

# **CERTIFICATION OF APPROVAL**

**An Efficient Method for Conducting Step Testing of Crude Distillation Unit**

by

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Approved by,



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TRONOH, PERAK  
MAY 2012

## **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 the original work contained herein have not been undertaken or done by unspecified sources or persons.



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**MOHD ZARUL IKMAL BIN ZULKIFLI**

## ABSTRACT

The objective in implementing the process control strategy is to maintain the process at desired condition, safely and efficiently, while satisfying environmental and product quality requirement. There are seven layers of a process control hierarchy which are instrument, safety, regulator, multivariable, real time optimization and planning and scheduling. Some of the strategies, as for example model predictive controller which located at multivariable stage requires a model to enable it to be implement. There are four phase in developing a model-required process control strategy such as MPC. The phases are; 1) pretest and preliminary MPC design 2) plant testing 3) model and controller development and 4) commissioning and training. The accuracy and reliability of the deliverables from each phases is extremely crucial in determining the success of the developed process control strategy.

According to literature, plant testing took the longest period of among all the stages. The plant testing could consume up to 50% of the time used in order to develop the model. In order to run the plant testing, taking step testing as for an example, there is a literature suggested that the step testing shall be made between eight and twelve step, where for each step, the developer have to let the process to reach steady state before implementing another step.

This study has the objective to reduced the effort, generally, and time particularly, while conducting a plant testing. In this report, the Case Study of Crude Distillation Unit by Aspen HYSYS was used to generating the experimental data. From the data generated, the MATLAB System Identification Toolbox was later used to generate the model. The model generated later was analyzed to investigate the project objective. All the necessary steps that are required will be explained through this report.

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# CHAPTER 1

## INTRODUCTION

### 1.1. Background of Study

The ultimate objective in implementing the process control strategy is to maintain the process at desired condition, safely and efficiently, while satisfying environmental and product quality requirement. The figure below shows the hierarchy of the process control strategy.

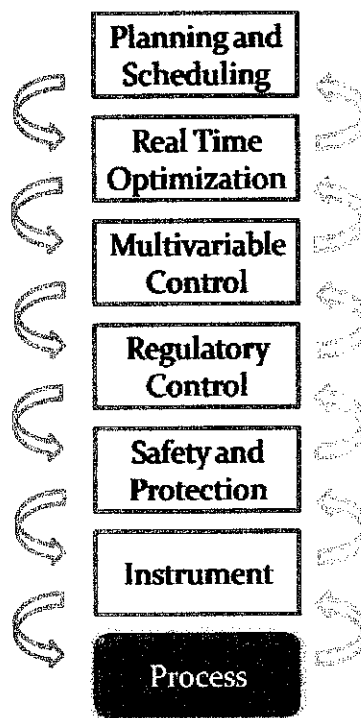


Figure 1: Process Control Hierarchy

The first level, instrument, consist of sensors and actuators for the purpose of measuring and implement the control actions. The second level, safety and protection, consist of safety instrument such as level sensors and relief valve to ensure the safety of the operation. At level three, regulatory control, the basic control strategy such as feedback and feedforward control is implemented to control the process. If the performance of the regulatory control is not satisfactory due to certain problem such as significant interaction between the control variables or inequality constraints exists for manipulated and controlled variable, control strategies such as model predictive control (MPC) will be implement at level 4, multivariable control. As for level 5, the real time optimization (RTO), the optimum operating condition for

a plant will be determined. At the level 6, planning and scheduling, the overall plant management such as production, storage and so on will be put into consideration.

As mentioned earlier, at level 4, multivariable control, one of the strategies is MPC. MPC is one of the classifications of Advanced Control (APC) (Paul S. Agachi, 2006) and it is one of the model-required process control strategies. Other examples of model required process control strategies are Internal Model Controller and Feedforward controller. In general, the MPC was implemented to generate a prediction of a selected process outputs. The generated prediction of process output could later be integrated with present data to determined necessary changes required for the process inputs.

There are four main stations of MPC. The stations are “Process”, “Model”, “Prediction”, “Set-point Calculation”, and “Control Calculation”. The block diagram of the MPC is available as shown in Figure 2 below (Dale E. Seborg, 2004).

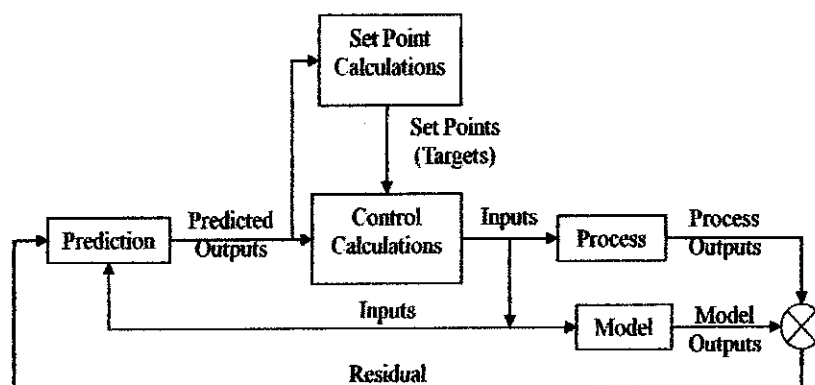


Figure 2: MPC Block Diagram

The prediction is made by the “Model” later compare with the actual outputs values obtained from the “Process”. The difference between the prediction and actual values resulted in “Residual” which later sent to the “Prediction”. Here, there are two types of calculation utilized, the “Set-point Calculation” and “Control Calculation”. The outcomes of these blocks later sent to the “Process” in order to complete the loop.

There are four phase in developing a model-required process control strategy such as MPC. The phases as referred to (Darby & Nikolaou, 2012) are; 1) pretest and preliminary MPC design 2) plant testing 3) model and controller development and 4) commissioning and training, where the controller is implement and its performance is observed.

## 1.2. Problem Statement

As mentioned in the background of study section, there are four phases in developing a process control strategy. The accuracy and reliability of the deliverables from each phases is extremely crucial in determining the success of the developed process control strategy. Taking the second phase, plant testing as an example, according to (Mark L. Darby, 2011), the plant testing labeled as very crucial phase in developing the process control strategy. The plant testing, along with the model identification could take up to almost 50% to the development phase duration. This is due to the relation between the deliverables of this phase to the accuracy of process control strategy's model is very sensitive and can never be overstated.

Any defects during the plant testing phase could lead to the establishment of a poor model and the model could not be simply tuned to compensate the problem. Furthermore, the effort involved in testing and identifying a process control strategy's model is not a one-time event. To ensure adequate performance of a process control strategy application and sustain its benefits over time, it is necessary to redo plant testing to update the MPC model (all or in part) when control performance deteriorates due to a process change, such as a process revamp.

The typical approach in running the plant testing is by conducting a manual, open-loop tests, concentrating on the testing of one manipulated variable at a time, but moving other process inputs as necessary to maintain process operation in a desired region. As for example, during the implementation of plant testing for a process unit, the input signal of the manipulated variable is design by the developer usually based on the experience possessed by the developer the particular process unit. This leads to variation of designs made for a particular process unit by different developer. The variation involves the process input design's amplitude, switching time, and others. Each selected parameters affects the dynamics response of the controlled variables in certain way and later affects the accuracy of model generated. As for example, to conduct a step testing, there is a standard procedure proposed by (Dale E. Seborg, 2004) where step testing shall be conducted between eight and twelve steps where for each steps; the process will be left to reach a steady state before next move is made.

This study will be focusing on the step time of the plant testing where it is to be investigating whether there is an approach to conducted a plant testing for a shorter period of time but could also generate a model which has the same quality as the model generated for a standard procedure as mentioned earlier.

### **1.3. Objective**

This study has the objective to reduced the effort, generally, and time particularly, while conducting a plant testing.

### **1.4. Scope of Study**

The study will be focusing on the following:

- Open loop
- Linear model
- Plant testing – Step Testing
- First Order Model
- Crude Distillation Unit (AGO and Diesel Side Stripper)

### **1.5. Thesis Outline**

This paper consists of seven chapters. In the first chapter, introduction, the paper generally explained the overview of hierarchy of process control strategies. In this chapter, the difference between model-required process control strategy and other strategy along with the development phases of the process strategy will be explained. The problem statement, objective and scope of study also highlighted in this chapter. The second chapter, literature review, mainly covers the published work by other researchers. The chapter content consists of plant testing, type of input signal, and crude distillation unit. The literature review later proceeds by chapter three, methodology. In this chapter, the overview of the methodology which had been and will be implemented throughout the project will be briefly explained. The chapter also provides the list of tools along with tables showing the project's activities, key milestone and Gantt chart. The fourth chapter, result, several outcomes from the simulation study will be presented. These results will be then discussed in the following Chapter 5. In Chapter 6, conclusion and recommendation, three recommendations were made for the purpose of future work of the project.

## CHAPTER 2

### LITERATURE REVIEW

This chapter elaborating the literature reviews relevant to the project based on the established problem statement, objective and scope of study. The chapter is divided into three sections, plant testing, types of input signal, and crude distillation unit

#### 2.1. Plant Testing

This section will be elaborating the overview of plant testing and the industrial application.

##### 2.1.1. Overview of Plant Testing

The model-required process control strategy calculation utilizes the dynamics model established from dynamics response data, collected along the plant test phase. As mentioned earlier, the phase consumed most of the time allocated for the process control strategy development project. As reference, the plant testing duration influence by the settling time of the controlled variables and the number of manipulated and disturbance variable involve (Dale E. Seborg, 2004).

