Development of 2x2 Model Predictive Control Model For Crude Distillation Unit

by

Vijendran Balakrishan

Dissertation submitted in partial fulfillment

of the requirements for the

Bachelor of Engineering (Hons)

(Chemical Engineering)

MAY 2012

Universiti Teknologi PETRONAS

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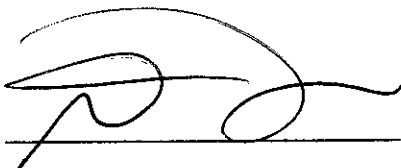**(CHEMICAL ENGINEERING)**

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

VIJENDRAN BALAKRISHAN

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ABSTRACT

This report is documented mainly discuss about the final year project entitled "Development of 2x2 Model Predictive Model for Crude Distillation Unit". Advancements in the oil and gas industries requires parallel progress both in maximizing production rate and profit. One sector in which those objectives are accessible is in the refinery business. Core business of the refinery sector is swarmed around the crude distillation unit (CDU) which separates raw crude into few marketable products. Due to its high nonlinearity profile and sensitivity of profit margin, any advancement in CDU is considered to be essential. Many researches and engineers use CDU as their case study for projects and paper works to contribute on the optimization, control and production problems. This piece of literature narrows it's scope to control issue of the CDU in which system identification and simulation of CDU system will be developed. Main purpose of this study is to investigate whether development of 2 by 2 MIMO model using Model Predictive Controller (MPC) can increase the performance and reproduce actual data of CDU to the respect to the variables chosen. Contribution of this research channels to error minimization produced by MPC in which evaluated by minimal controller moves and fluctuations of chosen control variables in comparative to its set points. Testing data from virtual plant will be used as base case to develop relevant robust mathematical model to be eligible for representing CDU system and performance analysis on the chosen model were conducted to derive relevant conclusions. Both research work is possible using MATLAB and HYSYS in which needed materials and toolboxes are available.

ACKNOWLEDGEMENT

CHAPTER 1 : INTRODUCTION

1.1 Background Study

Technical approach to develop empirical model from experimental data for a system or process has become the highlight in understanding the dynamic behavior of a plant system. Theoretical model requires vast information based on chemistry or physics nature of the system where rigorous model can be modeled to better imitate the actual real process.

The major disadvantage of theoretical model is that it requires numerous equations and properties. Instead of that, empirical model is a different approach of capturing dynamics of a system via experimental data or also known as system identifications (also known model identification or process identification in some literature) (Marlin, 2000).

1.1.1 Model Development Using Numerical Methods

Developing empirical model based on experimental data requires plotting many data to visualize the trends of the system outputs in regards to the inputs. Upon plotting and identifying appropriate model that might be reasonable for series of data, unknown parameters need to be calculated. According to Ljung, this step that is to calculate parameters value is known to be parameter estimation. Proper flow of methodology for typical system identification process is presented by Ljung (1999) and discussed in latter section.

This calculation relates the past input or past output matrix, Φ_k (with certain disturbances, e_k) as shown in Figure 1. The latest data, Z_k calculated over range inputs or outputs is related by θ, which is the unknown parameter that can be estimated through various numerical method such as Least Square Method, Linear Regression Method, Non-Linear Regression Method and et cetera (Freund, et. al, 2006). These methods are used in estimating model parameters in certain models which are further discussed in latter section.

$$Z_k = \theta \Phi_k + e_k$$

Figure 1 Parameter Estimation Basic Formula

1.1.2 Types of Model for System Identification

There are largely various types of model developed that uses similar concept of reading input and output from measured data then predicts the dynamic behavior of a system. This literature will focus on some of the most discussed model by Ljung (1999), Zhu (2001) , Camacho & Bordons (2003) and Seborg et al (2004). Models are categorised to be Single-Input-Single-Output (SISO) model or Multiple-Input-Multiple-Output (MIMO) model where the complexity of model increases as per mentioned in order.

As aforementioned, those considered models for the project are First Order Plus Time Delay (FOPTD) model , Auto Regressive Exogenous (ARX) model and Sub Space model. These models will be compared in latter works as a part of the methodology where each model possess its own criterion in confining dynamic behaviour of certain system. Suitability of model to a system is described by the reduction of error in imitating as much as plant data by reducing difference between simulated data from the model to actual measured data.

FOPTD model is an extension of First Order model where term of time delay is added to cater higher order dynamics that is abandoned in First Order model. According to Seborg, this model able to improve the conformity of the developed model to the experimental data. General formula for FOPTD is as follows (Figure 2, in transfer function). FIR model is type of discrete time model where deals with numerical values of functions at equally spaced intervals in which most computer deals with. Hence, continuous time dynamic system fit for FIR model.

ARX model is also type of discrete time model where it captures the dynamics for SISO and MIMO models (with certain modification) which relates to autoegressive model where it is defined generally as per shown in Figure 4. Besides that, State Space model works well for multivariable process with MIMO. Notations v(t) and w(t) denotes noises where all term in Figure 5 are in matrix form to reduce

the complexity of calcualtions. All formulas are in basic state where further derivation of formulation is not shown in this paper work. There are other models that can be fitted for the project however, these four are chosen as to popular literature (as aforementioned) suggests and discusses about these identification models.

$$G(s) = K \frac{e^{-\theta s}}{(\tau s + 1)}$$

Figure 2 FOPTD Model

$$y(t) = \varphi^T(t)\theta$$

Figure 3 ARX Model

$$x(t+1) = Mx(t) + N\Delta u(t) + Pv(t)$$
$$y(t) = Qx(t) + w(t)$$

Figure 4 State Space Model

1.1.3 Crude Distillation Unit

Distillation unit is vastly applied separation equipment in chemical plants or refineries which work based on the boiling points of the feed component. It is renowned technique of preferential separation of more volatile component(s) from the less volatile compounds by vaporization of the feed. Mass transfer and distribution of the feed components in the column is governed by vapor-liquid equilibrium relationship or properties (Dutta, 2007). This technique is widely used in the petroleum refinery arena for effective separation of crude assay which contains various hydrocarbons mixture which has high end users demand in global market (refer Appendices for Refinery Layout) .

Typical crude distillation unit, performed at atmospheric pressure (hereafter abbreviated as CDU) separates feed crude into products such as kerosene, naphthalene, diesel and many more depending on current economy constrains and market need (Prakash, 2003). Hence, the practical goal is to execute optimization for high production rate with standardized product quality and demand; which may

differ due to demand and supply thrust at low operating cost by maintaining optimal operating conditions of variables. Thus, control of a CDU becomes the core of refinery industry which directly touches the performance of the system that results in effective monetary consequences.

Various literatures suggests numerous techniques to further control to its final element level compromising up to higher level such as by Liau et al (2004), Motlaghi et al (2008) and Pannacchia et al (2006). Modifications in advanced control scheme and expert system were the results obtained by these authors where research on CDU performed. For example, performance of CDUs which have been executed with MPC controllers (both in simulation and plant environment) have been proved to be economically beneficial (Kemaloglu et al , 2006) (Pannacchia et al, 2006). Though system identification lies within MPC context, Kemaloglu et al, suggests improving each or any of the steps could lead to the solution of routine control issues.

*Note : Flow sheet for CDU regarding this project is attached hereafter in Appendices. Dynamic environment for virtual plant is obtained from ASPENHYSYS

1.2 Problem Statement

As aforementioned, CDU control system is proven to be feasible through appropriate system identification and implementation despite some control issues. However, there are still gap between theoretical and real environment of CDU due to non-linearity that CDU posts (Motlaghi, Jalali, & Ahmadabadi, 2008). These areas of mismatch can be curbed in various ways where any action adhered when implementing flow or sequence of System Identification process can be given much scrutiny. Through that, modifications can be made to various models to ensure real time dynamic behavior can be imitated. Thus, there is a issue of which identification model closely reproduces CDU data.

This project focuses on implementation and development of model identification tools with enhanced or better aspects upon proper plant testing in virtual plant environment with the aid of AspenHysys software. The driving factor for the problem statement is to develop robust mathematical model representation of a typical CDU system in empirical model based on measured data. System

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identification could be the way to attain more accurate process model out of plant testing data and hence enhance predictions and replications of data in need of better quantify the CDU system. The project could be a contribution in the refinery sector where it better CDU control could be achieved that benefits promising monetary effects

1.3 Objectives

. Objectives of the project are:

1. To develop 2 by 2 MIMO process model with MPC controller in order to produce efficient system identification algorithm.

2. To implement chosen MIMO model on CDU virtual plant (HYSYS).

1.4 Scope, Relevancy &Feasibility of the Project

. The scope of the project will involve knowledge of Process Control and Chemical Engineering field and knowledge of MPC technologies. Besides that, system identifications techniques and information is much needed to develop process model from input and output data. All these knowledge will be applied in the petroleum refinery area where CDU will be taken as case study. Hence, in-detail knowledge on crude oil and CDU are preferred for better handling and understanding of the matter investigated.

The project is requires MATLAB and AspenHysys where, identification models will be developed in MATLAB in which simulation data are obtained from AspenHysys Refining Package under Dynamic State. Within the proposed methodology and time frame which is 6-7 months, the project is feasible where upon completion objectives as listed would be fulfilled. The further methodology as listed in Section 3.2 will be executed in FYP 2 period. As an extra validation of the findings, actual plant data could be used to replace simulation data and hence vindicating the validity of the hypothesis proposed.

CHAPTER 2 : LITERATURE REVIEW AND THEORY

2.1 System Identification

Upon plant testing and data generation, proper model identification is vital to ensure model quality is at its best. Different types of model discussed in Section 1.1.2 gives a brief introduction to system identification. Practical identification practiced in industry accounts for high budget due to long plant testing time and disturbances imposed on process due to testing (Zhu & Butoyi, 2002). This gives opportunity for engineers to opt for different methods such as open loop testing, closed loop testing and et cetera.

