MODEL-BASED CONTROL DEVELOPMENT FOR BINARY PILOT PLANT DISTILLATION COLUMN

By

Muhammad Hafiz bin Mat Basri

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Dissertation submitted in partial fulfilment of

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Universiti Teknologi PETRONAS

32610 Bandar Seri Iskandar

Perak Darul Ridzuan

CERTIFICATION OF APPROVAL

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UNIVERSITI TEKNOLOGI PETRONAS

BANDAR SERI ISKANDAR, PERAK DARUL RIDZUAN

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CERITIFICATION OF ORIGINALITY

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

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(MUHAMMAD HAFIZ BIN MAT BASRI)

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ABSTRACT

The increasingly popular Model Predictive Control (MPC) strategy has been used in many process units either to improve the performance, save utility costs, or create a robust process able to cater to multiple variables. This project focuses on the development of model-based control for a distillation column in the Process Control laboratory at Universiti Teknologi PETRONAS (UTP) separating an ethanol-water and IPA-acetone mixtures. Specifically, the controller inputs are the reflux flow and the reboiler steam flow, while the outputs are distillate and bottom compositions respectively. Previous works have attempted to determine the dynamics of said column, therefore the MPC to be developed in this project is based on two of the derived models, one is a 2 X 2 Wood and Berry model and the other an inferential model. A comparison between the developed MPC controllers with standard PID controller is done to demonstrate the effectiveness and reliability of the MPC controller.

TABLE OF CONTENTS

CHAPTER 4: RESULTS AND DISCUSSION

CHAPTER 5: CONCLUSION AND RECOMMENDATION

LIST OF FIGURES

LIST OF TABLES

CHAPTER 1

INTRODUCTION

1.1 Background

The increase in knowledge and subsequent development of technology associated with industrial processes have resulted in increased demands for more efficient processing facilities able to supply products that meet the specifications as requested by the global consumer. That, in turn, will add to the existing demands of energy, product intermediates, and other raw materials to feed the industry. In that aspect, the oil and gas and petrochemical industries remained relevant due to an increased demand for fossil fuel products. Incidentally, one of the most important process in the industry is distillation. This can be seen as there are over 40000 columns operating worldwide (Rewagad & Kiss, 2012).

Distillation is defined as a process in which a mixture of two or more liquid or vapour is separated into its individual components with the desired purity by adding or removing heat (Adel, Elamvazuthi, & Hanif, 2009; Tham, 2009). It can be performed in a batch or continuous operation, with various types of column depending upon the nature of the feed, column internals, and number of product streams (Tham, 2009).

The highly nonlinear properties of a distillation column resulted in a complex model of the process, while simplifying it may lead to the development of an inaccurate model (Baiesu, 2011). In this report, a model-based controller will be developed for a binary pilot plant distillation column. In literature reviews further explained in Chapter 2, it was acknowledged that the main advantages of choosing model predictive control (MPC) are its ability to minimize cost functions and it can handle both input and output constraints (Martin, Odloak, & Kassab, 2013).

Therefore, choosing MPC to govern the control actions for a distillation process may result in products that meet specifications and the process parameters can be easily changed to suit the production demands without having the process spiral out of control. This, however, is dependent on the type of model used to represent the process and its accuracy, and also the configuration of the control system.

1.2 Problem Statement

The issue with model-based control is that the model developed by one research may not be suitable for application in another, or to be used by other distillation columns. This posed a unique opportunity in which every distillation column may have its own process model and control strategy, as is with other unit operations. Hence, in this study, the MPC performance in controlling a binary distillation column (ethanol-water and IPA-acetone mixtures) will be compared using various models to determine the best model structure.

1.3 Objectives

The work involved in this project will be based on the binary pilot plant distillation column in UTP laboratory. The two objectives of this study are:

1. To develop and evaluate MPC controllers from a 2x2 Wood and Berry model (Abdul Mutalib, 2014) and an inferential model (E.Zani, 2014).

2. To evaluate and compare the performance of the MPC developed in objective 1 against standard PID controllers.

To achieve these objectives, steps taken and their proposed time frame are detailed in Chapter 3. Since understanding the subject matter is important before undertaking any project work, a literature review is done and presented in Chapter 2.

1.4 Scope of Study

The project is focused on developing a model-based control for the binary pilot plant distillation column located at the Process Control Laboratory in UTP. Previous works have dealt with developing and identifying the model of the distillation column. Therefore in this project it is not intended to develop a different process model unless the existing ones are not suitable to be used or not accurate. The scope of this project is limited to computer-aided simulation of the resultant model and MPC strategy, and will not be implemented to the actual column. However, data from previous studies using the column may be used as a comparison to the simulation data gathered from this project.

CHAPTER 2

LITERATURE REVIEW

2.1 Model-based Control

By definition, model-based control or Model Predictive Control (MPC) is not referencing to any specific control strategy. However, it is used to refer to a wide range of control methods that use the model of the process to be controlled in order to gain the control signals. The final objective would then be to minimize a cost function (Camacho & Alba, 2013). Several examples of process models that have been used to represent distillation are the Wood and Berry model, the fundamental model, and the multi model representation (Martin et al., 2013; Mishra, Khalkho, Kumar, & Dan, 2013; Truong, Ismail, & Razali, 2010).

According to Darby and Nikolaou (2012), MPC has become the standard approach to deal with constrained, multivariable process control in the industries. Specifically, in the petrochemical industry, it is used to control large multivariable processes (Stewart, Venkat, Rawlings, Wright, & Pannocchia, 2010). In keeping the relevance of this proposal to its intended subject, Section 2.3 is dedicated towards the application of MPC in distillation column.

Other applications of MPC not limited to chemical engineering industries are demonstrated in studies aimed at developing a climate control system for buildings, one of them using stochastic MPC (Oldewurtel et al., 2012; Široký, Oldewurtel, Cigler, & Prívara, 2011). The electrical engineering field had also benefited from using MPC based one work which explored its model design and implementation to a permanent-magnet synchronous motor (PMSM) to represent an electrical motor drive (Bolognani, Bolognani, Peretti, & Zigliotto, 2009).

One paper summarized the structure and function of the MPC as follows: for every interval, the controller predicts the future output response of the process by a set number of steps where the value predicted is based on past and future actuation (Kumar & Ahmad, 2012). Then, the future control actions are calculated by minimizing the cost function. However, only the first step of this calculation is implemented. After each implementation, the predicted control action is corrected using the same steps as mentioned above.