The current practice in conducting a plant testing is manipulating the manipulating and disturbance variables separately. The magnitude of the variation of both variables is strictly monitored so that the quality of the data response generated is at the state of low noise and process fluctuations. This process is usually monitored by an experienced engineer who is highly competent in the particular processes.

There are several types of input signal use for the plant testing, which are, open-loop, which is widely used in the current practice and closed-loop, which became increasingly popular since late 1990s. The open-loop identification then could also be categorized into manual and automatic testing. The manual testing is conducted by manipulating the independent variable at a time by maintaining other independent variables while collecting the data or response of the dependant variable. The example of manual testing is Step Test.

On the other hand, as for the automatic testing, the condition is initially preset before the test which involving certain parameters for the selected test. The examples of

automatic module are Pseudo Random Binary Sequence (PRBS) and Generalized Binary Noise (GBN) (Mark L. Darby, 2011). (Dale E. Seborg, 2004) introduced others types of input signal such as ramp and sinusoidal input. The following figures show some of the examples of the input signals.

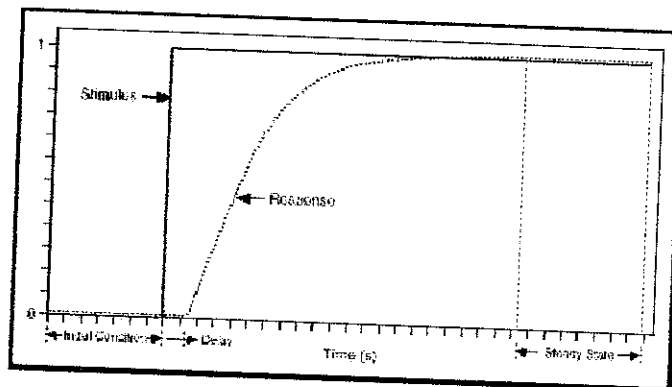


Figure 3: Step Input and Dynamics Response

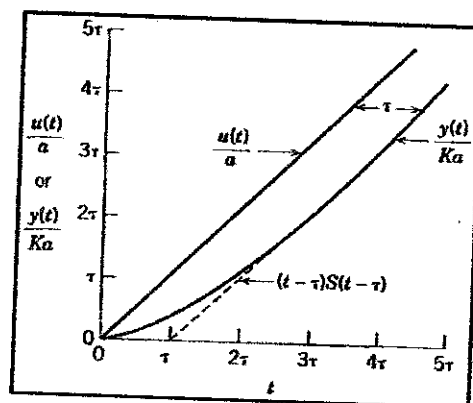


Figure 4: Ramp Input and Dynamic Response

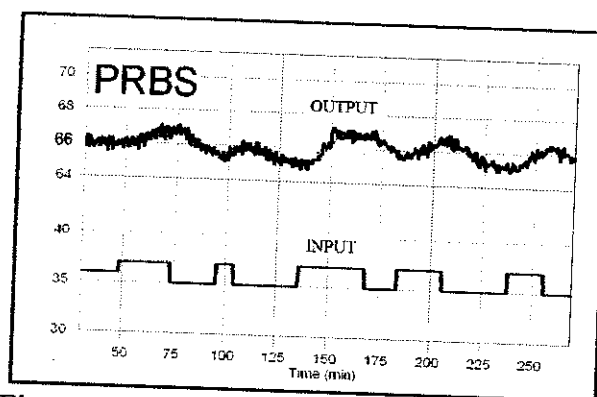


Figure 5: PRBS Input and Dynamics Response

### 2.1.2. Industrial Application

(S. Joe Qin, 2001) conducted a survey to study the current application of MPC among industries. In the report, the general introduction of developed model for MPC technology covering both nonlinear and linear which is supported by the data

from the model developers was introduced. At the early part of the report, a brief background of MPC was elaborated. The report later followed by the presentation regarding the survey of the MPC technology. The final section presents a vision of the next generation of MPC technology, with an emphasis on potential business and research opportunities.

Table 1: Companies and Products Included In Linear MPC Technology Survey

Company	Product
Adersa	HIECON
	PFC
	GLIDE
Aspen Tech	DMC-Plus
Honeywell Hi-spec	RMPCT
Shell Global Solutions (SGS)	SMOC-II
Invensys	Connoisseur

Table 2: Summary of Linear MPC Applications by Areas

Industry	Aspen Tech	Honeywell Hi-Spec	Adersa	Invensys	SGS	Total
Refining	1200	480	280	25	-	1985
Petrochemical	450	80	-	20	-	550
Chemicals	100	20	3	21	-	144
Pulp & Paper	18	50	-	-	-	68
Utility	-	10	-	4	-	10
Mining	8	6	7	16	-	14
Food	-	-	41	10	-	37

Table 3: Comparison of Linear MPC Identification Technology

Product	Test Protocol	Model Form	Estimation Method	Uncertainty Bound
DMC-Plus	Step, PRBS	VFIR, LSS	MLS	Yes
RMPCT	Step, PRBS	FIR, ARX, BJ	LS, GN, PEM	Yes
AIDA	Step, PRBS	LSS, FIR, TF	PEM-LS, GN	Yes
Glide	Non-PRBS	TF	GD, GN, GM	Yes
Connoisseur	Step, PRBS	FIR, ARX	RLS, PEM	Yes

Tables above show the application of MPC developed by several vendors. As shown in Table 2, the dominant vendors for refining industry are Aspen, Honeywell, and Adersa while in Table 3, the most popular test protocol or input signal use is Step

and PRBS. This lead to the selection of both Step and PRBS signals as scope of study for this project.

## **2.2. Type of Input Signal**

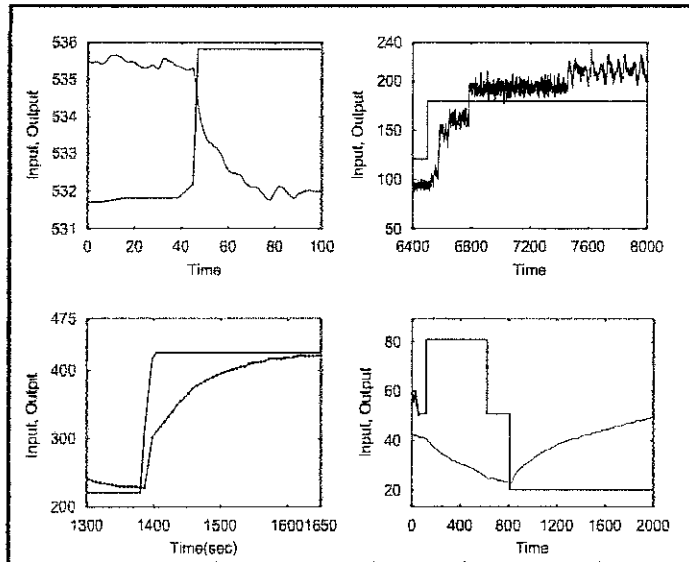
This section will be elaborating the selected input types which are step input.

### **2.2.1. Step Input**

Step response based methods are most commonly used for system identification, especially in process industries. However, (Salim Ahmed, 2006) has highlighted two important thought regarding the step input. The first thought is regarding the form of data obtained from industry, which is not in deviation form while the model developed was design to deal the data in the deviation form. One of the methods used to solve this uncertainty is by subtracting the initial steady state from the industrial data which is quite difficult since the initial steady state data is usually unavailable. This is due to the presence of noise and movement of the input before the system reaches its steady state.

The second thought is regarding the applicability of a method which is able to estimate the parameters in the presence of initial conditions. To the best of knowledge of the authors there is no step response based method available in the literature that can handle non-zero initial conditions. In addition if the input is applied before the system reaches the desired steady state, it is not possible to get the data in deviation form. The overview of some problem regarding the industrial data obtained is shown in **Figure 6** below.

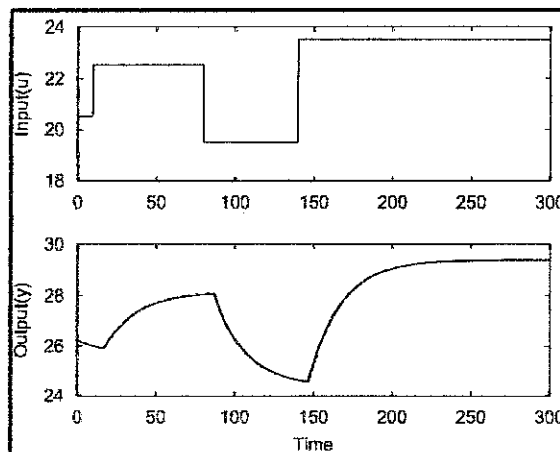




**Figure 6: Step Input and Dynamic Response of Different Industrial Processes**

The paper later introduced a method to overcome the difficulties and simulation study was conducted. As for the simulation study, a first order process using the following transfer function is used and three step input and dynamic response is collected as shown in **Figure 7**.

$$O = \frac{1.25}{20 + 1} s^{-7}$$



**Figure 7: Step Inputs and Dynamic Responses based on Given Transfer Function**

Three models was developed by both SYSID toolbox and proposed method based on the dynamic data generated and compared. The following figure shows the step response of the estimated model where the model developed by the SYSID toolbox on the left and proposed method on the right. From **Figure 8**, it is found that the parameters generated using the proposed method is less deviate compare to the one generated by SYSID toolbox.