Construction of models form available data accounts for few steps in order to accurately identify the dynamic system and convert it into mathematical model. First, the input output data need to be maximally informative and able to capture plants' dynamics through experiment designs or normal operation of the plant system. Next, set of possible candidates (models) is obtained and appropriate model is chosen with helps from experienced engineers. Lastly, letting the data as a guide, the best model is chosen by investigating which model performs by reproducing the measures data.

After those three steps, the model needs to be verified through series of tests that shows affirmative results along with plant operation data. Such analysis is known as model validation, where various procedures are adhered to relate the developed model with actual plant. Conclusively, the system identification procedure resembles a logical flow as apparent in Figure 5. Details on deriving proper model is well described by Ljung (refer References Section).
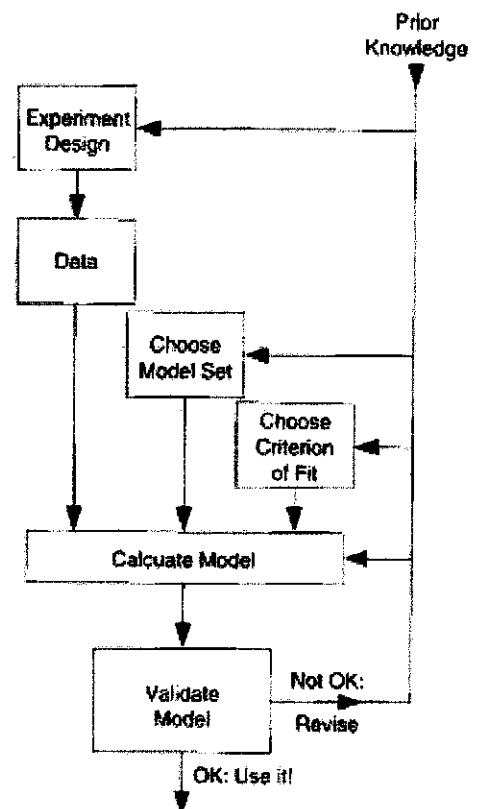

Figure 5 Logical Flow of System Identification Loop (Ljung, 1999).

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2.2 MPC Overview

Model Predictive Control (MPC) is established technology of implementing constrained that refers to a control algorithm that integrates process model to predict the future response of the plant thus, taking necessary action in order to optimize the performance of the plant. MPC is hierarchical control functions that based on dynamic constraints control either executed in a Distributed Control System (DCS) or directly manipulate the end control mechanism such as valves et cetera. MPC layers (refer Appendices A3) continuously send and retrieve targets values (setpoints) , limits and objective functions in order to keep the plant parameters at desired conditions.

Implementation of MPC is much welcomed due to integrated solution for control problems (Darby & Nikolaou, 2012), in which will be detailed in latter sections. Performances of CDUs which have been executed with MPC controllers (both in simulation and plant environment) have been proved to be economically beneficial (Kemaloglu et al , 2006) (Pannacchia et al, 2006). According to Darby M.I. et al, typical MPC project follows a sequence of actions which are:

1. Pretest and preliminary design
    - Determining base level regulatory control for MPC and rechecking plant instrumentation is satisfactory.
2. Plant Testing
    - Plant process is excited by altering variables to generate data for model identification
3. Model and controller development
    - Few models are developed and design of controllers must be completed
4. Commissioning and training.
    - Observing and testing performance of newly added controllers.
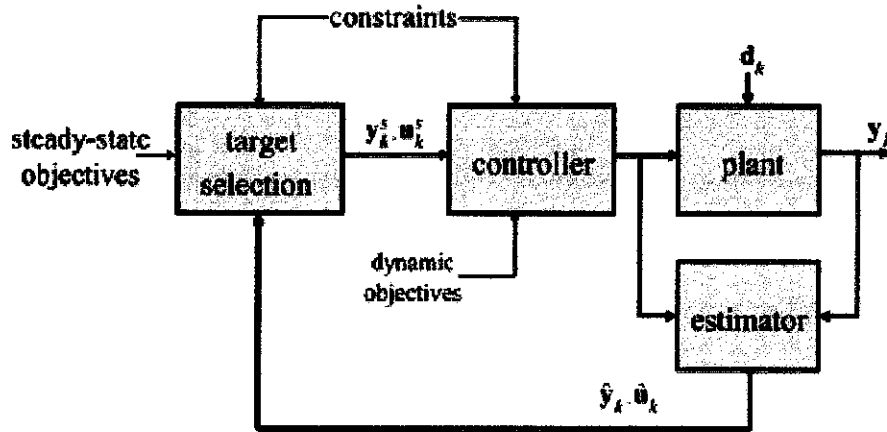
Figure 6 MPC Block Diagram

MPC consist of few sub-portions that performs calculation in order accurately predict future responses of plant variables. As evident in Figure 1 (Darby & Nikolaou, 2012), vital functions of MPC strategy relies on target selection, controller, plant and estimator. Target selection selects best operating point for the controlled output and some manipulated variables (y^s_k , u^s_k). The target selection relies on steady state gains of the model. Upon the best operating chosen, the controller selects the possible future input over a moving horizon to minimize predicted future controller errors. Whereas, the estimator updates the model predictions for disturbances and errors.

MPC algorithm can be represented by few mathematical model which are known as Prediction Model, Objective Function and Control Law. Prediction Model captured process dynamics and calculates future responses with available information instantaneously. Prediction Model can consists of an Actual Process Model such as Impulse Response Model, step Response Model, Transfer Function Model, State Space Model and many more. Other than that, some Prediction Model equipped with Disturbance Model to give some error in the input to imitate actual dynamics of the plant (Camacho & Bordons, 2003).

2.2 Test Design And Data Pre-Treatment

In order to gather necessary data as input to developed model, several tests need to be performed to gain adequate information on the process through excitation of the process. In order to achieve this, certain tests are carefully designed for the process get perturbed with certain values to observe the response of the dynamic system. Main function test design is to gain intrinsic and extensive knowledge on the fundamentals of the process and slowly progressing to the input and output data in expanding process model. The following section discusses the about test deigns and selecting appropriate data for system identification.

2.2.1 Test Design

Test design is carefully plotted for a given system by first understanding controller configuration and input-output structure of the system. Types of variables need to listed and shortlisted for its possibility to distract or alter response of the system. In usual practice, a experienced engineer and carried out as Plant Testing period (Campos, et al. 2009). Series of manipulated variable, disturbance variable and control variables are identitfied and to some extents, some guide from various literature can be used as guidance in determining appropriate variables before proceeding to tests (Zhu, 2001).

As suggested by Zhu (2001), in cases of inavailability or incapable to obtain certain data (i.e. analyzers to analyze compositions) due to shortage of instrumentation devices or sensors, an inferential model can be used to estimate the values. Identification tests are conducted and discussed by Zhu & Butoyi (2002), Li, et al. (2005), Kemaloglu et al., 2006), Akpan & Hassapsis (2011) and Darby & Nikolaou (2012).

2.2.2 Data Pre-Treatment

Upon obtaining plant data, it needs to be given much scrutiny on the output where unwanted trend need to be reasoned out and hence removed before using it in identification algorithm. This effort is known as data pre-treatment. Deviation from normal plant trend may occur due to presence of noise, spikes and outliers in the system. Besides that, nonlinearities may occur due to process shift in contrary to the routine of the system. According to Zhu (2001) following are types of pre-treatment that may apply to plant data which are peak shaving, signal slicing, high-pass filtering and normalization.

In practical terms, spikes and offset are induced by instrumentation devices and data acquisition structure. Hence, peak shaving procedures performed on series of data where prior information on conventional data needs to be known. Limits of the trends are identified ad standard deviations and certain statistical method is applied to know the out-of-range values (Freund, et al. 2006). Besides that, signal slicing is another pr-treatment of data whereportion of signals are removed due tounmeasured disturbance caused by process shift. Both pre-treatment aforementioned works well with visual aids suchas process trends and other relevant graphical user interface.

In some cases, slow offset and deviation from process value happends occur du to feed composition changes or temperature change. As mentioned by Qin (2003), drifts such as slow variation sets off negative influence in the process data andhence would be removed from being used in algorithms. For trend correction, data will be passed through a filter where necessary signals will be removed under a series of computations. Choice of filters and types of trends correction is further desciribed by Zhu (2001).

Apart from that, in order to curb variancein magnitude of inputs and outputs, normalization (in some literature labeled as scaling and offset correction) is performed. This method is useful in case of reducing weightage of high magnitude values that will affect quadratic functionfor determining the model.Data pre-treatment also ranges to delay correction, lowpass filtering and sampling rate reduction. Further explanationis given out by Zhu (2001) and Qin (2003).

2.3 Development and Limitations of System Identification

▶ Development of System Identification methods :

- Prediction Error method mostly used in industrial applications in the early years (Zhu & Butoyi, 2002).

- FIR & ARX Models remains popular using Linear Least Square method. Other numerical methods are reported to be used especially Linear Regression Method (Qin & Badgwell, 2003).

- Subspace model directly yields multivariable state space model in which complicated models are easily described by any nonlinearities exist (Darby & Nikolaou, 2012).

▶ Limitations/Findings of Identification Technology:

- Poses longer testing time to obtain data where proper plant testing requires procedural steps that consumes time. Though simpler methods are available, most of the developing system identification process lost in plant testing section. (Camacho & Bordon, 2003)

- Dynamic nonlinearities cannot be handled using certain identification methods due to certain extents of complexities (ex : FIR). Importance in identifying nonlinearities in a process is crucial in order to develop a reliable algorithm or model (Zhu, Multivariable System Identification, 2001) (Nikalaou & Darby, 2012)

- No tool to determine whether data are adequate to represent process dynamic of a plant. Most of the available plant testing iare aided by experienced engineers or technician in which prior knowledge on the system is vital (Qin & Badgwell, 2003).

