Model Predictive Control Using Orthonormal Basis Filter

by

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CERTIFICATION OF APPROVAL

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A project dissertation submitted to the
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Approved by,

…………………………...
(Dr. Lemma Dendena Tufa)

UNIVERSITI TEKNOLOGI PETRONAS
TRONOH, PERAK
September 2014

CERTIFICATION OF ORIGINALITY

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

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NIK SYAIRAH BT NIK MOHD NIZAM

ABSTRACT

Proportional Integral Derivative (PID) controller is the most common controller that acts as standard tool in a process control industry. However, when interacting with Multiple Input and Multiple Output (MIMO) process, the interaction is difficult to be controlled by PID controller. Therefore, this project will focus on Model Predictive Control (MPC) that is one of optimization strategy that can control MIMO interaction by predicting the effect of potential control action. In this project, a mathematical model of Orthonormal Basis Filter (OBF) will be developed on the distillation column based on Wood-Berry model with a feedback control (a closed loop system). A simulation of MPC is done by using MATLAB coding while PID is simulated using SIMULINK. Based on the simulation, the performance of MPC and PID controller are evaluated by using the Integral Error Criteria: Integral Absolute Error (IAE), Integral of the Squared Error (ISE) and Integral of the time-weighted absolute error (ITAE) and also with total input variation. Lower integral error criteria and total input variation value indicate a better model accuracy and efficiency of controller for MIMO system.

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Table of Contents

List of Figures

List of Graphs

List of Tables

ABBREVIATIONS AND NOMENCLATURES

ARX	Auto Regressive with Exogenous Input
ARMAX	Auto Regressive Moving Average with Exogenous Input
BJ	Box-Jenkins
FIR	Finite Impulse Response
IAE	Integral Absolute Error
ITAE	Integral Time-Weighted Absolut Error
ISE	Integral of Squared Error
MIMO	Multiple Input Multiple Output
MPC	Model Predictive Control
OBF	Orthornormal Basis Filter
OE	Output Error
PID	Proportional Integral Device
SISO	Single Input Single Output

CHAPTER 1

INTRODUCTION

1.1 Background

Development of control design initially starts with identification for control where consideration of the best possible approximate model set with characterization in term of bias error and variance error on the estimated transfer functions. The identification of model is significant to justify whether the control can be the main influence in model building and achieve high performance control even with basic dynamical features of a system. [1] Performance of control system is dependent on the quality of the models that reflects back the wide application in applied advance process control technology in chemical process. Once the model is identified, model validation need to be done as "quality control" that detects changes of the model parameters. The effectiveness and reliability, address the importance in application for monitoring critical process such as nuclear power, plants, gas turbines, catalytic converter, distillation column, etc. [2]

In this case, the approach is taken with Model Predictive Control (MPC), one of optimization strategy that predicts the effect of potential control action based on plant model. Generally, MPC is designed to compute a trajectory that optimizes the future behavior of the plant output y based on the future manipulated variable u. This optimization is performed with the plant information at the start of time window under a limited time constraint. In each time step, MPC is applied in an open-loop optimal control problem with the input profile injected into the plant until a new measurement becomes available in order to formulate and solve new open-loop optimal control problem.

There are three key elements that are required to design MPC that involves predicting the future (model), assessing the current activities (measurement) and implementing the planned activities (realization of control). [3-5] In a system, MPC is used to control Multiple Input Multiple Output (MIMO) process with inequality constraints on the input and output variables. The input variables play important roles in coordinating the input-output relationship that is represented by the process model. For MPC application, the input variables are referred as manipulated variables (MVs), the output variables are called control variables (CVs) and the feed forward variables is the measured disturbance variables (DVs). Theoretically, the MPC controller can prevent violations of input and output constraints by driving some output variables to their optimal set points while maintaining other outputs within specified ranges. In conjunction to that, the controller prevents excessive movement of the input variables and controls most of the variables when a sensor or actuation is not available. [3, 4] Thus, MPC shows several advantages over classical control methodologies like PID control where its ability covers from guiding the process in an optimal way by taking desired future behavior into account, tackle multiple inputs and outputs simultaneously and are able to incorporate with constraints.[6]

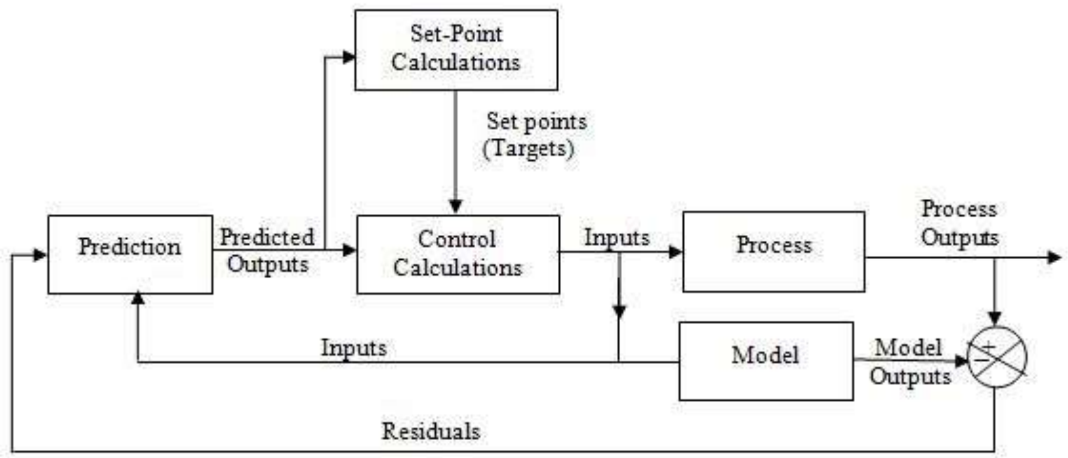


Figure 1: Block Diagram for Model Predictive Control

The block diagram of Model Predictive Control above shows the process model used to predict the current values of the output variables.

Two different types of MPC calculations used for prediction which are set-point calculations and control calculation at each sampling. The type of calculation also includes the inequality of constraints on the input and output variables of upper and lower limits. Constraints are varying based on the process conditions, equipment, instrumentation and economic data. [3] The set points of the control calculated from an economic optimization is based on steady-state model such as linear model. This optimization minimized the cost function and maximized production as well as profit function. In control calculation, the currents measurement and prediction is made by using a dynamic model. The dynamic model uses a multivariable of the step response or difference equation models. Objectively, MPC control calculation determines the sequence of control moved for the predicted response moves to optimum set point. Lastly, the feedback signals of residuals to the prediction block come from the differences between the actual and predicted outputs calculated. [3]

In performance of advanced, model accuracy plays important role in model predictive control algorithm. Basically, model fidelity affects the routine operating condition that requires re-identification that usually done under closed-loop condition. In this case, a direct approach for closed-loop identification is more suitable for MPC. This approach can achieve yield unbiased and consistent parameter estimation with parameterized noise model. On top of that, MPC system has several advantages whereby the process model captures the dynamic and static interaction between inputs, outputs and disturbance variables while constraints on inputs and outputs are being considered in a systematic manner. It also controls the calculation that will be coordinated with the calculation of optimum set points and give the accurate model predictions that can provide early warnings of potential problems. This shows that the accuracy of the process model is a vital aspect in MPC and become the method of choice for difficult multivariable control in industry. [3, 7]

Models for MPC are developed from physical and chemical principles in a system that are called first principle (white-box models) while the derivation using mathematical and statistical principle from experimental data is called empirical (black-box models). The white-box models are related to system properties whereby the value in principle can be measured directly from the real system or estimated. However, it is difficult to apply in process industries because of lack of knowledge of complex industrial processes. Thus, black-box models are commonly used in process industries. [8]

System identification is a process whereby developing models from experimental data. The model that is used related to control-system design or implementation known as control-relevant system identification. The major steps in system identification are design of the experiment, selection the class of models, selection of the model structure and model validation. These models can be categorized as linear or non-linear models. In linear models, the structures are divided into Auto Regressive with Exogenous Input (ARX), Auto Regressive Moving Average with Exogenous Input (ARMAX), Box-Jenkins (BJ), Finite Impulse Response (FIR) and Output Error (OE) model. [8, 9]

The structures of the various models are given below:

Auto Regressive with Exogenous Input (ARX):

$$y(k) = \frac{B(q)}{A(q)}u(k) + \frac{1}{A(q)}e(q) \tag{1.1}$$

Auto Regressive Moving Average with Exogenous Input (ARMAX):

$$y(k) = \frac{B(q)}{A(q)}u(k) + \frac{C(q)}{A(q)}e(q) \tag{1.2}$$

Box-Jenkins (BJ):

$$y(k) = \frac{B(q)}{F(q)}u(k) + \frac{C(q)}{D(q)}e(q) \tag{1.3}$$

Finite Impulse Response (FIR):

$$y(k) = B(q)u(k) + e(q) \tag{1.4}$$

Output Error (OE):

$$y(k) = \frac{B(q)}{F(q)} u(k) + e(q) \tag{1.5}$$

Where *A(q), B(q), C(q), D(q)* and *F(q)* are polynomials in the shift operator *q* and *u(k)*, *y(k)* and *e(k)* are the input, output and white noise sequences, respectively.

There are a few factors need to be considered in selecting model structures which are the computational load in estimating model parameters, the consistency of the model parameters and the number of parameters required to describe the model with acceptable accuracy. Normally, ARX and FIR models are the most common because of the computational simplicity with the model parameters estimated. For OE and BJ models are rarely used for complex problems like MIMO because of the heavy computational load to the parameter estimations that involves nonlinear optimization. [8, 9]

Lastly, the Orthonormal Basis Filter (OBF) models are considered under a generalization of FIR models. OBF models are very promising for control relevant system identification compared to most of the conventional linear models. The parameters are estimated based on the linear least square method that is the most practical for open-loop identification problems. The parsimonious OBF models can be developed when the dominant poles of the system are known and time delays are estimated by incorporating into the model. [8-10]

1.2 Problem Statement

PID controller is the most common form of feedback that has become a standard tool in a process control industry. The controller is combined with logic, sequential function, selectors and simple blocks to build the automation system. However, when interacting with Multiple Input and Multiple Output (MIMO) process, the control loop interact with another control loop that results a big interaction between one another. Practically, this interaction is difficult to be controlled by PID controller. Therefore, the solution to overcome this problem is by using Model Predictive Control that coordinate input-output relationship and delay the optimization of the process model.

1.3 Objectives

The objectives of Model Predictive Control using Orthonormal Basis Filter are

i. To develop a Distillation Column Model by using SIMULINK
ii. To develop and implement Model Predictive Control by using Orthonormal Basis Filter (Laguerre Model).
iii. To compare the performance of the Model Predictive Control and Proportional Integral Derivative in distillation column.

1.4 Scope of Study

The scope of study for this project is:

i. Closed loop system
   Open loop system will not be examined in this project
ii. Linear system
   Non-linear system is excluded in this Project
iii. Model Predictive Control (MPC)
   The performance of MPC Controller will be evaluated for distillation column.
iv. Multiple-Input and Multiple Output (MIMO) system
   Single-Input and Single-Output will not be considered in this project.
v. Orthonormal Basis Filter (OBF) Model
   OBF model will be used to develop the mathematical model
vi. Wood & Berry Distillation Column
   This type of distillation column will be used as a standard
vii. Proportional-Integral-Derivative (PID) Control
   The performance of MPC Controller will be compared with PID Controller

CHAPTER 2

LITERATURE REVIEW

Figueria et al identify that Model Predictive Control (MPC) is a technique that refers to a system of computer control algorithm that regulates the future behavior of plant through the use of an explicit process model. At each control interval MPC algorithm computes an open loop-sequence of manipulated variable adjustment to optimize future plant behavior. [11] MPC is also a form of control that is obtained by solving on-line, at each sampling instant. It is a finite horizon open-loop optimal control problem that used the current state of the plant as the initial state. The optimization yields an optimal control sequence and hence, the sequence is then applied to the plant. Type of MPC varies from robust, feedback, pre-computed and decentralized MPC. Robust MPC is guaranteed for its feasibility and stability as in [11] while feedback MPC mitigates shrinkage of feasible region. In addition to that, pre-computed MPC is a piecewise-linear solution that is stored in database or solves off-line using parametric of linear or quadratic programming and lastly, decentralized MPC used in autonomous air vehicle-speed up computation.

Generally, MPC is a moving horizon implementation and performance oriented time domain formulation. It is also the one that can incorporate with constraint and explicit system model that can predict future plan dynamics.[12] Chan et. al stated that the MPC designation is based on the intuitive simplicity approach and partly from flexibility offered that define a dynamic model of the system which therefore match the state and parameters of the system model to real time data. Besides, it also calculates control to satisfy constraints based on given performance objective and finally, implements controls according to the receding horizon principle.[13]

Camponogara et al mentions MPC also called as receding horizontal control whereby the control input is obtained by solving a discrete-time optimal control problem over a given horizon, producing an optimal open-loop control input sequence. For starter, the application of control in the sequence in MPC, sampling instant of a new optimal control problem is formulated and solved based on the new measurements. When the system is completely modeled, all the control inputs are computed in one optimization problem. In a large scale applications like power systems, water distribution system, traffic systems, manufacturing systems and economic systems, the distributed or decentralized control schemes are sometime necessary in order the local control inputs to be computed using local measurement and reduced-order models of local dynamics. In some application, multiple low level controllers are simply implemented using MPC to close local feedback loops. [14]

MPC is mainly basis of the development of controller synthesis schemes based on stochastic state space models that control sequence in moving horizon. However, the stochastic model with known state and measurement noise characteristics are seldom available. Therefore, stochastic models are developed for unmeasured disturbances directly from the input-output data. In developing stochastic model, the time series models with the assumption time delay between each input-output. The time delay generally known in a ratio of two transfer functions. Based on Wang [15], transfer function model gives a parsimonious description of process dynamics that are applicable to both stable and unstable plants. Apart from that, extra parameter of time delays makes estimation problem highly nonlinear and difficult to solve. Fundamentally, the time delay is estimated using other techniques before being developed into time series model. Time delay estimation methods are based on the analysis of open loop step response behavior that can be applied to system with reasonably fast dynamics. The measured and unmeasured disturbances can be maintained at their nominal levels during the step test. A major drawbacks is most of the available approach are applicable to time delay for Single Input Single Output (SISO) case but not applicable to multivariable case, MIMO. If one manipulated input is perturbed at a time, the identification test on the plant is inconsistent in achieving measured and unmeasured constant. [9, 16, 17]

Darby and Nikoloau [18] stated that MPC typically involve in pretest and preliminary MPC design, plant testing, model and controller development; commissioning and training in industries. A typical MPC contain a few components that play as target selection, controller and estimator. A target selection determine the feasibility of steady-state operating point for controlled outputs and manipulated inputs based on steady-state gain model. It is implemented to minimize deviations from desired steady-state as a result of economic-based steady-state optimization that include either liner program (LP) or quadratic program (QP). In controller, MPC determines optimal, feasible future inputs over a moving horizon to minimize the predicted future controlled errors of controlled outputs from targets determined. For estimator, it updates the model prediction for unmeasured disturbances and model errors that may include a deterministic part of model controller-manipulated variables.