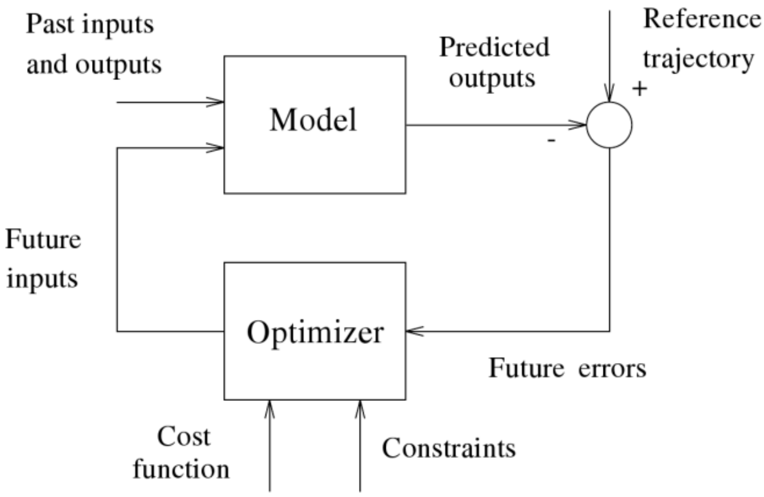


Figure 2.1: MPC Structure (Camacho & Alba (2013))

Based on Figure 2.1, the process model is used to calculate predicted future values, based on past and current values and the proposed future control actions. The optimizer then calculates the actions to be taken with consideration to the cost function and the process constraints (Camacho & Alba, 2013).

Seborg, Edgar, and Mellichamp (2006) summarized the implementation of MPC into eight steps: (i) Initial controller design. The controlled, manipulated, and disturbance variables are specified to determine the structure of the MPC. (ii) Pre-test activity. Plant instrumentation relevant to the implementation of the MPC is checked and the DCS loops are tested to verify their performance. (iii) Plant test. Pseudorandom Binary Sequence (PRBS) or step change is used to determine the effect of manipulated and disturbance variables to the process response. (iv) Model development. From (iii), the data is used to develop the dynamic model of the process, including an accuracy characterization of the model. (v and vi) Control system and operator interface design, simulation, and training. Based on control and optimization objectives, constraints, and the dynamic model, the MPC is designed by evaluation and modification of the initial controller in (i). After simulation to evaluate the controller performance, operators are trained to understand the relationship between input and output for an MPC. (vii) Installation and Commissioning. The system is installed and evaluated in a prediction mode where the model prediction is compared to the actual value, but control actions are only taken by the existing control system. (viii) Measuring results and monitoring performance. The performance of the MPC is evaluated by comparing process values to the target and constraints. A continuous monitoring of the system is important to ensure no degradation of performance occur during its lifetime.

Among the advantages of model-based control are its inherent robustness, low cost of computation to solve the optimization problem, and the ability to handle process constraints (Darby & Nikolaou, 2012; Kumar & Ahmad, 2012). The ability to predict future dynamics in a finite horizon, the control action may be employed early on. MPC can also be employed to a variety of processes, both linear and nonlinear. It also intrinsically contains compensation for time delays and compensates for disturbances like a feed-forward control (Kumar & Ahmad, 2012).

2.2 Binary Distillation Column

Distillation is highly significant among the separation processes in industries because it can be used to separate liquid and vapour mixtures in a large scale (Ravagnani, Reis, Filho, & Wolf-Maciel, 2010). It is the most practical and most extensively applied fluid separation method in process industries. The relevance of distillation is such that for large companies, investing for innovation in its technology is crucial to stay competitive (Olujić, Jödecke, Shilkin, Schuch, & Kaibel, 2009).

Based on the column types, conventional distillation may be divided into packed bed distillation and plate or tray distillation. In Figure 2, the schematic of a conventional tray distillation column is provided, showing feed (F), distillate (D), bottom product (B), reflux (R), condenser (Qc), and reboiler (Qr). However, apart from the conventional distillation, there exists several other distillation techniques such as vacuum, cryogenic, extractive, reactive, pressure swing (PSD), and azeotropic distillation (Naik et al., 2014). These distillation methods are selected based on the components to be separated.

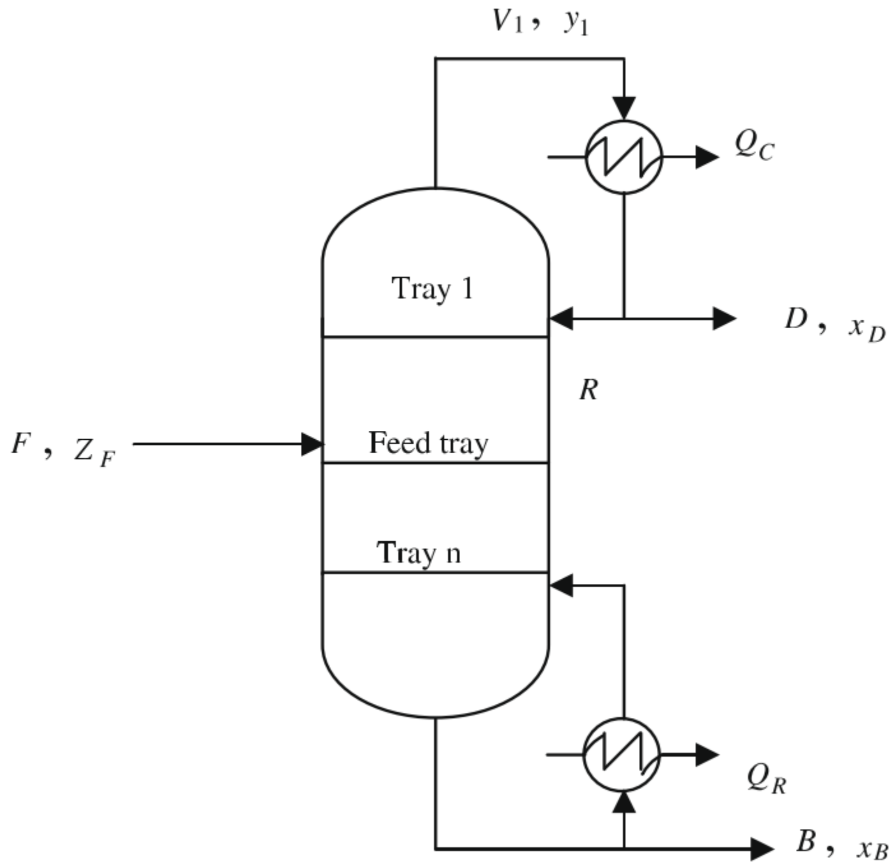


Figure 2.2: Schematic diagram of a conventional distillation column (Jana (2010))