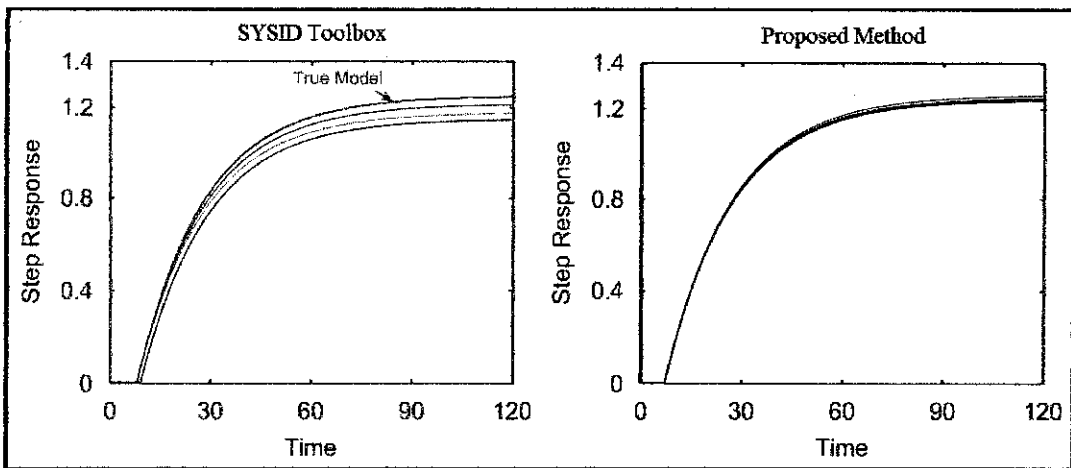


Figure 8: Step Response of the Estimated Models

Apart of the mentioned step input earlier, there are also another paper, (Ahmed, 2010), describing the applicability in using another type of input such particularly the non-ideal step inputs such as staircase, saturated sinusoid, saturated ramp, and filtered step. The illustration of these inputs is shown in Figure 9.

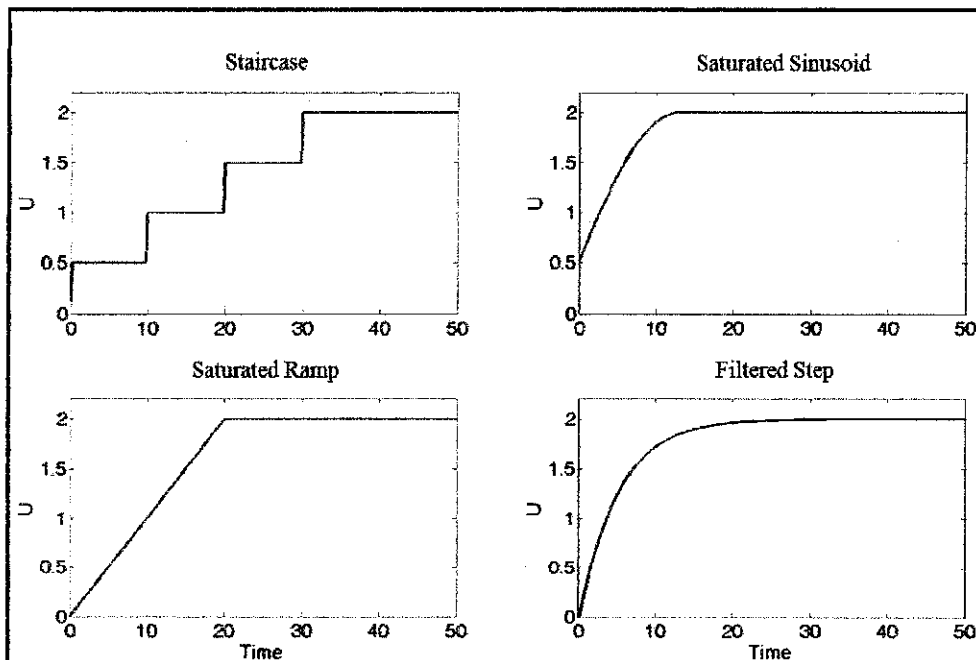
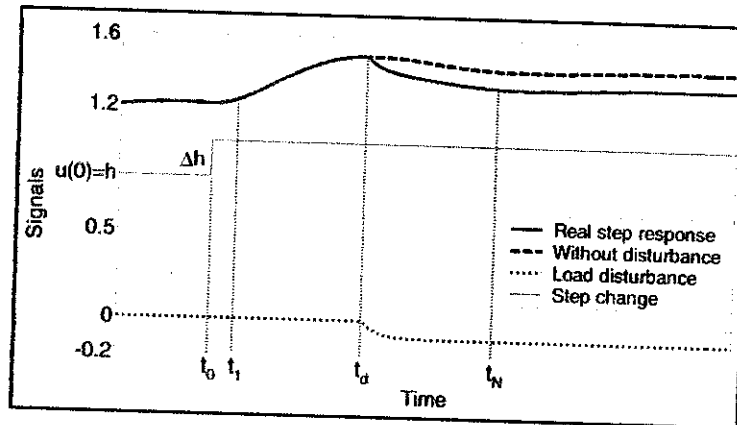


Figure 9: Non-ideal Step Inputs

In addition of the mentioned works, there are also another works done by (Tao Liu, 2010). This paper addressed the problem regarding the affect of load disturbance and unsteady initial state. In order to handle the inherent type load disturbance, a methodology in developing a model is proposed. The proposed model is applicable to handle simultaneous derivation of both the disturbance and process model that

generated from step test. **Figure 10** illustrate how the input being moved before the process reaches it steady state.



**Figure 10: Step Response Test under Nonzero Initial Conditions**

In order to assess the effectiveness of proposed method, a simulation was conducted by using second order transfer function as follow with number of data taken,  $M$  at 100 and sampling time,  $T_s$  at 0.01s.

$$O = \frac{1.2^{-6}}{s^2 + 2.4s + 1} O + \frac{-}{s + 1} O$$

NSR (%)	process model	load disturbance model
0	$\frac{1.2000e^{-6.04667s}}{8.9999s^2 + 2.4001s + 1}$	$\frac{0.1000e^{-1.0192s}}{1.0001s - 1}$
2	$\frac{(1.2007 \pm 0.013)e^{(-6.0458 \pm 0.26)s}}{(8.9946 \pm 0.35)s^2 + (2.4212 \pm 0.36)s + 1}$	$\frac{(0.1019 \pm 0.015)e^{(-1.0206 \pm 0.12)s}}{(1.0011 \pm 0.36)s + 1}$
10	$\frac{(1.2184 \pm 0.047)e^{(-6.2913 \pm 0.89)s}}{(8.4433 \pm 1.25)s^2 + (2.9135 \pm 1.38)s + 1}$	$\frac{(0.1123 \pm 0.046)e^{(-0.9539 \pm 0.24)s}}{(1.1894 \pm 0.79)s - 1}$
30	$\frac{(1.2531 \pm 0.055)e^{(-7.0594 \pm 0.75)s}}{(8.4726 \pm 2.09)s^2 + (3.8558 \pm 1.71)s + 1}$	$\frac{(0.1405 \pm 0.052)e^{(-0.8529 \pm 0.19)s}}{(1.2489 \pm 0.71)s - 1}$

**Figure 11: Step Response Identification Different Measurement Noise Levels**

**Figure 11** shows the model identification for both process and disturbance where the NSR is manipulated between 0% and 30%. There are two other model developed by adjusting the  $M$  at 500 and 100 but without disturbance and at nonzero initial state. The models generated are as below. Based on the generated models, it is obvious that the accuracy is better at  $M = 500$  rather than 100.

$$=_{500}0 = \frac{(1.2 \pm 0.0007)^{(-5.950 \pm 0.36)}}{(9.1 \pm 0.8)^2 + (2.41 \pm 0.46) + 1}$$

$$=_{100}0 = \frac{(1.2 \pm 0.0003)^{(-6.065 \pm 0.22)}}{(8.98 \pm 0.21)^2 + (2.39 \pm 0.09) + 1}$$

In addition of the concern highlighted by the mentioned works, there is also another work done by (Gang-Wook Shin, 2007) which proposed Genetic Algorithm (GA) that provides better fitness for both FOPTD and SOPTD. The convergence of the parameters of FOPTD ( $K$ ,  $\tau$ , and  $\Theta$ ) and SOPTD ( $K$ ,  $\tau_1$ ,  $\tau_2$ , and  $\Theta$ ) are approximately at 30<sup>th</sup> iterations. The initialize random take point use was  $0.8y_{\infty} \leq K \leq 1.2y_{\infty}$ ,  $0 \leq \tau \leq \text{rise time}/2$ , and  $0 \leq \Theta \leq 0.1y_{\infty}$ .

### 2.3. Crude Distillation Unit (AGO and Diesel Side Stripper)

According to (C.R. Porfirio, 2003), MPC is a standard practice in refining industry. There are several works done previously in order to regarding the application of MPC in the industry. As for example, (Lee, 1993) proposed that non-minimal order of state space model is applicable in approaching the MPC modeling.

The following figure showing a case study of a CDU. As for this study, Aspen HYSYS was used to generate the experimental dynamics data of the CDU.