In MPC, control decision *u(k)* are made at discrete instants *k=0,1,2,..*, which usually represent equally spaced time intervals. At decision instant *k*, the controller samples the state of the system x*(k)* and then solves an problem of the following form to find the control action:

$$\min_{X(k),U(R)} J(X(k),U(k)) \tag{2.1}$$

Where

$$X(k) = \{x(k+1|k),\dots,x(k+N|k)\} \tag{2.1.1}$$

$$U(k) = \{u(k|k),\dots,u(k+N-1|k)\} \tag{2.1.2}$$

s.t

$$x(k+i+1|k) = F(x(k+i|k),ux(k+i|k)) \qquad (i=0,\dots,N-1) \tag{2.1.3}$$

$$G\big(X(k),U(k)\big) \le 0 \tag{2.1.4}$$

$$x(k|k) = x(k) \tag{2.1.5}$$

In the preceding formulation, the performance index represents the difference measured between the predicted behavior and the desired future behavior: the lower the value, the better the performance. The variables $x(k+i|k)$ and $u(k+i|k)$ are respectively, the predicted state and the predicted control at time $k+i$ based on the system model, $x(k+1) = F(x(k), u(k))$. The constraints may represent physical limits to the system and can also to ensure the stability or robustness of the system. The optimization produces an open-loop optimal control sequence in which the first control value is applied to the system: that is, $u(k) = u(k|k)$. Then, the controller waits until the next control instant and repeats this process to find the next control action. [14]

Sun et al [19] reported MPC performance monitoring face a few challenges that the performance can come from many sources that include control horizon lengths, weights in the objective functions, poor model quality in either input-output plant channel or the disturbance channel, inappropriate constraint setup and inconsistency between upper level optimization and the dynamic MPC. Among these challenges, input-output plant model and the disturbance model is the main key that affect the control performance. Prediction from a poor model can result in computed inputs to be far from optimal control move. Therefore, models are being used for the design and development of new process besides for analyzing and improving existing process as stated by Lemma and Shuhaimi [20]. Models are extensively used in advanced process control design and implementation as a controller design, optimization, fault detection and diagnosis in process industries. Basically, the process of developing system models involves a general linear dynamic model. The general linear model shown below in equation (2.1):

$$y(k) = \frac{B(q)}{A(q)} u(k) + \frac{1}{A(q)} e(q) \qquad (2.2)$$

From the general model equation, it is then developed according to the parameter needed into ARX, ARMAX, BJ, FIR and OE as in equation (1.1) to (1.5). The ARX and FIR models are the most popular models in process industries. The parameters are easily estimated using linear least square method. ARX model facilitates estimation of the noise model simultaneously with the deterministic model rather than FIR model. Nevertheless, both models have flaw in the system as ARX model have inconsistent parameters and FIR model requires large number of parameter (non-parsimonious) to accurately capture system dynamics. When model parameters are non-parsimonious, large input-output data set is required in order to minimize variance error in model parameters. As a result, inconsistency in parameters and systematic error (bias) may occur in the estimated model parameters that cannot be easily removed by increasing the number of data points. [20, 21]

Then, the ARMAX is the next commonly used model structure that is estimated by using nonlinear optimization or extended least square method. However, the common denominator dynamics, *A(q)* in equation (1.2) may not determine whether the noise is not correlated with the input. Amongst all, BJ model is the most flexible of all linear models but it is very limited due to its difficulty in estimating the model parameters that involves non-linear optimization. BJ model is rarely applied in MIMO system due to its large number of parameter. The common problem that the entire linear problem share is that time delay is required to accurately estimate the model parameter. However, if we compare ARX with ARMAX and BJ model, relatively it is easier for ARX to identify high order models and can be used for identification of both unstable and stable model. [20, 21]

Further research has been done that results system identification based on Orthornormal Basis Filter (OBF). OBF are more preferable in modeling of system as having first- or second-order dominant dynamics respectively. OBF models allow incorporation of system dynamics into the model with a simple and elegant method of representing open loop stable systems that can be looked upon as a compact parsimonious in parameters.

Lemma et al [22] mentions that parsimonious OBF models only acceptable accuracy if there is the availability of appropriate type of filter and good estimates of dominant poles of the system. Alex da Rosa et. al [23] also said that the poles of OBF are free-design parameters that act as optimal selection in model identification problem. Hence, OBF can be used to solve parameter estimation problem analytically by using linear regression. This shows the contradiction with ARX models that have inconsistency parameter problem. OBF models are parsimonious in parameters compared to FIR and step response models. The parameters of OBF models can be easily determined using linear least square method. Time delays also can be easily estimated and incorporated into the models. Moreover, OBF models have output error structure that can determine component of model and estimate consistently the noise that is uncorrelated with the inputs. Orthornormal functions also represent signals that exhibit long time delays because of their similarity to Padé approximation. Thus, developments of OBF based models do not need any prior knowledge about system time delays. [16, 20-22, 24]

Basically, OBF can be considered as a generalization of FIR models where the filters $q^{-1}q^{-2}, \ldots,$ are replaced with more orthonormal basis filters that allow incorporation of prior knowledge of the system. Two filters, f_m and f_n are said to be orthonormal if they satisfy the property.

$$\langle f_m(q), f_n(q) \rangle = \begin{cases} 1 \ (m = n) \\ 0 \ (m \neq n) \end{cases} \quad (2.3)$$

Where <,> represents the inner product defined on the set of all stable transfer functions. Thus, a stable system, *G(q)*,can be approximately represented by a finite-length generalized Fourier series expansion as:

$$G(q) = \sum_{i=1}^{n} L_i F_i(q) \quad (2.4)$$

Where, q: forward shift operator; L_i: model parameters and $F_i(q)$: orthonormal basis filters for the system $G(q)$.

In time domain, the response *y(k)*, for an input *u(k)*, can be described as

$$y(k) = G(q)u(k) + H(q)e(k) \tag{2.5}$$

Where, $e(k)$ is white noise sequence with mean zero and variance σ^2.

Alex da Rosa et al [25], stated that a growing interest in using Orthonormal Basis Filter that involve in identification and control of dynamic process. This is because OBF have simpler solution to modeling and control as the orthonormality of these functions yield simpler general models. The development of OBF model includes the selection of an appropriate type of Orhonormal Basis Filters. The types of OBF available are Laguerre filter, Kautz filter, and Markov-OBF as below:

Laguerre Filter,

$$f_i = \sqrt{(1-P^2)}\frac{(1-pq)^{i-1}}{(q-p)^i}, \qquad |p| < 1 \tag{2.6}$$

Where, p is pole (estimated).

Laguerre filters are first-order lag filters with one real pole and more appropriate for well damped processes.

Kautz Filter,

$$f_{2i-1} = \frac{\sqrt{(1-a^2)(1-b^2)}}{q^2+a(b-1)q-b} g(a,b,q,i) \tag{2.7}$$

$$f_{2i} = \frac{\sqrt{(1-b^2)}(q-a)}{q^2+a(b-1)q-b} g(a,b,q,i) \tag{2.8}$$

Where,

$$g(a,b,q,i) = \left(\frac{-bq^3+a(b-1)q+1}{q^2+a(b-1)-b}\right)^{i-1} \tag{2.9}$$

$$-1 < \alpha < 1 \; and -1 < b < 1, n = 1,2, \ldots$$

The Kautz filters allow incorporation of a pair of conjugate complex poles that are effective for modeling weakly damped processes.

Markov-OBF,

Markov-OBF is used in a system that involves time delay and estimation of time delay. The time delay is included with placing some of the poles at the origin. [16, 20, 26, 27]

In OBF, Laguerre and Kautz bases are most commonly used in approximation control problems. However, Laguerre basis is more preferable in representing well damped dynamic system. The analytical developments lead to closed optimization solution that can be used in both linear and non-linear domains. Laguerre also involves in rational transfer functions from a simple recursive form and completely parameterized by a single real-valued pole. [28, 29] Several recent studies are focusing on Laguerre filters whereby discrete Laguerre filters are a method for the identification and approximation of signals or system, adaptive filtering or filter design as stated by Telescu et. al [30]. The Laguerre functions and filters depend only in a free parameter of a multiple-order single pole that predefines the denominator of the resulting rational model.

It also can reduce the number of parameters for optimization on-line by parameterization the future trajectory of the filtered control signals. The future control trajectory acts as a core technique in the design of MPC either the control signal [u(k)] itself or the difference of the control signal [$\Delta u(k)$] by forward shift operators. This Laguerre functions acts as a scaling factors that is used to reflect the time scale of predictive control system. For instance, there are cases of rapid sampling of complicated process dynamics and high demands on closed loop performance. Hence, satisfactory approximation of the future control signal may require a large number of forward shift operators.

Similarly, it applies to infinite impulse response model that is used in system identification. Other than that, lack of structural constraint on the future control signal could lead to fast and steep changes that may result optimal control signal. For both cases, the approach can be taken by parameterization of the control signal using orthonormal polynomial function. [30-33] The parameterization presents a parsimonious description of the future control signal that reduces the number of parameters required in modeling the control trajectory. This shows the difference of future control signal within the moving horizon window using a Laguerre impulse respond structure with appropriate dimensionality. The scaling factor in the Laguerre polynomials becomes a constraint on the decay rate of the incremental control signal that infers the control horizon and directly affects the closed-loop response speed. [31]

Wang [31] stated there are two mainstreams in order to achieve stability of model predictive control system. The first method is by using the terminal constraints in the state variable which forces the terminal state variables to be zero. The second is to use an infinite horizon in the cost function. However, the use of infinite horizon in the cost function may become unrealistic to solve the difference of the control signal as in [34] unless a pre-stabilizing strategy is used. Therefore, a distinct feature in designing is used through scaling factor chosen to be zero in the Laguerre polynomials.

CHAPTER 3

METHODOLOGY

Objective (i)

MATLAB is the main software used in this project. Distillation column will be developed based on Wood-Berry Model. The model is set-up as in Figure 2 below.

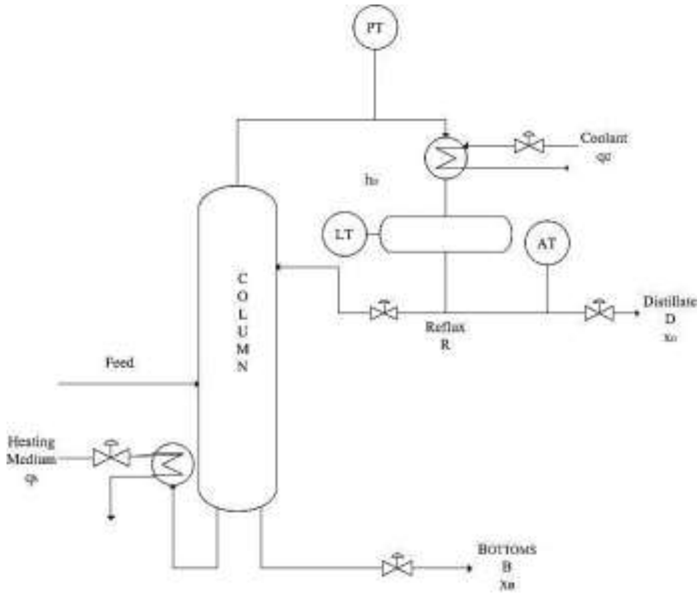


Figure 2: Distillation Column Model

To accomplish the first objective, the MPC design parameters for a MIMO problem is introduced into the distillation column by using Wood-Berry Model as in equation (3.1).

$$\begin{bmatrix} X_D(s) \\ X_B(s) \end{bmatrix} = \begin{bmatrix} \frac{12.8e^{-s}}{16.7s+1} & \frac{-18.9e^{-3s}}{21s+1} \\ \frac{6.6e^{-7s}}{10.9s+1} & \frac{-19.4e^{-3s}}{14.4s+1} \end{bmatrix} \begin{bmatrix} R(s) \\ S(s) \end{bmatrix} \tag{3.1}$$

The controlled variables are the distillate and bottom compositions (X_D and X_B); the manipulated variables are the flux flow rate and the steam flow rate to the reboiler (R and S). [3, 35]

The following steps are taken to accomplish the objectives:

1. Introduce step change in the distillation column
2. Collect the input-output data
3. Develop models
4. Evaluate the controller by using Integral Error Criteria and Total Input Variation.
5. Select the best performance between MPC and PID controller

Objective (ii)

A simulation is performed by using MATLAB Model Predictive Control Toolbox. The MPC Controller of Orthonormal Basis Filter (OBF) and Laguerre function is applied into the distillation column model. For each simulation, sampling period Δt=1min and set point of 0.2 are imposed on each input. After completed a simulation for MPC Controller, a PID Controller simulation also will be designed for distillation column model. The SIMULINK is designed as in Figure 3, Figure 4 and Figure 5.