A study which dealt with a heat integration distillation technique, namely the vapour recompression column, to separate an ethanol-water mixture to 90mol% ethanol purity (Enweremadu, Waheed, & Ojediran, 2009). According to another study, this method has the prospective for significant energy savings for fractionating a close-boiling mixture (Jana, 2010). This was confirmed in the first paper, although the system performance value was cited as "unrealistically high" due to assumption of several parameter (Enweremadu et al., 2009).

Because a distillation column has multiple input and multiple output variables, and due to the nonlinear behaviour, there will be difficulty when designing the control strategy for the process. As was mentioned in another, a system which is multivariable and nonlinear results in a complex control problem due to various input and output couplings (Fernandez de Canete, Gonzalez, del Saz-Orozco, & Garcia, 2010).

The unique characteristics of high purity binary composition distillation column like the complex dynamics, high nonlinearity and the interaction between the control loops makes dual composition control a challenging problem (Biswas, Ray, & Samanta, 2009).

Another difficulty in distillation is that eventhough composition control is important, online composition analyser are expensive and hard to maintain. Relating temperature to composition also is not a reliable method since tray temperature does not correspond to the composition at each stage. Thus, in one study, the authors used inferential control to regulate product purity in a reactive distillation column (Bahar & Özgen, 2010).

In another study, the use of Adaptive Feedback Linear Control (AFLC) managed to simulate successful control of a high purity distillation column. The rationale behind choosing this mode of control on a distillation column is to study the effect of parameter uncertainty and input saturation on Feedback Linearization Control (Biswas et al., 2009).

2.3 Model-based Control on Binary Distillation Column

MPC can and have been used in a wide range of industrial applications. From Section 2.1 several works were mentioned. This section will emphasize on research and application of MPC on binary distillation columns. It was stated that there are over a thousand application of MPC in distillation processes (Martin et al., 2013).

The reason why these studies are important is because traditional linear models representing distillation column dynamics and used in linear controllers only perform well in a limited range of the operating point and is not designed to handle large disturbances (Biswas et al., 2009).

Furthermore, from the economic viewpoint, control of distillation columns is crucial since the operation method affects the quality of the product, production rate, and utility usage (Szabó, Németh, & Szeifert, 2012). Therefore, effective control may result in products that meet specification as well as help in reduction of utility costs.

In one study, it was mentioned that there are three ways to model a distillation column which are fundamental modelling, empirical modelling, and hybrid modelling. These are part of the nonlinear models available to be used in a nonlinear MPC (Camacho & Alba, 2013). From all of the mentioned models, fundamental modelling is the easiest to explain and the simplicity of the model can be adjusted based on the level of accuracy of the assumptions made during the modelling. Meanwhile, in empirical modelling, the experimental data of a distillation column is used to create a correlation between the input and output. The hybrid modelling method combines empirical and fundamental modelling to gain benefits from both methods. However, a decision must be made to determine which method to be used on parts of the model (Truong et al., 2010).

One study which used the empirical method was done by taking data from an industrial distillation column and fitting it as a second-order transfer function with dead time (Baiesu, 2013). The model was then used to determine the PID parameters of a controller which provided sufficiently good control over the process. Another work which demonstrated the use of an Internal Model Control while the process is modelled by the Wood and Berry model also managed to get good control performance even with disturbance included (Mishra & Dan, 2013).

Apart from that, a comparison of MPC and PID controllers on a DWC distillation column separating a ternary mixture of Benzene-Toluene-Xylene (BTX) are illustrated in one study (Rewagad & Kiss, 2012). The authors selected the best PID controller based on their previous study on the same system and compared its performance with an MPC developed in the paper. It was concluded that the MPC reacts consistently accurate to the disturbance and set point changes applied to the system with smaller overshoot and settling time as compared to the PID controller (Kiss & Rewagad, 2011; Rewagad & Kiss, 2012).

Another paper concluded in their review, upon comparing multi-loop PID controllers to MPC and other advanced control strategies to control a DWC distillation column, that the MPC is the best controller to be used when SISO control is not sufficient. It was mentioned that the benefits of using advanced MIMO such as MPC are the significantly shorter settling time and better control performance (Kiss & Bildea, 2011).

Another work reviewed was concerning the effects of tuning parameters to the model predictive control in a binary distillation column. A 2x2 Wood and Berry model was used to describe the distillation column. By changing the tuning parameters, manipulated input and the horizon, to the step response model, it was discovered that at certain tuning parameters, the MPC performed better than other types of control (Mishra et al., 2013).

CHAPTER 3

METHODOLOGY

In this chapter, the project and simulation activities are presented in the form of flowcharts followed by explanation and a brief description of the distillation column to be simulated is also provided. The final section of this chapter provides an expected timeline of the project in FYP 1 and FYP II along with key milestones.