CHAPTER 3 : METHODOLOGY

3.1 Case Study : Crude Distillation Unit (CDU)

Taking into consideration that CDU is sensitive and complicated plant structure, selection of input (manipulated variable) and output (control variable) must reflect the dynamics of CDU. However, the issue of quantity of input-output is still intuitive-based and need some trials to run for. In this study, series of trials are being run from various blocks of input-output (IO) structure to further understand how many IO is adequate to capture the dynamics of CDU.
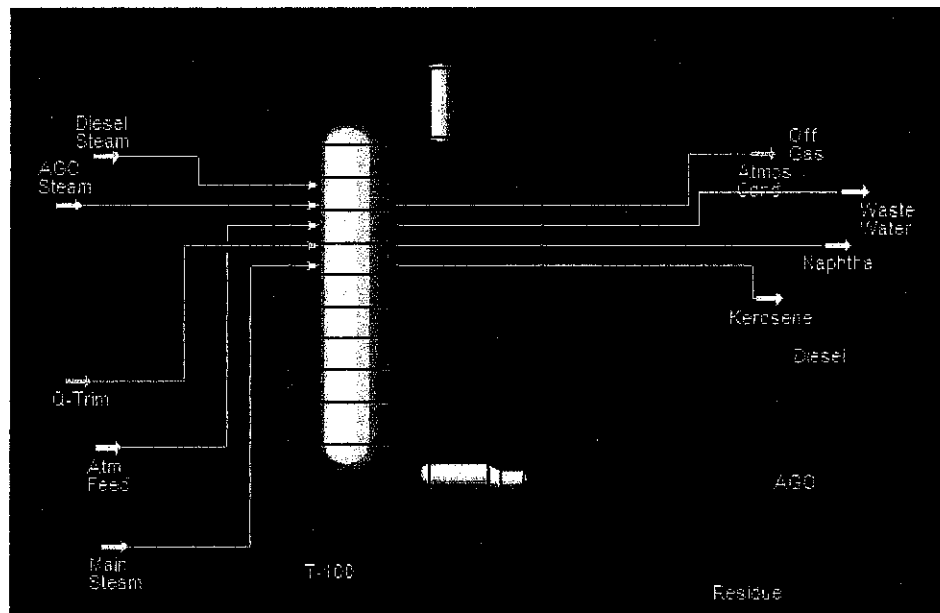
Figure 7 Dynamic Pressure-Flow Indication

CDU contains 3 side strippers and 3 pumparounds (without furnace in HYSYS). each stream details and specifications are studied for understanding the behavior of the process. The available model is highly nonlinear and sensitive with five sidedraws besides top and bottom outlet (Figure 6 shows the main layout of the plant).

Table 1 CDU Spesifications

Parameters	Value
Top Stage Pressure	20.70 psia
Bottom Stage Pressure	31.44 psia
Top Stage Temperature	135 C
Bottom Stage Temperature	358 C
Trays	29

3.2 Research Methodology

The research project required numerous trial and error methods for distinguishing the best model and procedure of developing one. Informations of paper works by authors aided the design of the detailed research methodology. The methodology was designed to develop a mathematical model sufficient to represent actual dynamic behaviors of the virtual CDU system. Upon obtaining desired model, the actions of the controllers are compared to the existing one and someendns were derived.
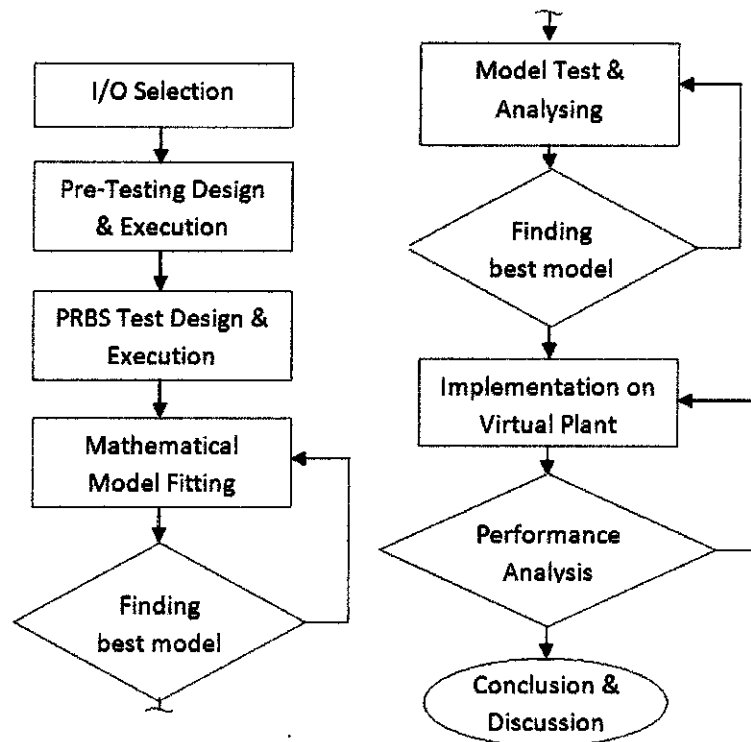
Figure 8 Research Methodology

Shown above is the detailed project methodology for the research project where steps taken into developing the models were adhered to. These steps are crucial in determining which model is appropriate for the chosen case study. As CDU is pre-determined to be the case study and as well satisfy the research objective, first, 2x2 model will be developed then series of model fitting and validation with some analysis will be done to test and understand the robustness of the developed model. Brief descriptions on the detailed methodology are as follows in latter section.

3.2.1 I/O Selection

For this case study, the model is based on two by two multiple-input-multiple-output (MIMO) system which the variables were selected on the literature reviews done by Kemaloglu et al and other relevant authors. Interference of input by introducing deviation from the steady state values requires the need of controllers in the streams. As such, two product streams were chosen as stated in Table 1. Pressure and flow profile of streams are main consideration of the CV and MV selections. For 2x2 block, the inputs are AGO Flow Controller Set Point (u2) and Diesel Flow Controller Set Point (u1). The corresponding outputs are AGO Volume Flow (y2) and Diesel Volume Flow (y1). It is ensured that the streams are independent of flow specifications to make sure the dynamic behavior is available [Indication: Purple (Pressure Specified) and Yellow(Flow Specified)-Figure 6].

Table 2 Input-Output for 2x2 Model

	Variable	Steady State Value
Input (Manipulated Variables)	AGO FC OP	u2 = 50.11 %
	Diesel FC OP	u1 = 51.64 %
Output (Controlled Variables)	AGO Volume Flow	y2 = 29.78 m^3/hr
	Diesel Volume Flow	y1 = 127.4 m^3/hr

3.2.2. Pre-Test Design & Execution
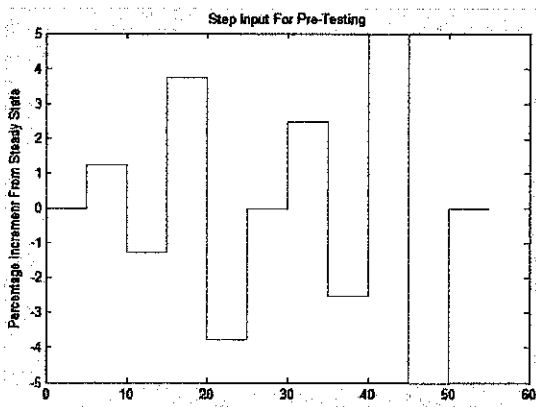
Figure 9 Step Input Change For SIMO Models

Upon selection of input and output configuration, pretesting design is carried out. According to Qin & Badgewell (2033) and Richmond & Chen (2012) pretesting execution in actual plant requires long hours and priori knowledge on the system. Moreover there are certain rules in designing the pretesting for system. In this case study, magnitude of ±5% is used with varying time length (the system is set to reach new steady state upon new input change). Moreover, limitations of ±10% change per shift at a time is adhered to ensure not much fluctuations or any nonlinearities caught in the data. For

simplicity, the model is to assumed as linear. The aim of this pretest is to obtain single-input-multiple-output (SIMO) data to be fitted into First Order models later within ten controller (input change from steady state) moves. Each input is excited in similar fashion and data is obtained for further testing and analysis.

3.2.3 PRBS Testing and Execution
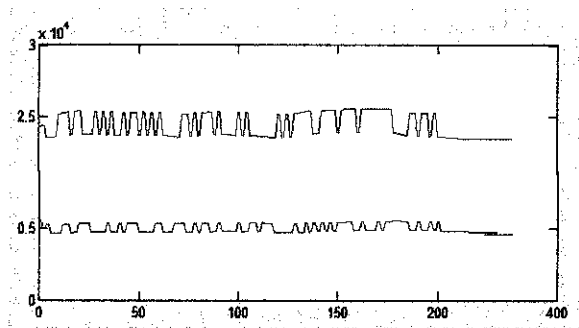
Figure 10 PRBS Test Signals for MIMO Models (u1 and u2)

Using the SIMO data (gain and time constant) we can design PRBS test signals accordingly to move multiple inputs simultaneously. Guide on how to calculate shift time and total time length is presented in Seborg et al (2004) and Gaikwad & Rivera. Figure 8 shows the input signals fro PRBS testing which is conducted in HYSYS (refer Appendix). The amplitude of PRBS signals is ±3% for diesel flow stream and ±5% amplitude for AGO flow stream (amplitude is obtained by observing the pretest data on the fluctuations and sensitivity). Time interval were made to be one minute and the testing time length were 1 hour 40 minutes with model tested for 100 moves. The result of the test is presented in the latter section.