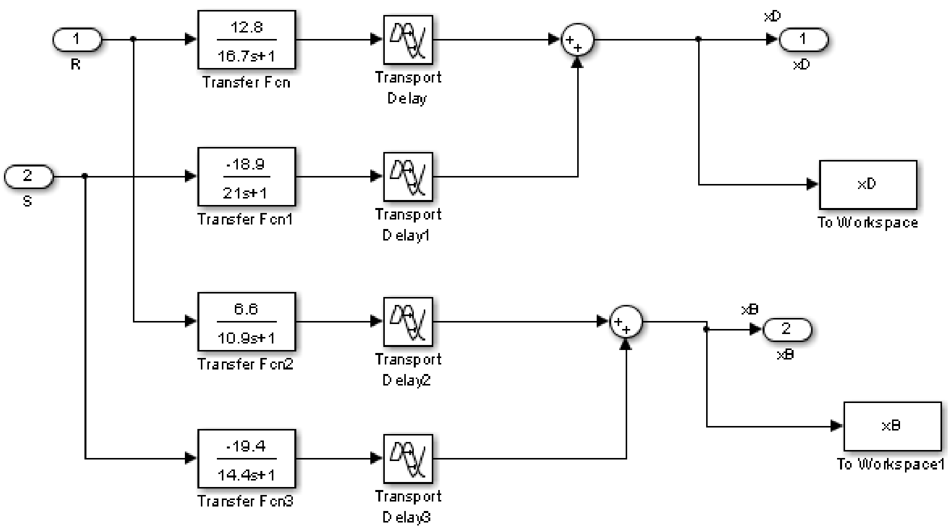


Figure 3: Subsystem of SIMULINK

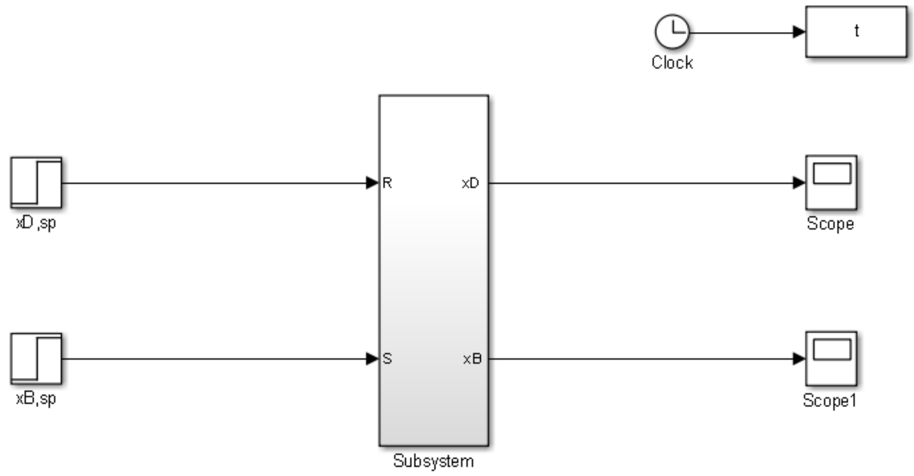


Figure 4: SIMULINK: MPC Controller

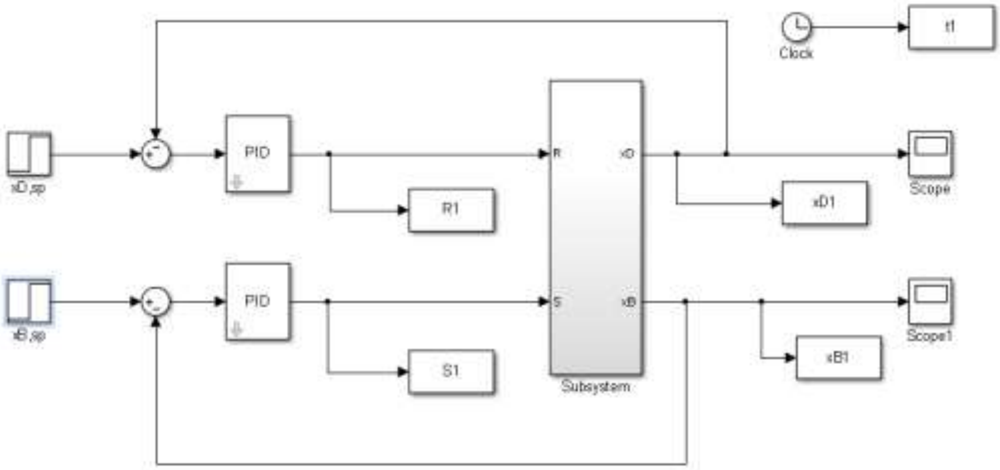
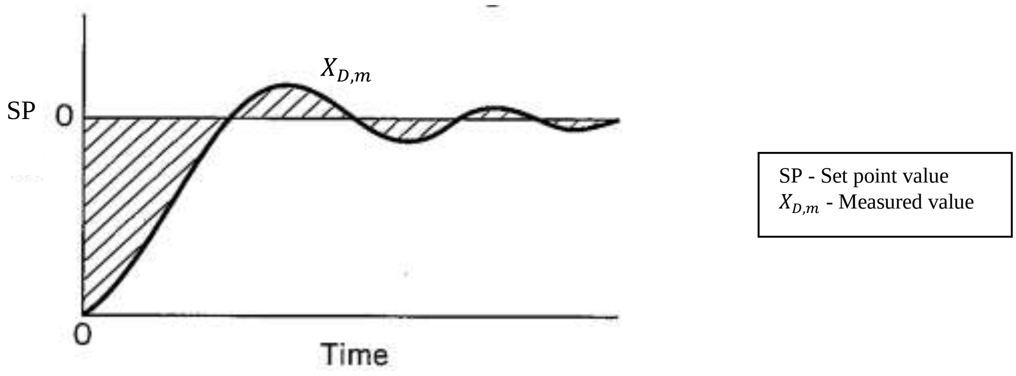


Figure 5: SIMULINK: PID Controller

Objective (iii)

The performance of MPC is evaluated based on Integral Error Criteria: Integral Absolute Error (IAE), Integral of the Squared Error (ISE) and Integral of the time-weighted absolute error (ITAE). The Integral Error Criteria indicates the cumulative error of how far the response is with respect to the applied reference (set point). Besides that, total input variation also will be evaluated as performance parameter.

In a current working distillation column, a step change is introduced for a period of time, *t*. Then, the difference between set point and the measurement is calculate as error signal *e(t)* whereby *e(t)=SP(t)-*$X_{D,m}$ as illustrated in Graph 1 below.



Graph 1: Graphical Interpretation of IAE

Integral Error Criteria are as follows:

1. Integral of the absolute value of the error (IAE).

$$\text{IAE} = \int_0^\infty |e(t)|dt \tag{3.2}$$

2. Integral of the squared error (ISE)

$$\text{ISE} = \int_0^\infty e(t)^2 dt \tag{3.3}$$

3. Integral of the time-weighted absolute error (ITAE)

$$\text{ITAE} = \int_0^\infty t|e(t)|dt \tag{3.4}$$

The MPC Performance is evaluated for a period of time. i.e, *t=0,1,…,n=40.* Then, Table 1 is tabulated based on the calculation above

Table 1: Data Collection

	MPC	PID
IAE		
ISE		
ITAE		

From the data collected in Table 1, MPC Controller and PID Controller is evaluated. The best performance is selected for application in distillation column.

CHAPTER 4

RESULTS AND DISCUSSION

4.1 Designation of the Controller

4.1.1 MPC Controller

MPC Controller System is used for system identification in system modelling whereby the system is represented by discrete-time impulse response of dynamic system by a Laguerre Model. Discrete-time Laguerre functions are orthonormal functions with orthonormal properties. The Laguerre functions is the time domain for this model. The parameters used in this designation is the Laguerre pole location, a and number of OBF terms, N. Basically, a is used for stability of the Laguerre Network and act as a scaling factor which needs to be selected by the user.

In MATLAB, the system modelling is designed into a discrete-time state space model based on equation (3.1) in Wood-Berry Distillation Column Model. The initial conditions of Laguerre function is first generated with discrete-time impulse response. The model is specified into Multiple-Input Multiple-Output (MIMO) with two inputs and two outputs system. The minimum realization is obtained in order to calculate the minimum possibilities for augmented state-space model. In this design, the data is generated with the cost function based on the minimization of the error between set-point signal and output signals. Then, the integral error criteria is calculated to determine the performance of the controller. In addition, the total input variation also will be determined based on the input signals.

4.1.2 PID Controller

PID Controller is the combination of the proportional, integral and derivatives control modes. Typically, the proportional control speeds up the process thus reducing offset of the response. Meanwhile, integral control eliminates the offset however it may result an oscillatory response.

As for derivative control, it reduces both the degree of oscillation and the response time. Besides, the control signal is affected by the controller gain, K_c and times delay, τ as in equation (4.1).

$$G = K_c(1 + \frac{1}{\tau_I S} + \tau_N s) \quad (4.1)$$

For distillation column design, the PID controller is simulated using $X_D - R/X_B - S$ Control configuration.

In SIMULINK, the subsystem is designed based on the Wood-Berry Distillation Column as previously in MPC Controller. The difference is the PID Controller is added with PID Block which contain controller gain and time delay that is inserted before entering the subsystem of controller model. The PID controller will monitor the output and compare it with reference set point. The error signal between actual and desired output will be applied as feedback to the input of controller to achieve the desired set point. The integral error criteria will compute the error signal to evaluate the performance of the controller.

4.1.3 Integral Error Criteria

The integral error criteria can be calculated based on the equation (3.2) to (3.4). The criteria is used to minimize the overshoot, settling time, steady state error and reference trajectory error of controller systems. In a system, IAE criterion utilize the magnitude of error by using integral expression either for positive or negative error. For ISE, it focusses on the square of the error function which penalize both the positive and negative value. Lastly, ITAE criterion penalize long duration transient that is the integral of time multiplied by the absolute value of the error. Hence, ITAE is the most preferred in the industry as it result in most conservative settings comparing to ISE that tends to produce aggressive setting.

4.2 MPC Controller

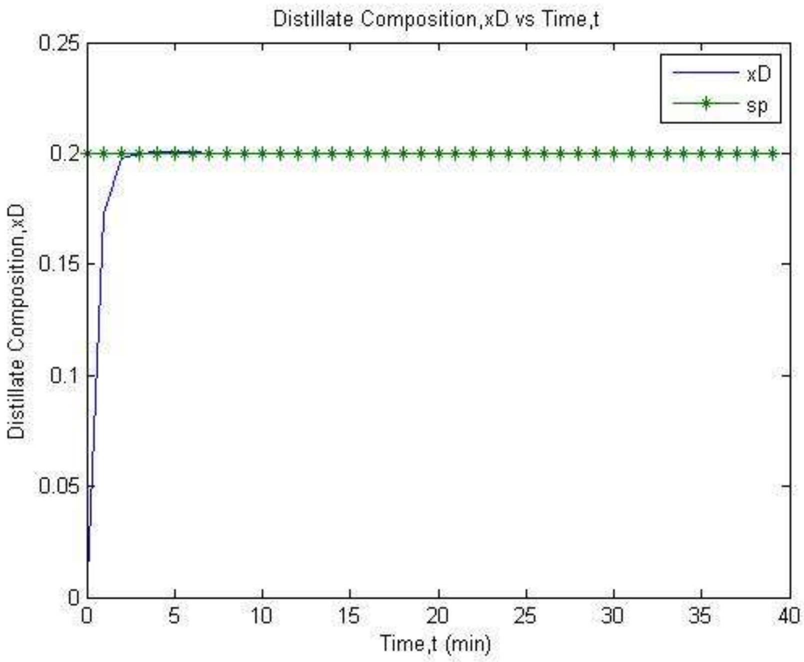
In order to illustrate the performance of MPC Controller, Wood-Berry Distillation Column Model is used for system modelling. The manipulated variables are the reflux flow rate, R and steam flow rate, S whereas the controlled variables are the Distillate, xD and Bottom Composition, xB. For each simulation the set point is 0.2 with sampling period of Δt=1min for period of time, t=40 min. This section will determine the best Laguerre pole location, *a* and number of OBF terms, *N* for MPC Controller.

4.2.1 Tuning of Laguerre Pole Location, a

In this section, the effective Laguerre pole location will be determined by observing the integral error criteria and total input variation from 0.2, 0.4 and 0.8. Number of OBF term, N used is 40.