For all works in this report, the models used are:

Model 1 by Abdul Mutalib (2014):

$$\begin{bmatrix} x_D \\ x_B \end{bmatrix} = \begin{bmatrix} \dfrac{0.187}{1.29s+1} & \dfrac{-0.0086}{0.73s+1} \\ \dfrac{0.0031}{0.96s+1} & \dfrac{-0.00024}{0.84s+1} \end{bmatrix} \begin{matrix} R(s) \\ S(s) \end{matrix}$$

Model 2 by E.Zani (2014):

$$x_D = 0.114T_{15} + 0.131T_R + 1.65$$

Where:

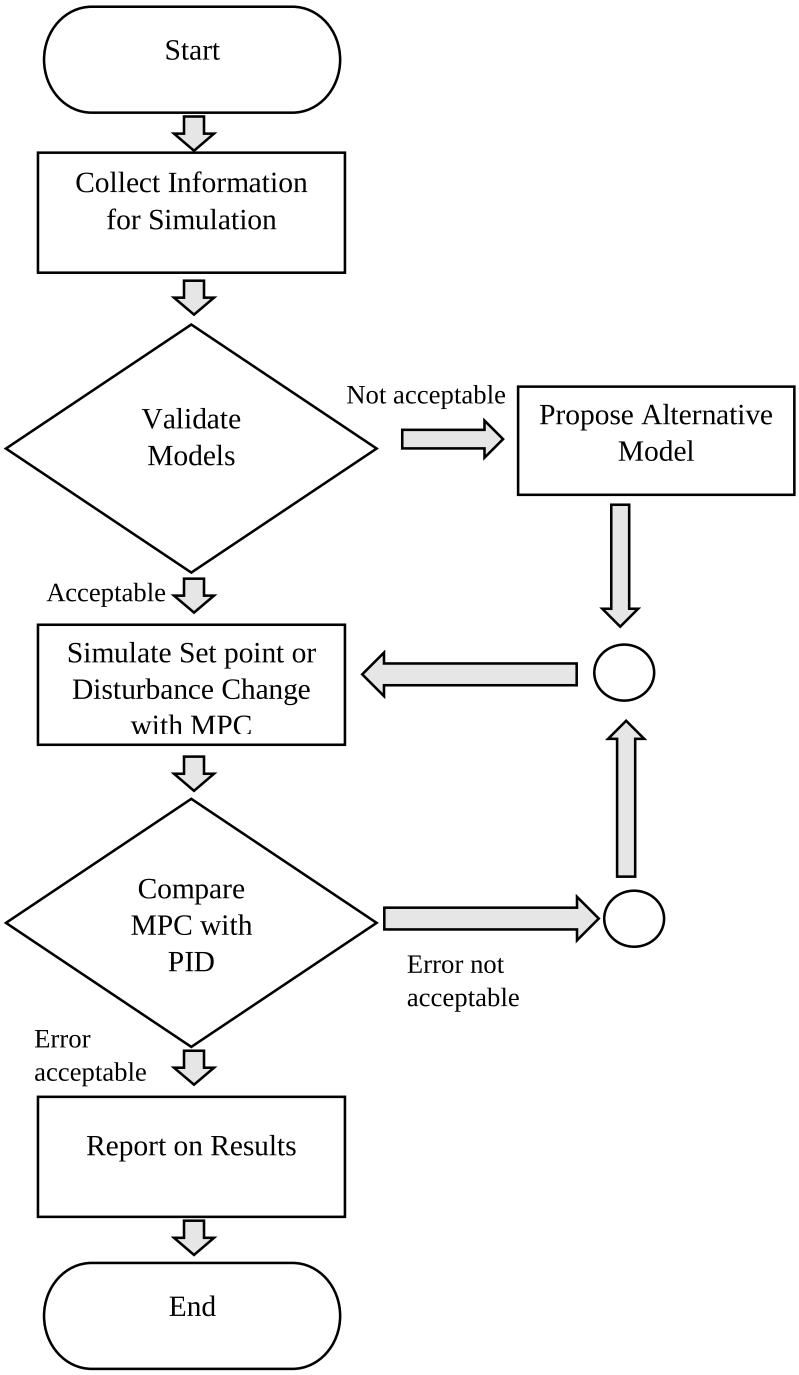
x_D = Acetone composition at the top product

x_B = Acetone composition at the bottom product

T_{15} = Temperature at the 15th tray

T_R = Temperature of the reflux

3.1 Project Activities



3.1.1 Collect Information for Simulation

Literature review is done to study how distillation works as well as to obtain information on how to utilize the software (MATLAB) for the purposes of this project. The relevant literature is found in Chapter Two, and the simulation activities are explained in the next section.

