section with SISO system the concepts is the same. the system with two input and two output it can be expressed as follows:

$$\begin{bmatrix} x_1 \\ x_2 \end{bmatrix} = \begin{bmatrix} G_{11}(s) & G_{12}(s) \\ G_{21}(s) & G_{22}(s) \end{bmatrix} \times \begin{bmatrix} u_1 \\ u_2 \end{bmatrix} \tag{3.16}$$

Where G_{ij} is the process transfer function matrix.

For each transfer function the four matrices Aij as (3.5) are constructed and DMC algorithm is applied so as a result the matrix A is regenerated as:

$$A = \begin{bmatrix} A_{11} & A_{12} \\ A_{21} & A_{22} \end{bmatrix} \tag{3.17}$$

Where Aij dynamic matrices for each transfer matrix

3.8 Tuning parameter of DMC

There are many tuning methods to evaluate the parameters N, P, M. also the weighting matrices R and Q .in this project, The method of Shridhar–Cooper [15] and the method of Iglesias et al [16] are used, knowing that in these methods the weighting matrices in equation (3.6) and (3.7) ae taken:

$$\begin{cases} \mathrm{Q} = \mathrm{I} \\ \mathrm{R} = \mathrm{rI} \end{cases} \tag{3.18}$$

Where:

I is the identity matrix

r is the weighting factor

so, the equation (3.10) becomes:

$$\boldsymbol{d}^T = \boldsymbol{c}^T(\boldsymbol{A}^T\boldsymbol{A} + rI)^{-1}A^T \tag{3.19}$$

The method of Shridhar–Cooper estimate the system to first order system with dead time FOPDT (2.2) and gives:

- Sampling period T_s :

$$T_s = \min\{\, 0.1T \,, 0.5\tau \,\} \tag{3.20}$$

- Response horizon N:

$$N = \frac{T}{T_r} + 1 \tag{3.21}$$

  Where Tr is the rising time

- Control horizon M:

$$M = int\left(\frac{\tau}{T_s}\right) + int\left(\frac{T}{T_s}\right) + 1 \tag{3.22}$$

- Prediction horizon P:

$$P = int\left(\frac{\tau}{T_s}\right) + int\left(\frac{5T}{T_s}\right) + 1 \tag{3.23}$$

- Weighting factor r:

$$r = \frac{M}{10}\left(\frac{3.5T}{T_s} + 2 - \frac{(M-1)}{2}\right)K^2 \tag{3.24}$$

According to Iglesias et al [16] the value of r causes aggressive behaviour and suggests r such that:

$$r = 1.631k\left(\frac{\tau}{T}\right)^{0.4094} \tag{3.25}$$

Understanding DMC algorithm and the effect of each parameter would be advantageous in fine tuning which is discussed briefly in chapter 4

3.9 Conclusion

This chapter has discussed the MPC theory and algorithm that shows the application of the advanced control theory.

Chapter 4: Results and Discussion

Chapter 4: Results and Discussion

4.1 Introduction

In this chapter, we will discuss the main objectives and the aims of this project, first, we will give an overview of the software we used in our study, and the main data to build the model for our simulation, then we will investigate the performance of the controllers we used, the first part is concerned with the different response for the conventional controllers, the second part is concerned with the new method of control (MPC) by comparing the results obtained with the one's from the conventional methods and then we will see the effect of different parameters used to tune the MPC.

4.2 Introduction To Aspen HYSYS [17]

Aspen HYSYS (abbreviation from Hyprotech and Systems) is one of the top leading Chemical Process simulators in the market, it is a deterministic type of simulation software and cannot support randomness. HYSYS is used extensively in the industry due to its steady-state and dynamic simulation, process design, performance modelling, and optimization, basically, it is a software that will allow the user to build a process model and then simulate it using complex calculations (models, equations, math calculations, regressions, etc), and can also handle very complex processes, such as:

- Dedicated Unit Operations for the Refinery Industry
- Multiple-column separation systems
- Chemical reactors
- Simulation of Petroleum Crude Oils
- Complex Recycle

4.3 Building The Model

HYSYS Models are not typically built in the dynamic mode, the best workflow is to build the model in steady-state and then convert it to dynamics.

4.3.1 Principles Modelling

Most columns handle multi-component feeds. But many of them can be approximated by binary or pseudo-binary mixture. For the DEPROPANIZER, they can be approximated by two components (Propane and Iso-Butane), but before we get these ideal components we carry out preliminary filtering stages, where the initial mixture contains several components (N2, CO2, C1, C2, C3, i-C4, n-C4, i-C5, n-C5, C6, and H2O) until we get propane (C3) and I-Butane (i-C4).Several assumptions and idealizations are made, the purpose of using this simplification is to reduce problems to their elementary form in order to focus more on the control part.