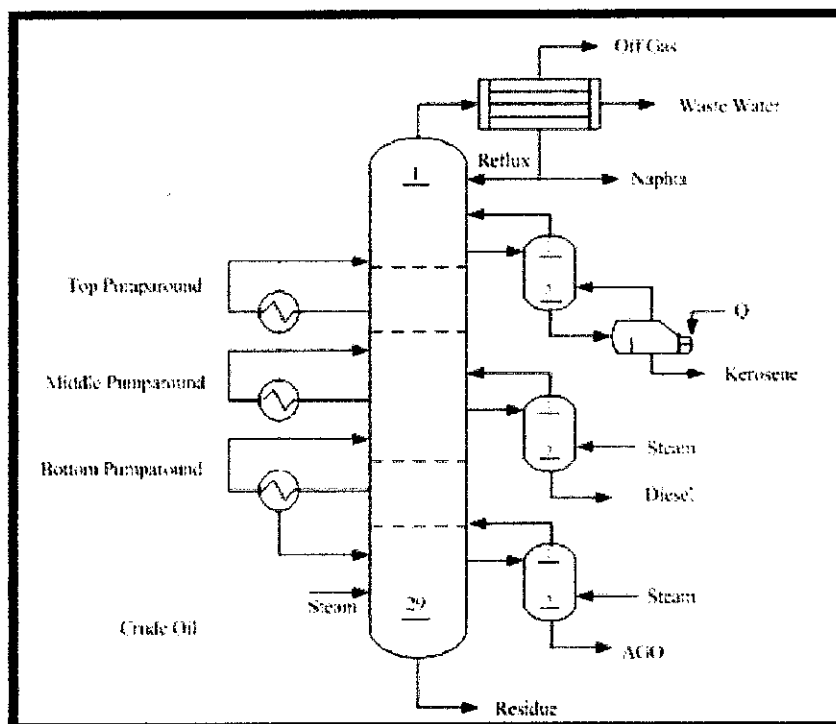


Figure 12: Schematic Representation of the CDU's AGO and Diesel Side Stripper

The CDU implemented in this simulation are producing AGO, Diesel, Kerosene, and Naphtha as its product along with wastewater and off gas as the waste. This unit consist of three side strippers, kerosene (draw at tray number 9), diesel (draw at tray number 17), and AGO (draw at tray number 22), three pump around sections which draws the fluid from tray number 2, 17, and 22, a condenser at the top of the main tower separator and a reboiler which placed after the kerosene side stripper. The number of trays of the main tower is 29 while for the side strippers are 3 each. The main tower has a feed with a flowrate of 2826 kgmole/hr with the composition of the main components in terms of mole fraction are as below.

*Table 4: Main Tower Separator Component Composition*

<b>COMPONENT</b>	<b>MOLE FRACTION</b>
Methane	0.0002
Ethane	0.0006
Propane	0.0008.
i-butane	0.0005
n-butane	0.0001

As for process controlling purposes, there are two flowrate controllers (AGO FC and Diesel FC) along with two level controllers (Reboiler LC and Condenser LC). The information gathered in the literature review will later be used to establish the project methodology which will be further explained in Chapter 3.

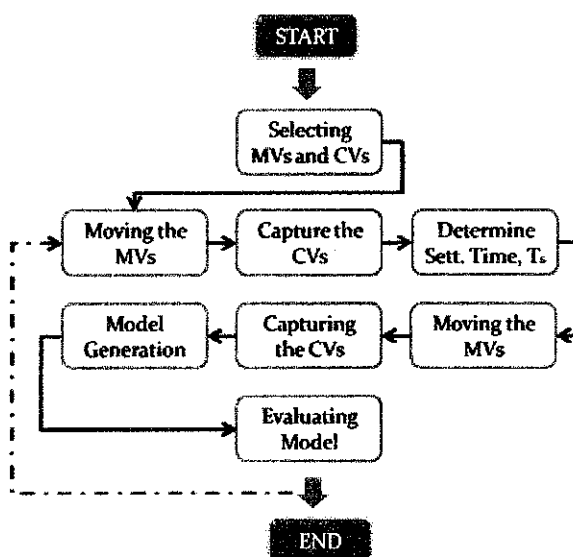
## CHAPTER 3

### METHODOLOGY

This chapter elaborating the methodology implement for the project. The chapter is divided into four sections, research methodology, project activities and key milestone, Gantt chart, and tools.

#### 3.1. Research Methodology

The research methodology of this project consist of six phase. Those phases are:



Further explanation on the research methodology is available in following sections.

#### 3.1.1. Identify/Selecting Independent (Manipulated and Disturbance) and Dependent (Controlled) Variables

During the first phase, relevant variable, both independent and dependant for the purpose of plant testing will be identify. As for example, the selected variables for the plant testing at the CDU are as shown in table below.

Table 5: Example of Variables Identification

INDEPENDENT	DEPENDANT
Manipulated	Controlled
<ul style="list-style-type: none"> <li>• AGO Steam molar flowrate (kmole/h)</li> <li>• Diesel Steam molar flowrate (kmole/h)</li> </ul>	<ul style="list-style-type: none"> <li>• AGO production molar flowrate (kmole/h)</li> <li>• Diesel production molar flowrate (kmole/h)</li> </ul>

### 3.1.2. Moving the Manipulated Variable and capture the Controlled Variable

During the second phase, the identified/selected manipulated variables (MV) will be moves for a single step and the response of the controlled variable will be captured. The following figure shows the movement of the first manipulated variable, AGO Steam molar Flowrate (U1), from 70 kgmole/hr to 77 kgmole/hr and the response of both manipulated variables, AGO production molar flowrate (Y1) and Diesel production molar flowrate (Y2). This sets of experimental data is generated by HYSYS

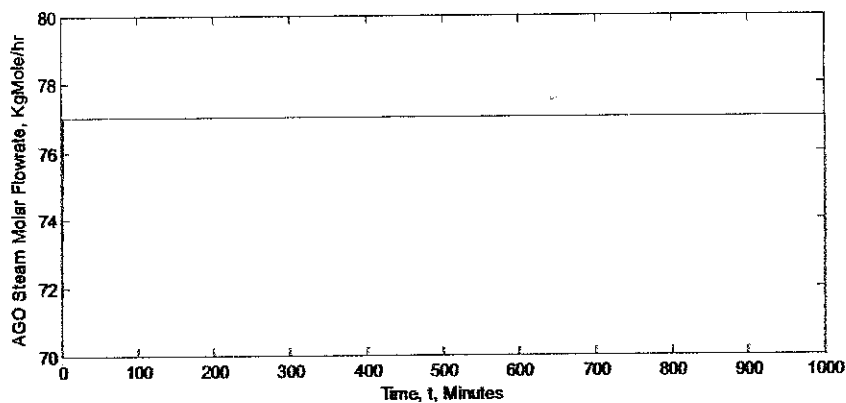


Figure 13: A step movement of AGO Steam (U1)

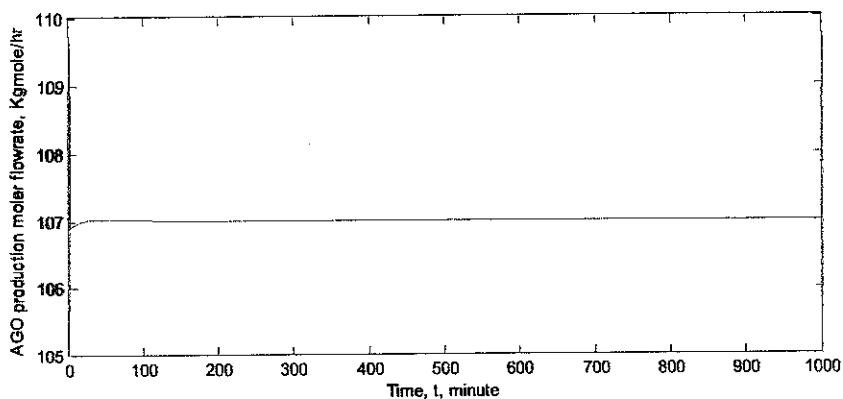


Figure 14: A step response of AGO production (Y1)

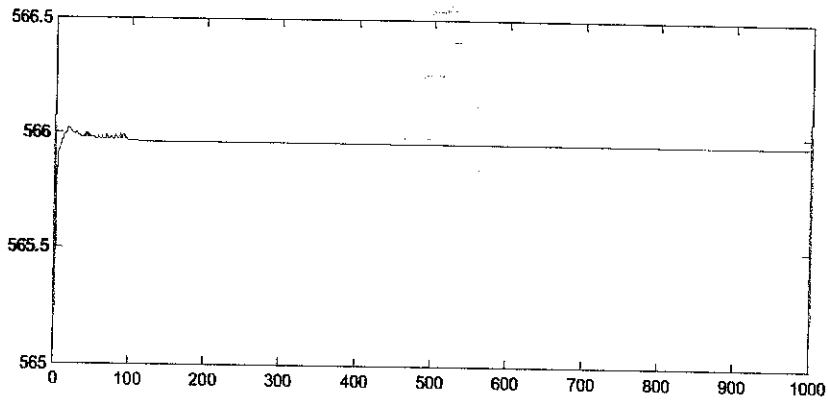


Figure 15: A step response of Diesel production (Y2)

### 3.1.3. Determined the Settling Time, $T_s$ for the Output Responses

At this stage, the settling time where the output reaches steady state value was determined. As for example, referring to the Figure 14, the settling time is 105 minutes while as for figure 15, the settling time is 110 minutes. As for multiple moves step testing, the longer settling time which is 110 minutes is selected.

### 3.1.4. Moving the Manipulated Variable and capture the Controlled Variable (eight steps)

After the settling time was determined, the eight steps testing was later conducted. First, the settling time was set as  $T_5$ . Later,  $T_4$  was determined by  $4/5 \times T_5$ . The  $T$ 's was determined until  $T_1$ . As for example, for the settling time obtained from the single step testing earlier which is at 110, the  $T$ 's was calculated as below.