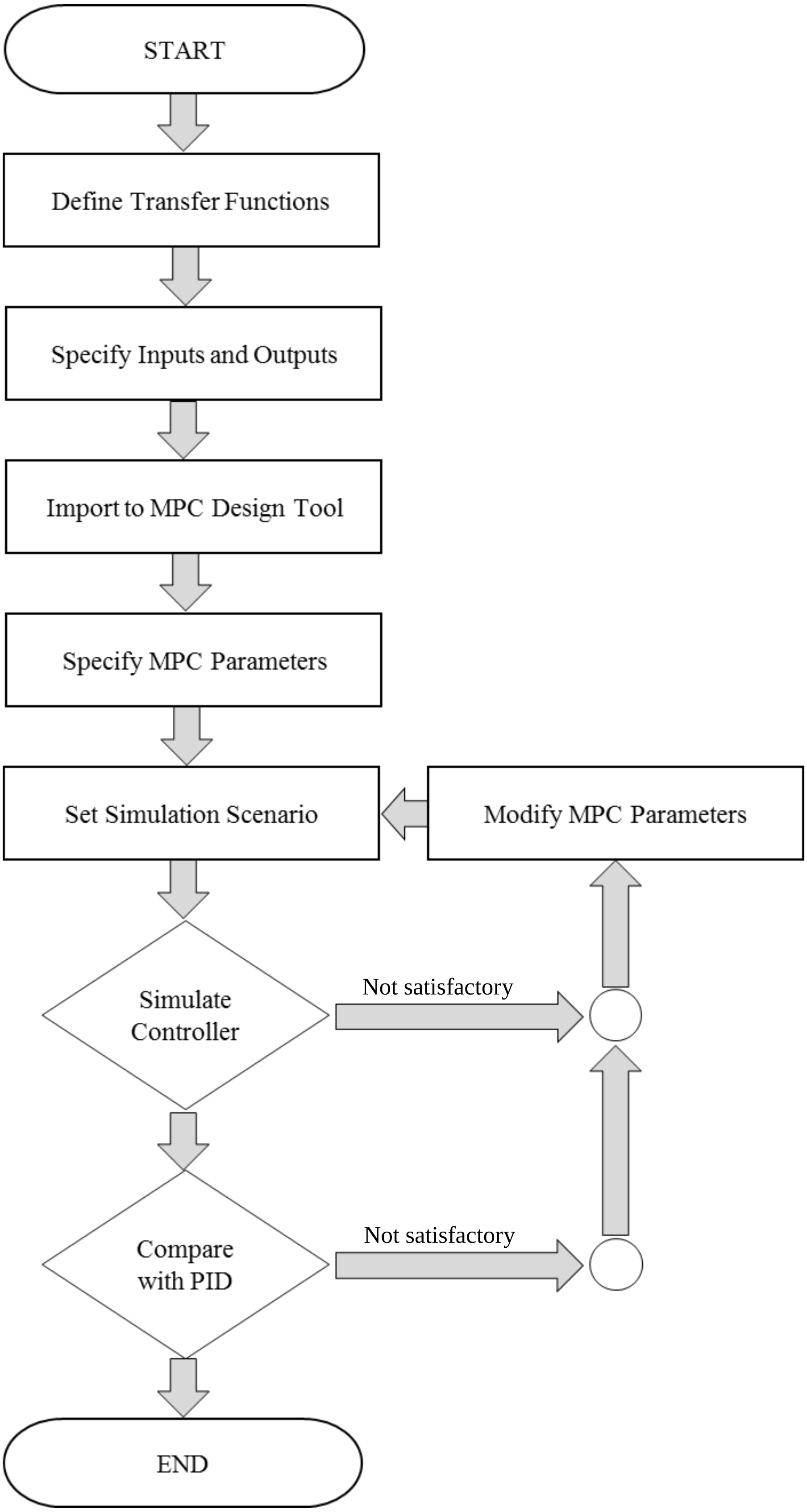
3.1.2 Validate Models

To ensure that the models used are a correct representation of the process, a validation of the models are done. This involves recreating the steps on how the models were developed. If the model is not an acceptable representation of the process, or if the model needs modification, an alternative model is to be proposed. This is the case with the inferential model being used in this project, where it is used alongside available data to develop a new model based on its correlation.

3.1.3 Simulate Set point or Disturbance Change with MPC

The simulation of set point and disturbance changes is then done using MATLAB to study the effectiveness of the MPC controller developed in regulating the process. A detailed explanation of the steps are available in the next section.

3.2 MATLAB Simulation Activities



3.2.1 Input Plant Model into MATLAB

To define the plant model in MATLAB, a variable must be used to contain each of the transfer functions present. In this case, the 2x2 Wood and Berry model has four transfer functions. Therefore, each transfer function will be defined as its own variable. The variables will then be defined as a matrix, thus compiling the model as one variable in matrix form. The example below shows how one of the models are defined in the MATLAB workspace.

```
G11=tf([0 -0.0848],[11.66 1])
G12=tf([0 -9.059E-5],[2.1 1])
G21=tf([0 0.0727],[11.66 1])
G22=tf([0 7.788E-5],[2.1 1])
DC=[G11 G12
G21 G22];
DC.InputName={'Reflux','Steam'};
DC.OutputName={'xd','xb'};
DC=setmpcsignals(DC,'UD',2)
```

3.2.2 Developing Transfer Function for Model 2

The model developed by E.Zani (2014) was an inferential model which only predicts the top composition based on temperature of the top tray (tray 15) and temperature of the reflux liquid. It is not in the form of transfer functions or state-space equations, therefore cannot be entered into MATLAB as a plant model.

Using the model, the top composition of 672 data points from a previous ethanol-water separation were predicted, and their respective bottom composition estimated from the top composition. With this data, the transfer function for model 2 was derived using methods explained in Abdul Mutalib (2014). The resulting plant model is given in a 2x2 Wood and Berry model form:

$$\begin{bmatrix} x_D \\ x_B \end{bmatrix} = \begin{bmatrix} \frac{-0.08481}{11.66s+1} & \frac{-9.06\times10^{-5}}{2.105s+1} \\ \frac{0.0727}{11.66s+1} & \frac{7.788\times10^{-5}}{2.10s+1} \end{bmatrix} \begin{matrix} R(s) \\ S(s) \end{matrix}$$

3.2.2 Importing Model to MPC Design Tool

In MATLAB workspace, the function ‘mpctool’ opens the Control and Estimation Tools Manager (from here on, for simplicity, the term MPC Toolbox will be used to refer to the Tools Manager) which is used in this project for the purposes of specifying the controller parameters and simulating all scenario.

To import the model defined in the workspace, the Plant Model Importer will list all variables defined and their properties. Selecting the appropriate variable and clicking the import button will set the variable as the plant model for the MPC Toolbox.

