Modelling & Predictive Control of a Crude Distillation Unit

by

Mohd Afil Bokhari bin Jamil

Dissertation submitted in partial fulfilment of
the requirements for the
Bachelor of Engineering (Hons)
(Chemical Engineering)

JULY 2010

Universiti Teknologi PETRONAS
Bandar Seri Iskandar
31750 Tronoh
Perak Darul Ridzuan

CERTIFICATION OF APPROVAL

Modelling & Predictive Control of a Crude Distillation Unit

by

Mohd Afil Bokhari Jamil

A project dissertation submitted to the
Chemical Engineering Programme
Universiti Teknologi PETRONAS
in partial fulfilment of the requirement for the
BACHELOR OF ENGINEERING (Hons)
(CHEMICAL ENGINEERING)

Approved by,

(Dr Nooryusmiza Yusoff)

UNIVERSITI TEKNOLOGI PETRONAS

TRONOH, PERAK

July 2010

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.

MOHD AFIL BOKHARI BIN JAMIL

ABSTRACT

The purpose of this project is to implement Model Predictive Control strategy to a Crude Distillation Unit model and to compare it to PI controllers in terms of controller performance. The motivation of this project comes to the fact that there is a need to reduce CO_2 emission and at the same time to reduce energy consumption within the unit. The author has developed the CDU model using HYSYS and also in state-space representation using MATLAB, the latter was being used to design MPC controllers. From this project, it can be seen that the success of MPC implementation depends on the accuracy of the plant model to represent actual process. The MPC controller proved to be more effective in regulating the percent liquid level of the condenser but not so effective for the other two variables being studied.

ACKNOWLEDGEMENTS

First and foremost, I would like to express my praises to God for His blessing. My deepest appreciation and gratitude is extended to my supervisor, Dr Nooryusmiza Yusoff for being very encouraging, supportive and responsive throughout the Final Year Project II to fulfil the university requirement. Without his constant supervision and guidance, I may not be able to complete this project successfully.

Apart from that, I am very thankful to my colleagues, Noree Stirak, Hooda bin-Useng, Sohibatul Muizzah Mohd Izhar and Mohd Aiman Mohd Noor who have always been accommodating and cooperative whenever I am in need of ideas and opinion throughout the completion of this project report. Their incessant assistances throughout the whole period of this project are very much appreciated.

Besides, thank you to the Final Year Project (FYP) coordinator, Dr Khalik B. Sabil for being very dedicated and stringent in handling the course effectively throughout the year. The management of the FYP is systematic and every submission datelines are perfectly scheduled.

Last but not least, I would like to acknowledge my family members for keeping me motivated throughout the year.

Thank you.

TABLE OF CONTENTS

LIST OF FIGURES

LIST OF TABLES

LIST OF NOMENCLATURES

AGO	Atmospheric Gas Oil
APC	Advanced Process Control
CDU	Crude Distillation Unit
DV	Disturbance Variable
GPC	Generalized Predictive Control
MIMO	Multiple Input, Multiple Output
MPC	Model Predictive Control
MV	Manipulated Variable
OP	Opening Percentage (for control valves)
PI	Proportional Integral
PID	Proportional Integral Derivative
PLC	Programmable Logic Controller

CHAPTER 1
INTRODUCTION

1.1 BACKGROUND OF STUDY

Carbon dioxide (CO_2) plays a very important role in global warming, as it is one of the greenhouse gases. Most of the current CO_2 emission comes from fossil fuel combustions. High CO_2 emission is also often linked to high energy consumption. This is especially true in distillation systems (Gadalla and co-workers, 2006).

As a result, Kyoto Protocol, a protocol to the United Nations Framework Convention on Climate Change (UNFCCC or FCCC), has been adopted on 1997 to stabilize the greenhouse gas emission to prevent global warming. As on 2009, 187 countries, including Malaysia has signed and ratified the protocol.

The primary objective of the protocol is to stabilize and control greenhouse gas concentration in the atmosphere to a "safe" level. By "safe", it means that the level of greenhouse gas emissions will not have adverse effects on the environment and world climate.

Therefore, over the years, process control in industry has been developed to meet the following objectives:

1. To maintain a process at the desired operating conditions, safely and efficiently
2. To satisfy product quality and environmental requirements

New technologies in process control have emerged with better responses to changes in process variables and more computational speed, aside from the advances in computer technology that enable more rigorous control calculation to be made.

One of such technologies is Model Predictive Control (MPC). Although MPC has been around in the industry since 1970s, new technologies are still under development to meet current demands in industry. MPC has significant applications in chemicals and other industries, aside from the traditional PID (Proportional, Integral & Derivative) controllers and Programmable Logic Controllers (PLCs).

1.2 PROBLEM STATEMENT

Current process control approach typically uses PI controllers, with some process utilized PID controllers. The type of controller used usually depends on the process requirement and also the nature of the process variables, with temperature being a slow-response variable and flow rate being the fast-response variable.

However, these controllers are not very energy-efficient, in which some cases; the controller requires a large control move to the input to enable the output to reach its desired set point. This large move will cause energy usage, and consequently CO_2 emission to be increased. Therefore, alternative control strategy is required that can mitigate this situation.

1.3 OBJECTIVES

The objectives of this Final Year Project are as follow:

1. To develop a steady-state and dynamic model for Crude Distillation Unit based on actual plant data.
2. To implement Model Predictive Control strategy on the CDU plant model by designing the appropriate MPC controllers.
3. To compare the action of the MPC controller with PI controllers in terms of its performances.

1.4 SCOPE OF STUDY

For this project, a Crude Distillation Unit (CDU) will be controlled by using MPC strategy. In order to apply MPC to CDU, a plant model must first be established through simulation program from actual plant data.

From the model, MPC calculations will then be executed on the plant model and the response from the model is then obtained and analyzed for response speed and accuracy. The response is then will be compared with that of PI controller for its performance.

1.5 SUMMARY OF REPORT

The report starts with an introduction to the project (Chapter 1), with an outline of the background, problem statement and objectives of study. Then, a section of the literature review and theory behind the study, i.e. Model Predictive Control (MPC) is presented in Chapter 2. In Chapter 2, an introduction to distillation systems, specifically that of CDU, will be presented. In addition, an overview of MPC concept, as well as its characteristics, advantages and limitations is also presented. Then, the methodology of research and project activities is outlined in the Chapter 3. After that, a detailed description of CDU is presented in Chapter 4, together with its operating conditions. The results of the project is presented and discussed in Chapter 5. Finally, a conclusion about this project is made and stated in Chapter 6.

CHAPTER 2
LITERATURE REVIEW

In this chapter, a discussion on CO_2 emission and its relation to distillation systems is presented first. Then, an overview of MPC technology is presented, along with its concept, advantages and disadvantages and also further developments in MPC.

2.1 CO_2 EMISSION AND DISTILLATION SYSTEMS

A distillation system such as Crude Distillation Unit (CDU) typically utilizes a lot of energy and consequently has significant contribution to the greenhouse gases (especially CO_2) emission. This is due to the usage of heat exchange network and auxiliary units within the CDU itself. Efforts have been made to reduce energy consumption and consequently, to reduce CO_2 emission.

There are many sources of high energy usage within the unit, some which are as below:

1. High feed preheating temperature in the column
2. Increased reflux ratio in the distillation column
3. Increased flow rate of the stripping steam at the column

By decreasing the three variables within the column, the energy consumption can be reduced by decreasing reboiler and condenser duties. This in turn will lead to lesser CO_2 emission.

2.2 CRUDE DISTILLATION UNIT

Crude distillation unit is at the core of any petroleum refinery and it is considered to be one of the most complicated operations in the field of separation processes (Dave and colleagues, 2003). The products from CDU are usually a mixture of hydrocarbon compounds that can be used as feedstock in petrochemical plants or as a source of fuel.

There are a large number of models that are available in literature (Inamdar and co-workers, 2004). These models are usually used for optimization problems, as well as for product estimation problems. For refinery scheduling of crude oil unloading, storage and processing from the CDU, a model predictive control strategy can be utilized. The next section will give an overview of Model Predictive Control

2.3 OVERVIEW OF MODEL PREDICTIVE CONTROL

Model Predictive Control can be described as an optimization based strategy in which a plant model is utilized together with current measurements of process variables to predict future values of the output or control actions. The plant model must be reasonably accurate to ensure the success of MPC.

The overall objectives of an MPC controller, as summarized by Qin and Badgwell (2003) are:

1. To prevent violations of input and output constraints.
2. To drive some output variables to their optimal set points, while maintaining other outputs within specific ranges.
3. To prevent excessive movement of the input variables.
4. To control as many process variables as possible when a sensor or actuator is not available.

In MPC application, the input variables are also called manipulated variables (MV) while the output variables are also referred to as controlled variables (CV). Disturbance variables (DV) that can be measured are sometimes called feedforward variables. These terms are used interchangeably in various MPC applications and literature.

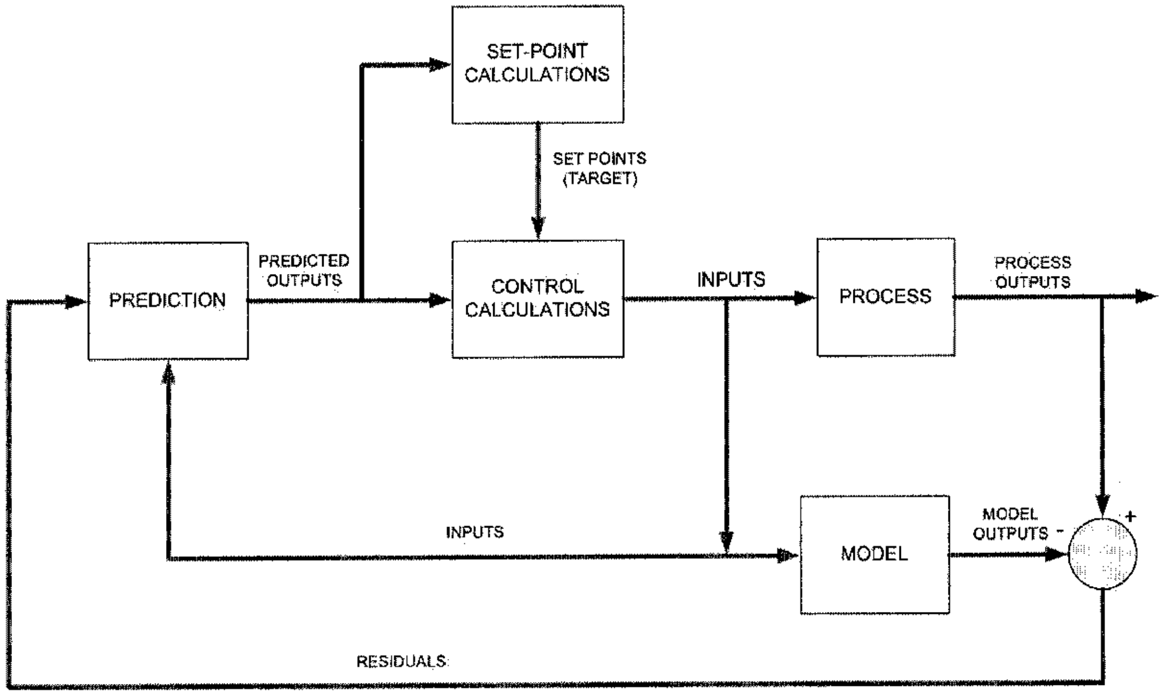

Figure 2.1: Block diagram for model predictive control

Figure 2.1 shows a block diagram of a model predictive control system. A process model is used to predict the current values of the MV, based on the measurements from the process. The differences between the two outputs, the residuals, are then being sent to Prediction block in feedback manner. The Prediction block is used in two types of MPC calculations: set-point calculations and control calculations. Both of these calculations are done at each sampling instant.

The set-point calculations are performed from an economic optimization based on a steady-state model of the process (usually a linear model). The optimization objectives are usually (but not limited) to maximize a profit function, to minimize a cost function or to maximize production rate In MPC, the set-points are typically calculated each time the control calculations are performed. Also, the optimum value of set-points can change due to varying process conditions.

The objective of the MPC control calculations are to determine a sequence of control moves or manipulated input changes so that the predicted response moves to the set point in an optimal manner. The control calculations are based on current measurements and predictions of future values of the outputs. The predictions can be made using a dynamic model (typically a linear model), transfer functions or state-space models. For non-linear processes, a non-linear dynamic model can be employed to predict future outputs.

At the current sampling instant k, the MPC strategy calculates a set of M values of the manipulated input u $\{u(k + i - 1), i = 1, 2, \ldots, M\}$. After M control moves, the input is held constant. The inputs are calculated so that a set of P predicted outputs $\{\hat{y}(k+i), i = 1, 2, \ldots, P\}$ reaches the set-point in an optimal manner. The number of predictions P is referred to as the *prediction horizon* while the number of control moves M is called the *control horizon*.

The following figure (Figure 2.2) illustrates the basic concept of model predictive control, with N denotes the prediction horizon and $t = t+k$, $k = 1, 2, \ldots, N$ denotes sampling instant.

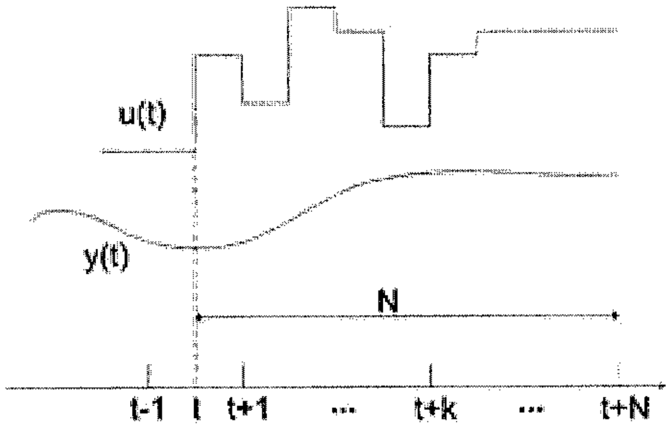

Figure 2.2: Basic concept of model predictive control (Adapted from Seborg & co-workers, 2004)

2.4 CHARACTERISTICS OF MODEL PREDICTIVE CONTROL

Following below are several important characteristics of an MPC strategy:

1. **Moving horizon approach**

   Although a sequence of M control moves is calculated at each sampling instant, only the first move is actually implemented. Then, a new sequence is calculated at the next sampling instant, after new measurements become available. However, only the first input move is implemented. This procedure is repeated at each sampling instant.

   This procedure utilizes the most recent measurements of the output to be used for next M sampling instant. If this procedure is not used, the multistep predictions and control moves would be based on old information which can be affected by unmeasured disturbances.

2. **Incorporation of constraints**

   Constraints usually come from variations or restrictions in process conditions, equipment and instrumentations, as well as economic requirements. These can be described as either hard constraints (constraints that cannot be violated at any time) or soft constraints (constraints that can be tolerated for small violations).