3.2.4. Mathematical Model Fitting

Using the PRBS and step test data, few models can be fitted using MATLAB System Identification Toolbox. Selected model such First Order Plus Time Delay model, ARX model and State Space model were tested for various parameters to find the best fit the data. Each tested data was divided into two sections, one for estimation and one for validation. Details and explanation on the toolbox are well explained by Ljung (1997).

The raw data from the test results were pretreated by removing means (normalization) and reverting some portion of data for Validation Data Set (Ident Toolbox) - an example on the layout is presented in the Appendix. Estimation of models chose to 'Prediction" compare to "Simulation" for higher data accuracy. Other settings in the Ident Graphical User Interface (GUI) kept as default. The best

fittings are evaluated by percentage match of the Validation Data Set to the Working Data Set (refer Appendix). Therefore, best model can be chosen and proceed further to next step.

3.2.5. Model Test & Analyzing

Obtained mathematical models with aid of System Identification Toolbox were tested with series of scenarios by installing Model Predictive Controller (MPC). The model is disturbed with set point change and load change using MPCToolbox available in MATLAB (refer Appendix). MPC will help to monitor the robustness of the model and the performance of the model can be inspected via controller performance to bring the new set point to its desired value.

Set point change scenario is tested to on Step Input of amplitude 1 where as the regulator problem were tested to be Gaussian Disturbance with Size = 1 and Time = 10. These disturbances are tested for acceptably moderate design of control horizon within 2 time interval. Aggressive move of the controller will deteriorate the MPC performance in cases of increasing the Control Horizon. The Simulation time is prolonged twice as the predication horizon for better performance response.

Constraints on the variables are set to be ±5% for the manipulated variables as for the controlled variables, the constraints are left blank in order to monitor how much it fluctuates than the desired value. The performance of the model is calculated by area under the curve (using One-Third Simpsons Rule).moreover, number of controller moves and overshoot were also considered.

Table 3 MPC Design Parameters

Controller Design Parameter	Values
Sampling interval	5 time units
Control Interval	1 time unit
Prediction Horizon (interval)	100
Control Horizon (interval)	2
Constraints on Manipulated Variables	Max Down Rate = -5%
	Max Up Rate = +5%
Simulation Time	200 time unit

3.3 Project Work
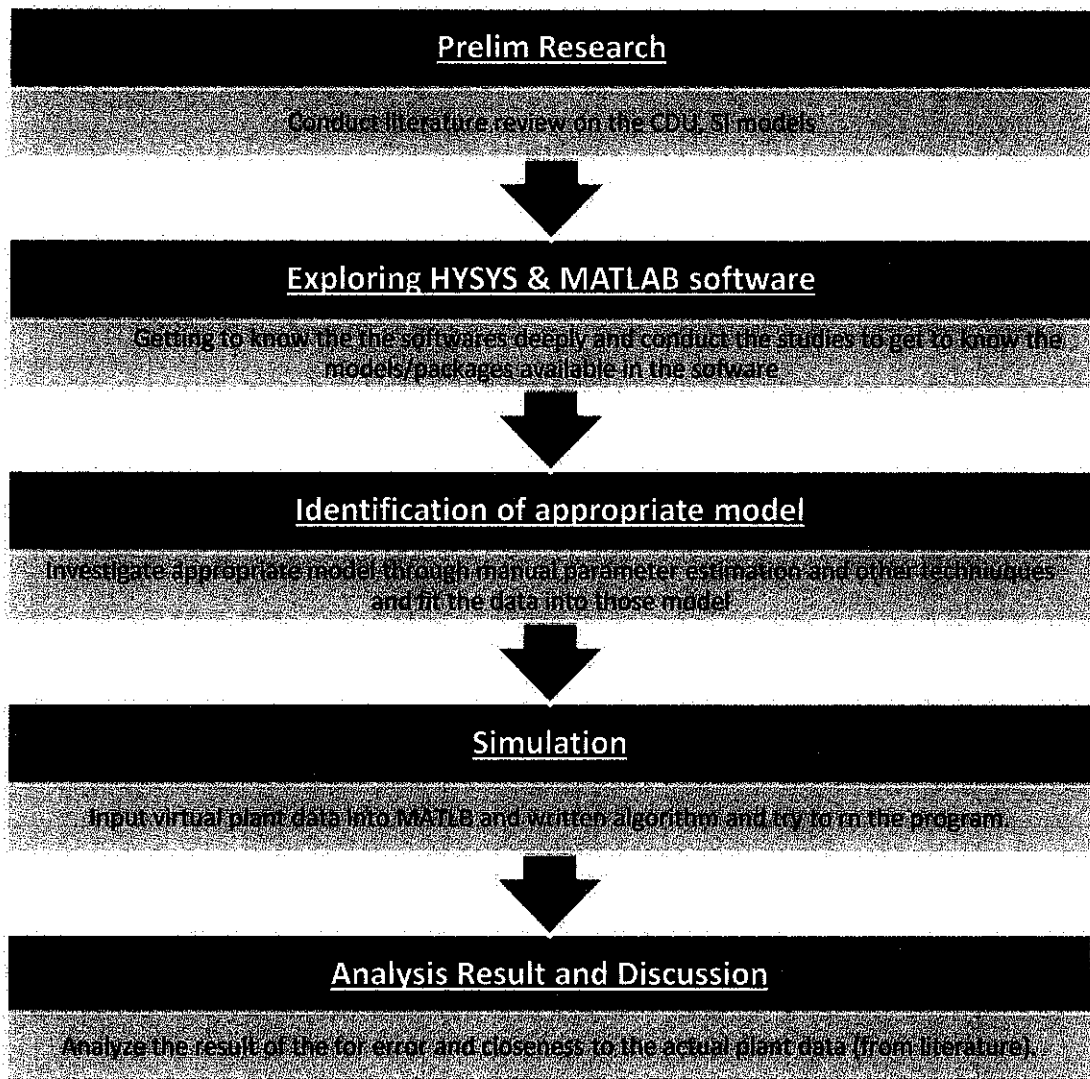
Figure 11 Project Activities / Work For FYP

From Figure 10, we can know the total flow of the project where development of model relies within second half of the hierarchy. FYP 1 methodology close governs the model selection and FYP 2 involves model development and validation process. Findings from the literature studies shows some advances made (refer Literature Review Section) lately and further studies on this project will contribute some knowledge to progression of plant control strategies. Progress of FYP 1 will be continued in FYP 2 where simulation of selected model with enhancement of algorithm will be made. Establishment of linkage between MATLAB and HYSYS is possible as reported by Yusoff et al. Detailed methodology as illustrated in Figure 8 is to mainly to understand CDU process behavior and concluding minimal testing effort that could be taken in plant.

3.3 Gantt Chart & Key Milestone of Project

No	Detail / Week	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
1	Analyze the simulation (Distillation Column)	■	■	■	■	■	■	■								
2	Pretesting/PRBS/Modeling	■	■	■	■	■	■	■								
3	Analyzing model	■	■	■	■	■										
4	Progress Report								■							
5	Pre-SEDEX											■				
6	1ST Draft Submission of Dissertation											■				
7	Submission of soft copy of Dissertation												■			
8	Submission of Technical Paper													■		
9	Oral Presentation															
10	Hard Bound Dissertation														■	■

MID SEM BREAK (weeks 8–10)

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3.4 Tools Required

The software chosen is the is MATLAB and for the simulation data HYSYS is chosen as it is available in UTP. This software was developed by MathWorks and AspenTarget respectively where MATLAB accounts for computation software with embedded toolbox (Identification & MPC Toolbox). Whereas, HYSYS offers dynamic simulated package for crude distillation unit in one of the tutorial packages.

3.5 Knowledge required

There are several things that need to be understood in order to conduct the project successfully. They are:

1) Understanding the process for CDU and its dynamic state and its advantages in oil refinery

2) Understanding the System Identification sector with its application in process plants with its latest advancements.

3) Understanding the mathematical models developed for process identification and its advancements in applications

4) Understanding the programming codes and usage of MATLAB software in order to generate algorithms.

5) Understanding the difference between models and selecting the appropriate model that describes CDU the best.

Thus several papers and several books need to be referred to understand all the topics that are given above in which listed in Reference Section.