4.3.2 Steady-State State Data and Column Specification

A Depropanizer distillation column (DDC) that is widely used in oil refineries, was simulated by Aspen HYSYS. The purpose of this simulation was to select the most appropriate model to accurately predict the separation process in the DDC of the mixture which contains Propane and Isobutane. The table below specifies the steady-state data as follows:

F	Feed flow rate[Kgmole/Hour]
F_T	Feed Temperature
D & B	Distillate (top) propane and Bottom Isobutane Product Composition [mole fraction]
N_T	Number of Trays
N_F	Feed tray number
T_1	Temperature of the first tray
The temperature	Temperature of the last tray
Ø	Column Diameter [meter]
L_E	Column Length[meter]

F	**F_T**	**D**	**B**	**N_T**	**N_F**	**T_1**	**T_2**	**Ø**	**L_E**
3700	48°C	0.6	0.4	30	14	42.6°C	83.4°C	11	30

The system in our project is

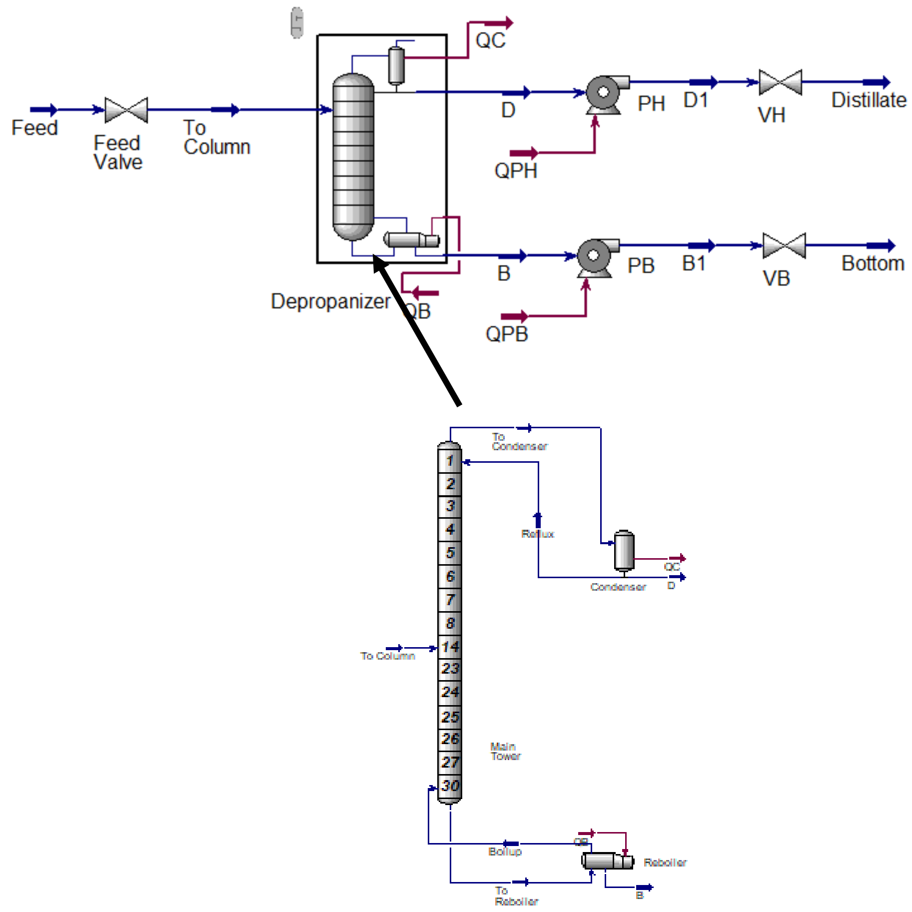


Figure 4-1:Distillation column with full reflux

To use dual ended control of the column to wave to select the sensitive trays using Maximum Slope Criterion.

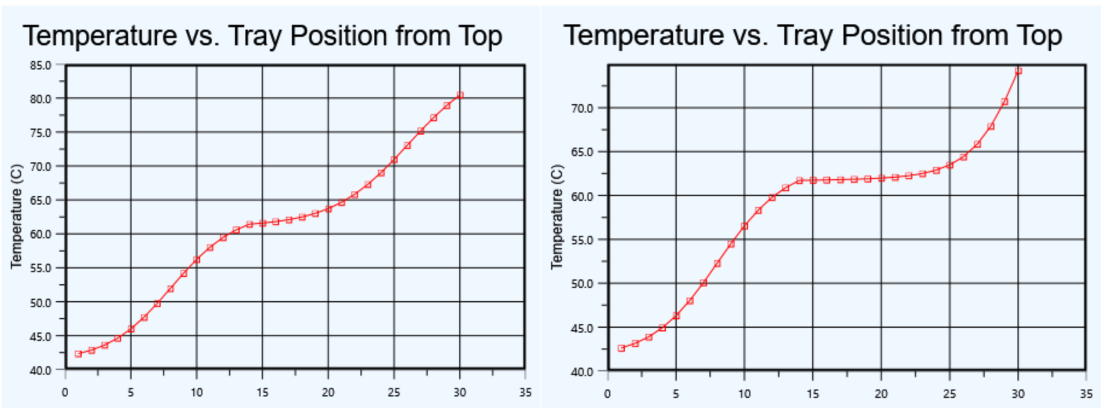


Figure 4-2: Maximum Slope Criterion

Setting the feed valve on 50% opening rate, then we adjust it by 10% for several times, we observe that the sensitive trays are 25 and 5.

4.4 Converting To Dynamic

In order to convert the system to dynamic mode we need to design the controllers for the system, and to do that we have to extract the system model, i.e., we must get the transfer function matrix. By using the **BROIDA** method we got the following transfer function:

$$\begin{bmatrix} T_5 \\ T_{25} \end{bmatrix} = \begin{bmatrix} \dfrac{-2.18}{1+127s} & \dfrac{3.12}{1+193s} \\ \dfrac{-2.17}{1+95s} & \dfrac{3.25}{1+111s} \end{bmatrix} \times \begin{bmatrix} \mathrm{L} \\ \mathrm{Q} \end{bmatrix}$$

T: Tray temperature

L: reflux flow rate

Q: reboiler duty

4.4.1 Designing a PID Controller

We design the PID controller of the loops as demonstrated in the following tables (4-1) and (4-2)