Table 6:  $T$ 's Calculation

$T$	FORMULA	MINUTES
$T_5$	$T_5 = \frac{5}{5} \times T_{setling}$	110
$T_4$	$T_4 = \frac{4}{5} \times T_{setling}$	88
$T_3$	$T_3 = \frac{3}{5} \times T_{setling}$	66
$T_2$	$T_2 = \frac{2}{5} \times T_{setling}$	44
$T_1$	$T_1 = \frac{1}{5} \times T_{setling}$	22

From the established  $T_5$  until  $T_1$ , the five sets of tests consists of eight steps each was conducted. The step time for each step is different and determined by the  $T$ 's



calculated earlier. Figures below shows the eight steps test along with the output responses. Each figure represents each set and noted that for each set, the step time is different from the others where as for example, at  $T_5$ , the step time between each step is at 110 minutes.

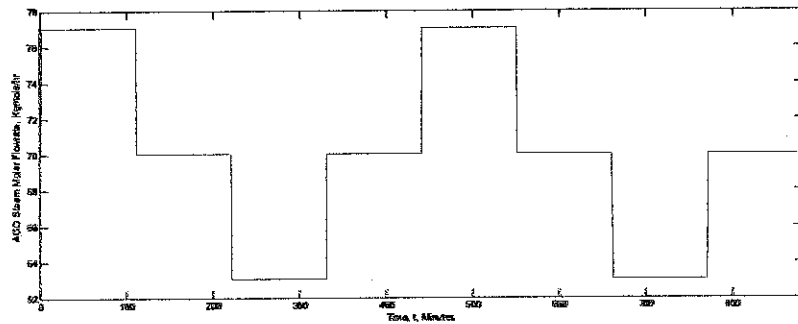


Figure 16: AGO Steam Eight Step Move at  $T_5$  (110min)

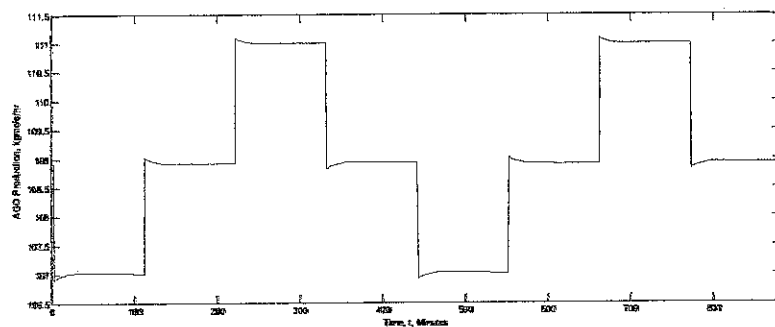


Figure 17: AGO Production at  $T_5$  (110min)

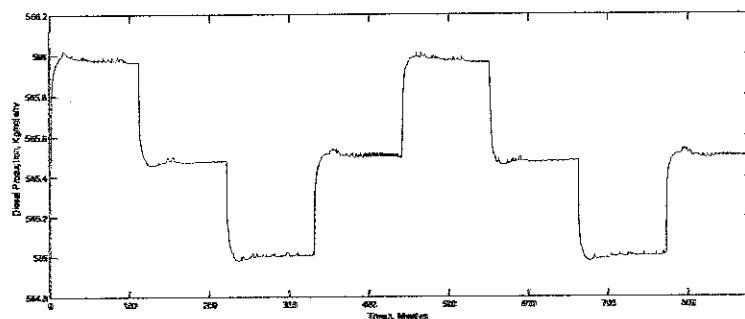


Figure 18: Diesel Production at  $T_5$  (110min)

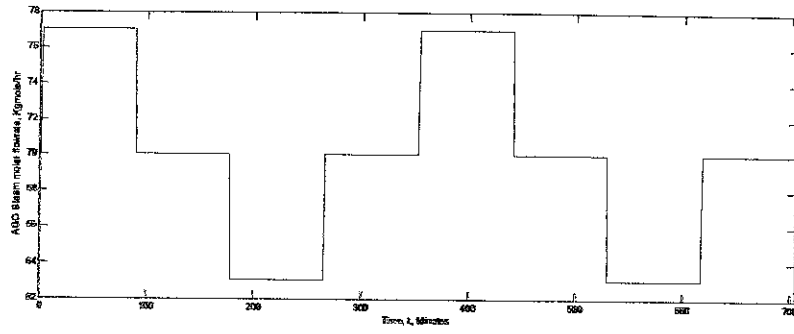


Figure 19: AGO Steam Eight Step Move at T4 (88min)

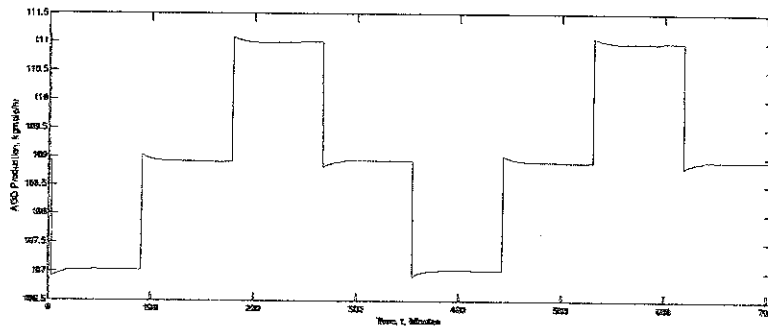


Figure 20: AGO Production at T4 (88min)

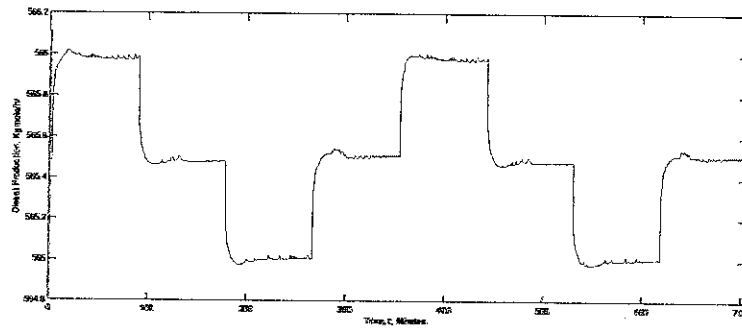


Figure 21: Diesel Production at T4 (88min)

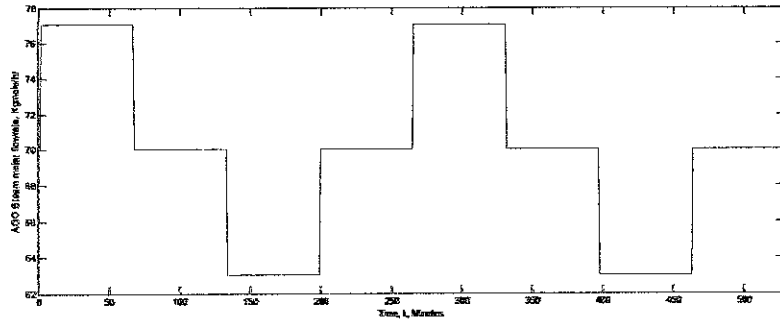


Figure 22: AGO Steam Eight Step Move at T3 (66min)

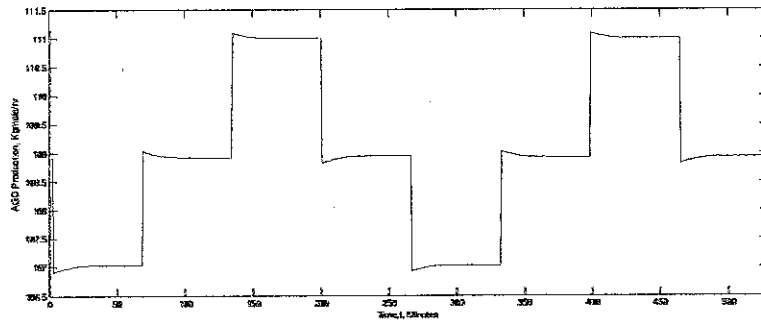


Figure 23: AGO Production at T3 (66min)

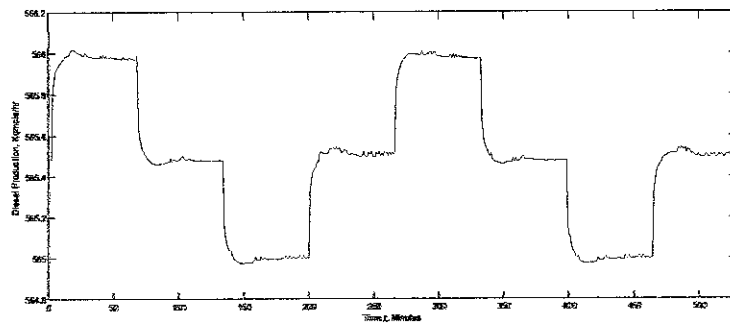


Figure 24: Diesel Production at T3 (66min)

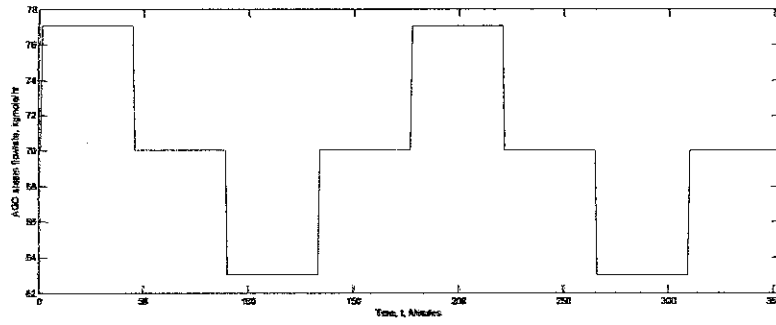


Figure 25: AGO Steam Eight Step Move at T2 (44min)