MPC Performance for a = 0.2

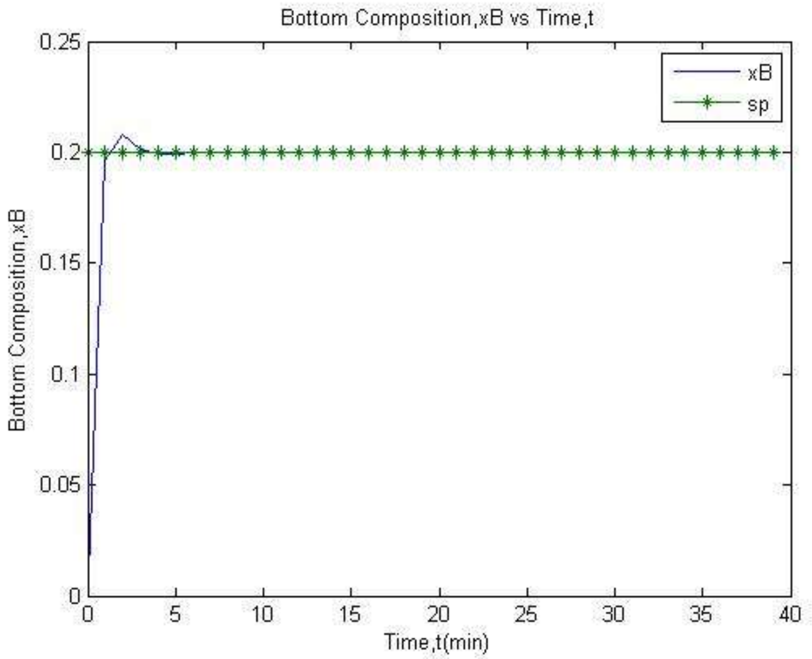
i. Distillate Composition



Graph 2: Closed-loop response for set point tracking in xD with *a=0.2*

Graph 2 indicates the response of the MPC Controller for distillate composition, xD over time, t. The distillate composition, xD increases steadily to the set point, sp. From this graph, it can be observed that xD requires shorter time (6 minutes) to achieve desired set point and achieve steady state.

ii. Bottom Composition



Graph 3: Closed-loop response for set point tracking in xB for *a=0.2*

Graph 3 indicates the response of the MPC Controller for bottom composition, xB over time, t. The bottom composition, xB increases to the set point, sp with a slight overshoot at 2 minutes. From this graph, it can be observed that xB requires shorter time (6 minutes) to achieve desired set point and achieve steady state than xD.

iii. Integral Error Criteria

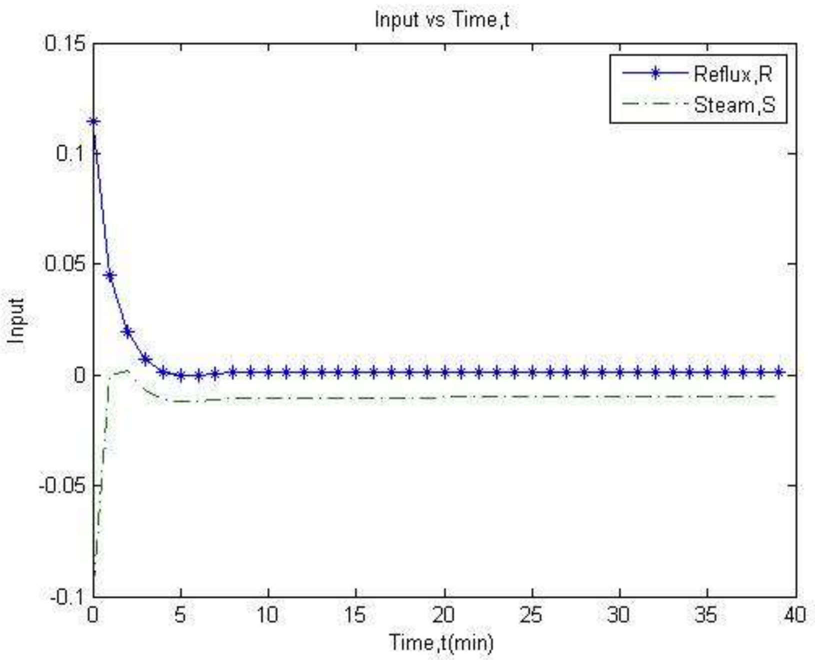
Based on Graph 2 and 3, the integral error criteria is being determined as in Table 2.

Table 2: Integral Error for set point tracking at *a = 0.2*

Integral Error Criteria		
Integral Error	**Distillate Composition, xD**	**Bottom Composition, xB**
IAE	0.1321	0.1155
ISE	0.0207	0.0201
ITAE	0.0466	0.0356

Bottom Composition, xB shows slightly lower error in the integral error criteria than Distillate Composition, xD. Even though xB has a slight overshoot, it takes a shorter time to achieve the desired set point and steady state than xD. Thus, low error represents high efficiency of control action at the bottom valve which prolongs durability and lifespan of valve.

iv. Input Variation



Graph 4: Input Variation for set point tracking at *a=0.2*

Graph 4 shows the input controller for Reflux, R and Steam, S over time, t. Reflux, R decreased steadily with time while the Steam, S increase with slight overshoot at 2 minutes before decreasing to the set point and achieve steady state.

From this graph, R and S need approximately 8 minutes to achieve steady state in the distillation column.

v. Total Input Variation

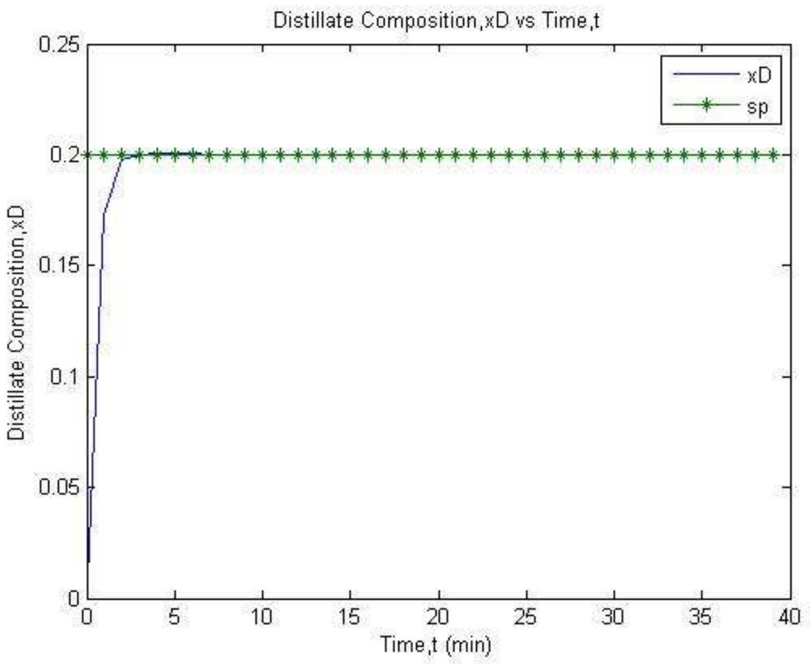
Table 3: Total Input Variation for set point tracking at *a = 0.2*

Input	Total Input Variation
Reflux, R	0.2321
Steam, S	0.2168

Based on Graph 4, the input variation is determined as in Table 3. Steam, S shows a lower variation compare to Reflux, R. The variation value indicates the interval of input within the time period. This shows that S has taken corrective action based on the measured output to reduce the error to the desired set point. Therefore, lower variation represents lower disturbance in the input controller which result in higher efficiency of the controller.

MPC Performance for a = 0.4

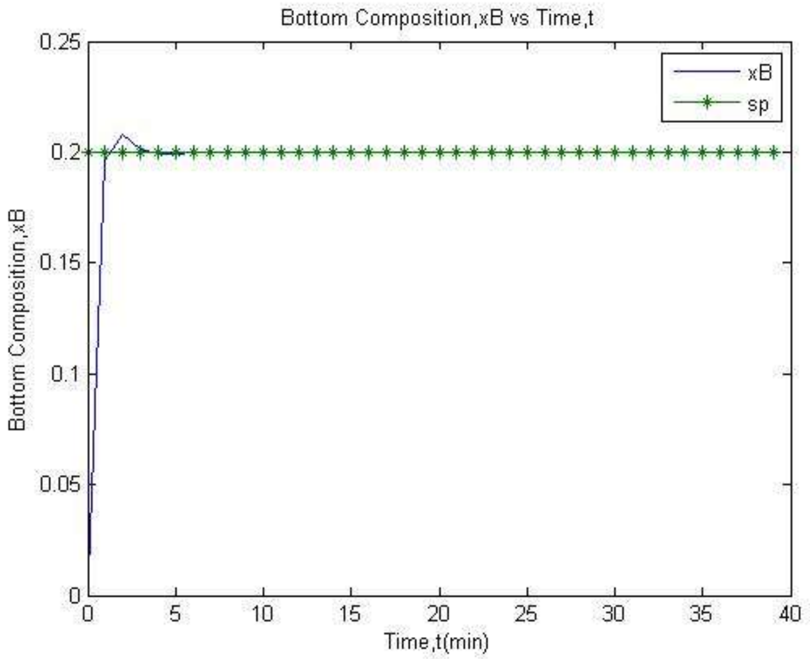
i. Distillate Composition



Graph 5: Closed-loop response for set point tracking in xD

Graph 5 indicates the response of the MPC Controller for distillate composition, xD over time, t. The distillate composition, xD increase steadily to the set point, sp. From this graph, it can be observed that xD at *a* =0.4 requires longer time (7 minutes) to achieve desired set point and achieve steady state with xD at *a* =0.2. Hence, the increment of Laguerre pole location results lower efficiency of controller to achieve desired set point and steady state.

ii. Bottom Composition



Graph 6: Closed-loop response for set point tracking in xB

Graph 6 indicates the response of the MPC Controller for bottom composition, xB over time, t. The bottom composition, xB increases to the set point, sp with a slight overshoot at 3 minutes slower than *a*=0.2 even though xB requires similar time (6 minutes) to achieve desired set point and achieve steady state with *a*=0.2. Thus, the increment of Laguerre pole location shows a distortion of the signal in xB.

iii. Integral Error Criteria

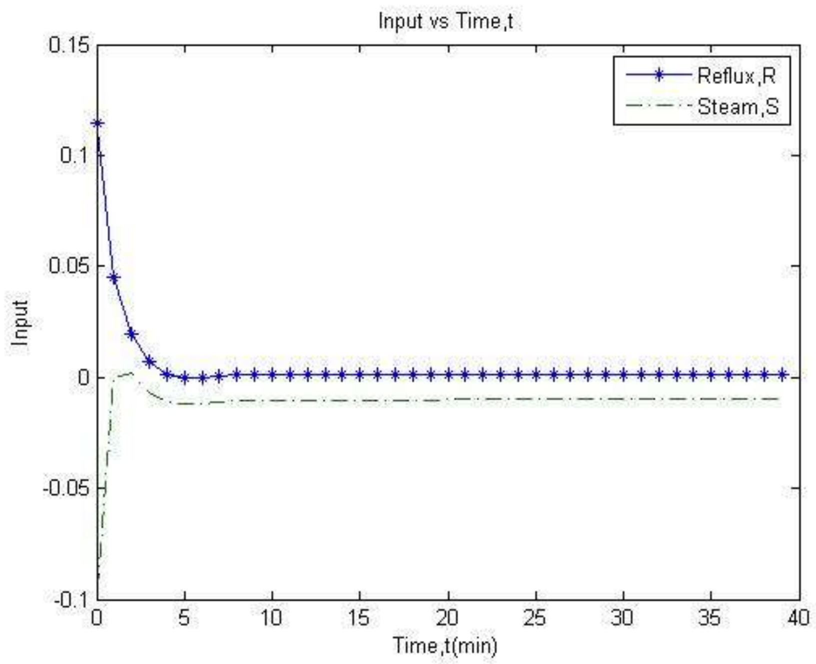
Based on Graph 5 and 6, the integral error criteria is being determined as in Table 4.

Table 4: Integral Error Criteria for set point tracking at *a = 0.4*

Integral Error Criteria		
Integral Error	**Distillate Composition, xD**	**Bottom Composition, xB**
IAE	0.1321	0.1155
ISE	0.0207	0.0201
ITAE	0.0464	0.0361

Bottom Composition, xB shows slightly lower error in the integral error criteria than Distillate Composition, xD. Even though xB has a slight overshoot, it takes a shorter time to achieve the desired set point and steady state than xD. At *a* =0.4, the IAE and ISE have similar error to *a* =0.2. Meanwhile the ITAE value results slightly higher error in xD and lower in xB than *a=0.2*. Thus, the integral error criteria is affected by the Laguerre pole location.

iv. Input Variation



Graph 7: Input variation for set point tracking at *a = 0.4*

Graph 7 shows the input controller for Reflux, R and Steam, S over time, t. Reflux, R decreased steadily with time while the Steam, S increase with slight overshoot at 2 minutes before decreasing to the set point and achieve steady state. From this graph, R and S need approximately 8 minutes to achieve steady state in the distillation column which is a bit similar to a =0.2.

v. Total Input Variation

Table 5: Total Input Variation for set point tracking at $a = 0.4$

Input	Total Input Variation
Reflux, R	0.2321
Steam, S	0.2168

Based on Graph 7, the input variation is determined as in Table 5. Steam, S shows a lower variation compare to Reflux, R. This shows that S has taken corrective action based on the measured output to reduce the error to the desired set point. However, the input variation at a=0.4 is similar to a=0.2. The increment of Laguerre pole location does not affect the input controllers.

MPC Performance for a = 0.8

Similar analysis has been done for a = 0.8 whereby the closed-loop response for set point tracking is plotted for distillate composition, xD and bottom composition, xB as in Appendix I. Then, the integral error criteria is determined and being compared with previous Laguerre pole location. The table for integral error criteria for set point tracking a =0.8 is as follows:

Table 6: Integral Error for set point tracking at $a = 0.8$

Integral Error Criteria		
Integral Error	**Distillate Composition, xD**	**Bottom Composition, xB**
IAE	0.1666	0.1439
ISE	0.0231	0.0568
ITAE	0.0891	0.0215

Bottom Composition, xB shows slightly lower error in the integral error criteria than Distillate Composition, xD. At *a* =0.8, the integral error criteria results in increment of error especially drastically increase at ITAE of xD and ISE of xB. Thus, as *a* increases, the integral error criteria also increases. The controllers proved at *a=0.8,* it has lowest efficiency among all the set point.

Apart from the integral error criteria, the total input variation also being determined as in Table 7.

Table 7: Total Input Variation for set point tracking at *a = 0.8*

Input	Total Input Variation
Reflux, R	0.2087
Steam, S	0.1647

Based on the table 7, steam, S shows a lower variation compare to Reflux, R. This shows that S has taken corrective action based on the measured output to reduce the error to the desired set point. However, at *a* =0.8 the input variation reduces than the both previous *a*. Therefore, this shows that at a=0.8, the disturbance decreases with the variations that even though it takes a longer time to reach steady state.