CHAPTER 4 : RESULTS AND DISCUSSION

4.1 Step Test Data

As detailed in Section 3.2.2, step test were performed on the model in open loop mode (related controller in Manual mode and others in Auto mode) for the related variables. Opening of valve is stepped in order to make changes in which in Manual mode the process variable will follow the opening of the valve prompted by user/technician. Pretest design as shown in Figure 8 and 11 was conducted on u1 and u2 and the respective response on y1 and y2 from HYSYS Data Monitor were saved (in .csv format file) to be analysed in MATLAB.
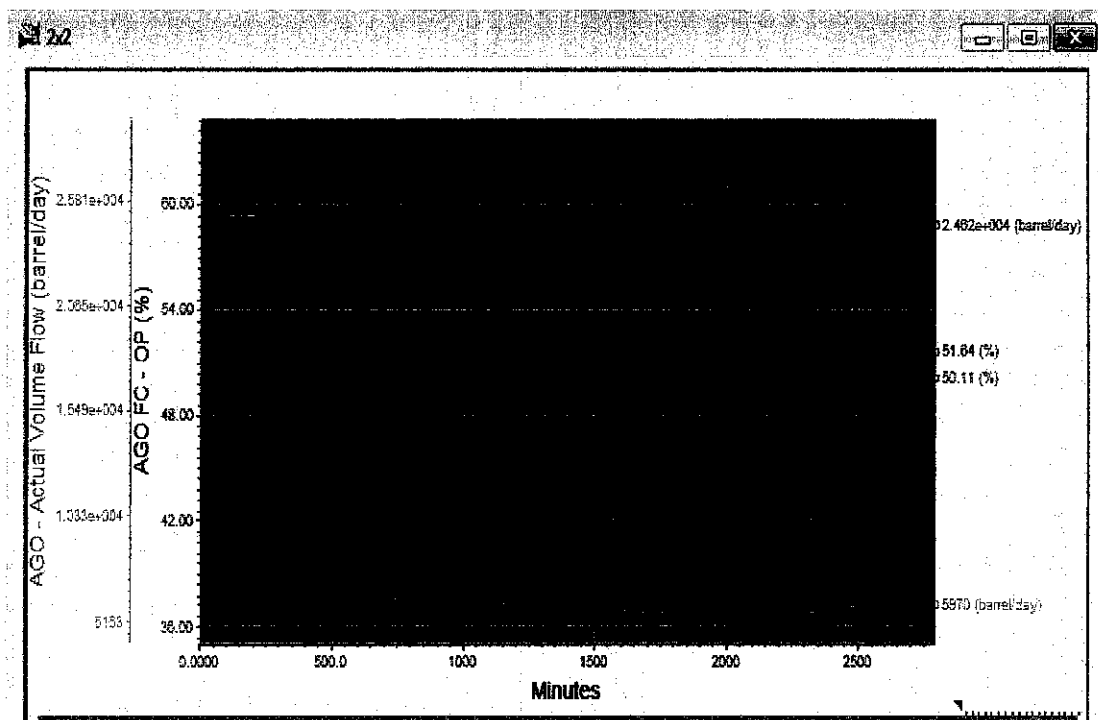

Figure 12 Designed Step Input of u1

As observed above, changes in u1 (Diesel FC OP) leaves significant change in Diesel flow and AGO flow. Some disturbance can be observed where the responses show some instability at instance of introducing a change over steady state conditions. Upon initiating a step change both output need to given ample time to reach new steady state for best result (and to avoid oscillation in response).

4.2 FOPTD Model

Using System Identification Toolbox, the data from 4.1 were fitted in first order model to get the intuition on time constants. Interaction of each input to each output is modeled in FOPTD model to latter design PRBS testing for higher order model estimation. Each SISO model were fitted to get the transfer function and the time constants, τ. From figure 14, we can say that, approximation for G_{u1y2} and G_{u2y1} gives out lesser best fit in Matlab due to the response of the variables.
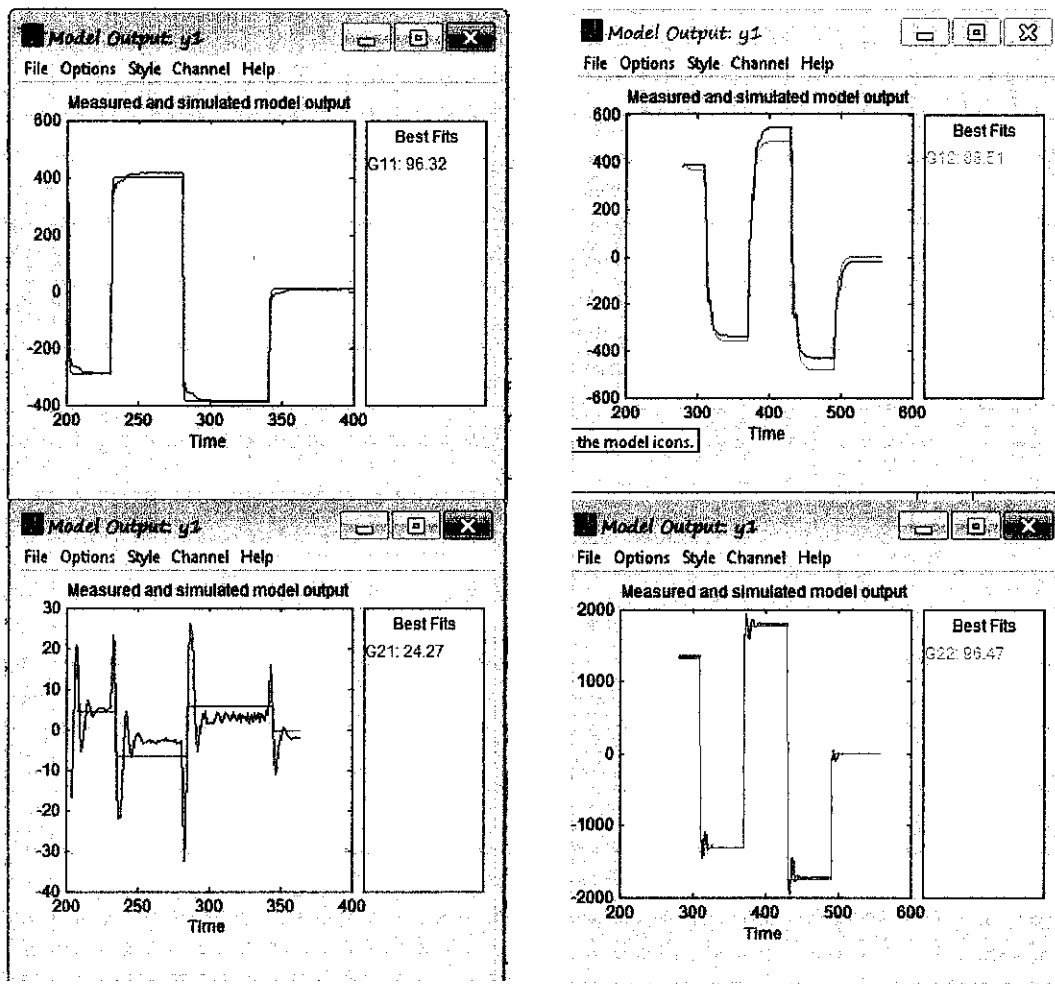

Figure 13 First Order Model Fitting Using Ident Toolbox

$$\begin{bmatrix} G_{u1y1} & G_{u2y1} \\ G_{u1y2} & G_{u2y2} \end{bmatrix} = \begin{bmatrix} \dfrac{194.42}{1+0.83973s} & \dfrac{-1.2129\,e^{-3.9909s}}{1+0.0073885s} \\ \dfrac{4.4816\,e^{-0.97888s}}{1+0.023604s} & \dfrac{200.87}{1+0.8963s} \end{bmatrix}$$

Figure 14 Transfer Functions for First Order Models

$$\begin{bmatrix} K_{11} & K_{12} \\ K_{21} & K_{22} \end{bmatrix} = \begin{bmatrix} 194.42 & -1.2129 \\ 4.4816 & 200.87 \end{bmatrix}$$

$$\begin{bmatrix} \lambda_{11} & \lambda_{12} \\ \lambda_{21} & \lambda_{22} \end{bmatrix} = \begin{bmatrix} \lambda_{11} & 1-\lambda_{11} \\ 1-\lambda_{11} & \lambda_{11} \end{bmatrix} = \begin{bmatrix} 194.4471 & -193.4471 \\ -193.4471 & 194.4471 \end{bmatrix}$$

As observed from the transfer function for G_{11} and G_{22} interaction is much evident than effect of u1 on y2 or u2 on y1. This easily could be conclude from Relative Gain Analysis (RGA) using the steady state gain from the transfer functions. The simple RGA analysis leaves us a clue that interaction between indirect variables (as aforementioned) are minor.

4.3 PRBS Test Data

Information gained from pretesting was used to design PRBS testing to gain MIMO model for higher order polynomial estimation. The result from the testing from HYSYS is shown in Figure 14. Using System Identification Toolbox again, the result were fitted under ARX and State Space models. PRBS specifications done in HYSYS were calculated using PRBS Design Guidelines as suggested by Gaikwad and Rivera.
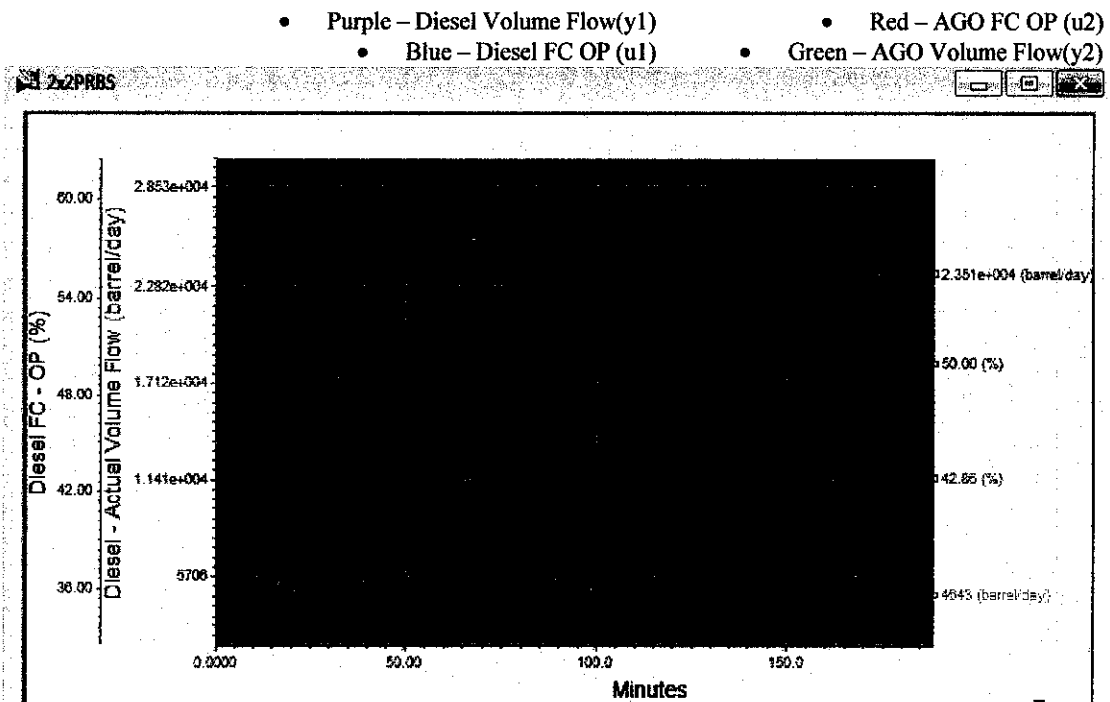
- Purple – Diesel Volume Flow(y1)
- Blue – Diesel FC OP (u1)
- Red – AGO FC OP (u2)
- Green – AGO Volume Flow(y2)

Figure 15 PRBS Test Data

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4.4 Mathematical Models

File Options Style Channel Help

Measured and simulated model output

Best Fits
arx861: 80.71
arx961: 74.84
arx961: 74.84
arx221: 67.86

Time

Confidence intervals removed.