   If there are any constraints to the system, these constraints can be included in either of the two MPC calculations described before. Consequently, MPC is very useful for controlling constrained MIMO (multiple-input, multiple-output) systems, since these constraints are accounted explicitly in the calculations.

3. **An explicit system model used to predict future plant dynamics**

   A system model is important and required in MPC strategy because the model serves as a replicate of the actual process. The model can be utilized to predict future outputs from current process measurements and also can capture dynamic and static interactions between MVs, CVs and DVs.

2.5 ADVANTAGES & DISADVANTAGES OF MODEL PREDICTIVE CONTROL

MPC has several important advantages that make it one of the common advanced process control (APC) technologies employed in industry. The advantages are:

1. Process and economical constraints are considered in a systematic manner.
2. The control calculations can be coordinated in a systematic manner.
3. Accurate model predictions can provide early warning of potential problems.
4. Online computations can be performed quickly.
5. MPC controllers are easier to be tuned than other types of controllers

However, MPC also has its own disadvantages and limitations, among them are:

1. High computational cost for complex systems limits MPC applications to linear processes with relatively slow dynamics (Rao & Rawlings, 2000)
2. Inaccurate process model can results in inaccurate predictions and control moves for the process.
3. Several MPC models are limited to only stable, open-loop processes (Anderson and colleagues, 2006).

Despite these limitations, MPC are still widely used in the industry, particularly in the refineries (Jämsä-Jounela, 2007). Appendix A shows the current MPC products and technologies that are used in the industry.

2.6 STEPS IN MODEL PREDICTIVE CONTROL CALCULATION

Outlined below is an overview of the MPC calculations. The seven steps are shown in the order they are performed at each control execution time, which for simplicity, will be assumed to be same as the measurement sampling instant.

Step 1: Acquire new data (CV, MV and DV values)

New process data are acquired via the regulatory control system (typically Distributed Control System (DCS)) that is interfaced to the process.

Step 2: Update model predictions (output feedback)

After new data has been acquired, new output predictions are calculated by using the process model together with the data.

Step 3: Determine control structure

Before each control execution, the current control structure is determined by identifying the currently available outputs (CVs), inputs (MVs) and disturbance variables (DVs) for MPC calculations. The numbers of variables available can change from one time to another for a variety of reasons, one of them being the unavailability of a sensor to measure one particular output variable.

Thus, output variables are often classified as being *critical* or *non-critical.* If the sensor is not available for a critical output, the MPC calculations can be stopped immediately or after a specified number of control moves. For a similar case involving non-critical output, the missing measurements could be replaced by model predictions or the output could be removed from the control structure.

Step 4: Check for ill-conditioning

Ill-conditioning occurs when the available input have very similar effects on two or more outputs. As a result, large input movements are required to control these output independently. Therefore, it is important to check for ill-conditioning before executing the MPC calculations.

If ill-conditioning is detected, three effective strategies are available:

1. Assign a priority to each output variable
2. Using singular value analysis
3. Adjusting *move suppression matrix* **R**

For the first approach, each output variable is assigned a priority. When ill-conditioning is detected, low-priority outputs are sequentially removed from the control structure until ill-conditioning is eliminated.

The second approach is based on singular value analysis. By omitting small singular values, the process model can be adjusted so that it is no longer ill-conditioned. This approach does not remove any of the output variables. However, the results depend on how the inputs and outputs are scaled.

The final approach is basically adjusting *move suppression matrix* **R**, a design parameter of MPC. **R** is a positive semi-definite matrix and is an unusually diagonal matrix with positive diagonal elements.

Step 5: Calculate set points/targets (steady-state optimization)

After ill-conditioning has been removed, the optimum set points / targets are then been calculated in the MPC calculations. This calculation optimizes a specified objective function while satisfying inequality constraints.

Step 6: Perform control calculations (dynamic optimization)

From the set points calculated together with the predicted output before, the control moves then can be calculated. The control moves are calculated in order to drive the process to the desired set point without violating constraints.

Step 7: Send MVs to the process

Finally, the calculated control moves are implemented to regulatory control loops at the DCS level, usually as set points.

2.7 TYPES OF MODEL PREDICTIVE CONTROL

The classification of MPC system depends on the process model used in the calculations. Typically the MPC system can be described as either *linear* or *non-linear*.

A linear MPC system uses linear model $x' = Ax + Bu$ and usually has quadratic-type cost function

$$F = \boldsymbol{x}^T \boldsymbol{Q}\boldsymbol{x} + \boldsymbol{u}^T \boldsymbol{R}\boldsymbol{u}$$

Where $\boldsymbol{x}$ = predicted error vector

$\boldsymbol{u}$ = control moves vector

R = move suppresion matrix

Q = positive-definite weighting matrix

A linear MPC also has linear constraints (usually in the form of $Hx + Gu < 0$) and the program is in the quadratic form.

On the other hand, a non-linear MPC uses non-linear model $x^{\cdot} = f(x, u)$ and its cost function can be non-quadratic in nature, F(x, u). The constraints and program for a non-linear MPC are non-linear in nature.

2.8 FUTURE DEVELOPMENT IN MODEL PREDICTIVE CONTROL TECHNOLOGY

MPC technologies are still evolving from the first-generation technologies developed in the 1970s until now (fifth-generation). The following areas of MPC are possible developments in the future:

1. **Adaptive MPC**

Currently, there are a few adaptive MPC algorithms, the most common being the Generalized Predictive Control (GPC) algorithms developed by Clarke, Mohtadi and Tuffs in 1987.

However, in the industry, only two of such algorithms have been employed: Connoisseur from Invensys and STAR from DOT Product, despite the market opportunity for self-tuning (adaptive) MPC controllers. Thus, there are possibilities that more adaptive MPC technologies may emerge in the market in the future.

2. **Nonlinear MPC**

In the future, new MPC technologies will allow nonlinear models to be developed by combination of process knowledge with operating measurements. In this process, first principle models and other modelling methods may be required for data based modelling of nonlinear systems.

3. Robust MPC

Robustness is an important feature of controllers as it can significantly reduces the time required for tuning and testing of industrial MPC algorithms. Robustness can also guarantee that the system is feasible and stable.

There is possibility that robust MPC technology to make their appearances in the industry, since a combination of robust stability guarantees with uncertainty estimates from identification software can greatly simplifies the design and tuning of MPC controllers.

CHAPTER 3
METHODOLOGY

For the project methodology, the project started with plant model development which consists of steady state and dynamic model by using HYSYS process flow diagram. The project then followed by MPC design implementation which are involve with plant testing, MPC design and implementation and lastly, the comparison with base layer control (PI Control) are implemented.

3.1 PROJECT ACTIVITIES

For this project, the author has outlined several important steps in the project. Figure 3.1 shows the flow of the activities that the author has done throughout the project time.

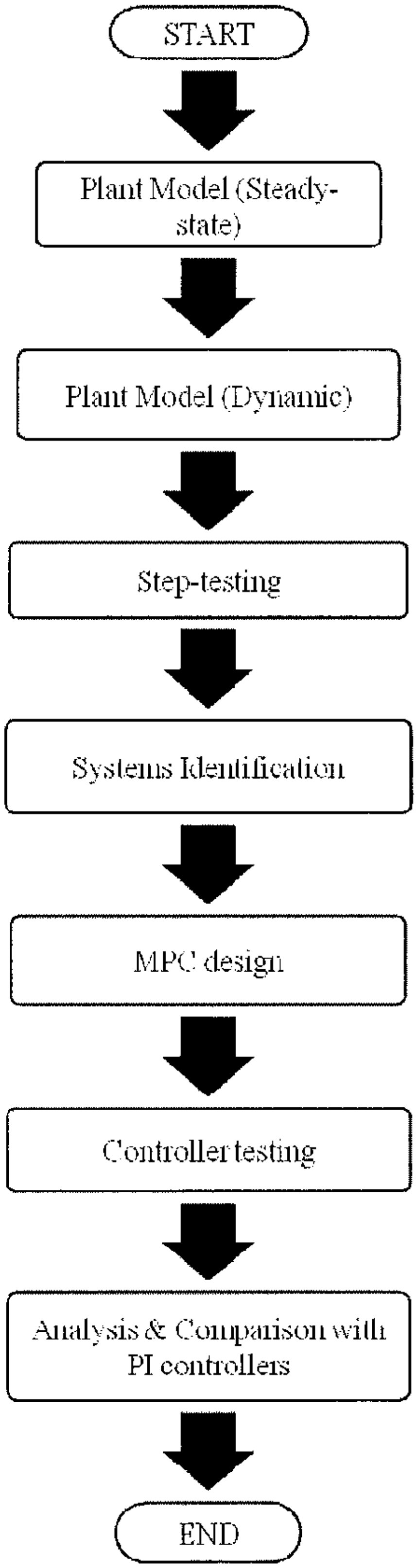

Figure 3.1: Project Activities Flow Chart

1. Literature Review

A literature review of the project and its underlying theory has been conducted by the author. Among other aspects of the project that are being reviewed are MPC applications in the industry and its advantages and limitations.

2. Familiarization with application of HYSYS and MATLAB

Since this project will be modelling-based, it is important for the author to be familiar with the functions and features of software that will be used throughout this project. For the beginning, the author has attempted the tutorials on HYSYS and MATLAB modules to understand its functions.

3. Simulation of CDU to obtain steady-state and dynamic model

After the author has familiarized with the software, the author proceeded with simulation of the CDU plant. Due to time constraints, the author decided (with approval from supervisor) to use the HYSYS simulation tutorial for the CDU as the plant model. The objective of the simulation is to get the CDU steady-state and dynamic model that will be applied to the MPC on MATLAB.

From the simulation, the author has identified three possible controlled and manipulated variables to be utilized in the next step. Table 3.1 shows the simulated variables, while Table 3.2 shows the selected variables in the CDU.

Table3.1: The Simulated CVs and MVs for the Atmospheric Crude Column

Controlled Variable	Manipulated Variable
Condenser Liquid Level	Reflux Flow Rate
Reboiler Liquid Level	Kero_SS_Draw Flow Rate
Off Gas Flow Rate	AtmosCond Flow Rate
AGO Stream Flow Rate	AGO_SS_Draw Flow Rate
Diesel Stream Flow Rate	Diesel_SS_Draw Flow Rate

Table 3.2: The Selected CVs and MVs for the Atmospheric Crude Column

No.	Controlled Variable, y	Manipulated Variable, u
1	y_1 = Condenser Liquid Level (%)	u_1 = Reflux Flow Rate (m^3/hr)
2	y_2 = AGO Liquid Flow Rate @ Std. Cond. (m^3/hr)	u_2 = AGO_SS_Draw Flow Rate (m^3/hr)
3	y_3 = Diesel Liquid Flow Rate @ Std. Cond. (m^3/hr)	u_3 = Diesel_SS_Draw Flow Rate (m^3/hr)

**Note: Std. Cond. @ P = 1 atm and T = 25°C*

4. Performing Step-testing on the model

The author then performed step testing on the plant model to determine the response of the CVs when a step change is imposed for each MV. From the test, the author was able to determine the relationship between the MVs' step changes to response of the corresponding CVs. The step test was done for one MV at a time for all MVs. After each step change, the MV will be brought back to its initial value to ensure the stability of the system.

Table 3.3 shows the step input moves that were used for the step testing. The changes are at the range of 5 to 10 percent change from the initial OP (opening percentage) of the control valve.

Table 2.3: The Step Input Moves CVs and MVs for the Atmospheric Crude Column

Controller	**PV**	**MV**	**SP**	**Input #**	**% Change**	**OP (%)**
Cond LC	% Liquid Level	Reflux Molar Flow	50%	1	5	5
				2	-5	0
				3	6	6
				4	-6	0
				5	7	7
				6	-7	0
				7	8	8
				8	-8	0
				9	9	9
				10	-9	0
				11	10	10
				12	-10	0
Diesel FC	Diesel Liquid Flow rate @ Std Cond	Diesel_SS _Draw Molar Flow	127.5 m^3/hr	1	-5	95
				2	5	100
				3	-6	94
				4	6	100
				5	-7	93
				6	7	100
				7	-8	92
				8	8	100
				9	-9	91
				10	9	100
				11	-10	90
				12	10	100
AGO FC	AGO Liquid Flow rate @ Std Cond	AGO_SS_ Draw Molar Flow	29.8 m^3/hr	1	-5	95
				2	5	100
				3	-6	94
				4	6	100
				5	-7	93
				6	7	100
				7	-8	92
				8	8	100
				9	-9	91
				10	9	100
				11	-10	90
				12	10	100

5. **Derivation of Plant Transfer Functions Model using Systems Identification (SI) tool in MATLAB**

After that, the author used System Identification tool in MATLAB to determine respective transfer functions for all the possible variable pairs. The control problem will be in 3-by-3 system, with 3 inputs and 3 outputs.

The process model for each variable pair was estimated by FOTPD (first order plus time delay) method.

Figure 3.2 shows the System Identification interface in MATLAB. For this case, the tool is used to estimate the process model for the pair [y_1, u_1], where y_1 is the condenser % liquid level and u_1 is the Reflux molar flow rate. Figure 3.3 shows the estimated process model for G_{11}. The rest of the transfer functions are presented in the results as per Chapter 5.