Effective Laguerre Pole Location

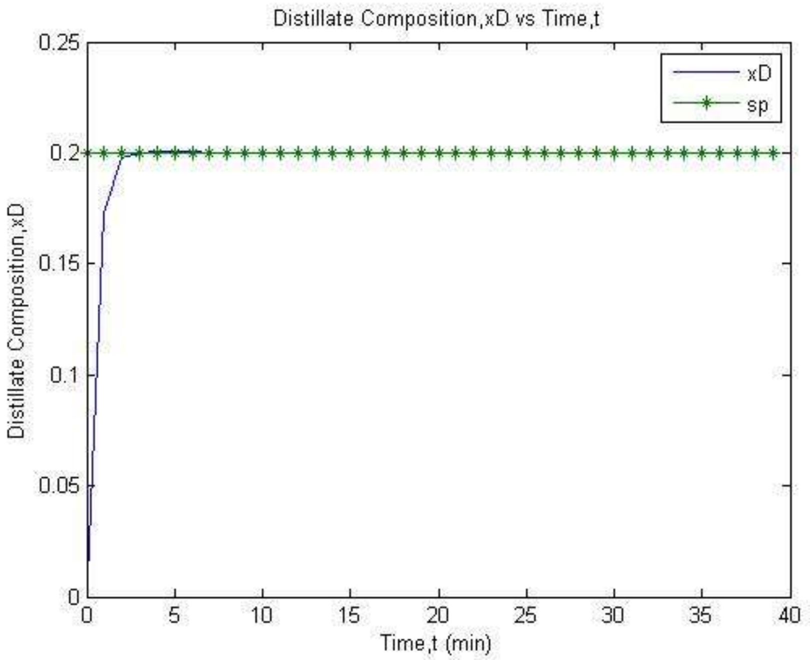
The controllers have been tested with 3 different Laguerre pole location of 0.2, 0.4 and 0.8. Based on the observation in the integral error criteria and total input variation. It can be concluded that the MPC controller works best at *a*=0.2 whereby it has the lowest integral error criteria, total input variation and settling time. When *a* =0.4, the total input variation is similar but the integral error criteria have a slight differences in ITAE whereby it has lower error in xD and higher in xB. Hence, the pole location is being compared with time taken to reach steady state that results *a=0.2* takes shorter time than *a=0.4.* In addition, lower value parameters indicates the efficiency of the controller. *a* =0.2 is the effective Laguerre pole location that minimizes the predicted deviations from the reference trajectory.

4.2.2 Tuning Number of OBF Terms, N

The effective Laguerre pole location obtained in section 4.2.1, *a* =0.2 is being applied in MPC Controller. In this section, effective number of OBF term will be determined by observing the integral error criteria and total input variation from 10, 50 and 100.

MPC Performance for N=10

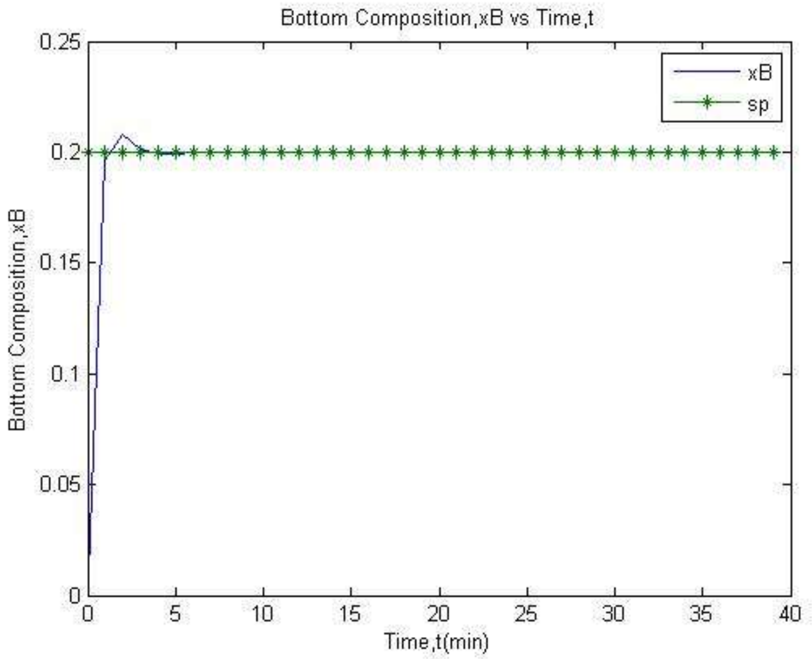
i. Distillate Composition



Graph 8: Closed-loop response for set point tracking in xD at *N=10*

Graph 8 indicates the response of the MPC Controller for distillate composition, xD over time, t. The distillate composition, xD increase steadily to the set point, sp. From this graph, it can be observed that xD requires short time (7 minutes) to achieve desired set point and achieve steady state.

ii. Bottom Composition



Graph 9: Closed-loop response for set point tracking in Xb at *N=10*

Graph 9 indicates the response of the MPC Controller for bottom composition, xB over time, t. The bottom composition, xB increases to the set point, sp with a slight overshoot at 2 minutes. From this graph, it can be observed that xB requires shorter time (6 minutes) to achieve desired set point and achieve steady state than xD.

iii. Integral Error Criteria

Based on Graph 8 and 9, the integral error criteria is being determined as in Table 8.

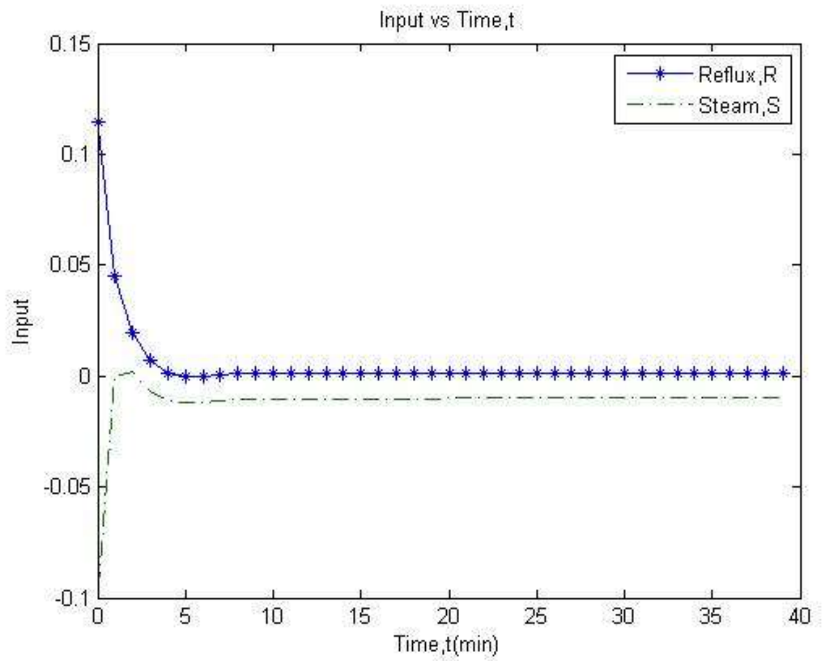
Table 8: Integral Error Criteria for set point tracking at *N = 10*

Integral Error Criteria		
Integral Error	**Distillate Composition, xD**	**Bottom Composition, xB**
IAE	0.1321	0.1155
ISE	0.0207	0.0201
ITAE	0.0460	0.0355

Bottom Composition, xB shows slightly lower error in the integral error criteria than Distillate Composition, xD. Even though xB has a slight overshoot, it takes a shorter time to achieve the desired set point and steady state than xD.

Besides, the ITAE in *N=10* is slightly lower than in the section 6.2.1 of *N=40*. Thus, lower N results in high efficiency of control action which results in high durability and lifespan of valve.

iv. Input Variation



Graph 10: Input variation for set point tracking at N=10

Graph 10 shows the input controller for Reflux, R and Steam, S over time, t. Reflux, R decreased steadily with time while the Steam, S increase with slight overshoot at 2 minutes before decreasing to the set point and achieve steady state. From this graph, R and S need approximately 8 minutes to achieve steady state in the distillation column.

v. Total Input Variation

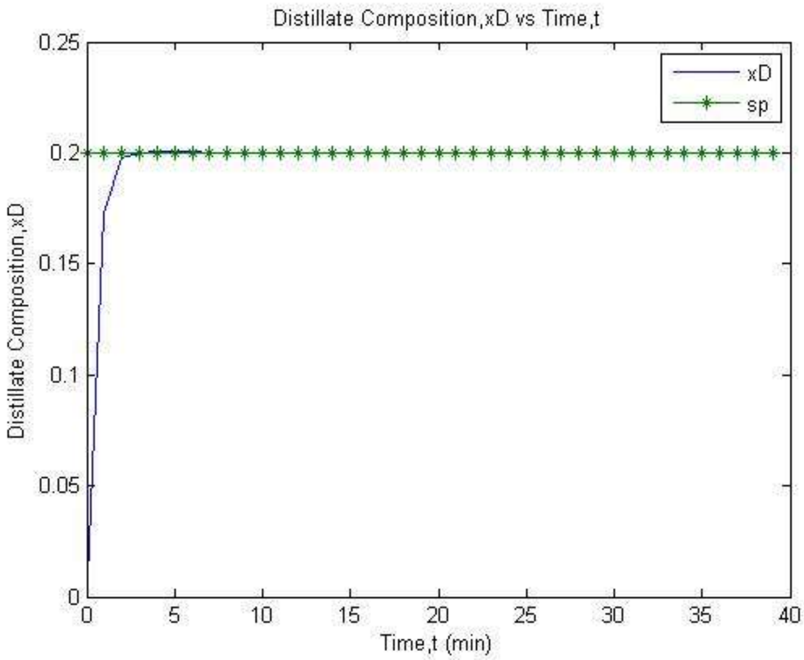
Table 9: Total Input Variation for set point tracking at *N = 10*

Input	Total Input Variation
Reflux, R	0.2321
Steam, S	0.2168

Based on Graph 10, the input variation is determined as in Table 9. Steam, S shows a lower variation compare to Reflux, R. Lower variation shows the accuracy of corrective action based on the measured output to reduce the error to the desired set point.

MPC Performance for N=50

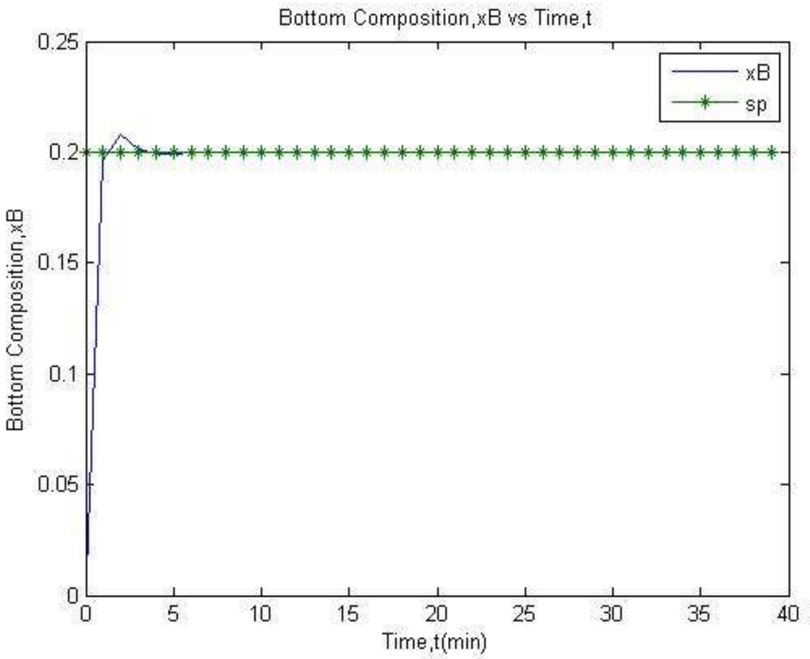
i. Distillate Composition



Graph 11: Closed-loop response for set point tracking in xD at *N=50*

Graph 11 indicates the response of the MPC Controller for distillate composition, xD over time, t. The distillate composition, xD increase steadily to the set point, sp. From this graph, it can be observed that xD at *N=50* requires similar time (7 minutes) to achieve desired set point and achieve steady state with xD at *N=10*. Hence, the increment of number of OBF term does not affect the efficiency of controller to achieve desired set point and steady state.

ii. Bottom Composition



Graph 12: Closed loop response for set point tracking in xB at *N=50*

Graph 12 indicates the response of the MPC Controller for bottom composition, xB over time, t. The bottom composition, xB increases to the set point, sp with a slight overshoot at 2 minutes slower similarly to *N=10* even though xB requires similar time (6 minutes) to achieve desired set point and achieve steady state with *N=10*. Thus, the increment of number of OBF term does not affect the efficiency of controller to achieve desired set point and steady state.

iii. Integral Error Criteria

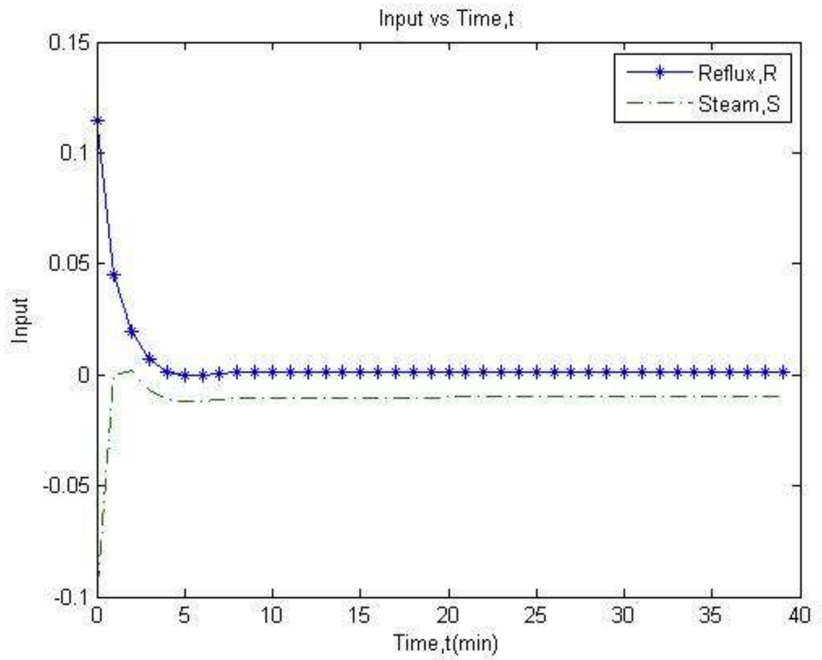
Based on Graph 11 and 12, the integral error criteria is being determined as in Table 10.