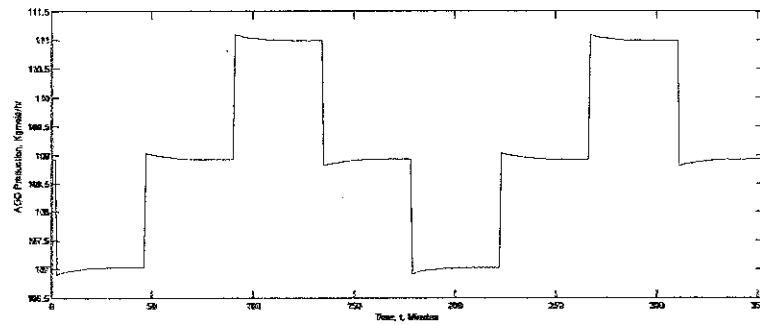


Figure 26: AGO Production at T2 (44min)

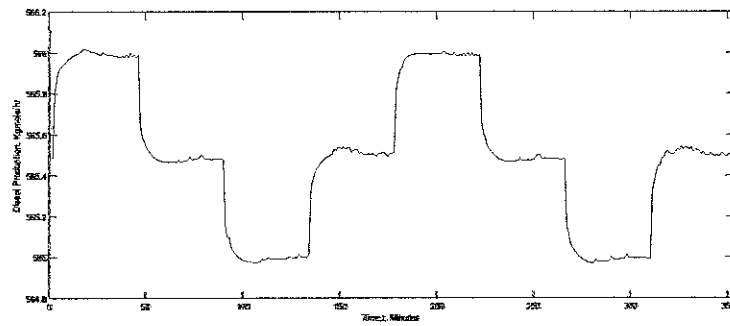


Figure 27: Diesel Production at T2 (44min)

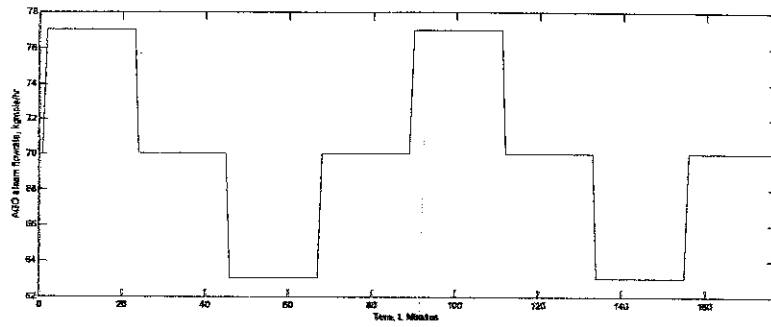


Figure 28: AGO Steam Eight Step Move at T1 (22min)

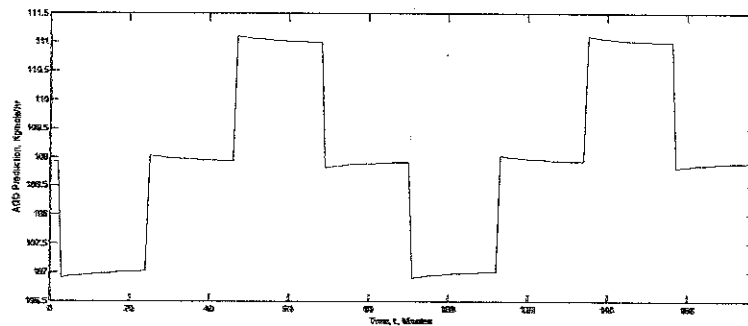


Figure 29: AGO Production at T1 (22min)

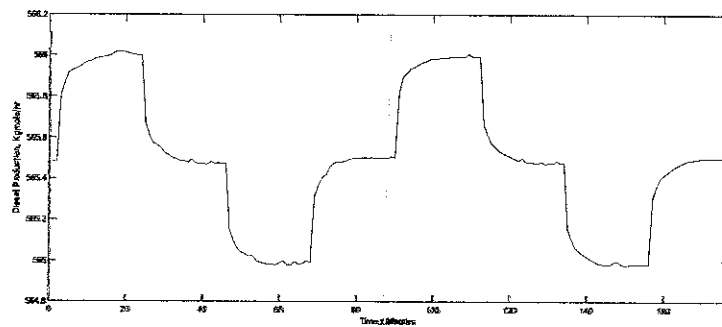


Figure 30: Diesel Production at T1 (22min)

### 3.1.5. Generate and Validate Model

At this stage, based on the generated experimental data shown previously as an example, MATLAB System Identification Toolbox was used to generate the process model transfer function for each set of experiment from  $T_5$  to  $T_1$ . The examples of a process model transfer function developed by MATLAB System Identification Toolbox for  $T_5$  from previous example are as follows.

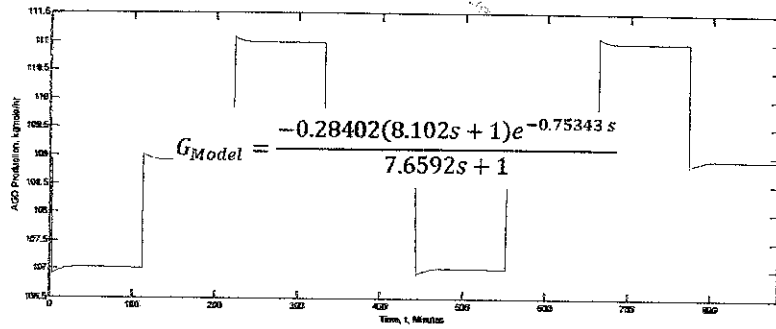


Figure 31: AGO Production at T5 (110min)

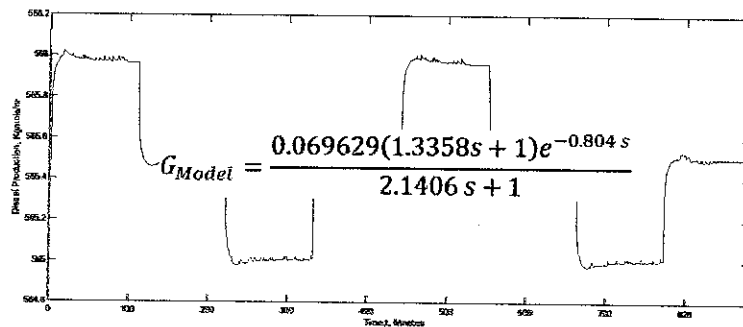


Figure 32: Diesel Production at T5 (110min)

As for model error evaluation, another single step test was conducted at  $dU=6\%$  or 4.2 kgmole/hr. The process response was stopped at steady state. The entire generated models were evaluated base on this model. The following figures shows the input (AGO Steam) and output responses (AGO and Diesel Production) of the validation data.

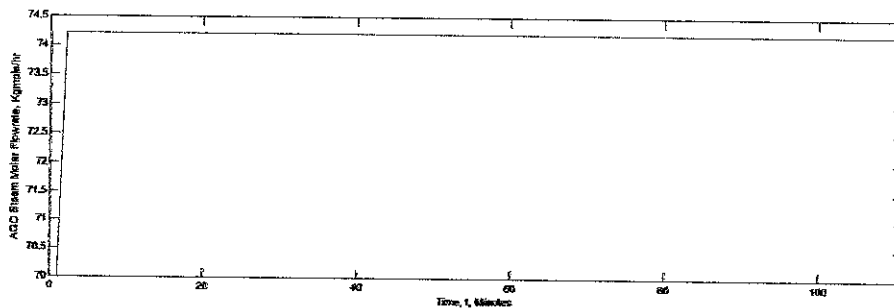


Figure 33: Validation Data (AGO Steam)

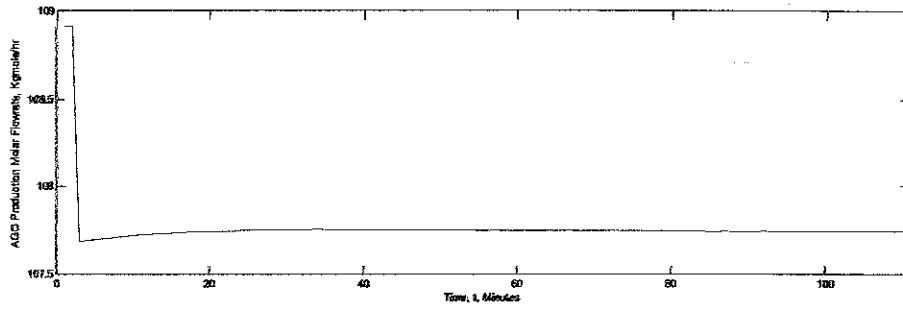


Figure 34: Validation Data (AGO Production)

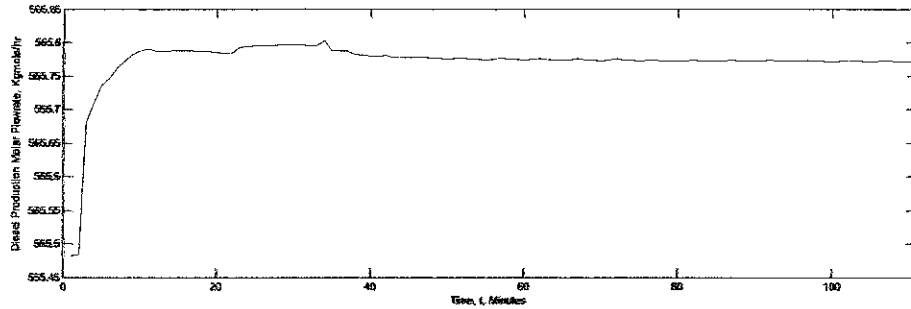


Figure 35: Validation Data (Diesel Production)

Based on the validation data, the fitting was calculated by using the algorithm provided in MATLAB System Identification Toolbox. The algorithm is as follows.

$$Fitting (\%) = \left[ 1 - \frac{norm(y_{actual} - y_{model})}{norm(y_{actual} - mean(y))} \right] \times 100$$

The calculated fitting for the Gmodel developed for AGO Steam - AGO Production (Figure 31) and AGO Steam - Diesel Production (Figure 32) are 96.14% and 77.73%.