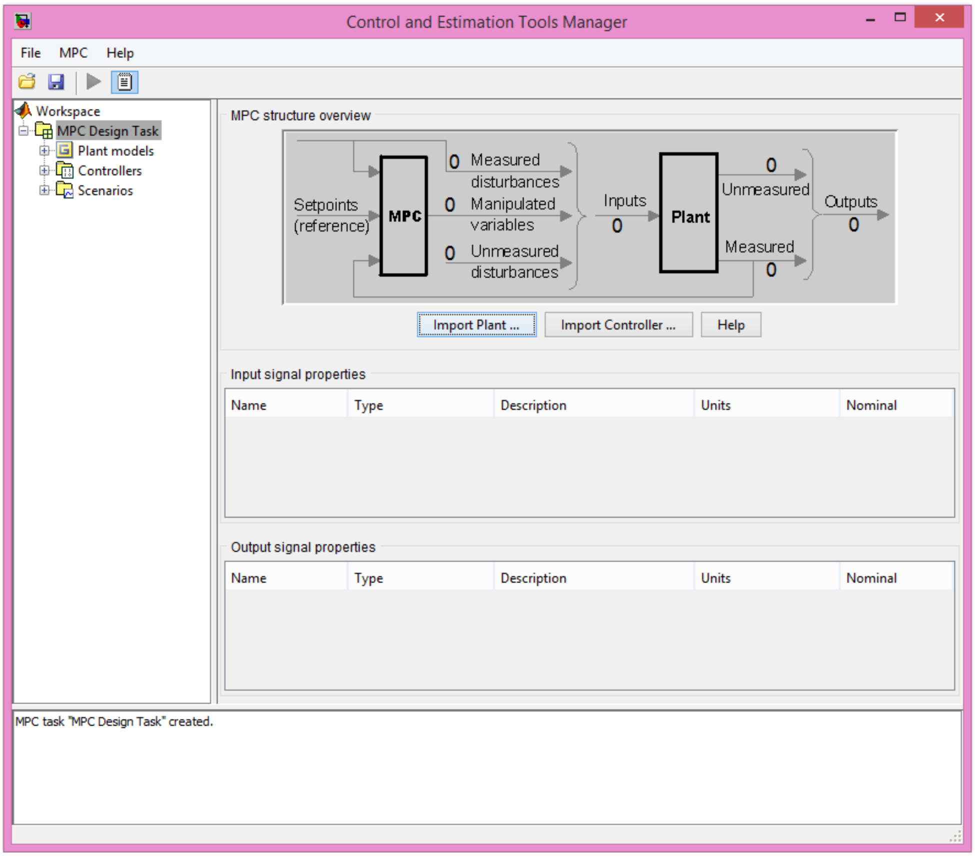


Figure 3.1: The Control and Estimation Tools Manager in MATLAB

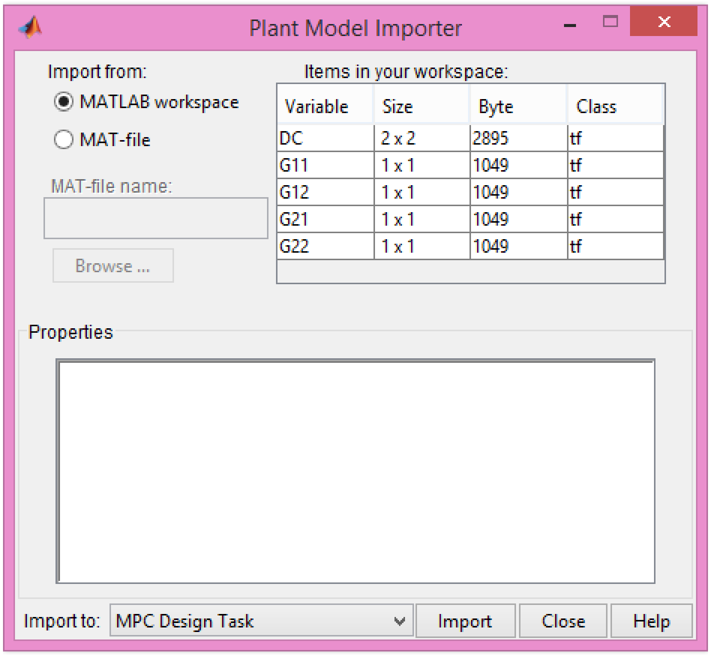


Figure 3.2: The Plant Model Importer in MATLAB

3.2.3 Specifying MPC Parameters

In the controller menu, the MPC parameters can be specified. For the purposes of this project, the parameter specification is limited to the Model and Horizon tab and the Weight Tuning tab. A full list of parameter values studied and their effects on input and output variables are available in the appendices.

3.2.4 Simulating Controller for Different Scenario

After the MPC parameters are specified, the controller can be tested in various user-defined conditions. The scenario menu allows for set point and disturbance change for all variables defined in the model. In this project, the set point changes are set as a step signal and disturbance changes are set as pulse signals.

Table 3.1: Set Point for Simulation

Model	Top Composition Set Point	Bottom Composition Set Point
Model 1	0.6	0.3
Model 2	0.3	0.1

Table 3.2: Values for Disturbance Rejection Simulation

Disturbance	Trial 1	Trial 2	Trial 3	Trial 4	Trial 5	Trial 6
Top Composition	0.1	0.2	0.3	-	-	-
Bottom Composition	0.1	0.2	0.3	-	-	-
Reflux	0.1	0.2	0.5	1	2	5
Steam	0.1	0.2	0.5	1	2	5

3.2.5 Comparison with PID

To compare the MPC with PID controller, a 1-1/2-2 PID control strategy was created in Simulink. The same set point and disturbance changes were applied to the system as in the MPC simulation, and the results were compared with the performance of the MPC controller. Tuning of the PID controllers were done automatically using MATLAB itself. The figure below shows how a 1-1/2-2 PID control loop is set up for controlling the process.

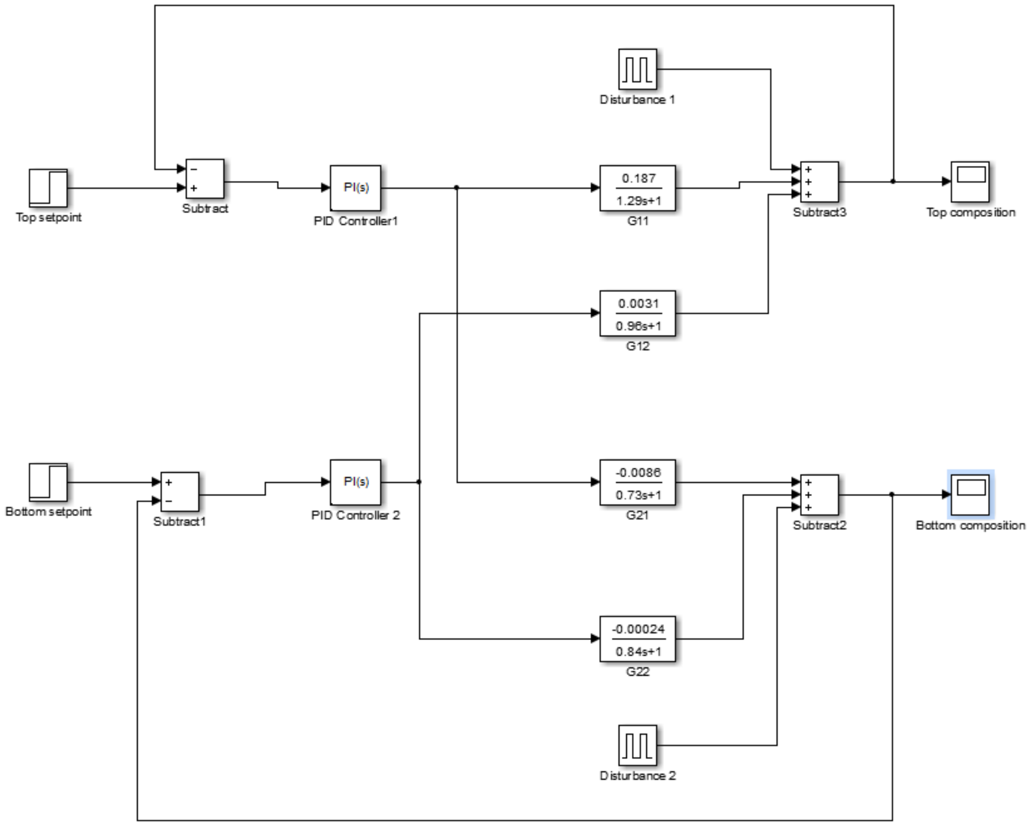


Figure 3.3: 1-1/2/2 PID loop using Simulink in MATLAB

3.3 Description of the Distillation Column

The MPC for binary distillation column will be modelled based on the distillation column located in the process control laboratory in Block 3 of Universiti Teknologi PETRONAS. A brief description of the column of interest is provided below.