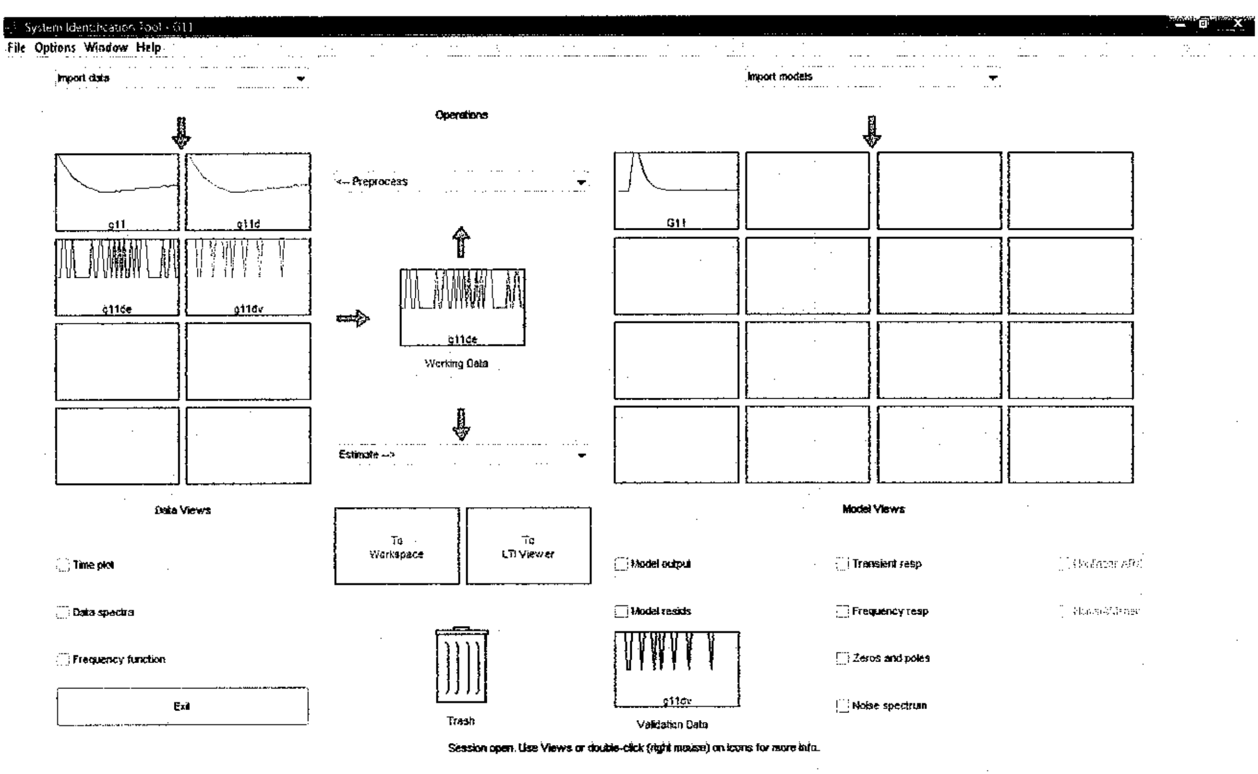

Figure 3.2: System Identification Toolbox interface

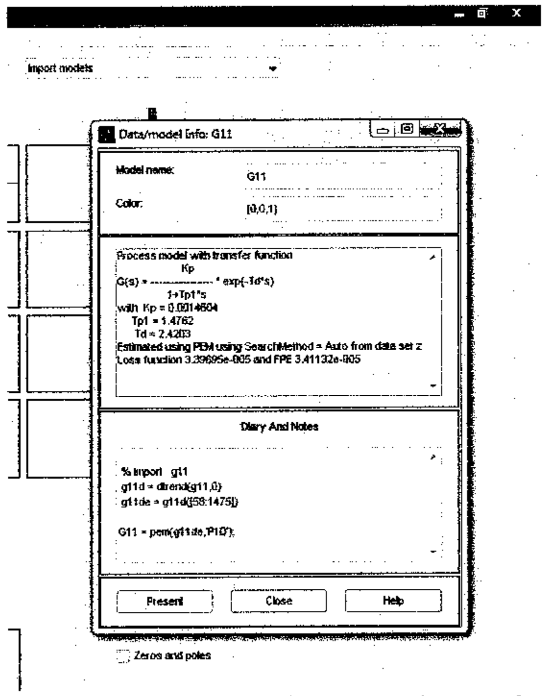

Figure 3.3: The resulting process model estimated using System Identification

For the process model, the transfer function is in the form of:

$$G_{ij}(s) = \frac{K_p\, e^{-\tau_d s}}{\tau_p\, s + 1}$$

Where K_p = Process Gain

τ_p = process time constant

τ_d = process time delay

6. Utilization of MATLAB and HYSYS to run MPC on plant model

The plant model from the previous activity was used on MATLAB (via Simulink) to apply MPC strategy on the model. The MPC calculation steps as per Figure 3.5 and Chapter 2 of this report was applied to this activity. The resulting controller was then implemented on the plant model via HYSYS. The results from this activity were interpreted and analysed to be compared with that of PI controllers. Figure 3.4 shows the MPC implementation done on CDU plant model via HYSYS.

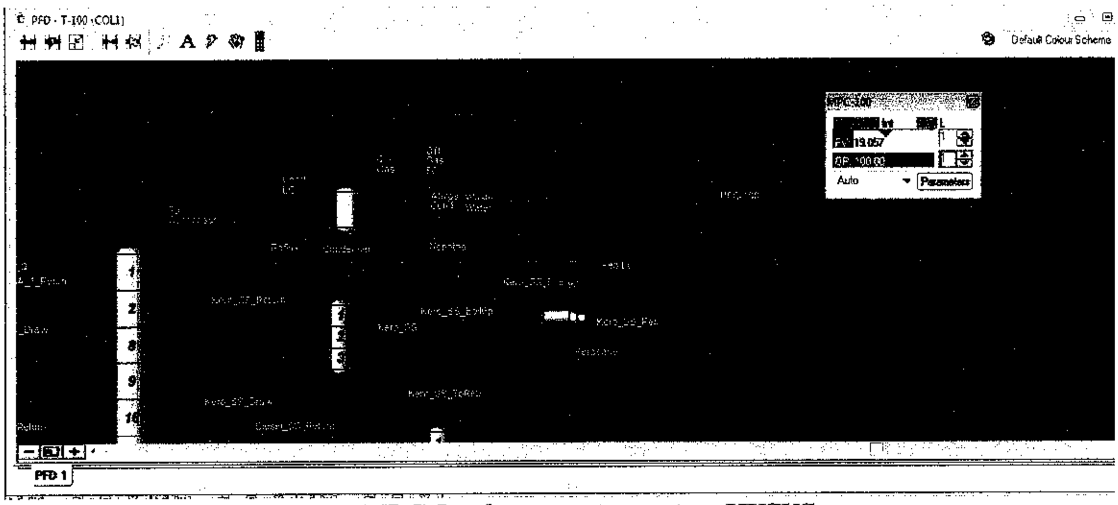

Figure 3.4: MPC Implementation using HYSYS

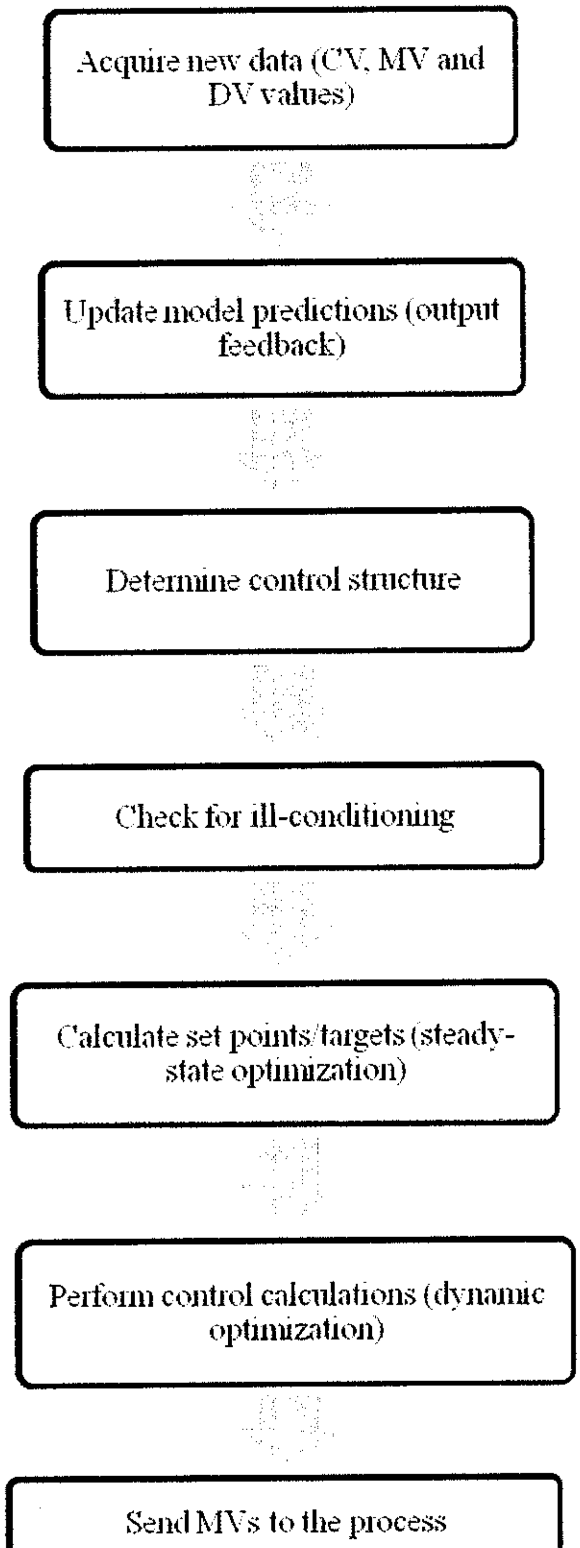

Figure 3.5: Flow chart for MPC calculation (modified from Qin & Badgwell 2003).

3.2 GANTT CHART

Figure 3.6 shows the Gantt chart and key milestones for the Final Year Project.

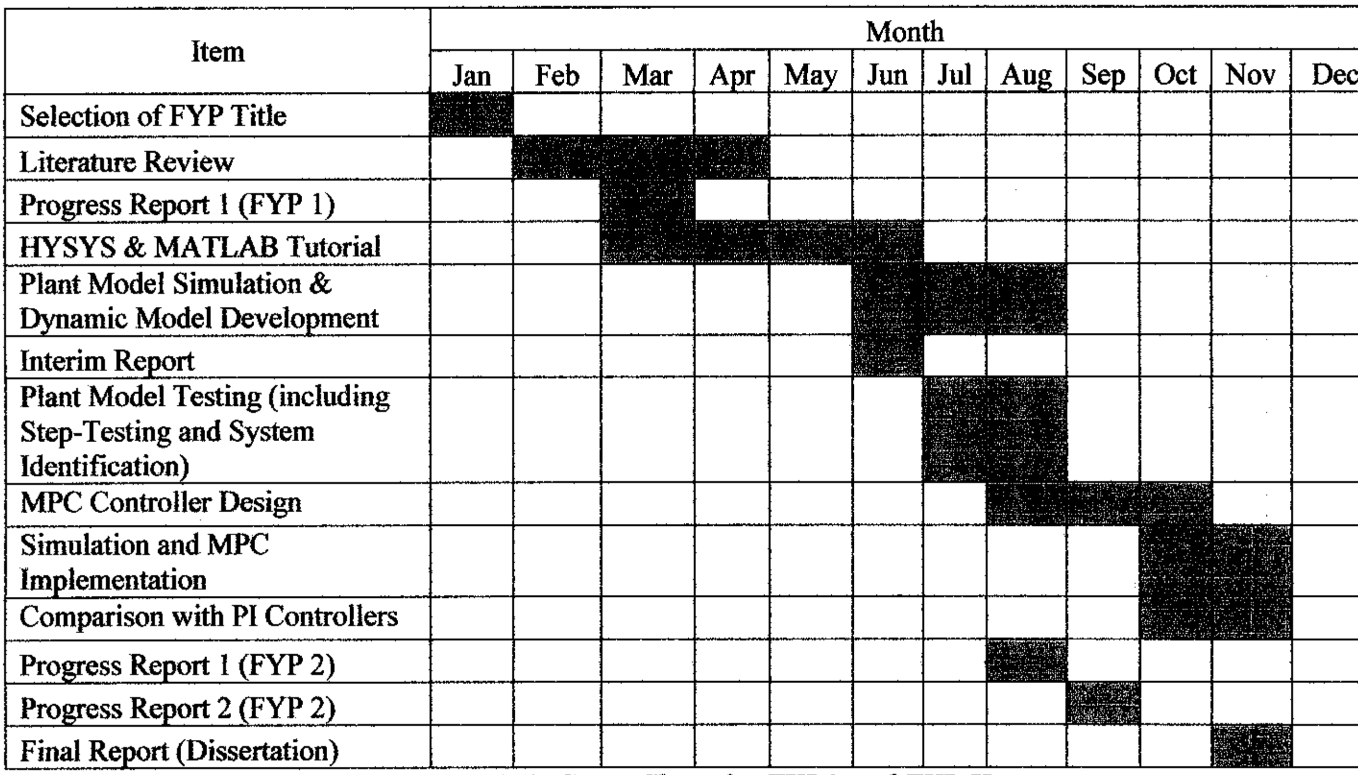

Figure 3.6: Gantt Chart for FYP1 and FYP II

To ensure the project run smoothly and will be finish on time, a Gantt chart is needed. For the FYP 1 progress, literature reviews are needed for the author to get the understanding on project throughout the semester. For the steady state model simulation, it was completed on June. After steady state model is simulated, the dynamic model is the next step by using maximum two months which was finished by the end of July.

For FYP 2 planning progress, MPC design and implementation were done within two months. After that, MPC design was done from August until September. After MPC design is done, MPC implementation is the next step in this project and it was done throughout October and November.

3.3 SOFTWARE REQUIRED

The following software will be utilized in the project:

1. AspenTech **HYSYS**

   HYSYS is common simulation software developed by AspenTech. This software will be used for simulation of CDU and thus, development of steady-state and dynamic model for CDU.

2. **MATLAB** (with Simulink or MPC toolbar)

   MATLAB is a mathematical software and also fourth-generation programming language developed by TheMathWorks. For this project, MATLAB will be used for MPC application on the CDU dynamic model using the Model Predictive Control toolbar available in the MATLAB.

CHAPTER 4
PROCESS DESCRIPTION

In this project, a Crude Distillation Unit is being simulated using HYSYS and from this simulation, the author has expected to obtain a steady-state and dynamic model of the CDU. The CDU in this project consists of a pre-fractionation train and an atmospheric crude column, as shown in Figure 4.1. The pre-fractionation train heats the crude oil, while the atmospheric crude column separates the crude oil into its respective products or fractions.