Table 10: Integral Error Criteria for set point tracking at *N=50*

Integral Error Criteria		
Integral Error	**Distillate Composition, xD**	**Bottom Composition, xB**
IAE	0.1321	0.1155
ISE	0.0207	0.0201
ITAE	0.0476	0.0360

Bottom Composition, xB shows slightly lower error in the integral error criteria than Distillate Composition, xD. Even though xB has a slight overshoot, it takes a shorter time to achieve the desired set point and steady state than xD. At *N=50*, the IAE and ISE have similar error to *N=10*. Meanwhile the ITAE value results slightly higher error than *N=10*. This shows there is existence of sustained error for long period of time.

iv. Input Variation



Graph 13: Input variation for set point tracking at at *N=50*

Graph 13 shows the input controller for Reflux, R and Steam, S over time, t. Reflux, R decreased steadily with time while the Steam, S increase with slight overshoot at 2 minutes before decreasing to the set point and achieve steady state. From this graph, R and S need approximately 8 minutes to achieve steady state in the distillation column which is a bit similar to *N=10*.

v. Total Input Variation

Table 11: Total Input Variation for set point tracking at *N=50*

Input	Total Input Variation
Reflux, R	0.2322
Steam, S	0.2168

Based on Graph 11, the input variation is determined as in Table 10. Steam, S shows a lower variation compare to Reflux, R. However, the R varies slightly higher than *N=10*. This shows that as number of OBF term increases, the variation in the input increases accordingly. This may result from the presence of disturbance in the input signal of R.

MPC Performance for N=100

Similar analysis also has been done for *N=100* whereby the set point tracking of closed-loop response for is plotted for distillate composition, xD and bottom composition, xB as in Appendix II. Then, the integral error criteria is determined and being compared with previous Laguerre pole location. The table for integral error criteria for set point tracking *N=100* is as follows:

Table 12: Integral Error Criteria for set point tracking at N=100

Integral Error Criteria		
Integral Error	**Distillate Composition, xD**	**Bottom Composition, xB**
IAE	0.1324	0.1158
ISE	0.0207	0.0201
ITAE	0.0526	0.0435

Bottom Composition, xB shows slightly lower error in the integral error criteria than Distillate Composition, xD. At *N=100*, the integral error criteria results in increment of error only in ITAE. Thus, as *N* increases, the integral error criteria also increases accordingly. The controllers shows that at *N=100*, the error increases thus, reduces the efficiency of the controllers.

After that, the total input variation also being determined as in Table 13.

Table 13: Total Input Variation for set point tracking at *N=100*

Input	**Total Input Variation**
Reflux, R	0.2322
Steam, S	0.2168

Based on the total input variation determined, Steam, S shows a lower variation compare to Reflux, R. At *N=100*, the input variation is similar with *N=50* but slightly higher than *N=10*. Therefore, this shows that as *N* increases, the variations of the input also increases with a slightly changes due to the disturbances.

Effective Number of OBF Terms

The controllers have been tested with 3 different Number of OBF Terms, N of 10, 50 and 100. Based on the observation in the integral error criteria and total input variation, it can be concluded that the MPC controller works best at *N=10* whereby it has the lowest integral error criteria and total input variation. In the case of IAE and ISE, the error is similar for the 3 different number of OBF terms. It shows that the increment of OBF term number only affected ITAE. This may occur because ITAE have an additional time multiplier of the error function, that emphasize on measuring long-duration errors that results in accuracy measurement of integral error criteria. For total input variation, the differences only occur in R input that is caused by slight disturbance available from the controller. The R input is varies accordingly to the measured disturbances based on the output responses.

4.3 PID Controller

In SIMULINK of PID Controller, the controller gain and time delay is used to manipulate the Wood Berry Distillation Column Model. The PID Controller is simulated by using the $X_D - R/X_B - S$ control configuration. The set point for PID Controller is similar with MPC Controller at 0.2 for period of time, t=40min. In this section different controller gain, K_c and times delay, τ will be used to determine the best control configuration for PID Controller.

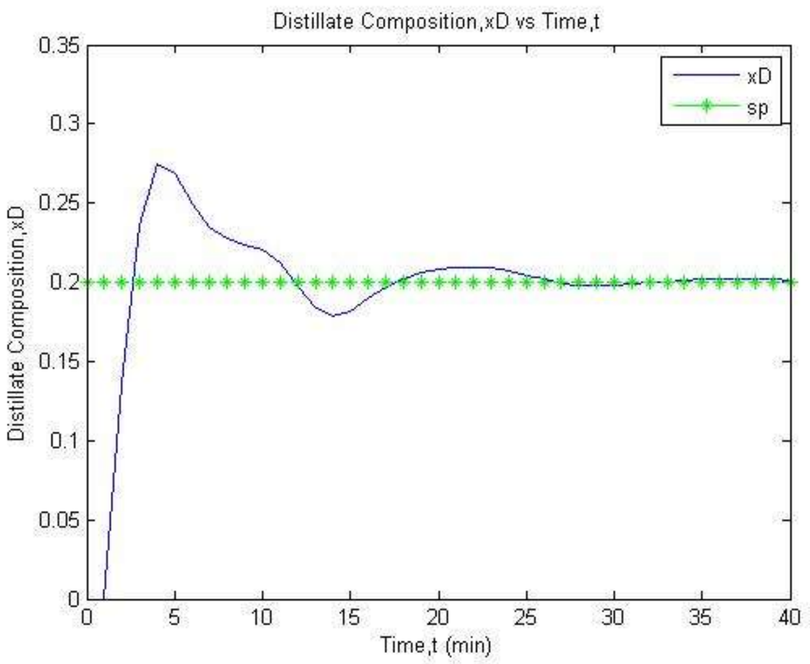
4.3.1 Control Configuration 1, C1

The PID controller is simulated using $X_D - R/X_B - S$ by using Control Configuration 1 as in the Table 14.

Table 14: *C1* Configuration

Control Loop	K_c	τ_I
$X_D - R$	0.85	7.21
$X_B - S$	-0.089	8.86

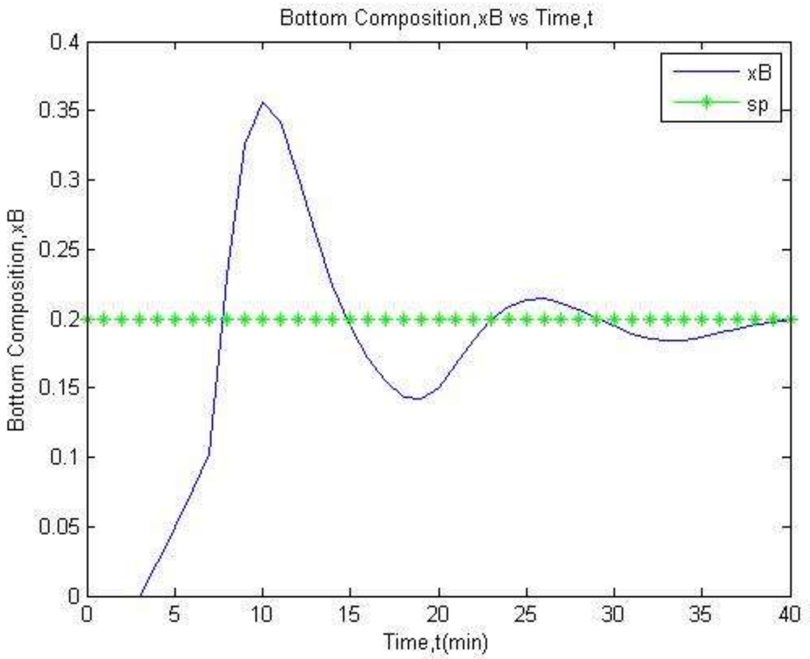
i. Distillate Component, xD



Graph 14: Closed-loop response for set point tracking in xD

Graph 14 indicates the response of the PID Controller for distillate composition, xD over time, t. The distillate composition, xD overshoot for the first 5 minutes before it decreases and produces oscillatory responses towards the set point, sp. From this graph, it can be observed that xD requires a long time (34 minutes) to achieve the steady state. This shows that there is high deviation and disturbance presence in the controller.

ii. Bottom Composition, xB



Graph 15: Closed-loop response for set point tracking in xB

Graph 15 indicates the response of the PID Controller for bottom composition, xB over time, t. The bottom composition, xB results in overshoot at first 10 minutes with oscillatory response towards the desired set point, sp. From this graph, it can be observed that xB require longer settling time than 40 minutes to achieve desired set point. Hence, this shows that in PID controller will produce sluggish responses in the output signals of distillation column.

iii. Integral Error Criteria

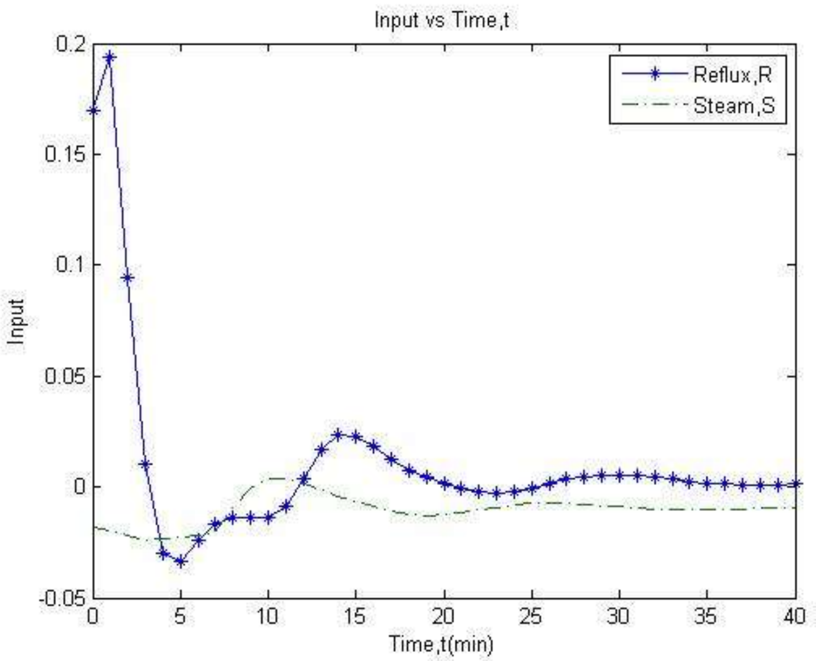
Based on Graph 14 and 15, the integral error criteria is being determined as in Table 15.

Table 15: Integral Error Criteria for set point tracking at *C1*.

Integral Error Criteria		
Integral Error	**Distillate Composition, xD**	**Bottom Composition, xB**
IAE	0.8648	2.3399
ISE	0.0830	0.3096
ITAE	5.4451	21.2903

Bottom Composition, xB shows higher error value in the integral error criteria than Distillate Composition, xD. At *C1*, the integral error criteria results in drastic increment of error especially in xB which is shown by sluggish response in Graph 20. Both the xD and xB have overshoot at the beginning of the response and take a long time to reach steady state. Therefore, this represents a low efficiency of control action which shorten the durability and lifespan of valve.

iv. Input Variation



Graph 16: Input variation for set point tracking at C1

Graph 16 shows the input of PID Controller for Reflux, R and Steam, S over time, t. Reflux, R overshoot at 1 minute before decreasing steeply and oscillates till the end of period time. Meanwhile the Steam, S shows oscillatory response throughout the period of time. From this graph, R and S need a longer time approximately 37 minutes to achieve steady state in the distillation column.

v. Total Input Variation

Table 16: Total Input Variation for set point tracking at C1

Input	**Total Input Variation**
Reflux, R	0.5154
Steam, S	0.0777

Based on Graph 16, the input variation is determined as in Table 16. Steam, S shows a lower variation compare to Reflux, R. This shows that S has taken more corrective action based on the measured output to reduce the error to the desired set point. Therefore, lower variation represents lower disturbance in the input controller which result in higher efficiency of the controller.

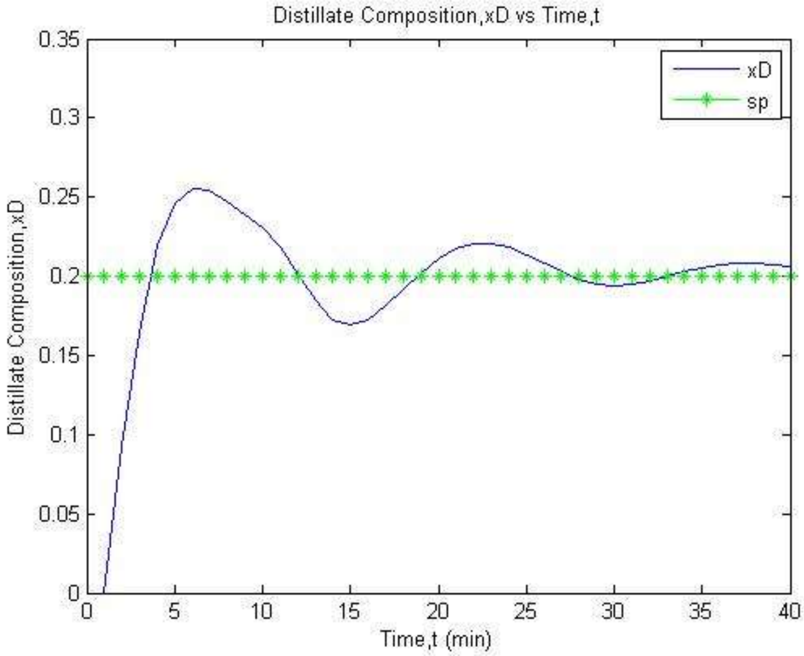
4.3.2 Control Configuration 2, *C2*

The PID controller is simulated using $X_D - R/X_B - S$ by using Control Configuration 2 in the Table 17.