Connections	
Name	TIC-100
Process Variable Source	Main Tower / Stage Temperature 5
Output Target Object	Reflux / Control Valve
Parameters	Configurations
Action	Direct
PV Minimum	0
PV Maximum	100

Table 4-1:Tray 5 temperature controller connections and parameters

Connections	
Name	TIC-101
Process Variable Source	Main Tower / Stage Temperature 25

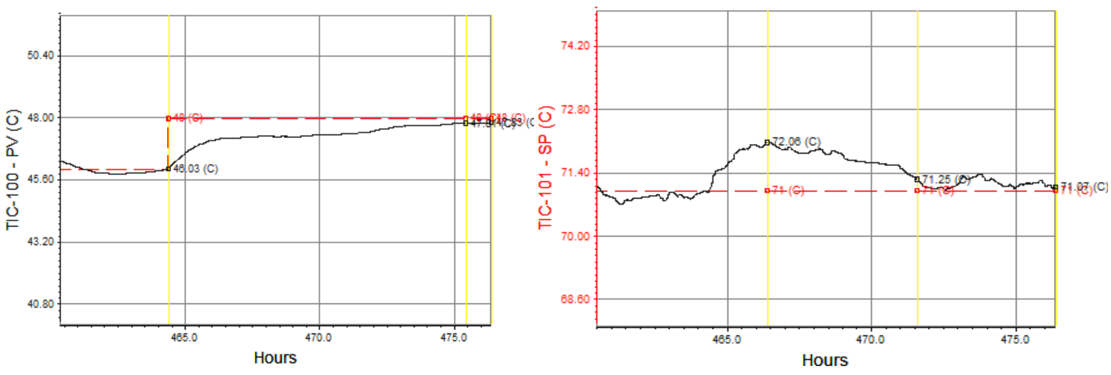
Output Target Object	Reflux / Control Valve
Parameters	Configurations
Action	Reverse
PV Minimum	30
PV Maximum	130

Table 4-2: Tray 25 temperature controller connections and parameters

PID parameter obtained using the methods shown in section (2.3.3)

TIC-100	**kp= 0.45**	**Ti=127mn**
TIC-101	**kp= 0.3**	**Ti=111mn**

Table 4-3:TIC parameters -1



(a) **(b)**

figure 4-3: (a) response to setpoint changing in Tray 5 temperature, (b)and its effect on tray 25 using table 4-3 parameters

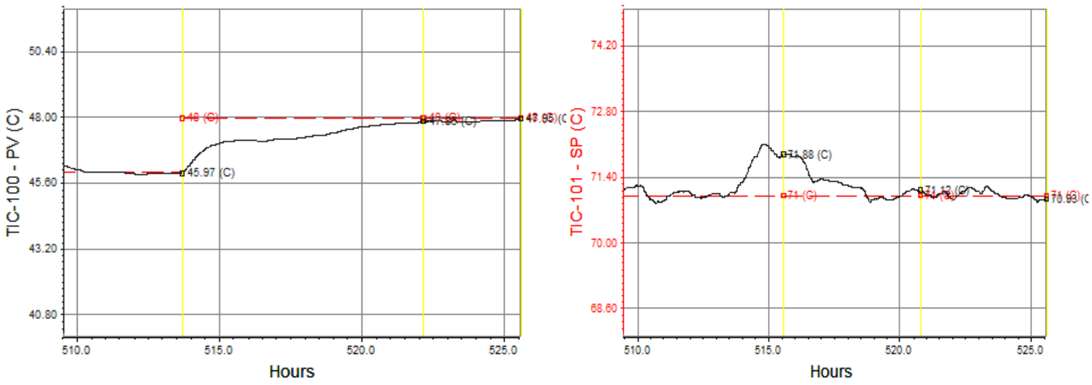
We see that temperature in tray 5 take long time to settle 10 h from figure (4-3) so we should increase kp in controller TIC-100 according to what we have discussed in section (2.2)

Also, we notice oscillation of tray 25 temperature, so we should decrease Ti of the controller TIC-100 this is called fine tuning,

TIC-100	**kp= 0.6**	**Ti=127mn**	**Td=0**
TIC-101	**kp= 0.3**	**Ti=50mn**	**Td=0**

Table 4-4:TIC parameters -2

We obtain the following plots:



(a) **(b)**

figure 4-4(a) response to setpoint changing in Tray 5 temperature,(b)and its effect on tray 25 using table 4-4 parameters

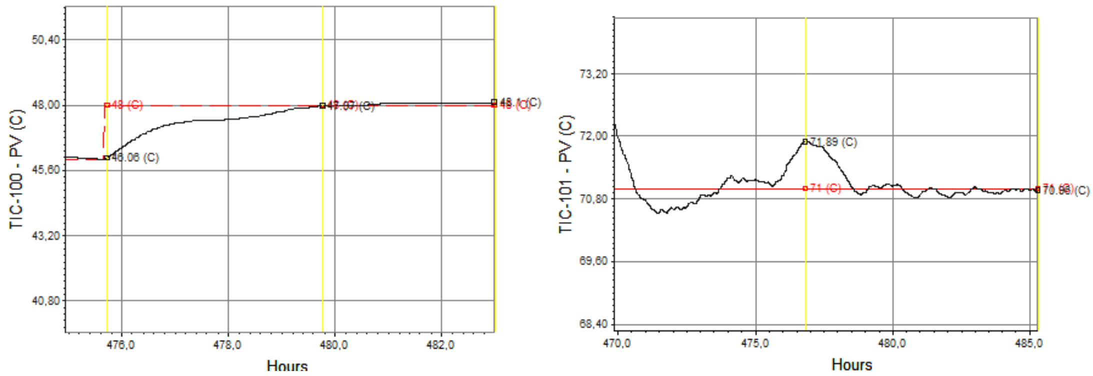
We continue in error trial method till we get the desired response, after multiple trying based on the deep understanding of the effect of PID parameters we concluded that we need to decrease in Ti of the controller in TIC-100 and increase in Kp of the controller TIC-101

The following PID values shown in tables below are adopted.