Table 1.3: Distillation Column Description

Construction Material	Stainless Steel
Height	5.5 m
Diameter	0.15 m
Number of Trays	15
Type of Tray	Bubble Cap
Tray Spacing	0.35 m
Feed Tray	Trays 3, 7, or 11
Maximum Feed Flowrate	110 L/min
Reboiler Duty	9.36×10^6 J/hr
Measurable Temperature	0.0-150.0^o C
Measurable Pressure	0.00-4.00 bar
Control System	Honeywell Experion PKS DCS

3.4 Gantt Chart and Project Milestone

Table 3.4: Gantt Chart for FYP I

Week / Activity	1	2	3	4	5	6	7	8	9	10	11	12	13	14
Project selection														
Literature review														
Methodology and planning														
Extended proposal drafting														
Extended proposal submission														
Proposal defence														
Project Work														
Interim report drafting														
Interim report submission														

Table 3.2: Gantt Chart for FYP II

Week / Activity	1	2	3	4	5	6	7	8	9	10	11	12	13	14
Develop MPC for Model 1	■	■	■	■	■	■	■	■						
Validate Model 1						■	■	■	■					
Progress Report Submission								●						
Simulation Work on Model 1 and 2								■	■	■	■	■		
Pre SEDEX											●			
Comparison of MPC with PID											■	■	■	
Submission of softbound report													●	
Submission of Technical Paper													●	
Oral Presentation														●
Submission of hardbound dissertation														●

Legend: ■ Proposed duration of work

● Milestone

CHAPTER 4:

RESULTS AND DISCUSSION

4.1 Set point Change on Model 1

Based on the study by Abdul Mutalib (2014), in deriving the model, data obtained show an acetone top composition ranging from 0.54 to 0.73, and a bottom composition of 0.45 to 0.66. The top composition set point for this simulation is 0.6. For the bottom composition, a value of 0.3 was chosen. Each MPC parameter studied was measured against its ability to track the process to the required set point.

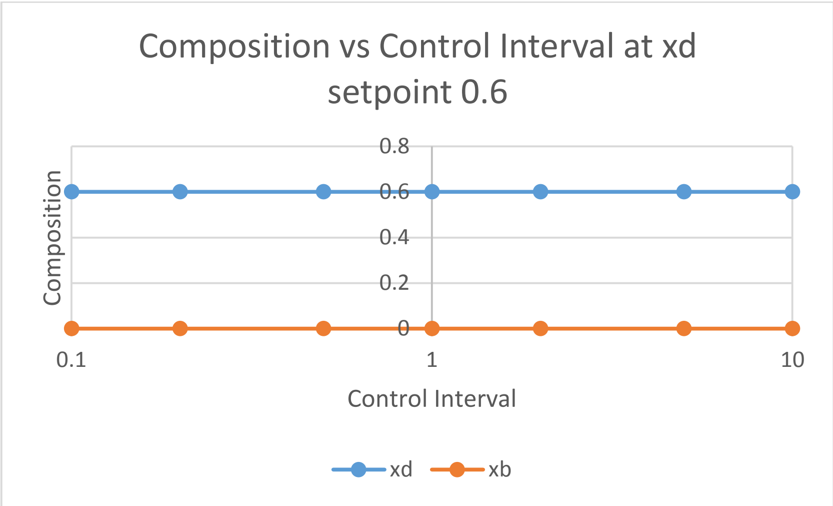


Figure 4.1: Effect of Control Interval on Controlled Variables for Top Composition Set Point

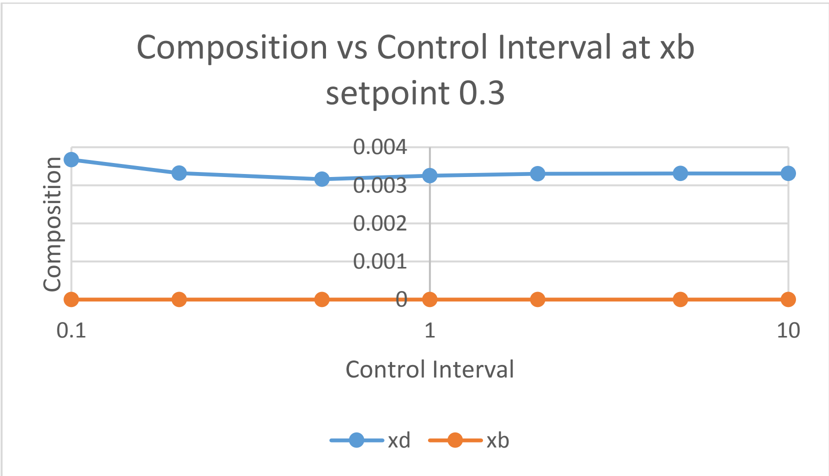


Figure 4.2: Effect of Control Interval on Controlled Variables for Bottom Composition Set Point

As can be seen from Figures 4.1 and 4.2, the control interval does not affect the process output. However, it does affect the input variable movements. For all the control intervals, the reflux flow obtains steady-state at 7.9. At a control interval of 5, it can be seen that the reflux and steam flow maximum values are approaching the steady-state. Thus, for the control interval, a value of 5 is selected.