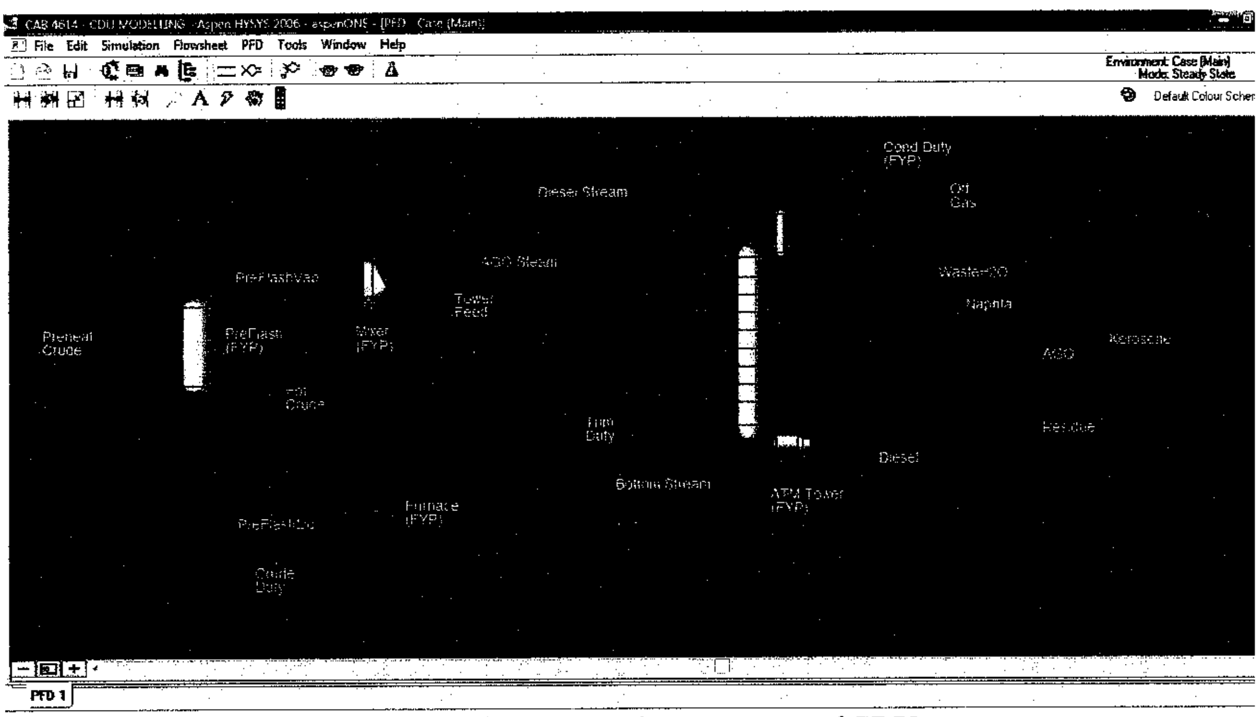

Figure 4.1: Overall Process Flow Diagram of CDU

Crude oil is processed in a CDU to produce several products, namely naphtha, kerosene, diesel, atmospheric gas oil and atmospheric residues. Crude oil is first preheated and fed to pre-flash drum, where vapours at the top of drum are separated from liquids, which flows at the bottom of the drum. The liquid products are then heated in a furnace at a temperature of 650 °F and the resulting hot crude is mixed with the vapour product before being fed to the atmospheric tower at the CDU for fractionation.

For the purpose of simulation, the pre-flash drum is modelled as a Separator, while the furnace is modelled as a Heater. Also, the atmospheric column is modelled as a Refluxed Absorber with a Condenser

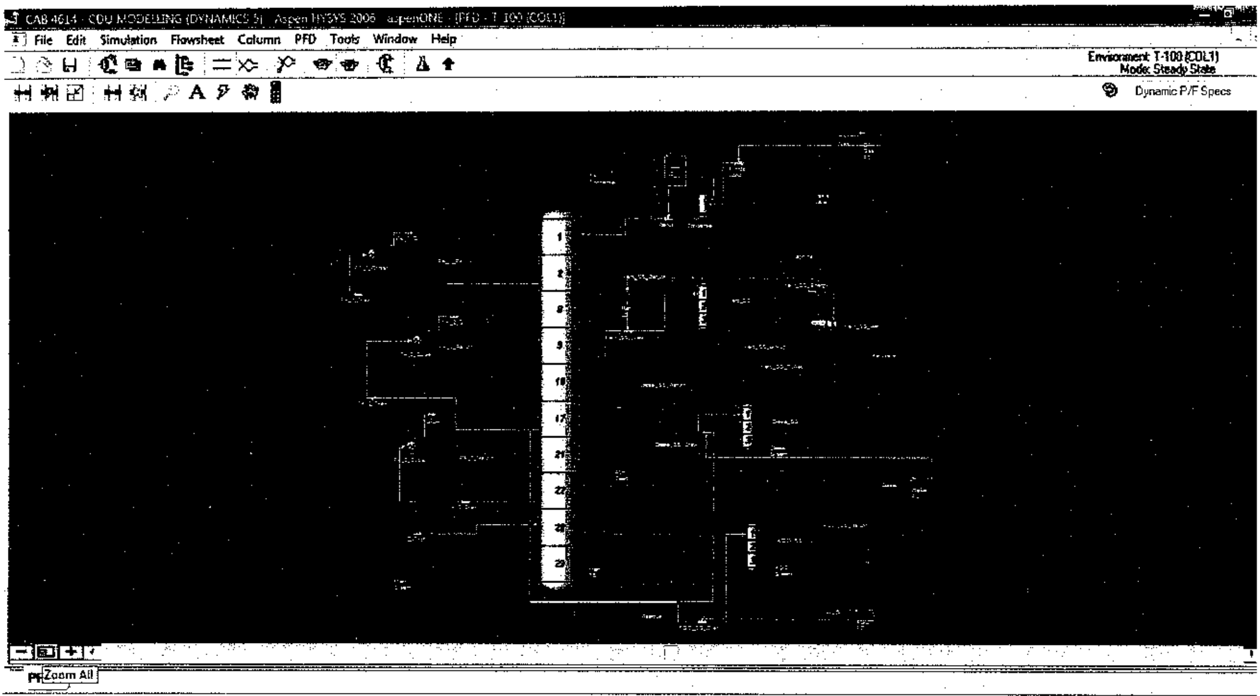

Figure 4.2: PFD of Atmospheric Crude Tower

Figure 4.2 shows the PFD of atmospheric crude tower or column that is used to fractionate the crude oil into its components. The column has 29 trays or stages, plus a partial condenser. The feed, labelled "Atm Feed" enters the column on stage 28 as shown in Figure 4.3, while the "Main Steam" stream enters the bottom stage and an additional energy stream representing the Trim Duty enters on stage 28 as well.

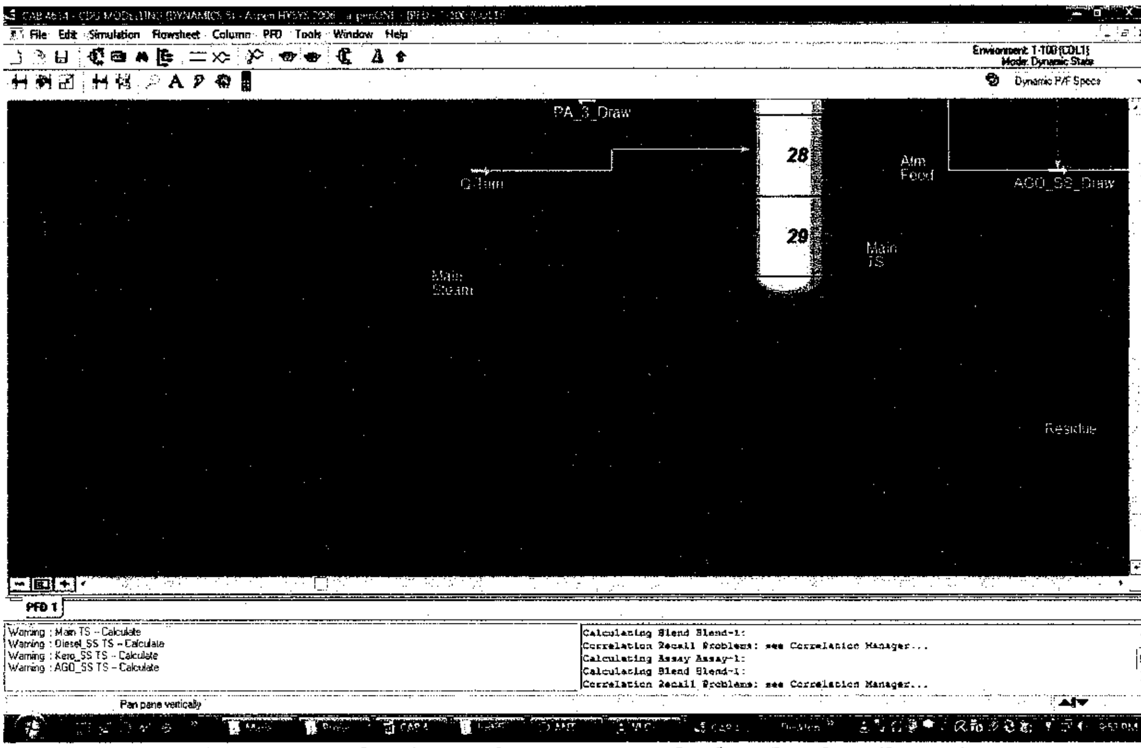

Figure 4.3: Section of Column showing main feed and utility (Steam) streams

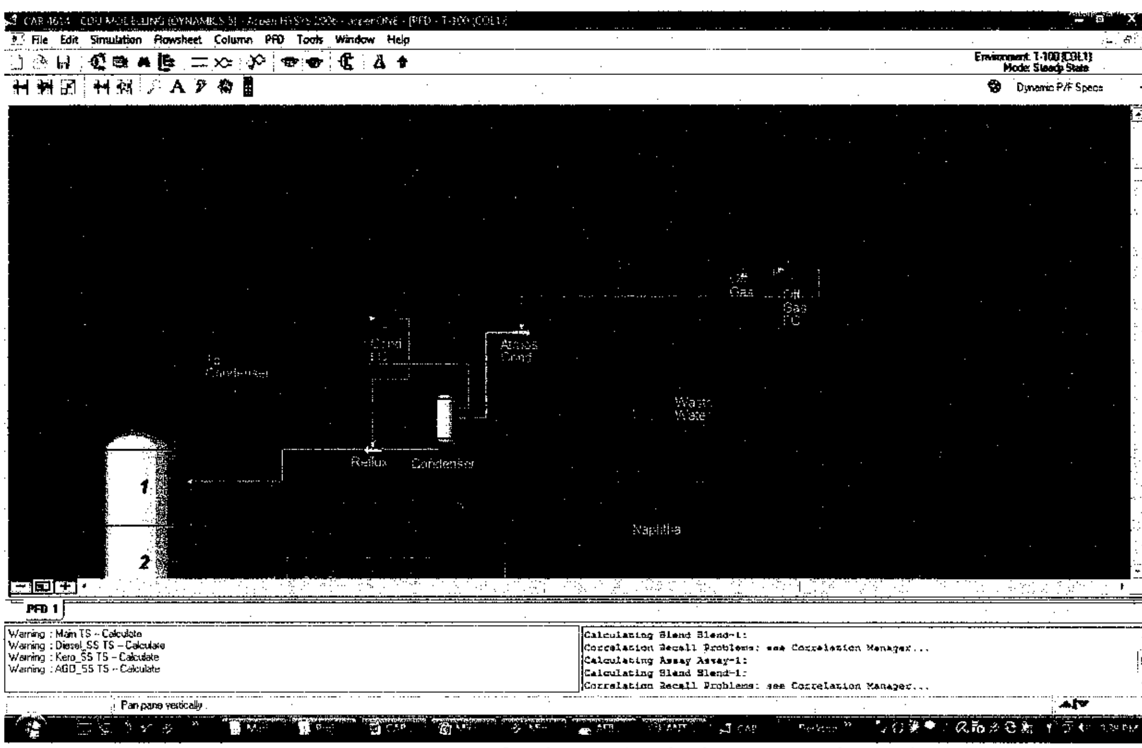

Figure 4.4: Top section of column (including partial condenser)

From Figure 4.4, it is shown that the outputs from the three-phase condenser at the top of column are Naphta as a product and waste water (represented as "Waste H2O").

The column contains three-stage side strippers; each stripper yields a straight run product. The following figures (Figures 4.5 through 4.7) shows the three-stage strippers. The Kerosene Side Stripper contains a reboiler that produces Kerosene from the stripper, while the Diesel Side Stripper and AGO Side Stripper does not contain such reboiler; the respective products being produced via steam stripping of the side streams.