Figure 16 ARX Models

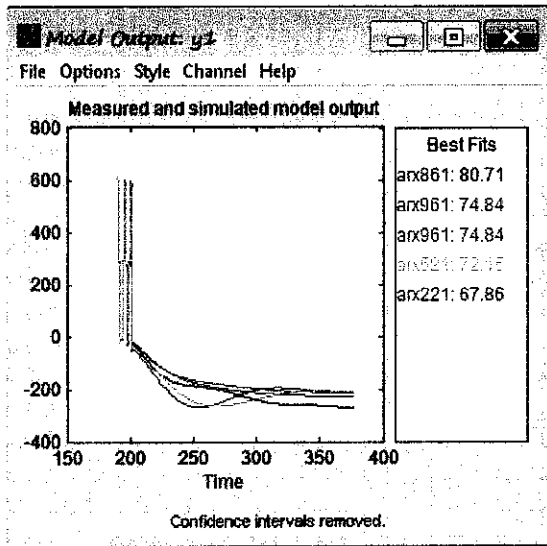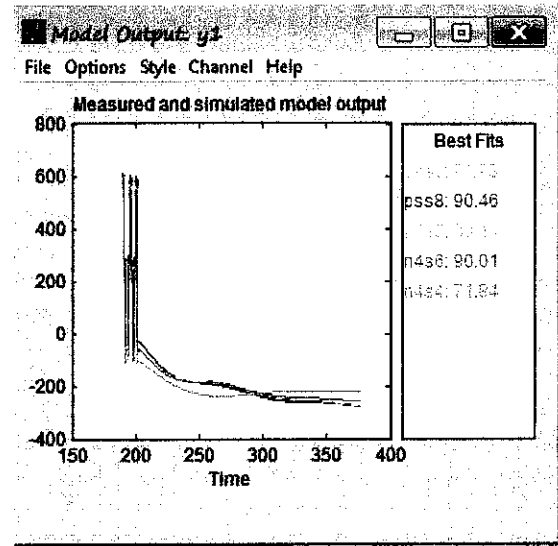Measured and simulated model output

Best Fits
pss8: 90.46
n4s6: 90.01

Time

Figure 17 State Space Models

As evident in the results, ARX models have lower fittings than the State Space models. The fit percentage are better for those State Space models which estimated using Parameter Estimation Method (PEM) which involves little complex mathematical form. However, for simplicity State Space order 4 and ARX with parameter [8 6 1] were chosen to be further implemented with MPC controller.
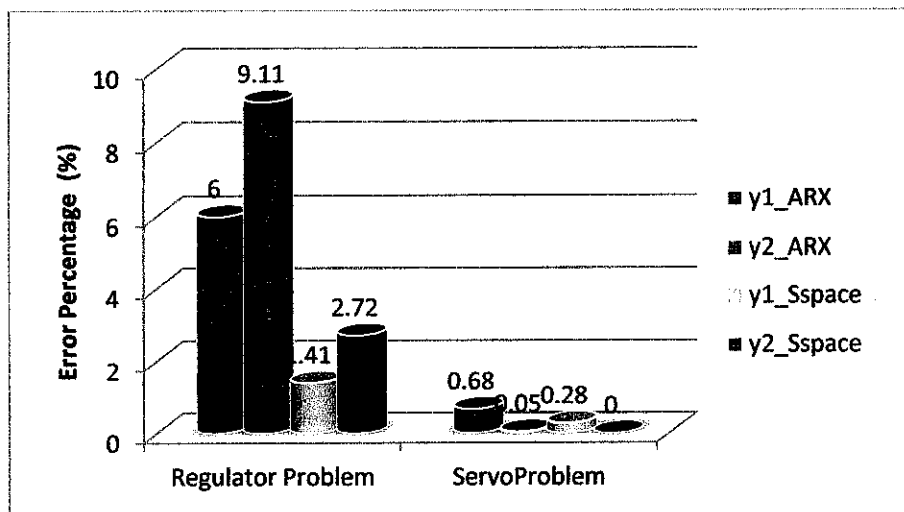
4.5 Servo & Regulator Problem

Figure 18 Area Under Curves of Output respect to MPC Scenarios

The results shows that ARX model fluctuates more that State Space model in which were excited with set point change and load change, ARX exhibits higher area under the curve (error) percentage. This implies that the higher order polynomials

behaves unreliably under regulator and servo problems. Comparatively to State Space model, exhibition of lower percentage of error is evident.

4.6 Implementation on Virtual Plant
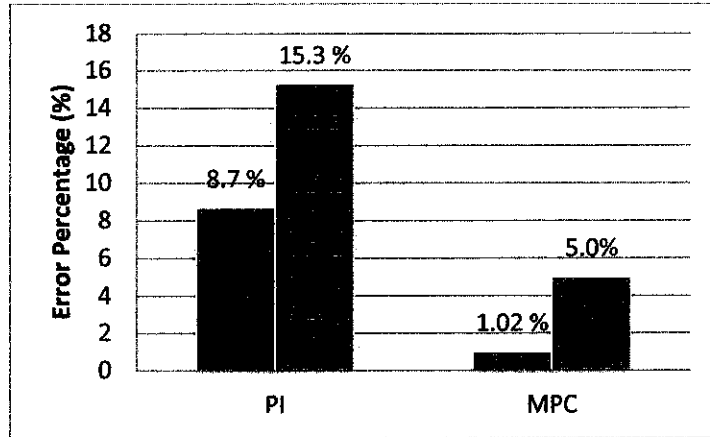
Figure 19 Controller Performance of PI and MPC

The state space model is found to be reliable and hence implemented on the virtual plant for comparison of controller performances. The controllers designed in the model in HYSYS software are proportional-integral (PI) controllers for both AGO Flow and Diesel Flow. Figure 6 shows the dynamic performance of PI controller (in DYNTUT2.hsc) is higher. Settling time and fluctuations are reduced for the MPC controller using State Space model.

CHAPTER 5 : CONCLUSION & RECOMMENDATIONS

5.1 Conclusion

Major conclusion can be drawn is that higher order mathematical model exhibit less robust performance under certain disturbances. MIMO model of 2x2 able to recapture actual CDU system if there is simpler representation of mathematical model or plant models. At the early of the research assumption made that the CDU behaves linearly where actual case it is not is. The setback of this is that it is impossible to be validated using actual plant data. However the error reduction in the estimating lower order state space model is clearly promising.

5.2 Recommendations

The main setback of the research is that is uses virtual plant data obtained from HYSYS. Better picturization would be evident when using actual CDU data that has been pre-tested similarly.

- Conduct higher input-output block experiment
- Validate findings with actual plant data
- Pre design PRBS testing and MPC controller using proven methodology.
- Consider nonlinearities calculation and estimation method for better capture the dynamics of CDU.