Table 17: *C2* Configuration

Control Loop	$\boldsymbol{K_c}$	$\boldsymbol{\tau_I}$
$X_D - R$	0.604	16.37
$X_B - S$	-0.127	14.46

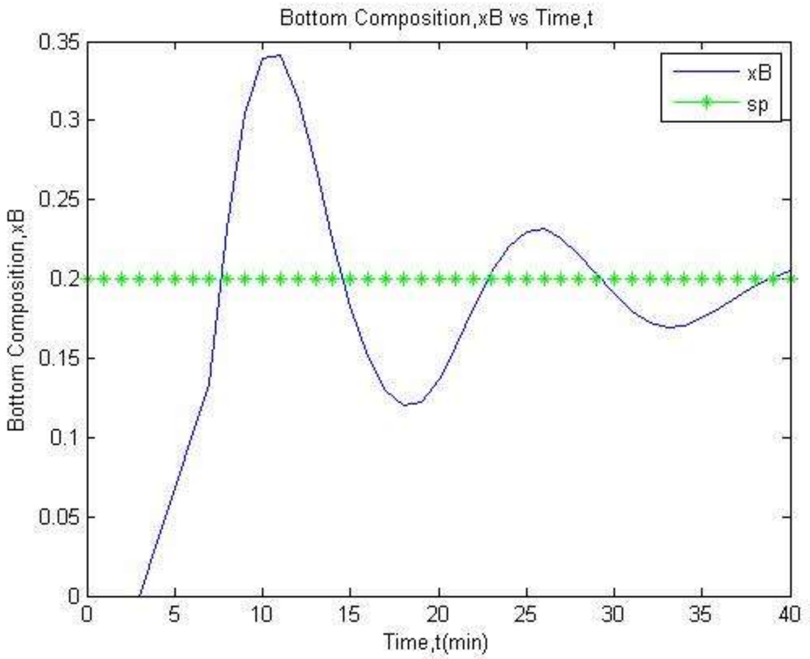
i. Distillate Component, xD



Graph 17: Closed-loop response for set point tracking in xD

Graph 17 indicates the response of the PID Controller for distillate composition, xD over time, t. The distillate composition, xD produces oscillatory responses towards the set point, sp without overshoot like *C1*. It can observed that xD requires a longer time to achieve the steady state more than 40 minutes. This shows that there is high disturbance presence in the controller.

ii. Bottom Composition, xB



Graph 18: Closed-loop response for set point tracking in xB

Graph 18 indicates the response of the PID Controller for bottom composition, xB over time, t. The bottom composition, xB results in overshoot between 10 and 11 minutes with oscillatory response towards the desired set point, sp. From this graph, it can be observed that xB require longer settling time than 40 minutes to achieve desired set point. Hence, this shows that in *C2* the responses is more sluggish in the output signals than *C1*.

iii. Integral Error Criteria

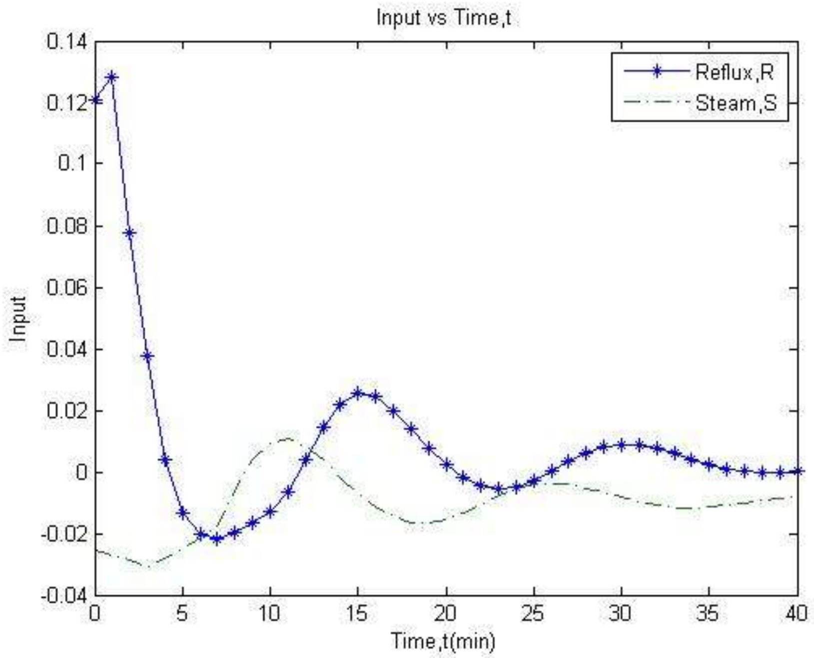
Based on Graph 17 and 18, the integral error criteria is being determined as in Table 18.

Table 18: Integral Error Criteria for set point tracking at *C2*.

Integral Error Criteria		
Integral Error	**Distillate Composition, xD**	**Bottom Composition, xB**
IAE	1.0634	2.5133
ISE	0.0918	0.3020
ITAE	9.6239	27.4301

Bottom Composition, xB shows higher error value in the integral error criteria than Distillate Composition, xD. At *C2*, the integral error criteria also results in drastic increment of error especially in xB which is shown by sluggish response in Graph 18. In this case, only xB have overshoot at the beginning of the response. As for settling time, both xD and xB take a long time to reach steady state. Therefore, this represents a low efficiency of controller system.

iv. Input Variation



Graph 19: Input variation for set point tracking at *C2*

Graph 19 shows the input of PID Controller for Reflux, R and Steam, S over time, t. Reflux, R overshoot at 1 minute before decreasing steeply and oscillates till the end of period time. Meanwhile the Steam, S shows oscillatory response throughout the period of time. From this graph, R and S need a longer time for more than 40 minutes to achieve steady state in the distillation column.

v. Total Input Variation

Table 19: Total Input Variation for set point tracking at *C2*

Input	Total Input Variation
Reflux, R	0.3808
Steam, S	0.1244

Based on Graph 19, the input variation is determined as in Table 19. Steam, S shows a lower variation compare to Reflux, R. This shows that S has taken more corrective action based on the measured output to reduce the error to the desired set point. Therefore, lower variation represents lower disturbance in the input controller which result in higher efficiency of the controller.

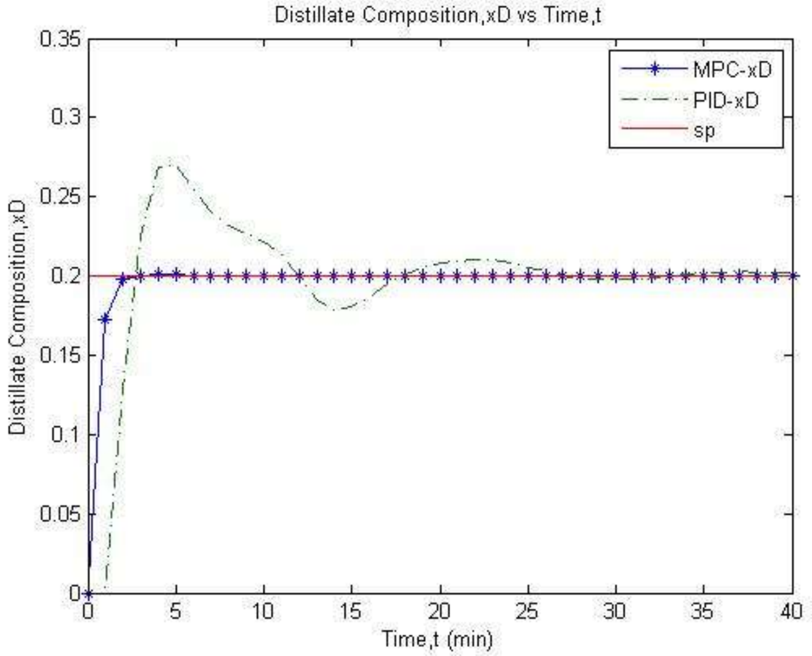
Effective Control Configuration

The controllers have been tested with 2 different control configuration that have different controller gain, K_c and times delay, τ of $X_D - R/X_B - S$ control loop. Based on the observation in the integral error criteria and total input variation, it can be concluded that the PID controller works best at *C1* whereby it has the lowest integral error criteria, total input variation and settling time. In integral error criteria, only the ISE in xB shows slightly higher error value than *C2.* For total input variation, both *C1* and *C2* shows contradict variation in R and S flow rate whereby R has shown more corrective action in *C2* while S shown more corrective action in *C1*. Therefore, settling time to reach steady state is being considered which *C1* shows better stability than *C2*.

4.4 Comparison of MPC and PID Controller

In Section 4.2 and 4.3, the effective parameters and configuration have been determined in both MPC and PID Controller. The comparison is made in order to determine the best performance for controller system.

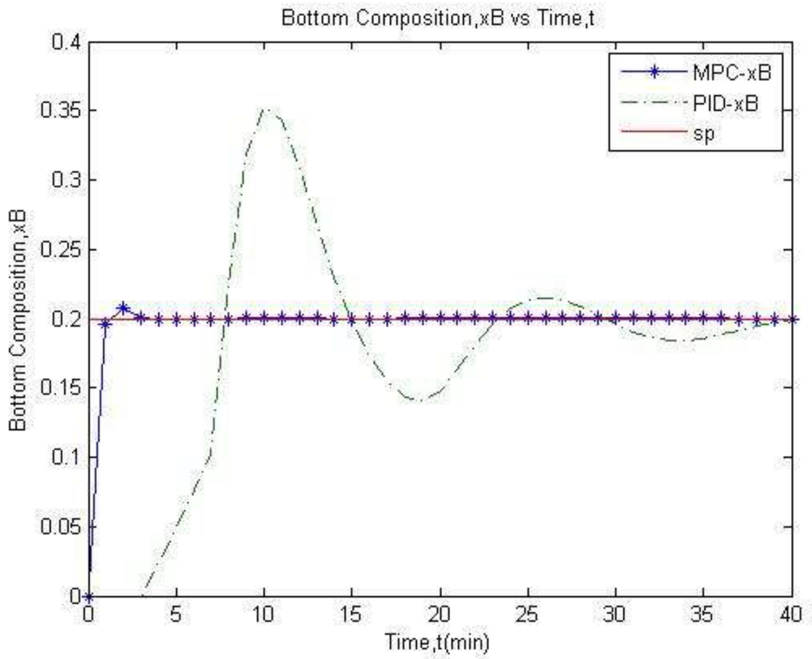
i. Distillate Component, xD



Graph 20: Closed-loop response for set point tracking in xD

Graph 20 indicates the distillate composition, xD comparison between MPC and PID Controller over time, t. The distillate composition, xD of MPC increase gradually to the desired set point while overshoot occur in PID Controller before it decreases and produces oscillatory response towards the set point, sp. Hence, it shows that MPC Controller is superior to the MIMO System because the distillate composition exhibit faster setting time to reach steady state without oscillatory response.

ii. Bottom Composition, xB



Graph 21: Closed-loop response for set point tracking in xB

Graph 21 indicates the bottom composition, xB comparison for MPC and PID Controller for over time, t. The bottom composition, xB of MPC increase with a slight overshoot but PID Controller results in oscillatory response towards the desired set point. Hence, it also shows that MPC Controller results in faster setting time to reach steady state even though there is presence of overshoot at the beginning of time period. So, MPC is suitable for MIMO System in term of performance of output responses.

iii. Integral Error Criteria:

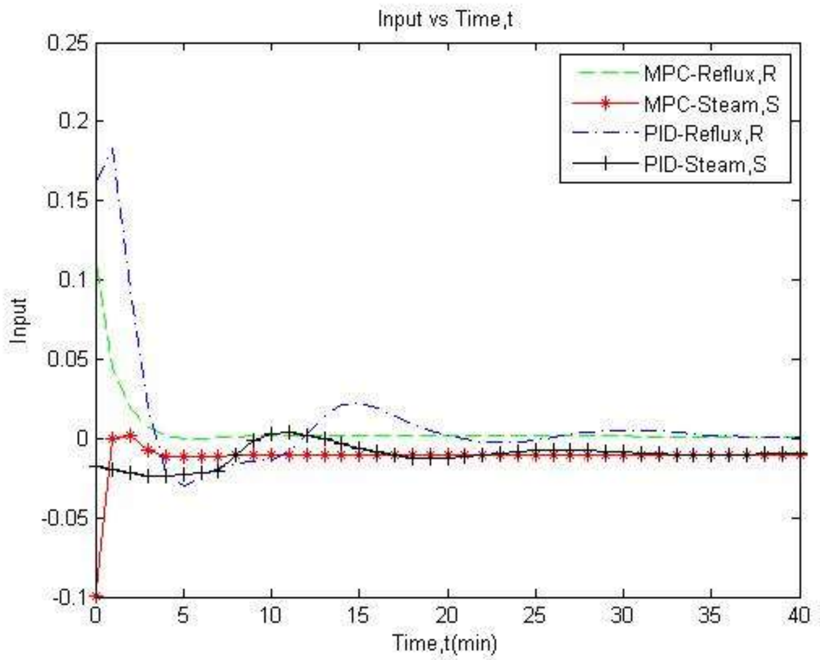
Based on Graph 20 and 21, the integral error criteria is being determined as in Table 20.