TIC-100	**kp= 0.56**	**Ti=45.5min**	**Td=0**
TIC-101	**kp= 0.5**	**Ti=40min**	**Td=0**

Table 4-5: TIC parameters-3

The first test of our controller is changing the set point of Tray 5 from 46°C to 48°C, the figures below show this change and the corresponding effect on Tray 25 temperature.



(a) **(b)**

Figure 4-5: **(a) response to setpoint changing in Tray 5 temperature, (b)and its effect on tray 25 using table 4-5 parameters**

	Overshoot	**Settling time**	**Oscillation**
Tray5	0	240mn	NA
Tray25	1.89°C	210mn	NA

Table 4-6: PID results after set point changing

As can be seen, changing in temperature of tray5 has a big effect on tray25 temperature by 1.89°C with a large settling time

4.4.2 Interaction Problem and Decoupling the system

As seen before, due to the interaction happened between the loops (interactions in temperature), we will use the RGA method to evaluate the amount of interaction between the loops:

by applying the equation (2.10) in section (2.5.1) we got:

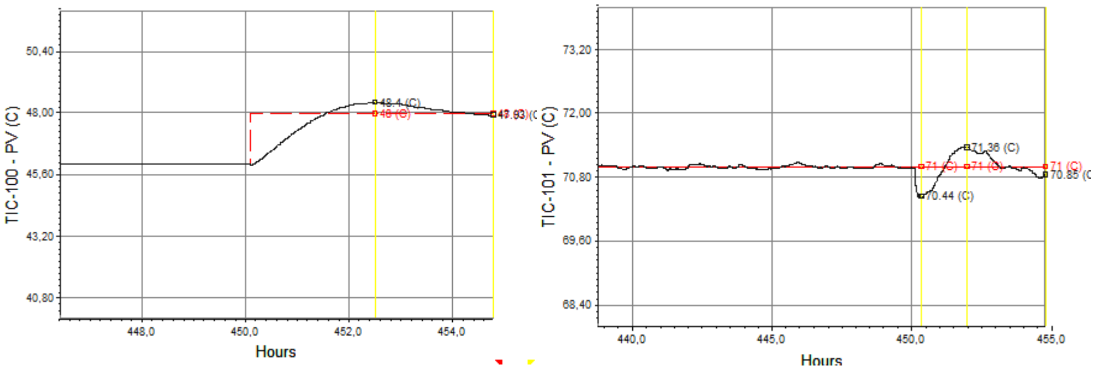
$$\mathrm{RGA} = \Lambda = \begin{bmatrix} 22.5207 & -21.5207 \\ -21.5207 & 22.5207 \end{bmatrix}$$

as we can see the elements are far from one, and as mentioned in section (2.5.1) the interaction in that case becomes very large and dangerous, thus the decouplers are more than necessary. Due to the large interaction happened between the two trays temperatures, decoupler is used to remove or make a negligible interaction. The decoupling elements are as follow:

$$Dc_1 = -\frac{G_{12}}{G_{11}} = 1.43$$

$$Dc_2 = -\frac{G_{21}}{G_{22}} = 0.67$$

The figures below show the effect of applying the decoupler on the system, by applying a setpoint change on tray 5 temperature from 46°C to 48°C and the corresponding change in tray 25 temperature.



(a) **(b)**

Figure 4-6: (a) response to setpoint changing in Tray 5 temperature, (b)and its effect on tray 25 using Forward decoupler

	Overshoot	Settling time	Oscillation
Tray5	0.4°C	240mn	NA
Tray25	0.56°C	240mn	small

Table 4-7: PID Decoupler results

By comparison of table 4-6 and 4-7, interaction between the loops is reduced from 1.89 °C to 0.56°C so the change in tray 5 temperature has a negligible effect on tray 25 and adding the decoupler not affecting system stability because there is no oscillations so the loops are well decoupled.

By Applying a disturbance of 10% opening in feed valve the response is shown below:

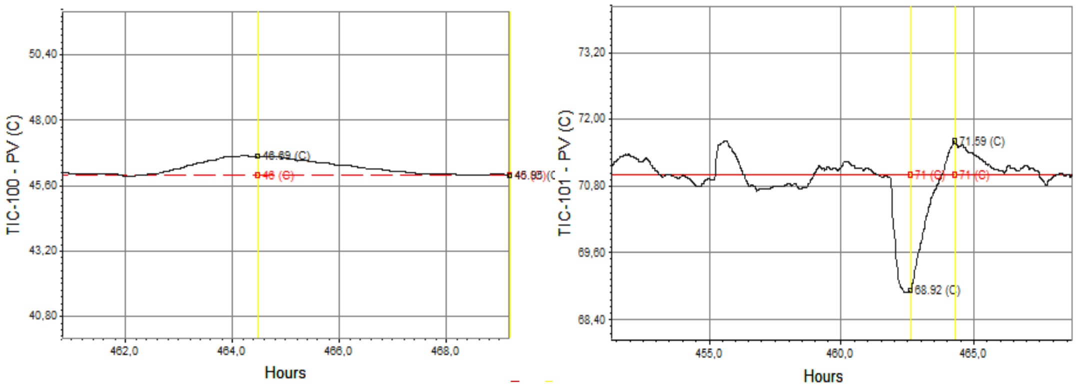


Figure 4-7: response to disturbance in (a) tray 5 and (b)tray 25 temperature

Because the feed temperature is cooler (48°C) than tray 25 temperature (71°C) and near to tray 5 temperature (46°C), the feed is affecting tray 25 more than tray 5 nearly reduced by (2.08°C), it can be deduced that the disturbance cannot be handled by the decoupler.