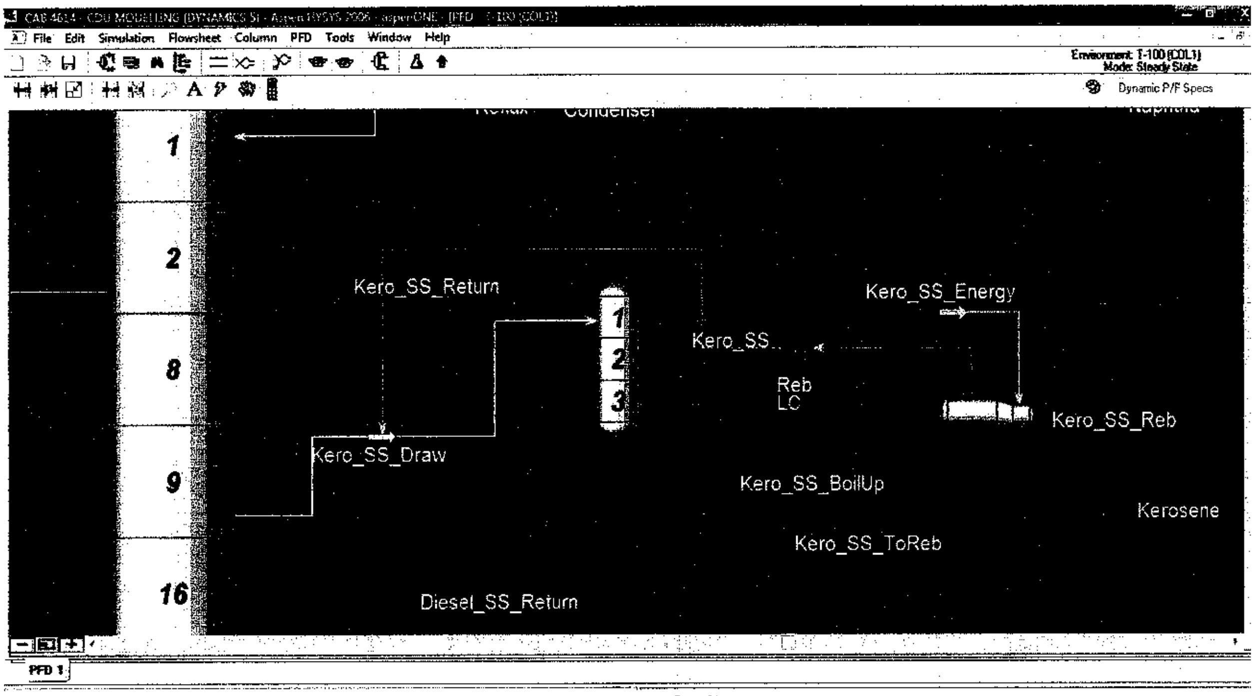

Figure 4.5: Kerosene Side Stripper

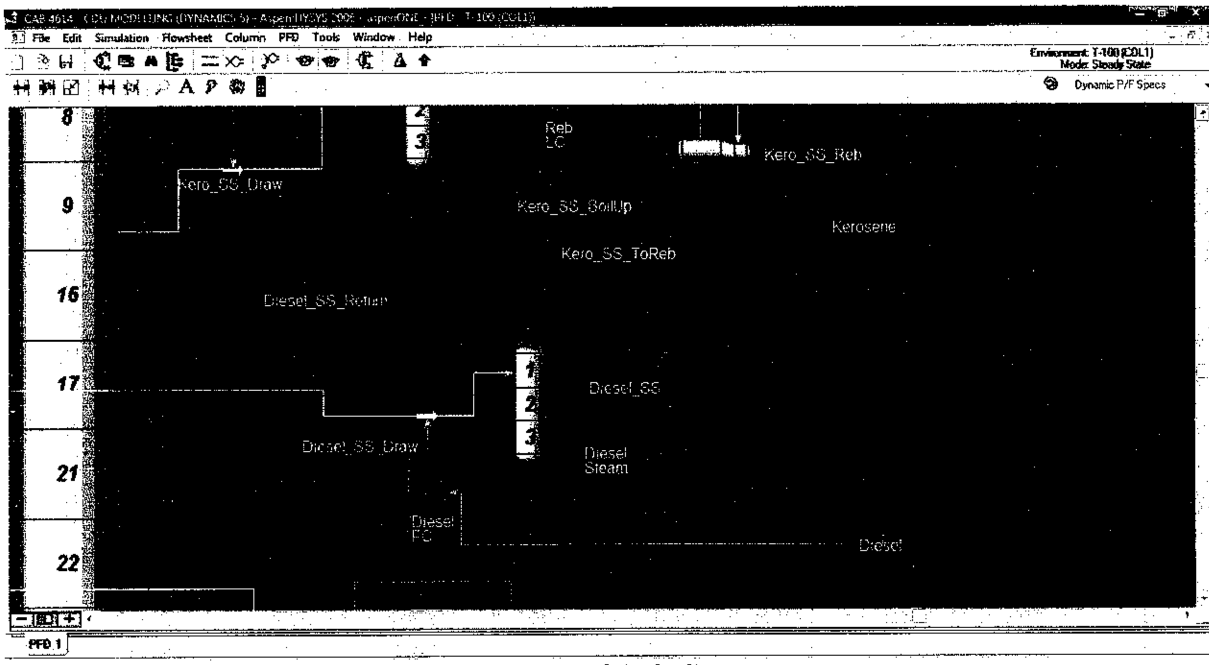

Figure 4.6: Diesel Side Stripper

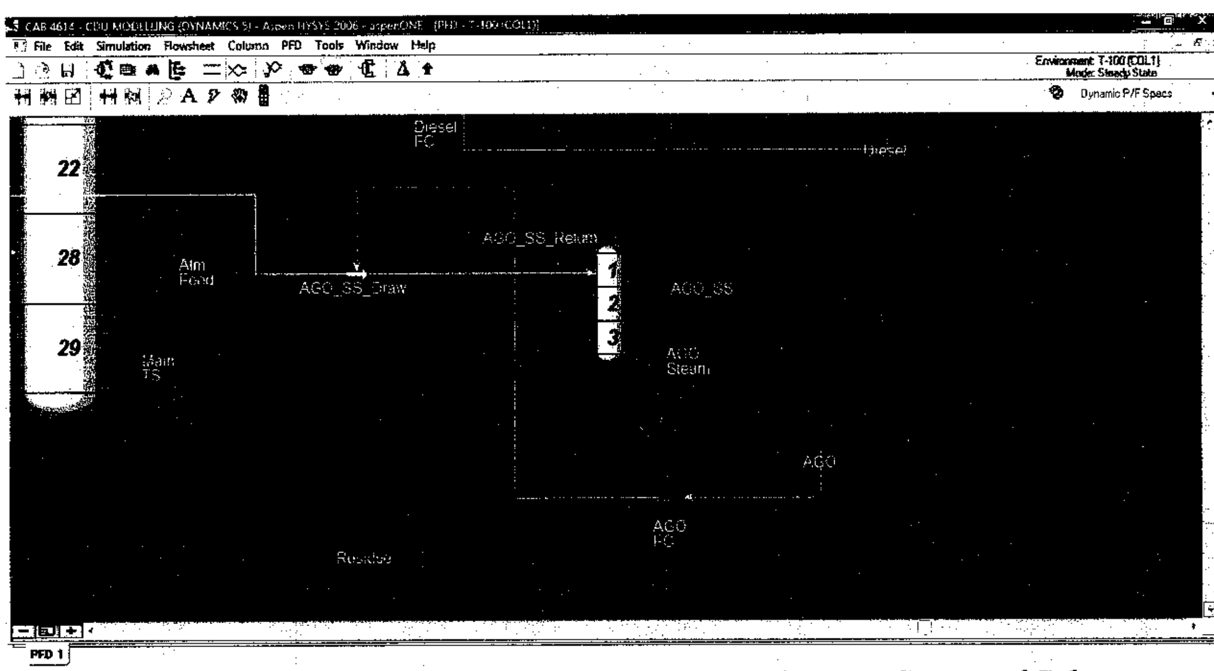

Figure 4.7: Atmospheric Gas Oil (AGO) Side Stripper and Bottom Section of Column

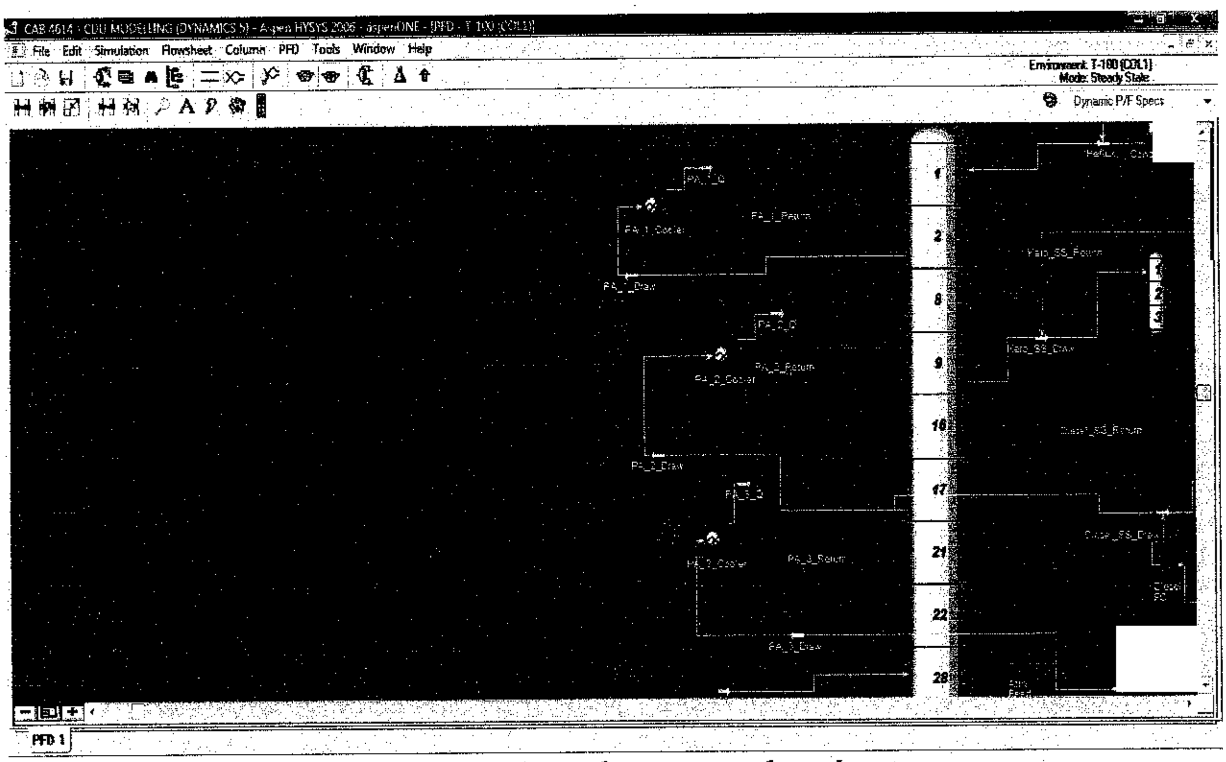

Figure 4.8: Pump-Around streams at the column

Figure 4.8 shows the three pump-arounds at the column; the purpose being to recover process heat from the product streams and also acts as reflux, to increase the composition of end products at each stage by further separation of the refluxed streams.

For this project, the feed enters the pre-fractionation train at temperature of 232.2 °C and pressure of 517.1 kPa, with a molar flow rate of 1730 kgmole/hr. After the train, the heated crude oil then enters the atmospheric column at temperature of 338.5 °C and pressure of 448.2 kPa, an increase in temperature but a decrease in pressure of crude oil. The molar flow rate remains unchanged after the train.

CHAPTER 5

RESULTS AND DISCUSSION

Firstly, the author has developed the dynamic model for CDU using HYSYS. The model used is based on the simulation tutorial provided by HYSYS. As shown in Figure 5.1, the face plates represent the control valves that are used to control the flow of the streams.

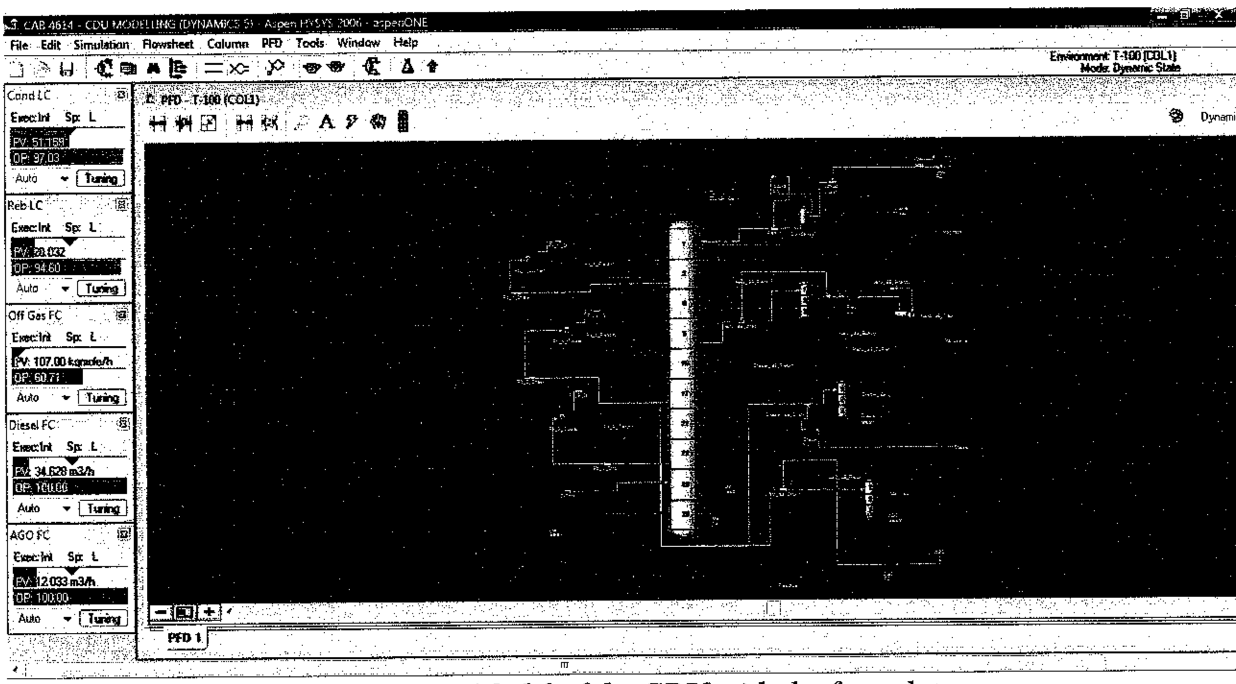

Figure 5.1: Dynamic Model of the CDU with the face plates.

5.1 STEP TESTING

Figure 5.2 shows the response of the PV of Condenser LC with step change of +10% (10% increase) from initial OP, while Figure 5.3 shows the response of the PV with step change of -10% (10% decrease) from initial OP.