Table 20: Integral Error Criteria for set point tracking in MPC and PID Controller

	MPC		**PID**	
Integral Error	**Distillate Composition, xD**	**Bottom Composition, xB**	**Distillate Composition, xD**	**Bottom Composition, xB**
IAE	0.1321	0.1155	0.8648	2.3399
ISE	0.0207	0.0201	0.0830	0.3096
ITAE	0.0460	0.0355	5.4451	21.2903

Table 20 shows the Integral Error Criteria comparison between xD and xB. MPC Controller shows that the integral error criteria is higher in xD than xB. In contrast, the integral error criteria of xB is higher than xD in PID Controller. Based on the three criterion calculated, it shows that MPC Controller has a better performance than PID Controller as it has lowest overall error which means low deviation and disturbance presence in the controller. Therefore, MPC Controller has high efficiency in control system and may prolongs the durability and lifespan of valve.

iv. Input Variation



Graph 22: Input variation for set point tracking

Graph 22 shows the input comparison of MPC and PID Controller for Reflux, R and Steam, S over time, t. MPC Controller has a slight overshoot in S at the beginning of time period simultaneously S decreases gradually to the set point. As for PID Controller, both R and S produces oscillatory responses before achieve steady state with R overshoot at the beginning of time. This shows that MPC more stable than PID Controller. Besides that, the PID Controller is responded based on the feedback control of the output signals. The controller gain in PID Controller manipulates the input and tends to produce sluggish responses that results in longer time taken to reach steady state than MPC Controller.

v. Total Input Variation

Table 21: Total Input Variation for set point tracking in MPC and PID Controller

Total Input Variation		
Input	**MPC**	**PID**
Reflux, R	0.2321	0.5154
Steam, S	0.2168	0.0777

Based on Graph 22, the input variation is determined as in Table 21. In both controllers, S shows a lower variation compare to R. Lower variation shows the accuracy of corrective action based on the measured output to reduce the error to the desired set point. This variation occurs as a response from the predicted and measured output responses. From this table, MPC shows a higher efficiency of the controller than PID with lower total input variation. In essence, the changes in input are coordinated after considering the input-output relationship. So, MPC Controller has a better performance than PID Controller in MIMO system.

CHAPTER 5

CONCLUSION & RECOMMENDATION

This project was able to fulfill all the objectives and requirements needed. The distillation column model have been designed with Wood-Berry model and being implemented with MPC by using OBF and Laguerre model. Based on the comparison of distillation column control, MPC has higher efficiency compares to PID controller. This is proven whereby MPC having the lowest integral error criteria and total input variation. Generally, lower integral error criteria and total input variation value indicate a better controller with higher accuracy and efficiency for MIMO system. Thus, efficiency of MPC shows that OBF successfully minimized the error between the output signals and reference trajectory based on manipulated variables. OBF also has proved that it can coordinates the interaction of MIMO system especially for distillation column. Therefore, MPC Controller using OBF has a better performance for control industry.

It is recommended that MPC Controller is being tested and applied in plant-wide control for further analysis. On top of that, MATLAB software learning should be included in the undergraduate studies as one of major subjects in order to develop better understanding on the functionality of MATLAB.

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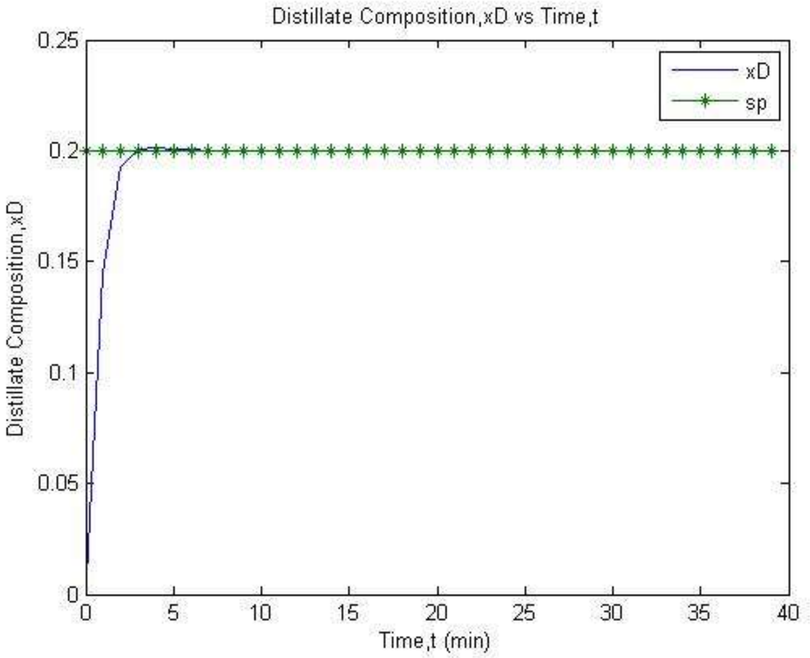
APPENDIX I

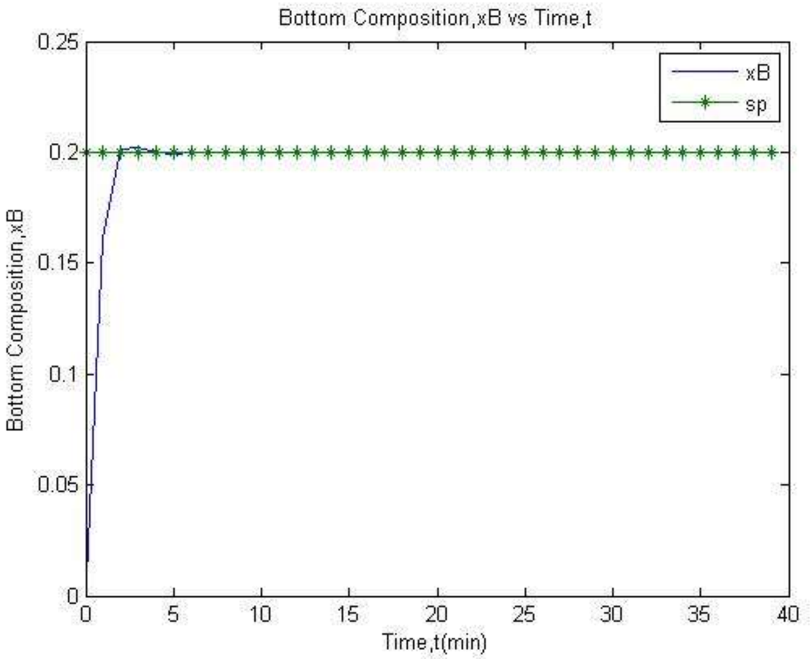
MPC Performance for a = 0.8

i. Distillate Component, xD



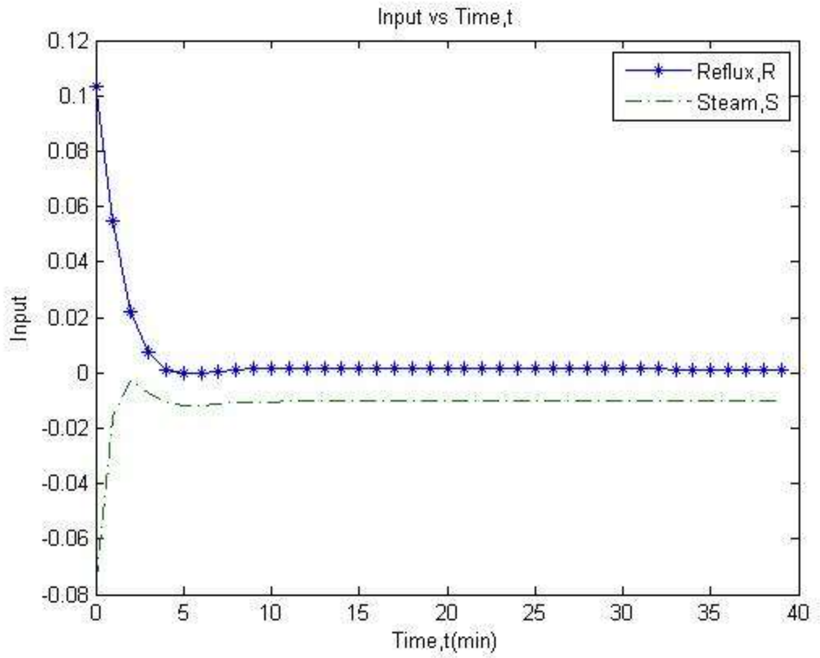
Graph 23: Closed-loop response for set point tracking in xD with *a=0.8*

ii. Bottom Composition, xB



Graph 24: Closed-loop response for set point tracking in xB with *a=0.8*

iii. Input Variation

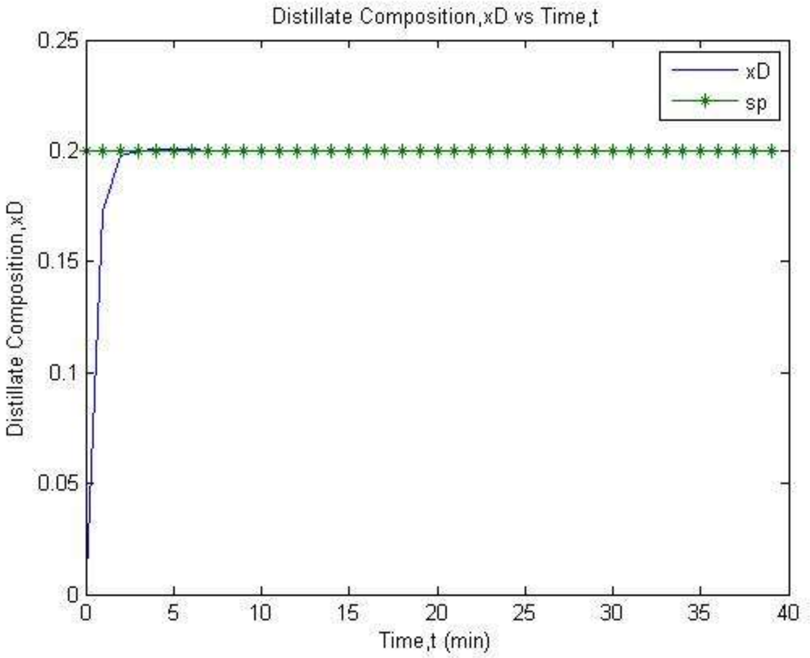


Graph 25: Input variation for set point tracking at *a=0.8*

APPENDIX II

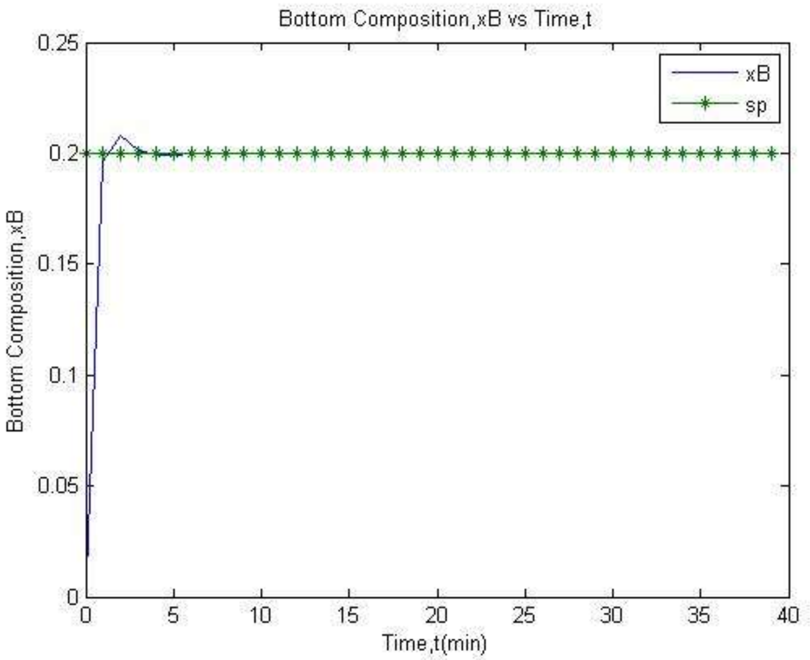
MPC Performance for N=100

i. Distillate Component, xD



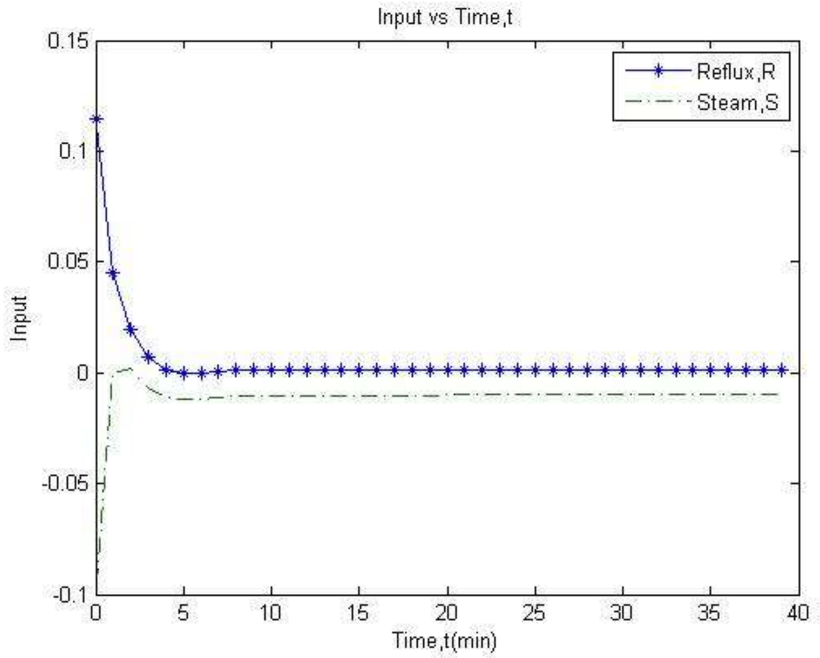
Graph 26: Closed-loop response for set point tracking in xD at *N=100*

ii. Bottom Composition, xB



Graph 27: Closed-loop response for set point tracking in xD at *N=100*

iii. Input Variation



Graph 28: Input variation for set point tracking at *N=100*