4.5 Applying MPC controller

The problem faced is the previous section listed as dealing with the loop interaction and the disturbance rejection and also the difficulty of tuning the loops can be solved by adding the MPC controller, the system is shown in figure (4-8)

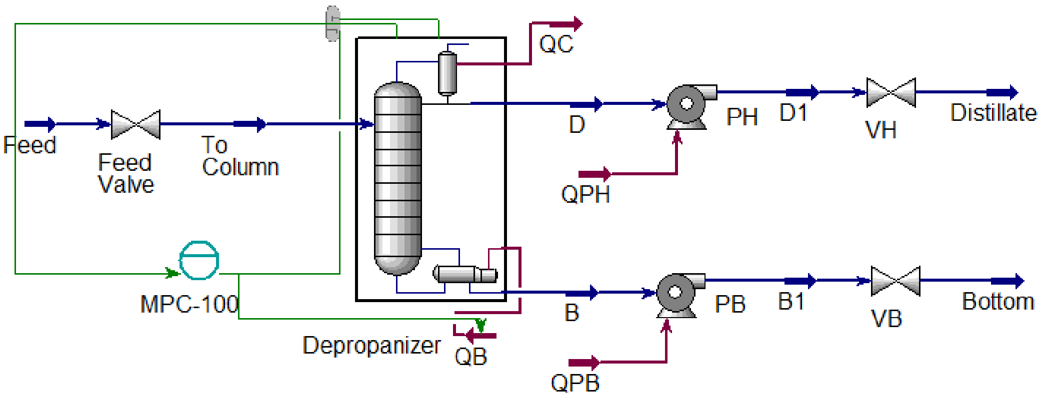


Figure 4-8: Control of Distillation column using MPC

The advantage of using MPC over PID-Decoupler is illustrated:

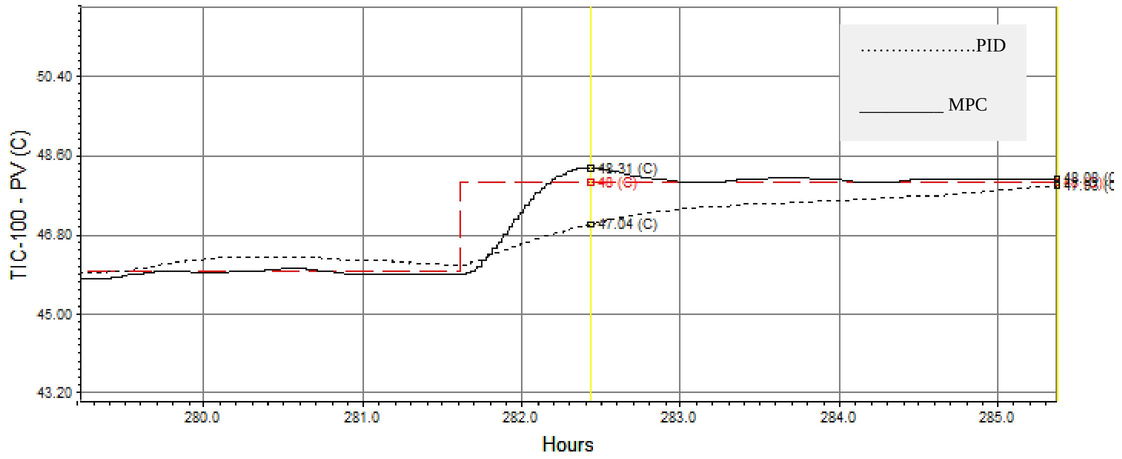


Figure 4-9:Response to step change in tray 5 using MPC and PID-Decoupler

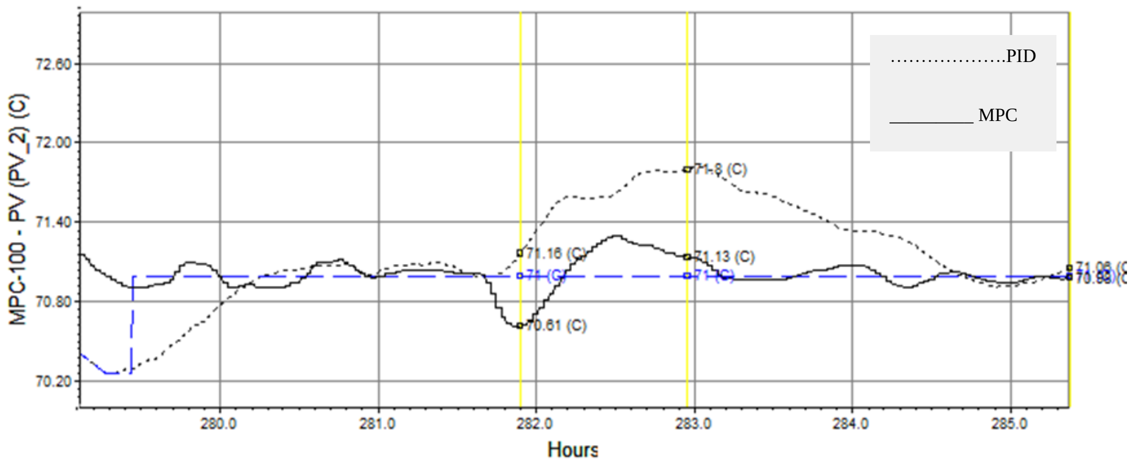


Figure 4-10: Response to step change in tray 25 using MPC and PID-Decoupler

MPC controller respond faster to step change from figure (4-9) after 90 min the temperature reaches the desired value and also for loops decoupling MPC reduces the overshoot and stabilize if after 120 min as seen in figure (4-10)

In other hand MPC works well when adding disturbance as shown in figure (4-11) and figure(4-12).