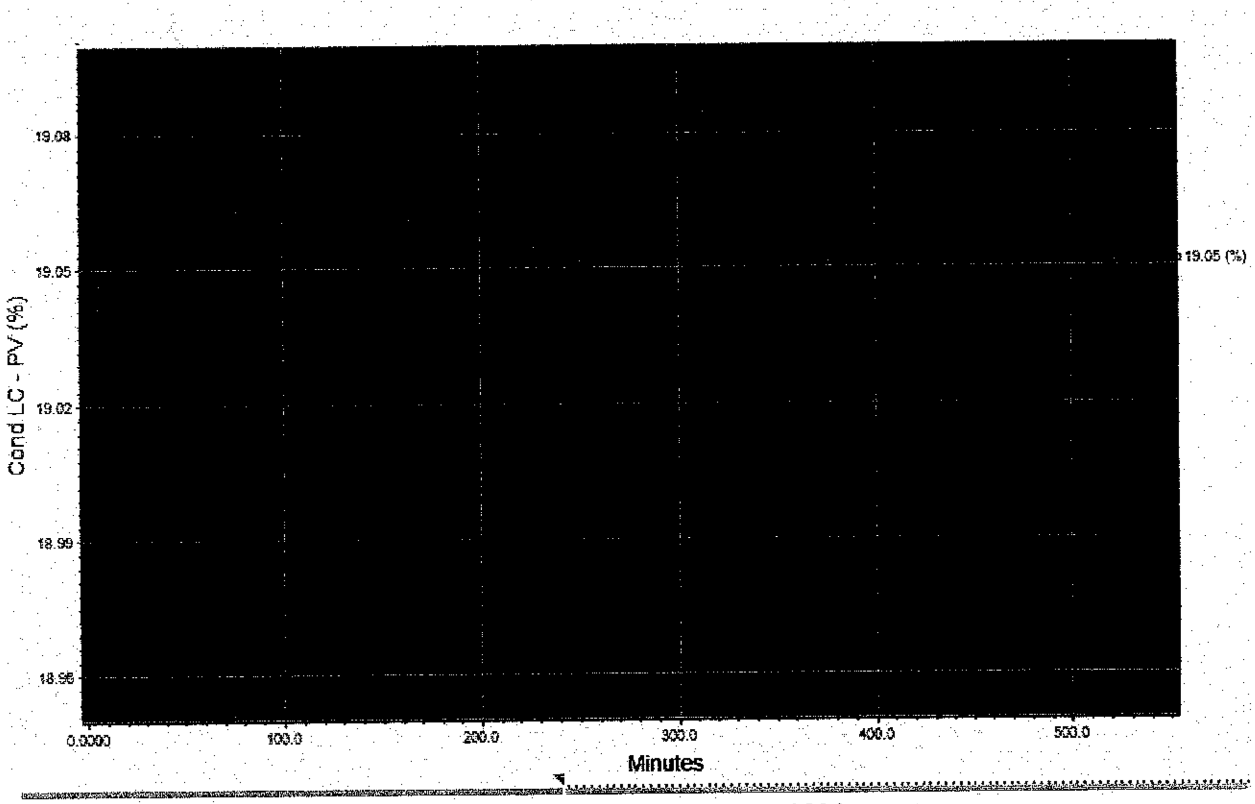

Figure 5.2: Condenser LC – PV response to +10% step input

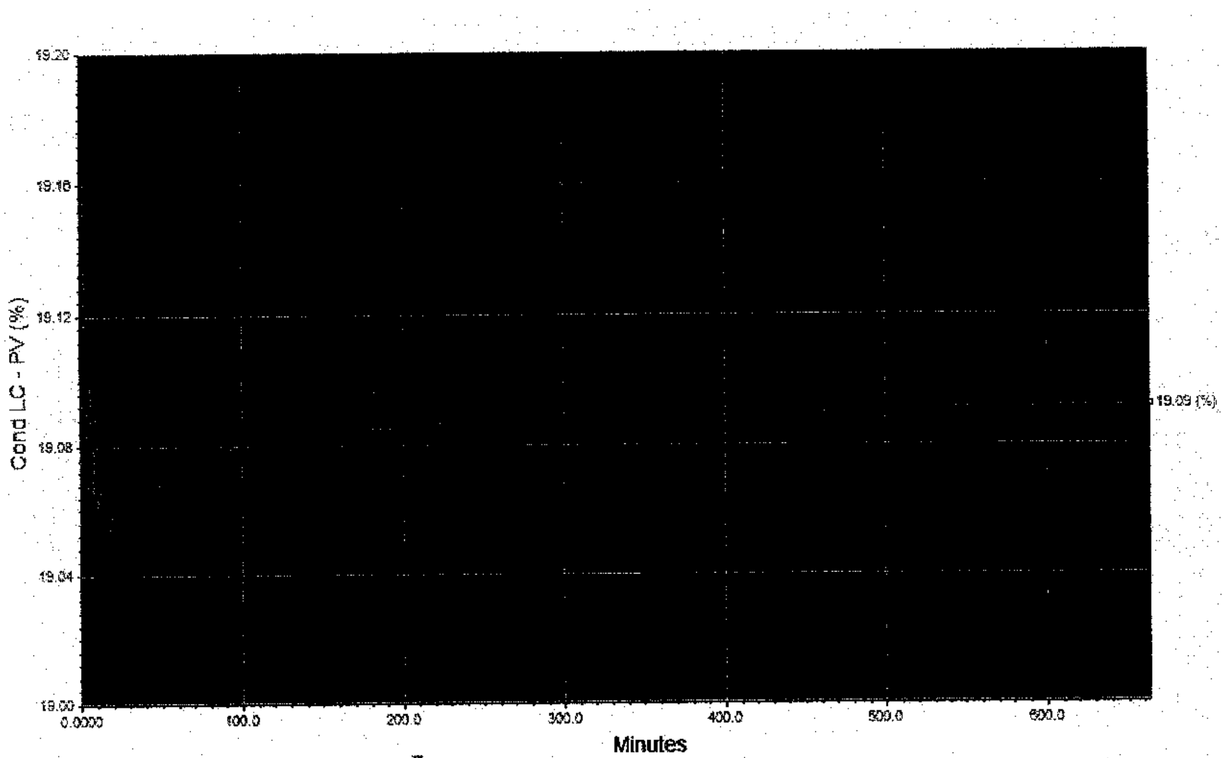

Figure 5.31: Condenser LC – PV response to -10% step input

From Figure 5.2, it is shown that when a step input is introduced to the plant, the system will initially increase slightly above its steady-state value and then the value of PV decreases until it reaches its steady state value (19.05%). For the step decrease case (Figure 5.3), the PV value will decrease to below its steady state value before increases again until it reaches its steady state value (19.09%).

Figure 5.4 shows the response of the PV of Diesel FC with step change of +10% (10% increase) from initial OP, while Figure 5.5 shows the response of the PV with step change of -10% (10% decrease) from initial OP.

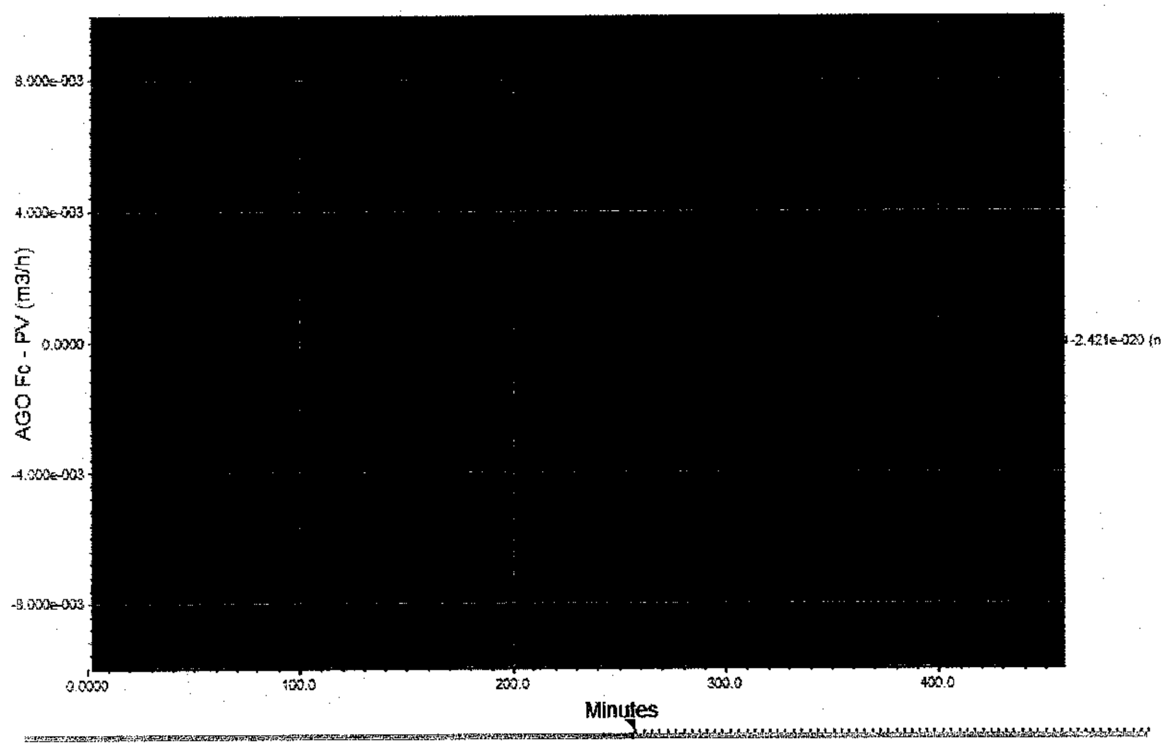

Figure 5.42: Diesel FC – PV response to +10% step input

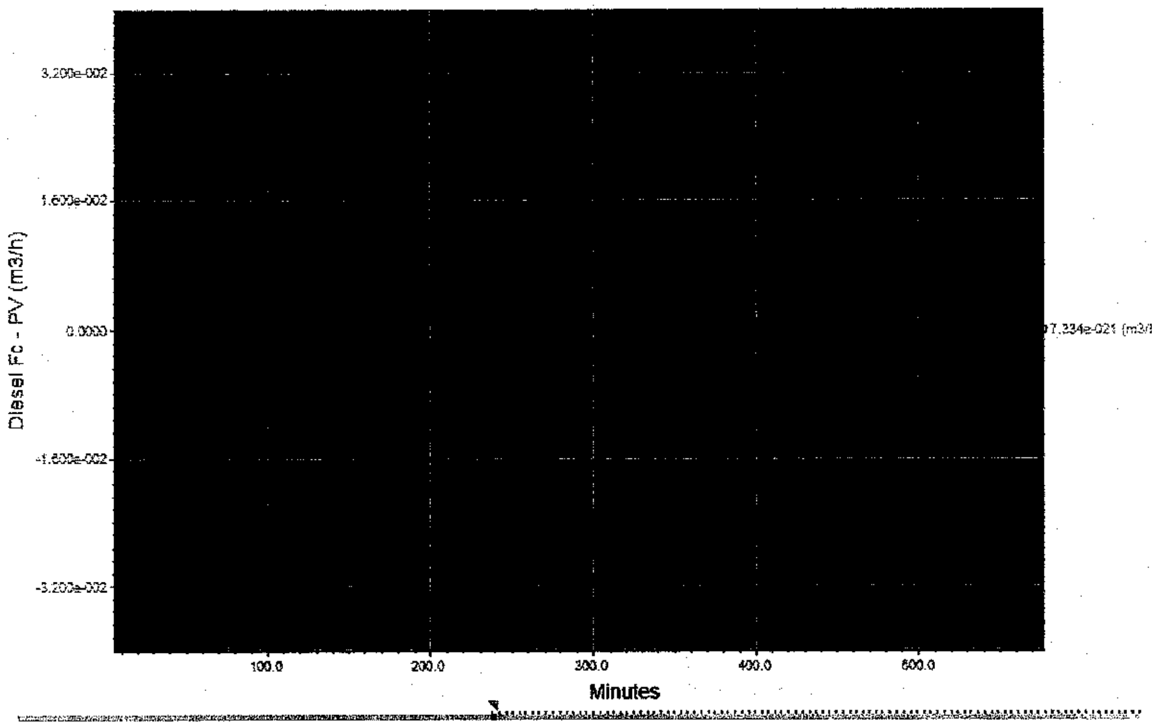

Figure 5.53: Diesel FC – PV response to -10% step input

From both figures, it can be seen that even when step change in input is introduced to the system, the value of the PV did not change significantly from its steady state value (7.334×10^{-21} m^3/h). This is probably due to the low flow rate of the product stream (Diesel).

Figure 5.6 shows the response of the PV of AGO LC with step change of +10% (10% increase) from initial OP, while Figure 5.7 shows the response of the PV with step change of -10% (10% decrease) from initial OP.

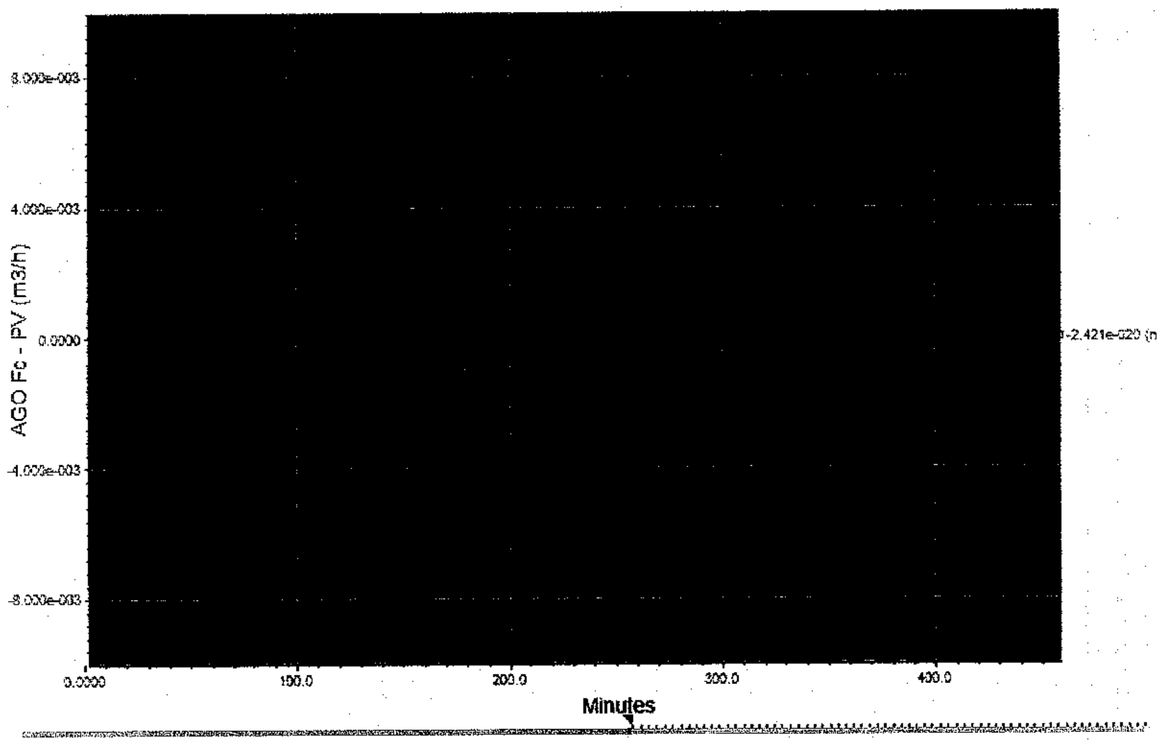

Figure 5.6: AGO FC – PV response to +10% step input

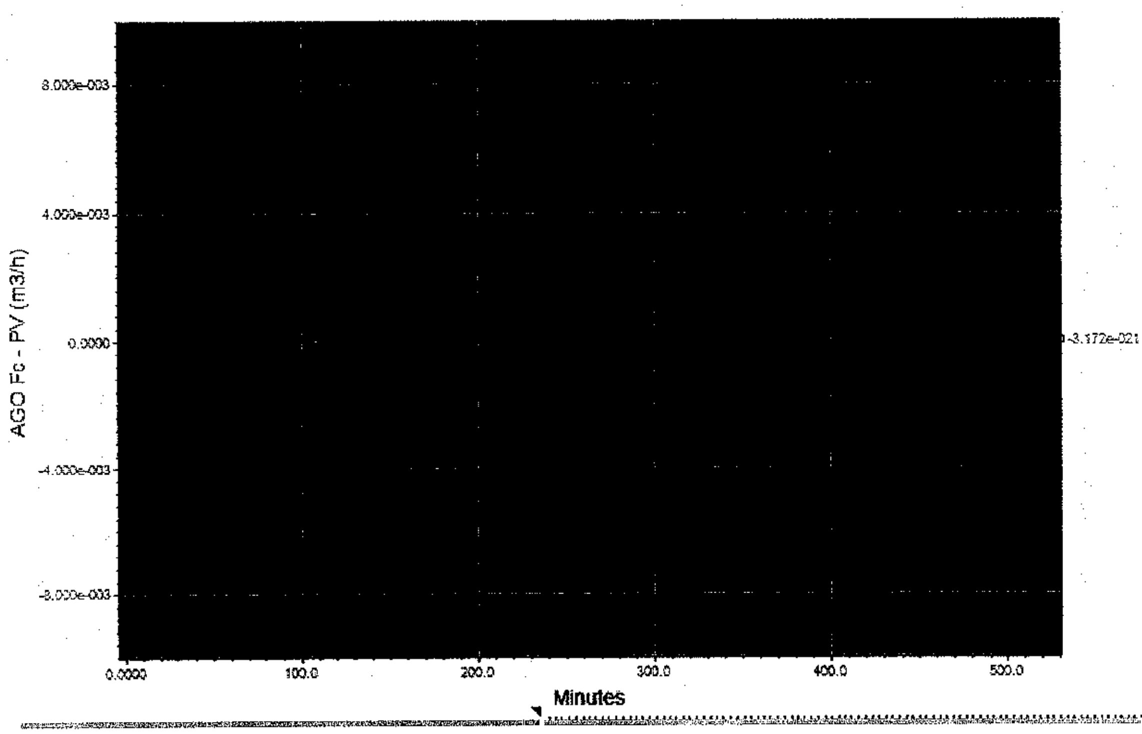

Figure 5.7: AGO FC – PV response to -10% step input

From both figures, it can be seen that even when step change in input is introduced to the system, the value of the PV did not change significantly from its steady state value (2.421×10^{-20} m^3/h). This is probably due to the low flow rate of the product stream (AGO).