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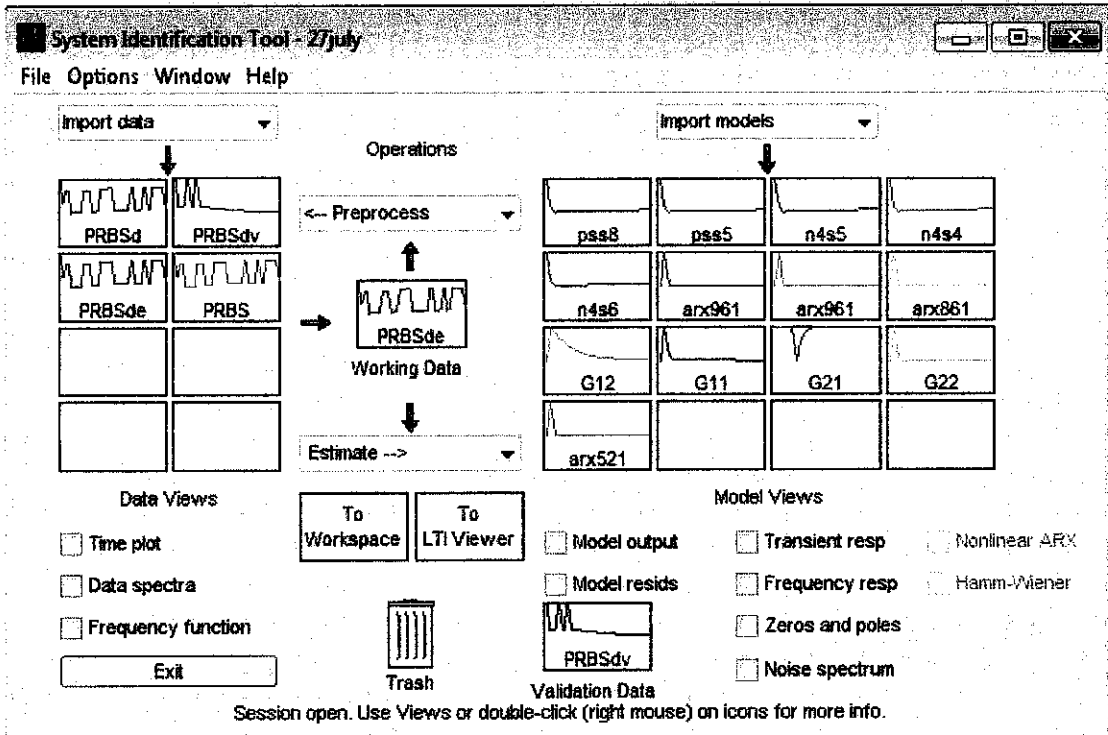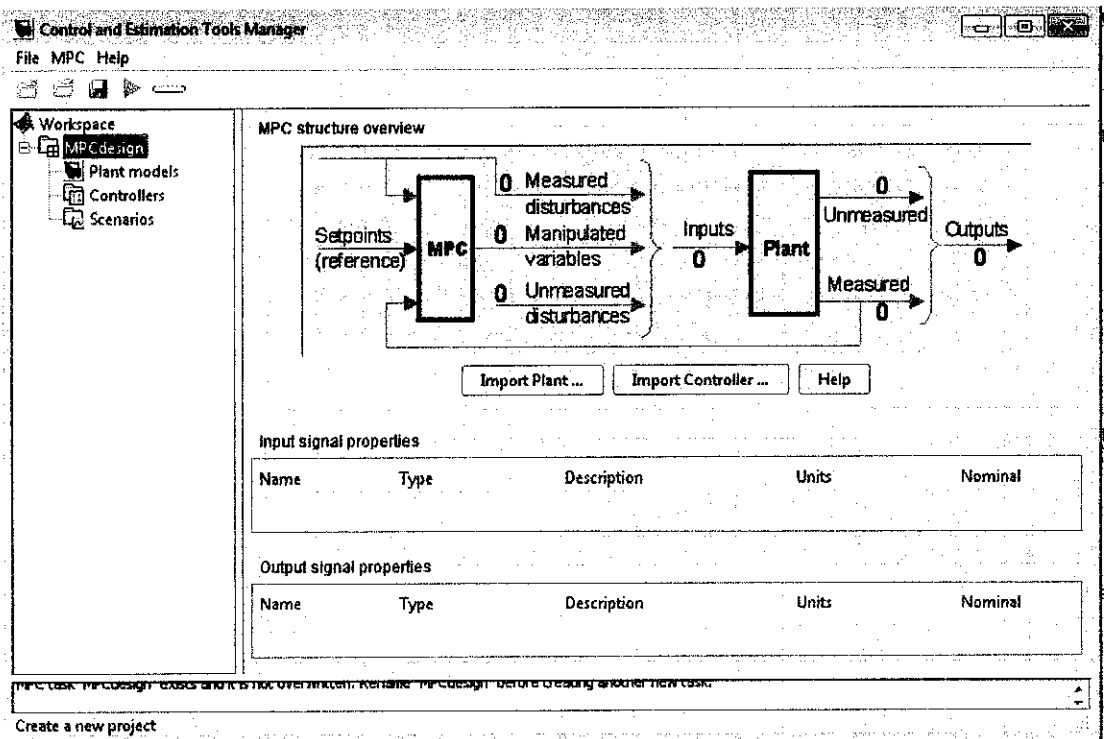
APPENDIX
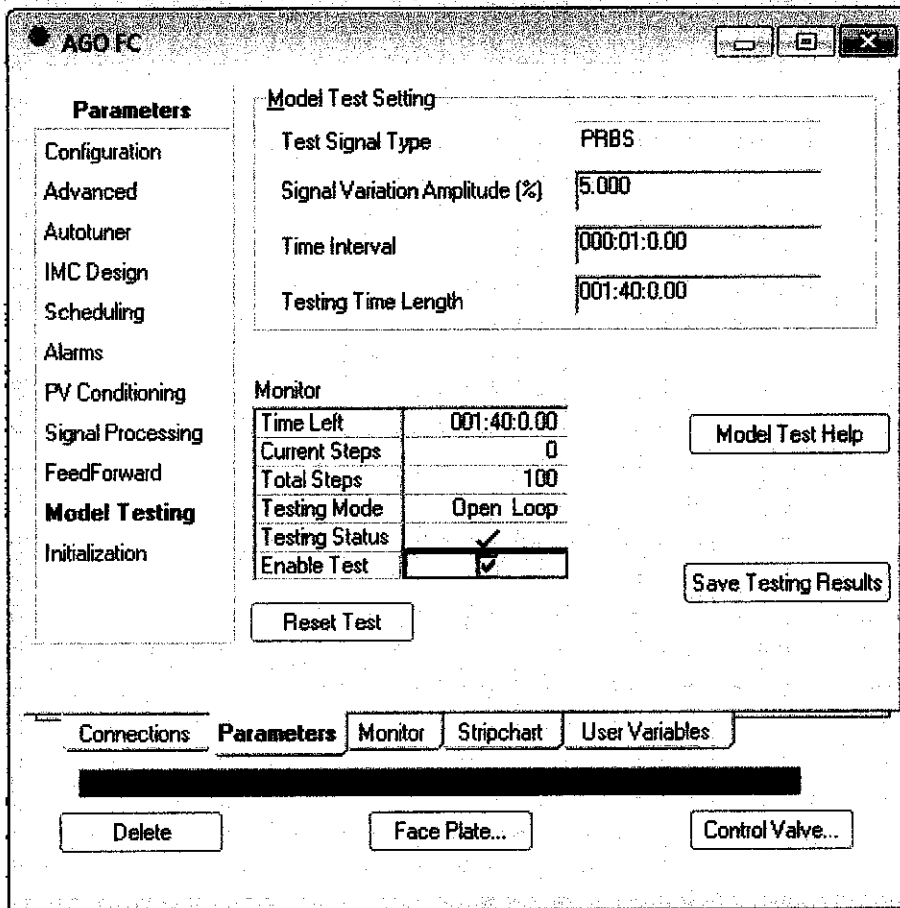
Screen Shot of Model Tecting – PRBS in HYSYS
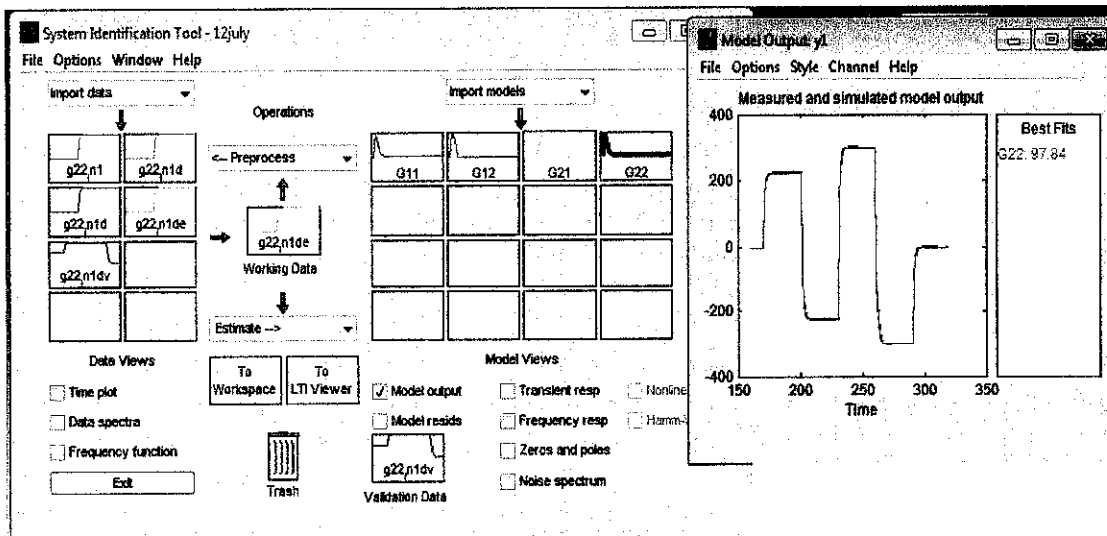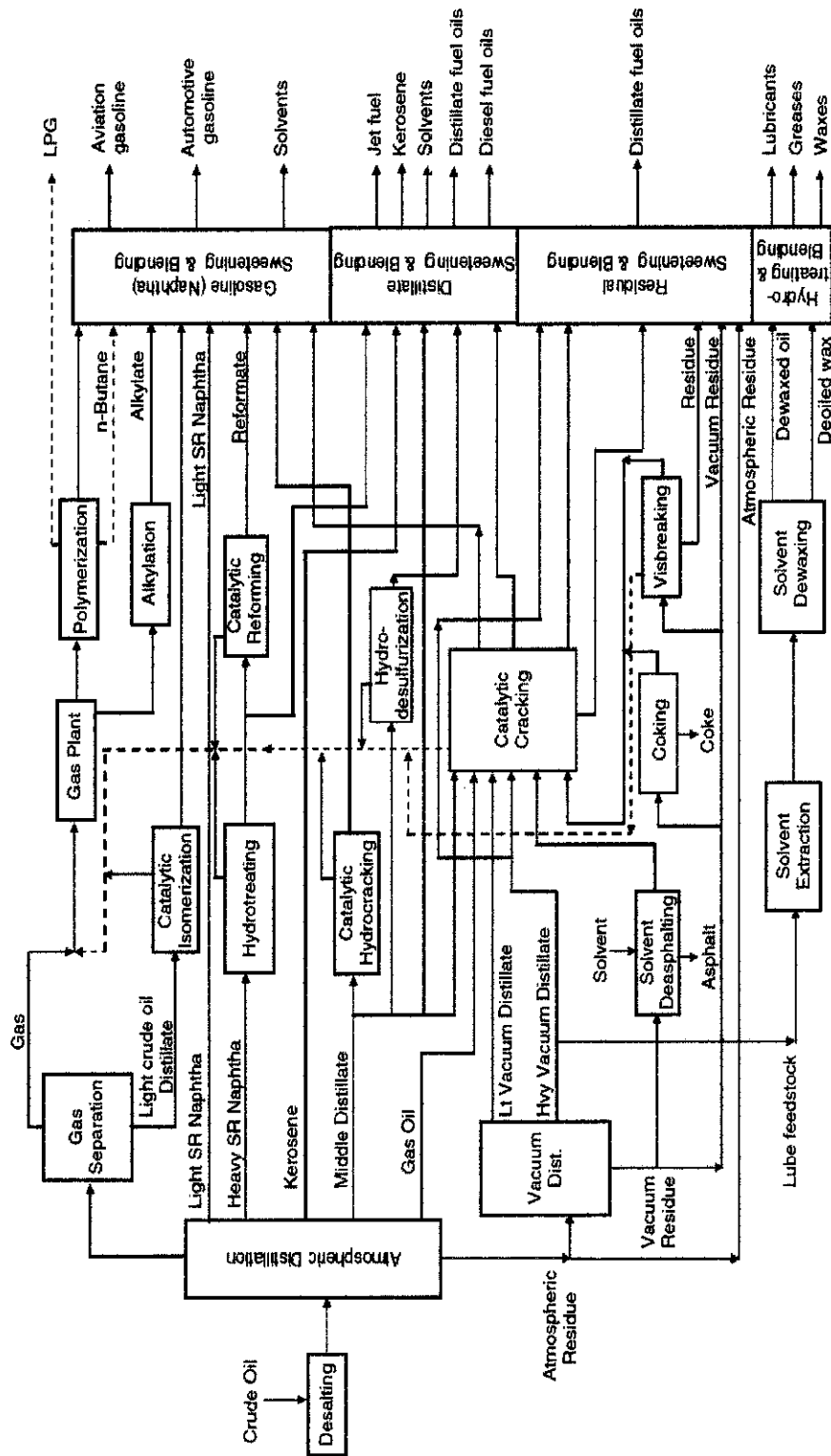