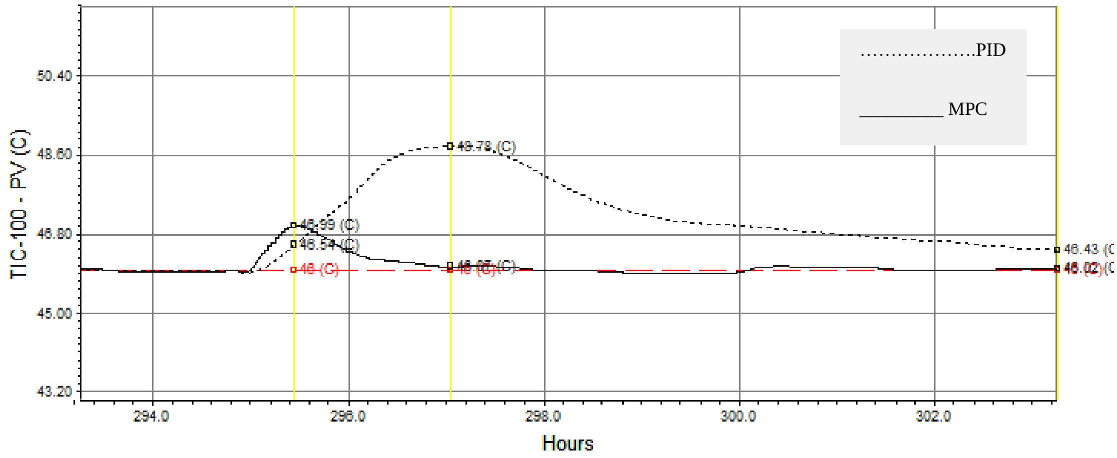


Figure 4-11: Response to disturbance in tray 5 with MPC and PID-Decoupler

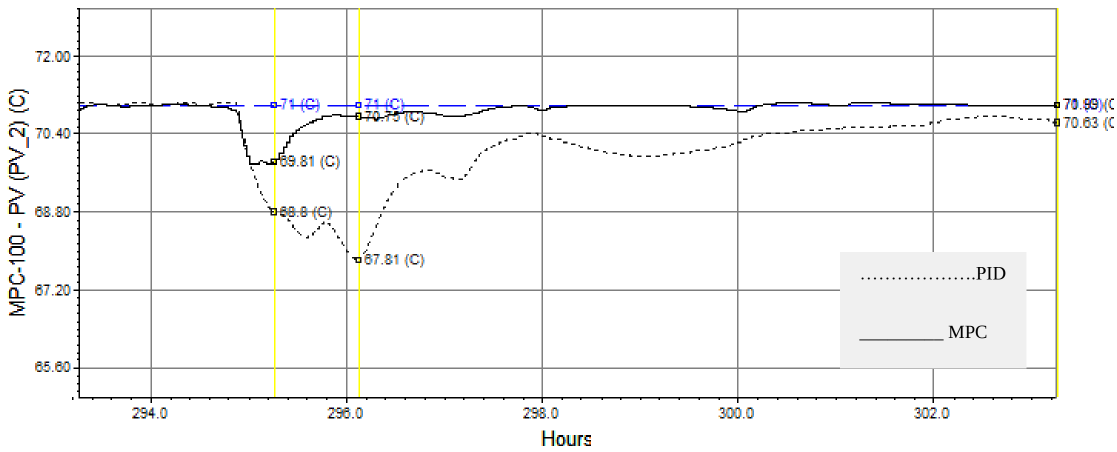


Figure 4-12: Response to disturbance in tray 25 with MPC and PID-Decoupler

By comparing the curve of the MPC controller and PID-Decoupler, we concluded that MPC controller respond faster than PID Decoupler and forbid massive overshoot.

Results:

-MPC handles MIMO system effectively, but for PID controller it is difficult to get response to a complex system.

-MPC respond faster than PID and more effective in Set point tracking and disturbance rejection:

4.6 Tuning MPC Controller

In this section will see the effect of each parameter to conclude the right way to tune MPC for the desired response, after using the method of Shridhar–Cooper and the method of Iglesias et al mentioned in chapter 4 we have found:

Ts	N	P	M	r
9.5	81	65	15	0.5

Table 4-8: MPC parameter

Changing the response horizon N, prediction horizon P, control horizon M weighting factor r