### 3.2. Tools

The tools that will be using throughout the project will be as follows:

- Aspen HYSYS™
- Mathlab
- Simulink

The results obtained from throughout the study based on the elaborated methodology will be represented in the next chapter.

### 3.3. Project Activities and Key Milestone

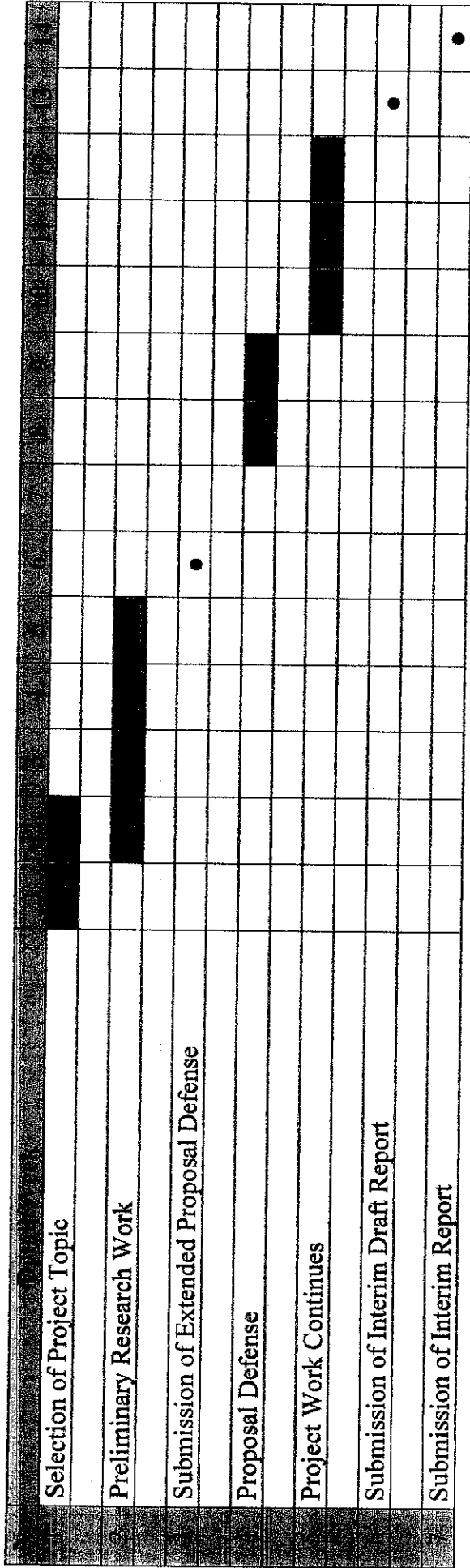
Table 7: Project Activities and Key Milestone

	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug
Completion of Topic Selection	•							
Completion of Extended Proposal		•						
Completion of HYSYS and Matlab Tutorial				•				
Completion of Proposal Defense			•					
Completion of Interim Report				•				
Completion of Aspen HYSYS and MATLAB Simulation						•		
Finalization and Analysis of the Results (Phase 6)								•
Completion of Final Thesis								•



**3.4. Gantt chart**

**Table 8: Project Gantt Chart**



## CHAPTER 4

### RESULT

This chapter will be presenting the result of the study. As mentioned in the methodology, the first phase is determining the control objective, Controlled Variables (CVs), and Manipulated Variables (MVs). As for this study, the selected CVs and MVs are as follows.

Table 9: Selected CVs and MVs

MANIPULATED VARIABLES	CONTROLLED VARIABLES
<ul style="list-style-type: none"> <li>• AGO Steam molar flowrate (kmole/h)</li> <li>• Diesel Steam molar flowrate (kmole/h)</li> </ul>	<ul style="list-style-type: none"> <li>• AGO production molar flowrate (kmole/h)</li> <li>• Diesel production molar flowrate (kmole/h)</li> </ul>

As for the second phase, determining the relevant input design parameters, the input step time and step size was selected as mentioned in Chapter 3. The completion of Phase 2 leads to the commissioning of Phase 3, running the simulations. The Phase 3 was conducted in two parts, Part 1 and Part 2. In Part 1, the AGO Steam will first be move while maintaining the Diesel Steam at original condition while for Part 2, the Diesel Steam will be move while maintaining the AGO Steam.

#### 4.1. Part 1 – $G_{11}$ (AGO Steam, $U_1$ – AGO Production, $Y_1$ )

As for this process the experimental data was fit into  $G_{model} = K \cdot \frac{\tau_z+1}{\tau_p+1} \cdot e^{-\theta s}$ . The generated transfer function for each of the T's is shown in table below.

Table 10:  $G_{model}$  Generated by MATLAB for  $G_{11}$

	Gain, K	Time Constant 1, $\tau_p$	Time Constant 2, $\tau_z$	Time Delay, $\Theta$
<b>T<sub>5</sub></b>	-0.2836	7.9377	8.4055	0.6910
<b>T<sub>4</sub></b>	-0.2833	8.2947	8.7945	0.7559
<b>T<sub>3</sub></b>	-0.2840	7.6592	8.1020	0.7534
<b>T<sub>2</sub></b>	-0.2829	8.9717	9.5352	0.5876
<b>T<sub>1</sub></b>	-0.2827	10.8810	11.5630	0.5748

#### 4.2. Part 1 – G<sub>21</sub> (AGO Steam, U1– Diesel Production, Y2)

As for this process the experimental data was fit into  $G_{model} = K \cdot \frac{\tau_z+1}{\tau_p+1} \cdot e^{-\theta s}$ . The generated transfer function for each of the T's is shown in table below.

Table 11: G<sub>model</sub> Generated by MATLAB for G21

	Gain, K	Time Constant 1, $\tau_p$	Time Constant 2, $\tau_z$	Time Delay, $\Theta$
T <sub>5</sub>	0.0702	2.1818	1.1731	0.2931
T <sub>4</sub>	0.0696	2.1406	1.3358	0.8040
T <sub>3</sub>	0.0708	2.3830	1.3812	0.4953
T <sub>2</sub>	0.0715	2.4766	1.4808	0.6184
T <sub>1</sub>	0.0723	2.8850	1.6924	0.4735

#### 4.3. Part 2 – G<sub>12</sub> (Diesel Steam, U2– AGO Production, Y1)

As for this process the experimental data was fit into  $G_{model} = K \cdot \frac{1}{\tau_p+1} \cdot e^{-\theta s}$ . The generated transfer function for each of the T's is shown in table below.

Table 12: G<sub>model</sub> Generated by MATLAB for G12

	Gain, K	Time Constant 1, $\tau_p$	Time Delay, $\Theta$
T <sub>5</sub>	-0.0169	30.2930	17.5630
T <sub>4</sub>	-0.0178	32.9550	17.5720
T <sub>3</sub>	-0.0181	34.8490	16.6460
T <sub>2</sub>	-0.0184	35.6260	16.9800
T <sub>1</sub>	-0.0184	35.7350	16.6290

#### 4.4. Part 2 – G<sub>22</sub> (Diesel Steam, U1– Diesel Production, Y1)

As for this process the experimental data was fit into  $G_{model} = K \cdot \frac{\tau_z+1}{\tau_p+1} \cdot e^{-\theta s}$ . The generated transfer function for each of the T's is shown in table below.

Table 13: G<sub>model</sub> Generated by MATLAB for G22

	Gain, K	Time Constant 1, $\tau_p$	Time Constant 2, $\tau_z$	Time Delay, $\Theta$
T <sub>5</sub>	-0.8535	42.8030	42.4980	1.0000
T <sub>4</sub>	-0.8544	43.9030	43.3980	1.0000
T <sub>3</sub>	-0.8543	45.9030	45.3980	1.0000
T <sub>2</sub>	-0.8549	41.8030	41.1980	0.9389
T <sub>1</sub>	-0.8549	43.8030	43.1980	1.0000

## CHAPTER 5

### DISCUSSION

Based on the model developed by MATLAB System Identification, there are two ways in analyzing the results. The result will first be evaluated by calculating the deviation between the parameters developed for  $T_4$  until  $T_1$  with  $T_5$ . This is because, according to the literature, the standard step testing is conducted at  $T_5$  which means before each step, the output will be assured to reach the steady state before stepping it again.

The second analysis that could be made is by analyzing the fittings of the generated model as shown earlier in Chapter 3. The analysis will be further elaborated in next subchapters.

#### 5.1. Part 1 – $G_{11}$ (AGO Steam, U1– AGO Production, Y1)

The calculated deviations of the parameters of  $T_4$  until  $T_1$  as compare to  $T_5$  are as follows.