Screen shots of System Identification GUI in MATLAB

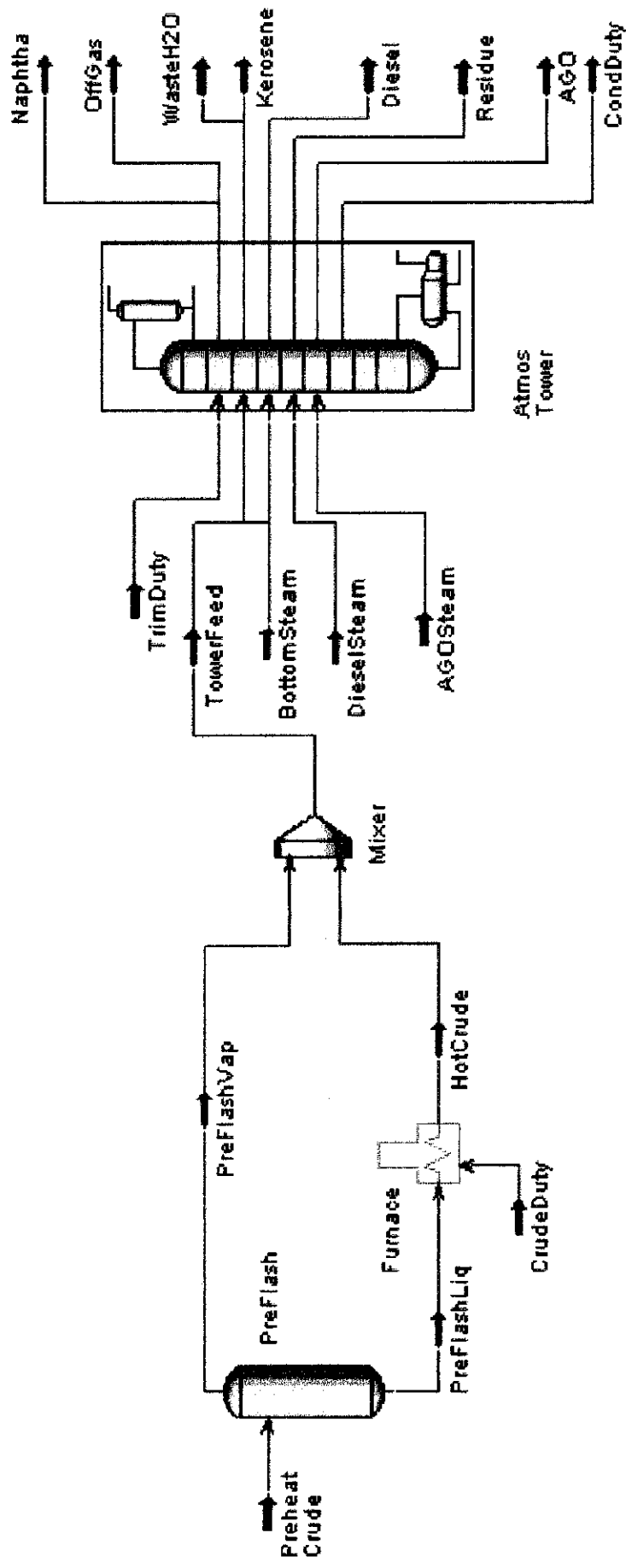*Screen Shot of Developed Model in SysIdent GUI - MATLAB*

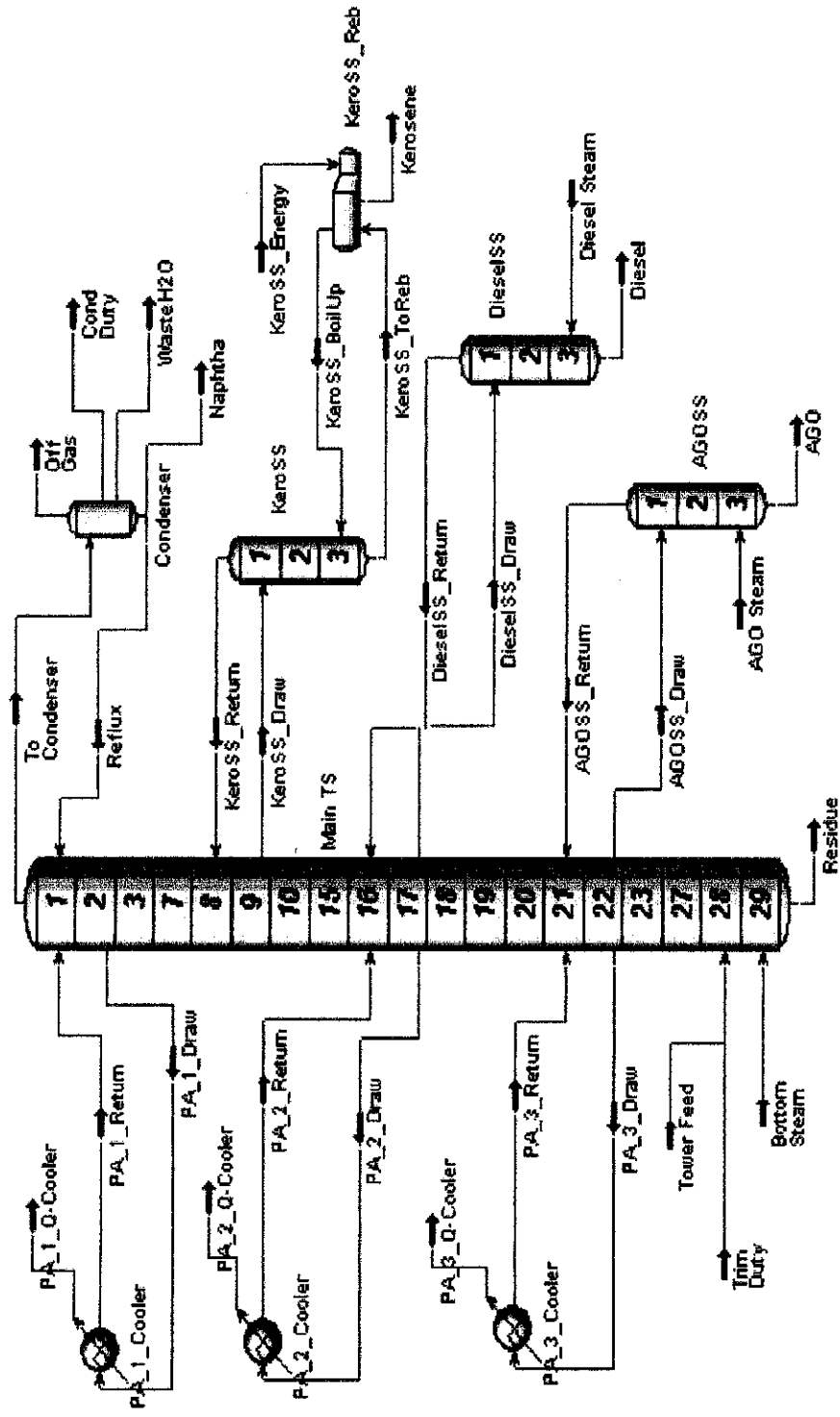*MPCToolBox in MATLAB for Mathematical Model Testing*

Modern Refinery Layout [1]

[1] "Modern Refinery Layout" from : Fahim, M., et al. (2010), *Fundamentals Of Petroleum Refinng*. Oxford: Elsevie

Crude Oil Fractionation Facility Flow Sheet [2]

[2] "Crude Oil Fractionation Facility Flow Sheet" from : ASPENHYSYS *Refining Tutorial*

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Crude Column Sub-Flow Sheet [3]

[3] "Crude Column Sub-Flow Sheet" from : ASPENHYSYS *Refining Tutorial*

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