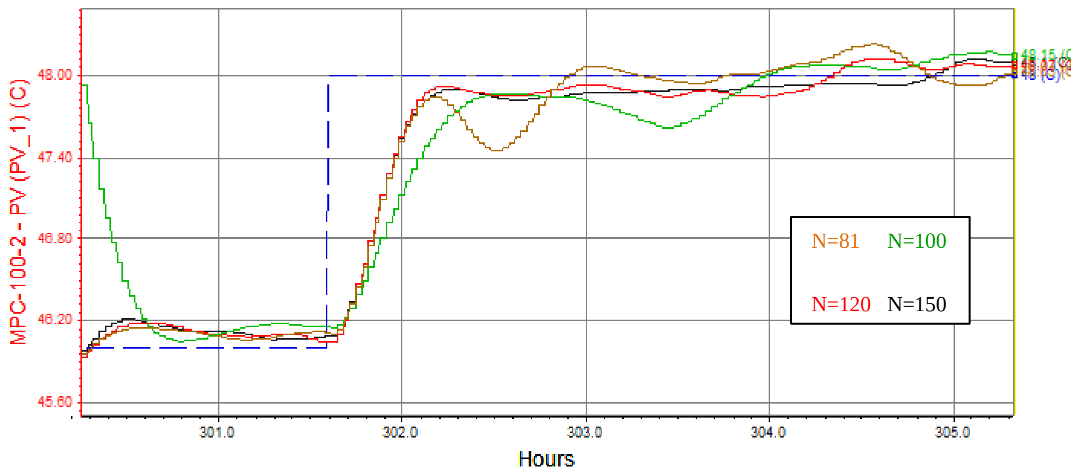


Figure 4-13: response to step change with different response horizon

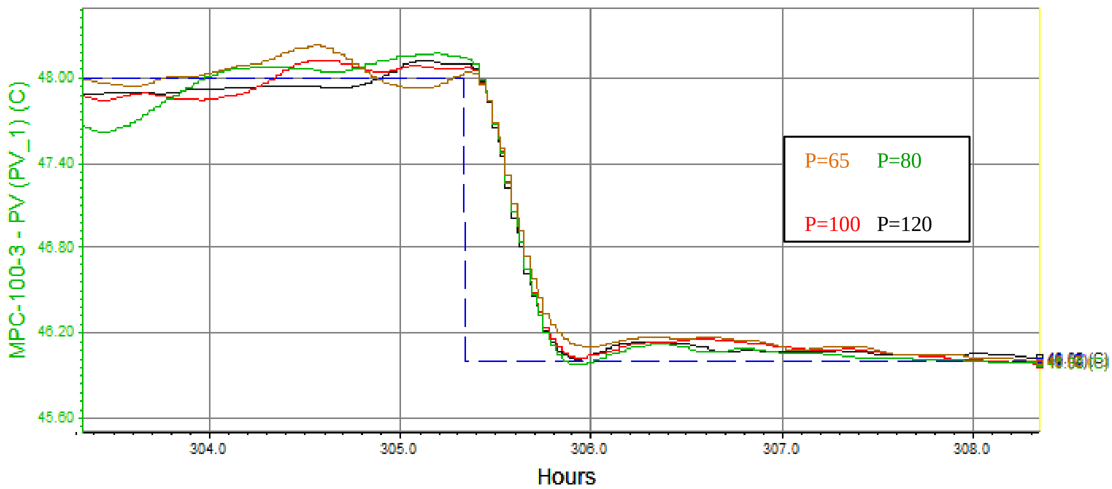


Figure 4-14: response to step change with different prediction horizon

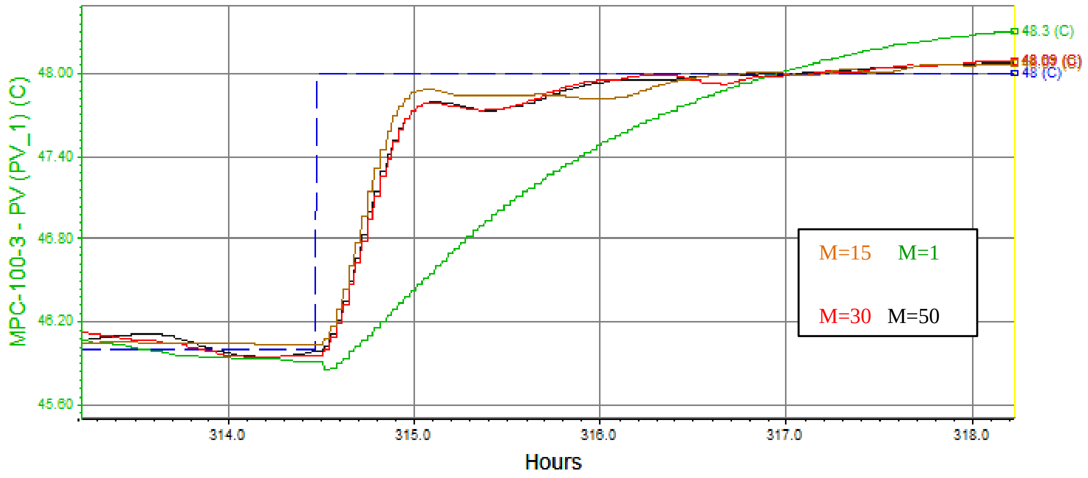


Figure 4-15: response to step change with different control horizon

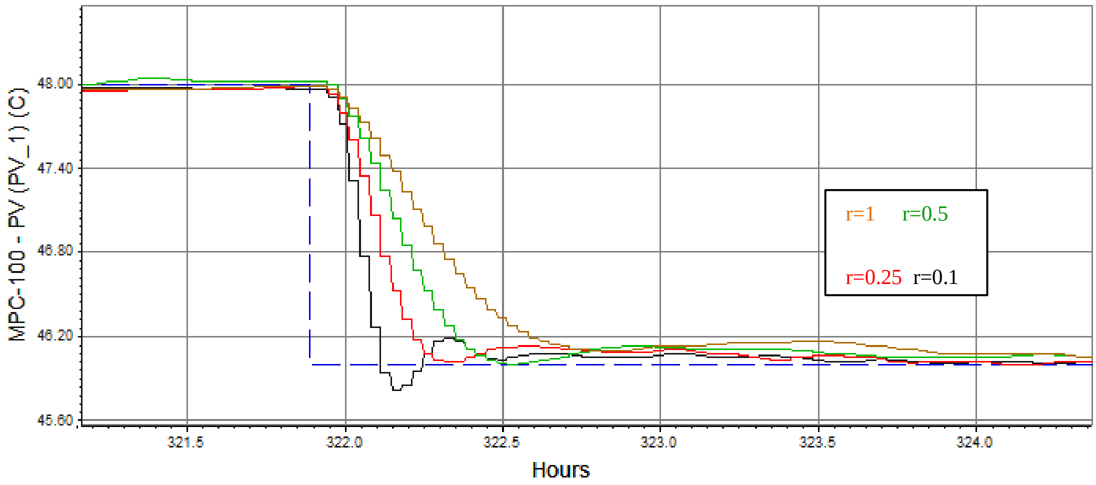


Figure 4-16: response to step change with different weighting factor

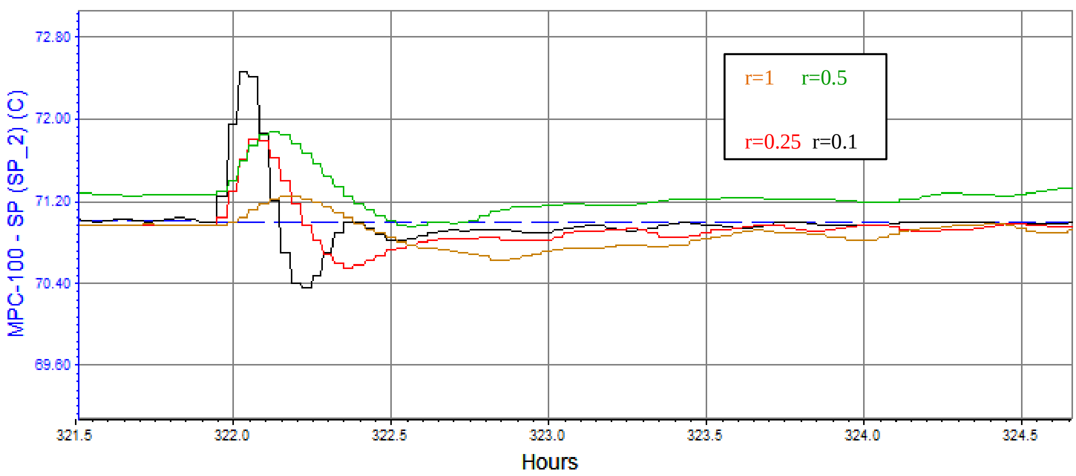


Figure 4-17: response to disturbance with different weighting factor

Results:

Response horizon: from figure (4-13) small value of N which means large sampling time can make the system oscillate.

Prediction Horizon: in figure (4-14) it can be seen that changing the prediction horizon does not affect the system

Control horizon: changing the control horizon as in figure (4-15) affect the response precisely the settling time, when choosing a very small M the response will be smooth and the settling time will decrease but for large length of M the response is the same.

Weighting factor: it is clearly seen in figure (4-16) and (4-17) that the weighting factor is affecting the response of the system so with small value of "r", the controller is aggressive its rising time is 15 min and small oscillation for the disturbance rejection the controller does not reject well the disturbance (1.4°C) overshoot but with large value of r the response to step change has settling time of 45 min ,and the response to the disturbance has an overshoot of 0.3°C

Procedure:

After the study of DMC and the result obtained ,we suggest the following procedure to tune MPC controllers.

Tuning MPC
▪ **The model** should be accurate enough to capture the key dynamics of the system ▪ **Sampling time** should be small and the **response horizon** N should be selected such that the last step response model parameter is equal to the steady state gain. ▪ **Prediction horizon** is not a tuning parameter but it should be selected such that the control horizon can be selected at acceptable range. ▪ **control horizon** should be taken large enough to the computation of the next optimization moves and not small which can cause poor control performance. ▪ **weighting factor** in choosing the weighting factor it should be taken into account that the less value of r the more aggressive the controller will that