Table 14:  $G_{11}$  Parameters Deviation (%)

	Gain, K	Time Constant 1, $\tau_p$	Time Constant 2, $\tau_z$	Time Delay, $\Theta$
$T_4$	0.1058	-4.4975	-4.6279	-9.3922
$T_3$	-0.1410	3.5086	3.6107	-9.0304
$T_2$	0.2468	-13.0264	-13.4400	14.9638
$T_1$	0.3173	-37.0800	-37.5647	16.8162

As for the fittings, the calculated fittings from the MATLAB System Identification are as follows.

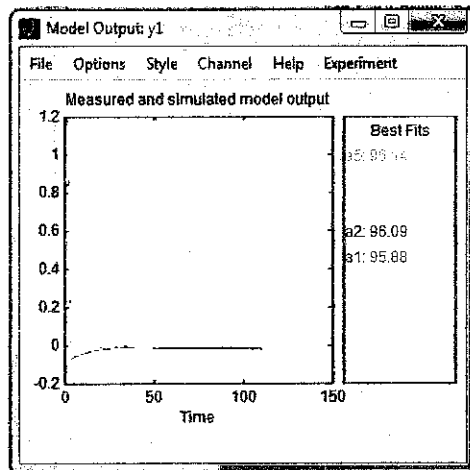


Figure 36:  $G_{11}$  Fitting

### 5.2. Part 1 – $G_{21}$ (AGO Steam, U1– Diesel Production, Y2)

The calculated deviations of the parameters of  $T_4$  until  $T_1$  as compare to  $T_5$  are as follows.

Table 15:  $G_{21}$  Parameters Deviation (%)

	Gain, K	Time Constant 1, $\tau_p$	Time Constant 2, $\tau_z$	Time Delay, $\Theta$
$T_4$	0.8547	1.8883	-13.8692	-174.3091
$T_3$	-0.8547	-9.2217	-17.7393	-68.9867
$T_2$	-1.8519	-13.5118	-26.2296	-110.9860
$T_1$	-2.9915	-32.2303	-44.2673	-61.5490

As for the fittings, the calculated fittings from the MATLAB System Identification are as follows

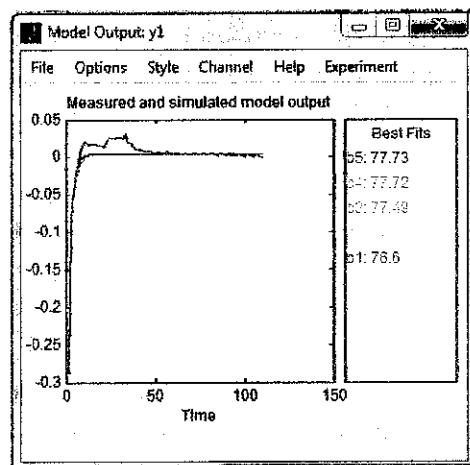


Figure 37:  $G_{21}$  Fitting

### 5.3. Part 2 – $G_{12}$ (Diesel Steam, U2– AGO Production, Y1)

The calculated deviations of the parameters of  $T_4$  until  $T_1$  as compare to  $T_5$  are as follows.

Table 16:  $G_{12}$  Parameters Deviation (%)

	Gain, K	Time Constant 1, $\tau_p$	Time Delay, $\Theta$
$T_4$	-5.3254	-8.7875	-0.0512
$T_3$	-7.1006	-15.0398	5.2212
$T_2$	-8.8757	-17.6047	3.3195
$T_1$	-8.8757	-17.9645	5.3180

As for the fittings, the calculated fittings from the MATLAB System Identification are as follows

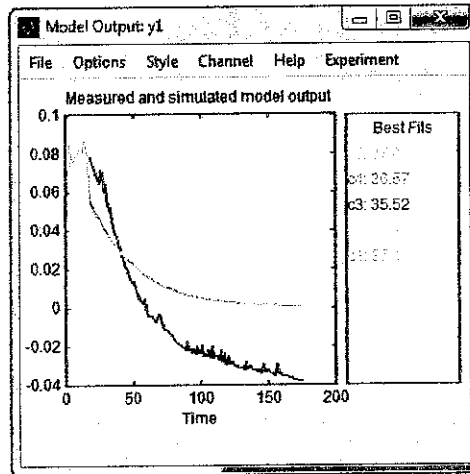


Figure 38:  $G_{12}$  Fitting

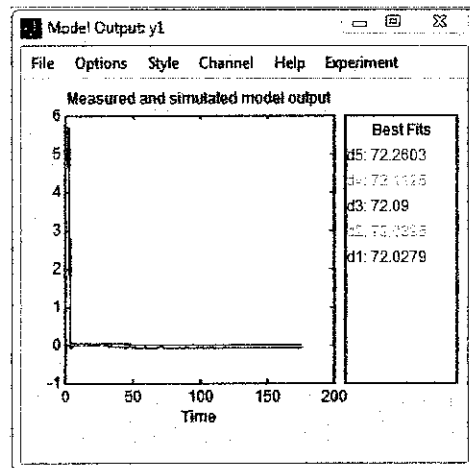
### 5.4. Part 2 – $G_{22}$ (Diesel Steam, U1– Diesel Production, Y1)

The calculated deviations of the parameters of  $T_4$  until  $T_1$  as compare to  $T_5$  are as follows.

Table 17:  $G_{22}$  Parameters Deviation (%)

	Gain, K	Time Constant 1, $\tau_p$	Time Constant 2, $\tau_z$	Time Delay, $\Theta$
$T_4$	-0.1054	-2.5699	-2.1177	0.0000
$T_3$	-0.0937	-7.2425	-6.8239	0.0000
$T_2$	-0.1640	2.3363	3.0590	6.1100
$T_1$	-0.1640	-2.3363	-1.6471	0.0000

As for the fittings, the calculated fittings from the MATLAB System Identification are as follows



**Figure 39:  $G_{22}$  Fitting**

Based on the analysis made above, the deviation between  $T_4$  until  $T_1$  with the standard method at  $T_5$  is varies. The deviation range of  $K$ ,  $T_p$ ,  $T_z$ , and  $\Theta$  is (-37%) to (1.8%), (-37%) to (3.5%), (-37%) to (3.6%), and (-174%) to (16%) respectively.

Although the value of deviation is quite large for several parameters for several transfer function, the fittings between the  $T$ 's (From  $T_5 - T_1$ ) is quite similar. Although some of the model generated, as for example  $G_{12}$ , has quite a lower fitting as compare to other model, the fitting could be increase by exploring the other model such as second order plus time delay (SOPTD), ARX, ARMAX, and many more.

## CHAPTER 6

### CONCLUSION AND RECOMMENDATION

#### 6.1. Conclusion

As a conclusion, the objective in reducing the plant testing period by implementing step testing is met by the implementation of MATLAB as a tool to generate the transfer function based on the small difference in term of the fitting/error between the models developed with shorter period as compared to the standard procedure proposed by (Dale E. Seborg, 2004) which suggested the output response shall be made to reach steady state before another step. This could significantly reduce the duration of plant testing and subsequently the effort and cost.

#### 6.2. Recommendation

The data obtained from the study up to this stage is yet sufficient to provide recommendation on the methodology of conducting plant testing at CDU as a whole process unit. Further works is required to analyze in greater detail by expanding the matrix from 2 by 2 to a bigger matrix so that any interaction between other variables could also be accounted.

It is also recommended to develop an algorithm that could reduce the deviation between parameters generated for  $T_4$  until  $T_1$  as compared to  $T_5$ . Apart from that, it is also recommended to study the possibility in reducing the number of step which from the literature is to be between 8 to 15 steps along with the most efficient step size to be made for the step testing. This could further reduce the time and cost consumed in order to conducted the test.

There is also several other interesting points to be highlighted as future works of this project. The first one is regarding the expansion of the scope of study into closed-loop system. As mentioned by (Mark L. Darby, 2011), the application of the close-loop system is gaining more and more interest since the last decade. Since the current understanding towards the implementation of close-loop is a bit immature as compare to the open-loop, it would be great advantage to support the academic community to further strengthen the understanding regarding this area.



## BIBLIOGRAPHY

- 1) Ahmed, S. (2010). Process Identification using Nonideal Step Inputs. *Dynamics and Control of Process Systems*. Leuven, Belgium.
- 2) C.R. Porfirio, E. A. (2003). Multi-model predictive control of an industrial C3/C4 splitter. *Control Engineering Practice* , 765–779.
- 3) Dale E. Seborg, T. F. (2004). *Process Dynamics and Control*. John Wiley and Sons Inc.
- 4) Gang-Wook Shin, Y.-J. S.-B.-K. (2007). Genetic algorithm for identification of time delay systems from step response. *International Journal of Control, Automation, and Systems* , 79-85.
- 5) Lee, J. H. (1993). State-space interpretation of model predictive control. *Automatica* , 707-717.
- 6) M. Tvrzská de Gouvêa, D. O. (1997). ROSSMPC: A New Way of Representing and Analysing Predictive Controllers. *Chemical Engineering Research and Design* , 693–708.
- 7) Mark L. Darby, M. N. (2011). MPC: Current Practice and Challenges. *Control Engineering Practice* .
- 8) Paul S. Agachi, Z. K.-L. (2006). *Model Based Control: Case Studies in Process Engineering*. Weinheim: Wiley-VCH.
- 9) S. Joe Qin, T. A. (2001). A Survey of Industrial Model Predictive Control Technology. *Control Engineering Practice* , 733-763.
- 10) Salim Ahmed, B. H. (2006). Novel Identification Method from Step Response. *Control Engineering Practice* , 545-556.
- 11) Tao Liu, F. Z. (2010). Step Response Identification under Inherent-Type Load Disturbance with Application to Injection Molding. *Industrial Engineering Chemistry Research* , 11572-11581.