All step-test data for the three controllers were stored in a csv file, where the file is used in system identification tool in MATLAB.

5.2 SYSTEM IDENTIFICATION

Table 5.1 shows the parameters for all the process models estimated by System Identification tool. It is noted that G_{yu} is the transfer function for a particular MV (or u) and CV (or y) pair.

Table 5.1: The Transfer Function Parameters for All Variable Pairs

Transfer Function	Kp	τ_p	τ_d
G11	0.0014604	1.47625	2.4203
G12	-0.0027793	177.5026	30
G13	-5.5909×10^{-5}	136.5467	30
G21	1.5269×10^{-2}	0.010081	0.52765
G22	-5.2072×10^{-22}	0.01013	0.4722
G23	-1.2531×10^{-22}	0.010318	0.48041
G31	6.1182×10^{-24}	0.01056	0.4722
G32	-3.2871×10^{-22}	0.010043	0.4722
G33	208383×10^{-22}	0.010503	0.4722

For the transfer function, a negative value of the process gain indicates that the process is reverse-acting, i.e. an increase in the input will cause a decrease in the output. For a positive value of the gain, the process is direct-acting, that is an increase in the input will cause an increase in the output as well.

5.3 MPC DESIGN

The author used the MPC toolbar in MATLAB to design the MPC controllers and implement the controllers on the plant model. However, at this time, the author is only able to come up with the state-space model of the plant. The author then used this model to design the MPC controllers to be implemented to the CDU.

The state-space model is in the format of matrix notations, as follows:

$$\dot{x} = Ax + Bu$$
$$y = Cx + Du$$

Where **A** = the system matrix (n × n)

B = the input matrix (n × r)

C = the output matrix (m × n)

D = the transmission matrix (m × r)

x = process states matrix (number of states, n = 9)

u = input (manipulated) variables matrix (number of inputs, r = 3)

y = output (controlled) variables matrix (number of outputs, m = 3)

The MATLAB m-file that is used to derive the state-space model of the CDU are as shown:

```
%% Model (sys) Setup
g11=data(1,:); g11=g11';
g12=data(2,:); g12=g12';
g13=data(3,:); g13=g13';
g21=data(4,:); g21=g21';
g22=data(5,:); g22=g22';
g23=data(6,:); g23=g23';
g31=data(7,:); g31=g31';
g32=data(8,:); g32=g32';
g33=data(9,:); g33=g33';

model=[g11 g12 g13 g21 g22 g23 g31 g32 g33]';

%% Rearranging the model parameters
% Kp=gain; Tp=time constant; Td=time delay
k=1;
for i=1:3
    for j=1:3
```

```
        Kp(i,j)=model(k,1);
        Tp(i,j)=model(k,2);
        Td(i,j)=model(k,3);
        k=k+1;
    end
end

%% Linearization of plant model
%sysc='PlantModel2x2_Pade_1'; % Simulink model
%[A B C D]=linmod(sysc);
%sysc=ss(A,B,C,D);
%return

% -- multiple SISO
g(1,1)=tf(Kp(1,1),[Tp(1,1) 1],'IOdelay',Td(1,1));
g(1,2)=tf(Kp(1,2),[Tp(1,2) 1],'IOdelay',Td(1,2));
g(1,3)=tf(Kp(1,3),[Tp(1,3) 1],'IOdelay',Td(1,3));
g(2,1)=tf(Kp(2,1),[Tp(2,1) 1],'IOdelay',Td(2,1));
g(2,2)=tf(Kp(2,2),[Tp(2,2) 1],'IOdelay',Td(2,2));
g(2,3)=tf(Kp(2,3),[Tp(2,3) 1],'IOdelay',Td(2,3));
g(3,1)=tf(Kp(3,1),[Tp(3,1) 1],'IOdelay',Td(3,1));
g(3,2)=tf(Kp(3,2),[Tp(3,2) 1],'IOdelay',Td(3,2));
g(3,3)=tf(Kp(3,3),[Tp(3,3) 1],'IOdelay',Td(3,3));

% -- MIMO (continuous)
sysc_tf=[g(1,1) g(1,2) g(1,3); g(2,1) g(2,2) g(2,3); g(3,1) g(3,2) g(3,3)]; % in TF form
sysc=ss(sysc_tf); % in SS form
```

From the file, the state space model for the CDU is as follows:

$$
\begin{bmatrix} x'_1 \\ x'_2 \\ x'_3 \\ x'_4 \\ x'_5 \\ x'_6 \\ x'_7 \\ x'_8 \\ x'_9 \end{bmatrix}
=
\begin{bmatrix}
-0.6774 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\
0 & -99.2 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\
0 & 0 & -94.7 & 0 & 0 & 0 & 0 & 0 & 0 \\
0 & 0 & 0 & -0.005634 & 0 & 0 & 0 & 0 & 0 \\
0 & 0 & 0 & 0 & -98.72 & 0 & 0 & 0 & 0 \\
0 & 0 & 0 & 0 & 0 & -99.57 & 0 & 0 & 0 \\
0 & 0 & 0 & 0 & 0 & 0 & -0.007324 & 0 & 0 \\
0 & 0 & 0 & 0 & 0 & 0 & 0 & -96.92 & 0 \\
0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & -95.21
\end{bmatrix}
\begin{bmatrix} x_1 \\ x_2 \\ x_3 \\ x_4 \\ x_5 \\ x_6 \\ x_7 \\ x_8 \\ x_9 \end{bmatrix}
+
\begin{bmatrix}
0.03125 & 0 & 0 \\
1 & 0 & 0 \\
2.91 \times 10^{-11} & 0 & 0 \\
0 & 0.003906 & 0 \\
0 & 2.328 \times 10^{-10} & 0 \\
0 & 2.328 \times 10^{-10} & 0 \\
0 & 0 & 0.0004883 \\
0 & 0 & 1.164 \times 10^{-10} \\
0 & 0 & 5.96 \times 10^{-8}
\end{bmatrix}
\begin{bmatrix} u_1 \\ u_2 \\ u_3 \end{bmatrix}
$$

$$
\begin{bmatrix} y_1 \\ y_2 \\ y_3 \end{bmatrix}
=
\begin{bmatrix}
0.03166 & 0 & 0 & -0.004008 & 0 & 0 & -0.0008386 & 0 & 0 \\
0 & 1.515 & 0 & 0 & -2.209 \times 10^{-10} & 0 & 0 & -1.041 \times 10^{-10} & 0 \\
0 & 0 & 1.991 \times 10^{-11} & 0 & 0 & -1.407 \times 10^{-10} & 0 & 0 & 3.323 \times 10^{-8}
\end{bmatrix}
\begin{bmatrix} x_1 \\ x_2 \\ x_3 \\ x_4 \\ x_5 \\ x_6 \\ x_7 \\ x_8 \\ x_9 \end{bmatrix}
+ [0] \begin{bmatrix} u_1 \\ u_2 \\ u_3 \end{bmatrix}
$$

5.4 COMPARISON OF CONTROLLER PERFORMANCES ON CDU MODEL

After MPC implementation was done on the plant model via HYSYS, the resulting responses of the output variables were compared with that of PI controllers. The measure used to compare both controllers' performance is the time taken for the controller to bring the output to its steady state value.

Figure 5.8 shows the response of the 1st PV (liquid level percent inside the condenser) to change in input variable using PI controller, while Figure 5.9 shows the same PV response using MPC controller.

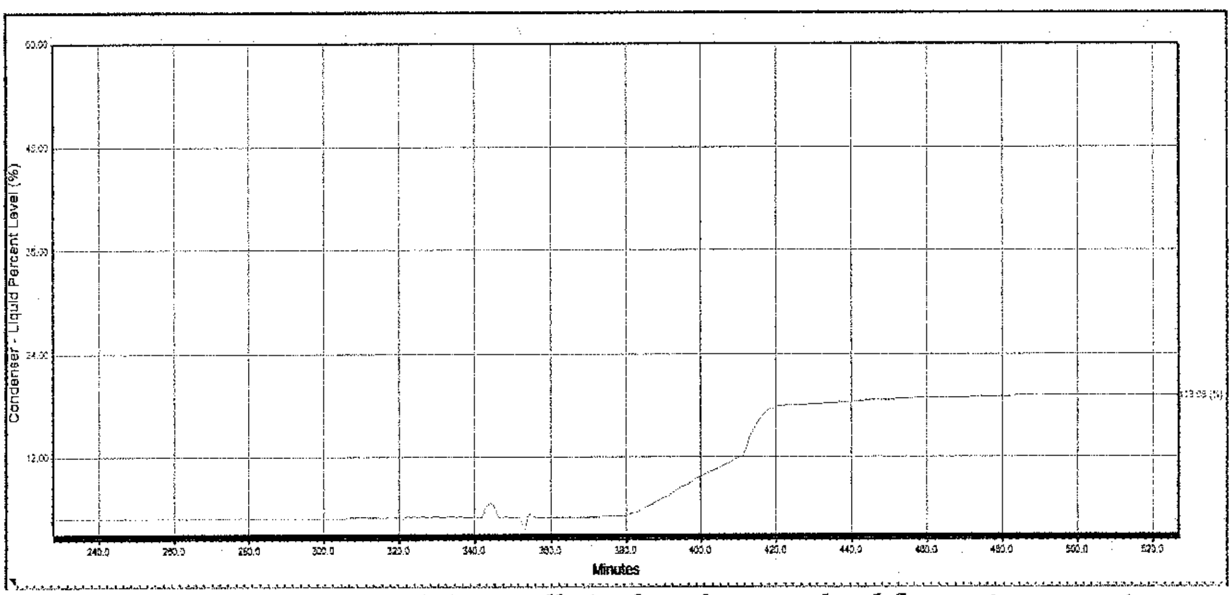

Figure 5.8: Condenser LC (PI controller) – liquid percent level fluctuations over time

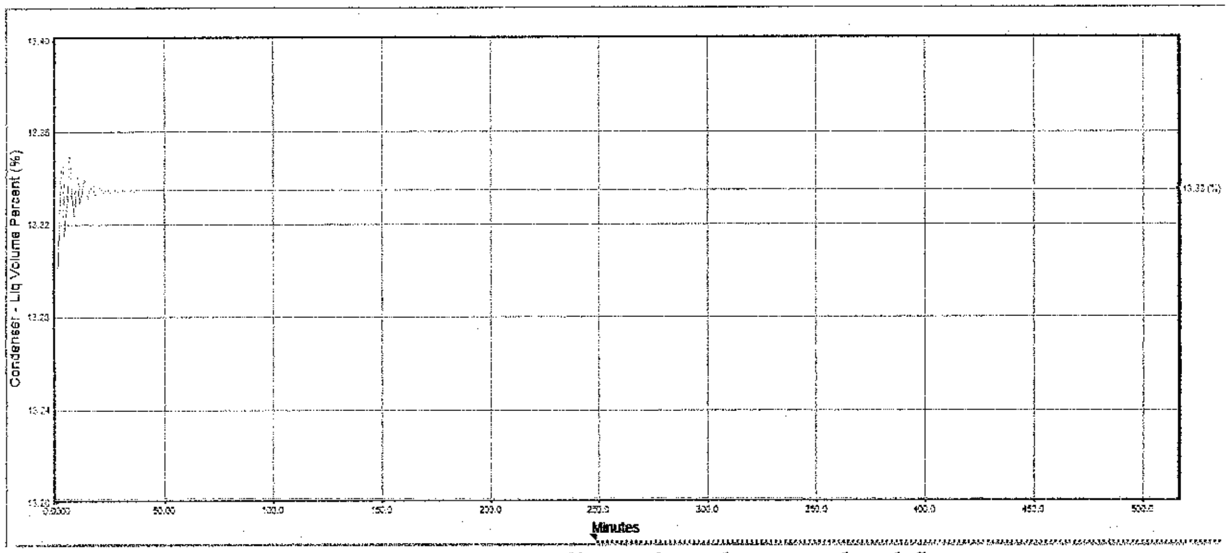

Figure 5.9: Condenser LC (MPC controller) – liquid percent level fluctuations over time

From Figure 5.8, the percent level was initially lower than 12% due to less liquid containment inside the condenser at the beginning of the simulation. However, after around 360 minutes (6 hrs) of simulation, the percent liquid level increases as the control valve opening percentage decreases to avoid more liquid being refluxed back to the column. The steady state value of the liquid level, 19.09% has been reached after around 420 minutes from the start of simulation.

From Figure 5.9, the controller took less than 50 minutes to bring the percent liquid level around its steady state value, which is 13.33%. This shows that the MPC controller takes less time to control the liquid percent level inside the condenser than that of PI controller (50 minutes vs., 420 minutes).

Figure 5.10 shows the response of the 2nd PV (AGO liquid flow rate) to change in input variable using PI controller, while Figure 5.11 shows the same PV response using MPC controller.