leads to large oscillation so it is advised to start with setting r=1 and then change it slightly to the desired response

General conclusion

In this project, we have dealt with distillation column starting from the understanding of its types, characteristics to the ways of controlling it

The first part of the project was to control the system using the conventional methods, because of the MIMO system we have, the main objective of this part was to quantify and measure the interaction between the loops of the system using the Relative Gain Array method that based on the steady-state gain of the system, this method allowed us to quantify the interaction, however for our system we have met the worst case of RGA with a diagonal elements more than 1, in other word the interaction becomes very large and dangerous, to overcome the weakness caused by using only PID controller, Decoupling the system using forward decoupler was needed, after applying it, we overcome the problem of interaction between the loops, but this method was limited when we applied a disturbance on the system.

Due to that, the main purpose of this project was to represent a new method of control to overcome the problems that the conventional method faced while controlling the column, and this done by MPC. The last section we implemented it and compared it with the results obtained from the conventional controllers, we have noticed its advantages in set point following and disturbance rejection, after that we proposed a tuning procedure.

Along this project we faced many problems and difficulties mainly in working with a new software, building the model, getting the good parameters for the PID controller and getting the more effective parameters for the MPC controller.

Future Scope

Due to restriction of time, some jobs are still there to be done in this project work. PID and MPC as supervisory controller, Procedure to implement the MPC in different distillation column and continuous columns processes, optimal work must be performed to reduce computation complexity.

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