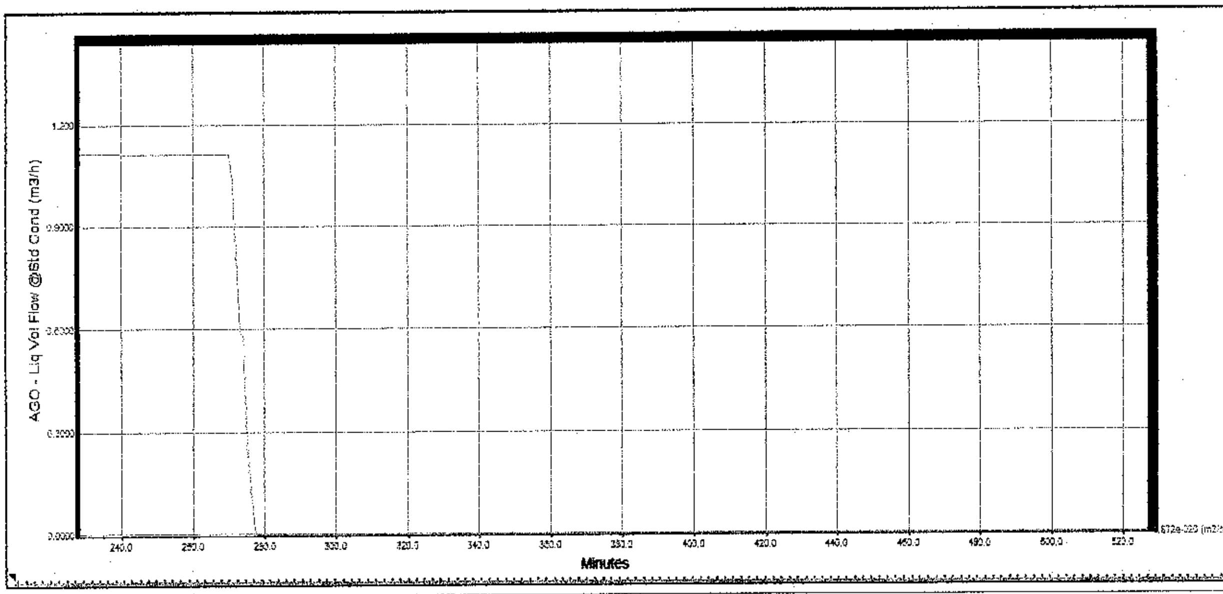

Figure 5.10: AGO FC (PI controller) – liquid flow rate fluctuations over time

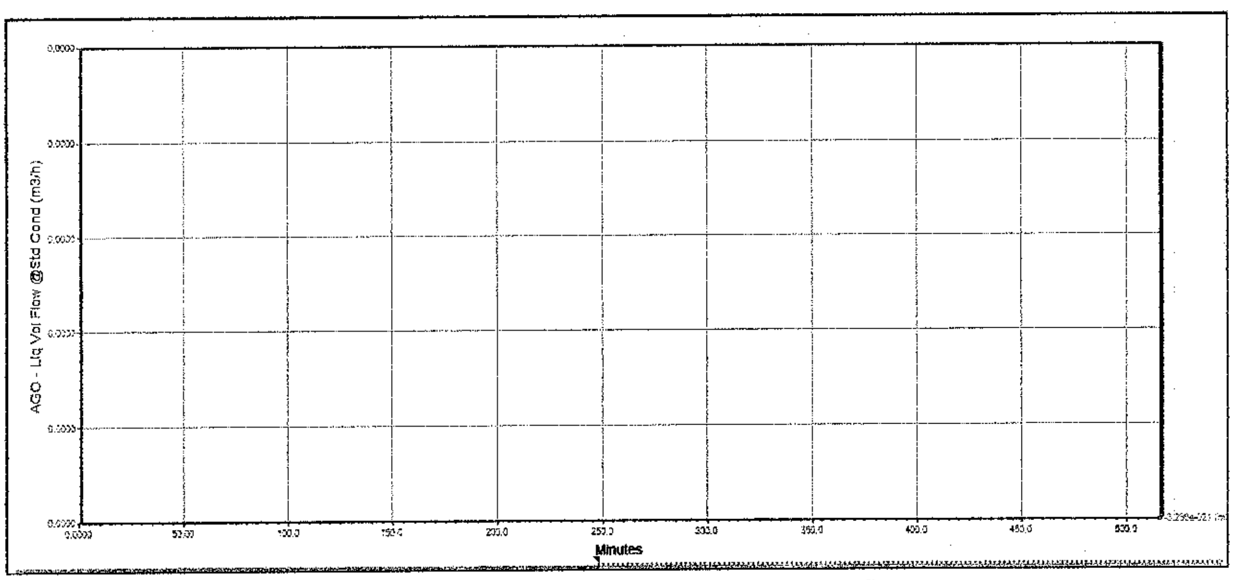

Figure 5.11: AGO FC (MPC controller) – liquid flow rate fluctuations over time

From Figure 5.10, it can be seen that at the beginning of the simulation, the liquid flow rate of AGO from the AGO side stripper is around 1.0 m^3/h. However, due to problems associated with the pump-arounds at the column, the flow rate decreases significantly to 1.872×10^{-22} m^3/h after around 280 minutes from the start of simulation.

From Figure 5.11, the value of AGO flow rate is constant around 3.296×10^{-21} m^3/h. This is due to material and energy balance problems inside the column that results in the significant least amount of AGO being produced from the side stripper.

Figure 5.12 shows the response of the 3rd PV (Diesel liquid flow rate) to change in input variable using PI controller, while Figure 5.13 shows the same PV response using MPC controller.

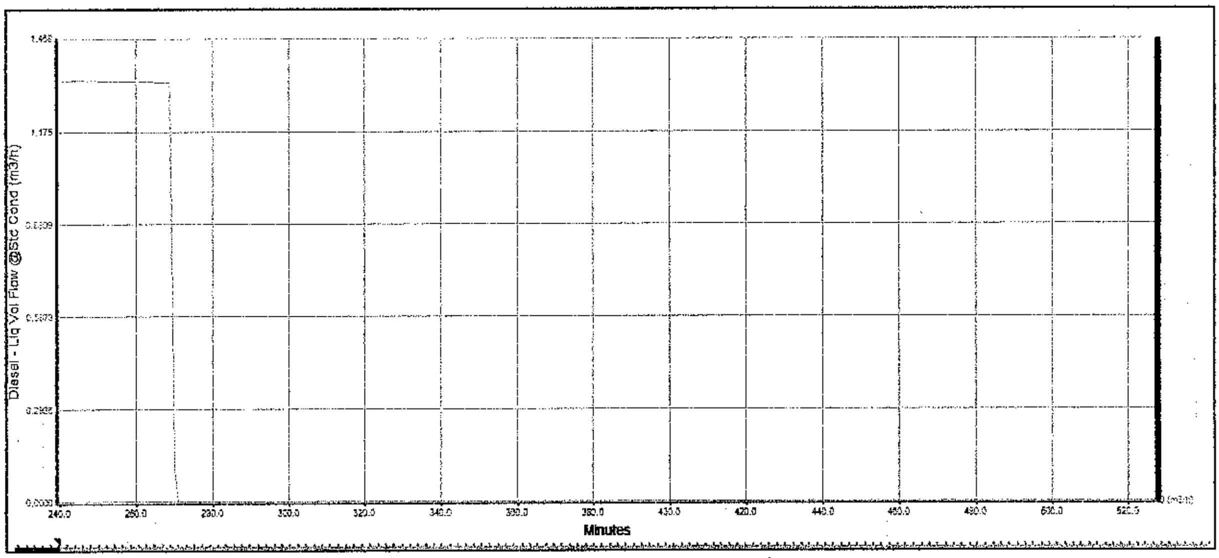

Figure 5.12: Diesel FC (PI controller) – liquid flow rate fluctuations over time

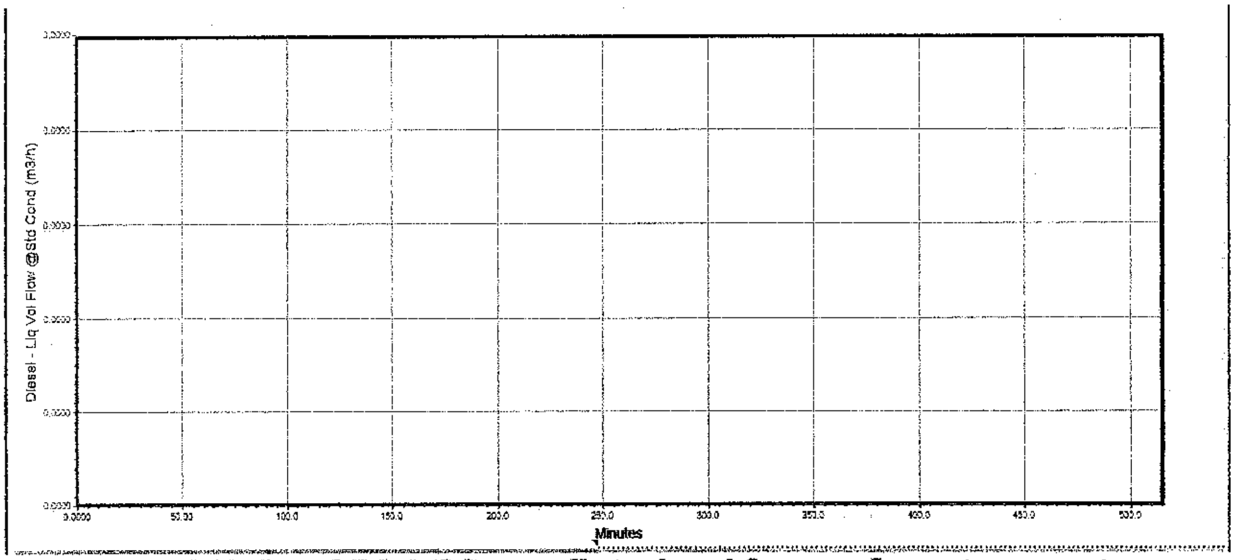

Figure 5.13: Diesel FC (MPC controller) – liquid flow rate fluctuations over time

From Figure 5.12, it can be seen that at the beginning of the simulation, the liquid flow rate of Diesel from the Diesel side stripper is around 1.0 m^3/h. However, due to problems associated with the pump-arounds and flash calculations at the column, the flow rate decreases significantly to 0 m^3/h after around 270 minutes from the start of simulation.

From Figure 5.13, the value of Diesel flow rate is also constant around 0 m^3/h. This is also due to material and energy balance problems inside the column that results in the significantly no Diesel being produced from the side stripper.

5.5 OVERALL DISCUSSIONS ON MPC IMPLEMENTATION

From the results of controller performances, it can be seen that the plant model may not be reasonably accurate enough to predict future input moves for the process model. The controller performances can be compared for condenser percent level but cannot be compared for the other two variables due to insignificant steady state value and inability of the author to determine the time taken for the output to reach steady state.

Therefore, it is important for a plant model to be accurate enough for successful implementation of MPC, since an accurate plant model is one of the requirements and characteristics of MPC.

CHAPTER 6

CONCLUSION & RECOMMENDATIONS

From the project, the author was able to develop a dynamic model of CDU using HYSYS and then the state-space model of the plant was also presented. The author was able to see the difference of performances of the MPC controllers with that of PI controllers in terms of speed of response of the CVs with step change in MVs. The author also realized the importance of having an accurate plant model to ensure successful implementation of MPC.

For further improvements of this project, the author would like to suggest that this model been modified to include actual plant data from a current operating CDU. Also, the input and output variables must be chosen in such a way that their responses to input changes can be seen clearly.

REFERENCES

Adetola, V., & Guay, M. (2010). "Integration of real-time optimization and model predictive control." *Journal of Process Control*, **20(2)**, 125-133.

Al-Gherwi, W., Budman, H., & Elkamel, A. (2010). "Selection of control structure for distributed model predictive control in the presence of model errors." *Journal of Process Control*, **20(3)**, 270-284.

Anderson, Bradley , Bennick, Aaron and Salciccioli, Michael. (11th July 2006) "Model Predictive Control" <http://controls.engin.umich.edu/wiki/index.php/MPC> (date of access: 16th March 2010)

Dave, D. J., Dabhiya, M. Z., Satyadev, S. V. K., Ganguly, S., & Saraf, D. N. (2003). "Online tuning of a steady state crude distillation unit model for real time applications." *Journal of Process Control,* **13(3),** 267-282.

Froisy, J. B. (2006). "Model predictive control—Building a bridge between theory and practice." *Computers & Chemical Engineering,* **30(10-12),** 1426-1435.

Gadalla, M., Olujić, Ž., Jobson, M., & Smith, R. (2006). "Estimation and reduction of CO2 emissions from crude oil distillation units." *Energy,* **31(13),** 2398-2408.

Hyprotech (a subsidiary of Aspen Technology Inc.), (2002). *Refining Tutorial AspenTech HYSYS 2006,* Cambridge, MA

Inamdar, S. V., Gupta, S. K., & Saraf, D. N. (2004). "Multi-objective optimization of an industrial crude distillation unit using the elitist non-dominated sorting genetic algorithm." *Chemical Engineering Research and Design*, **82(5),** 611-623.

Jämsä-Jounela, S. (2007). "Future trends in process automation." *Annual Reviews in Control,* **31(2),** 211-220.

Orukpe, P.E. (14th April 2005) "Basics of Model Predictive Control." Imperial College, London. <http://www3.imperial.ac.uk/portal/pls/portallive/docs/1/50918.PDF> (date of access: 16th March 2010)

Qin, S. J., & Badgwell, T. A. (2003). "A survey of industrial model predictive control technology." *Control Engineering Practice,* **11(7),** 733-764.

Rao, C. V., & Rawlings, J. B. (2000). "Linear programming and model predictive control." *Journal of Process Control,* **10(2-3),** 283-289.

Seborg, D.E., Edgar, T.F. and Mellichamp, D.A., (2004). *Process Dynamics and Control,* 2nd Ed., John Wiley & Sons.

The United Nations Framework Convention on Climate Change (1997) "Kyoto Protocol to the United Nations Framework Convention on Climate Change", < http://unfccc.int/resource/docs/convkp/kpeng.html> (Date of access: 4th May 2010)

Van Antwerp, J. G., & Braatz, R. D. (2000). "Model predictive control of large scale processes." *Journal of Process Control,* **10(1),** 1-8.

Yüzgeç, U., Palazoglu, A., & Romagnoli, J. A. (2010). "Refinery scheduling of crude oil unloading, storage and processing using a model predictive control strategy." *Computers & Chemical Engineering,* In Press, Corrected Proof

APPENDICES

APPENDIX A

MODEL PREDICTIVE CONTROL TECHNOLOGY & PRODUCTS

Table A.1 summarizes the currently available MPC products that are employed in the industry.

Table A.1: MPC Industrial Technology

Company	Product Name	Description	MPC Type
Aspen Tech	DMC-plus	Dynamic Matrix Control package	Linear
	DMC-plus model	Identification package	Linear
	Aspen Target	Nonlinear MPC package	Nonlinear
Adersa	IDCOM	Identification and Command	Linear
	HIECON	Hierarchical Constraint Control	Linear
	PFC	Predictive Functional Control	Linear & Nonlinear
Honeywell Profimatics	RMPCT	Robust Model Predictive Control Technology	Linear
	PCT	Predictive Control Technology	
Shell Global Solutions	SMOC-II	Shell Multivariable Optimizing Control	Linear
Pavillion Technologies Inc.	PP	Process Perfecter	Nonlinear
Invensys	Connoisseur	Control and Identification Package	Linear
Continental Controls, Inc.	MVC	Multivariable Control	Nonlinear
DOT Products	NOVA-NLC	NOVA nonlinear controller	Nonlinear

Linear MPC products are usually employed by refining, petrochemicals and chemicals plants, while nonlinear MPC products have wide applications in chemicals, polymers and air & gas plants. (Qin & Badgwell, 2003)