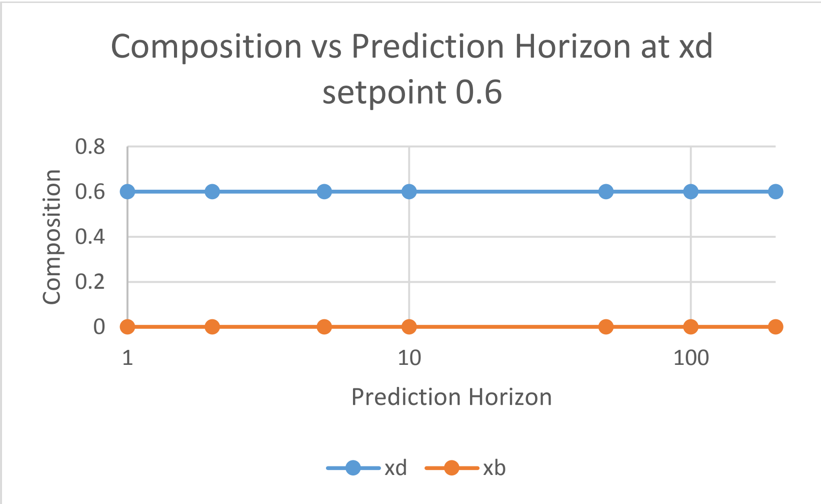


Figure 4.3: Effect of Prediction Horizon on Controlled Variables for Top Composition Set Point

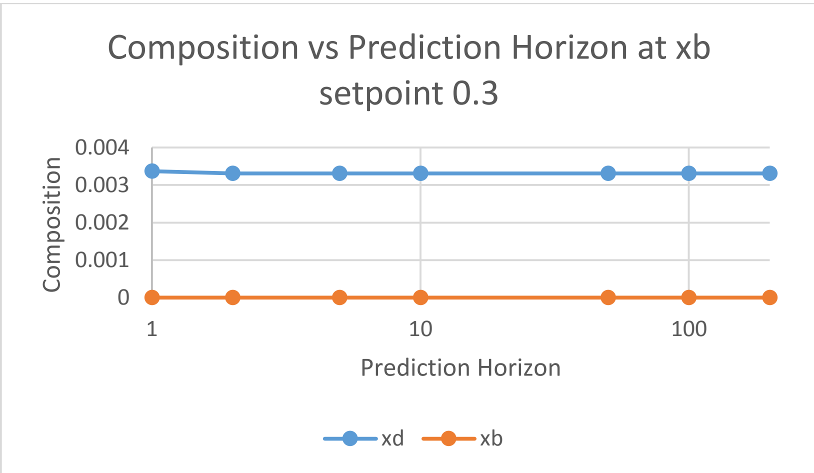


Figure 4.4: Effect of Prediction Horizon on Controlled Variables for Bottom Composition Set Point

According to Wojsznis, Gudaz, Mehta, and Blevins (n.b), the prediction horizon must be sufficiently large that the controller performance is no longer affected by further increments. During the tuning of prediction horizon in this simulation, it was observed that the composition were not affected by its change. The reflux and steam input also showed minimum change with respect to changes in the prediction horizon. It can be seen, however, that the input response begins to level off at a prediction horizon value of 50.

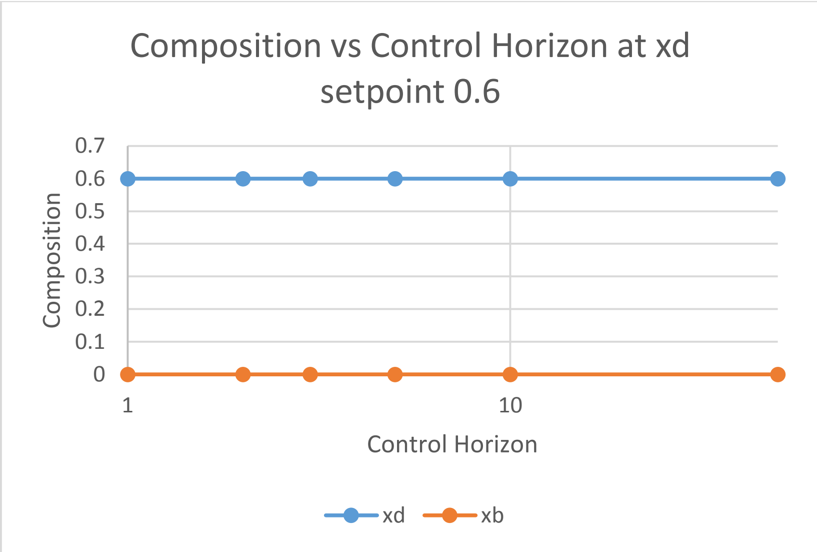


Figure 4.5: Effect of Control Horizon on Controlled Variables for Top Composition Set Point

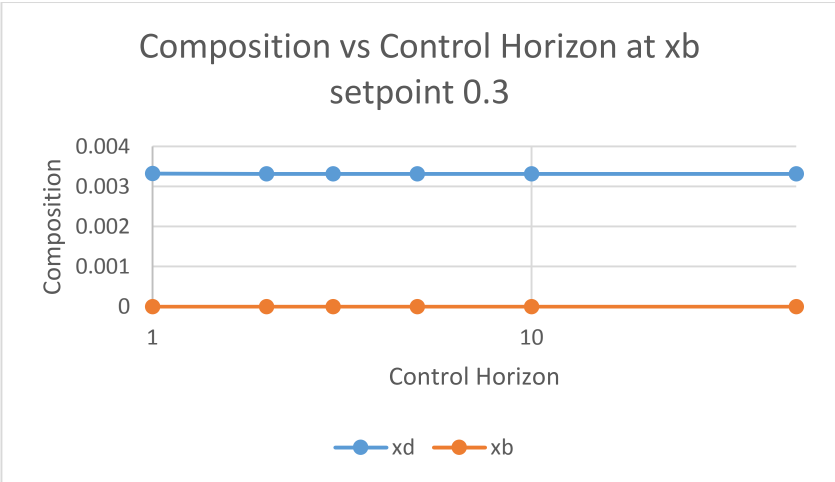


Figure 4.6: Effect of Control Horizon on Controlled Variables for Bottom Composition Set Point

The control horizon values were increased from 1 to 50 in six trials. The results for each value of control horizon present no effect to the controlled variables. It also shows very little effect on the movement of the manipulated variable, reaching a steady value of manipulated variables from control horizon at value 3 onwards.

Overall, for the model and horizon parameters, the controller was able to obtain the top composition set point with relative ease as compared to the bottom composition which was not reached despite various changes in the tuning parameters.

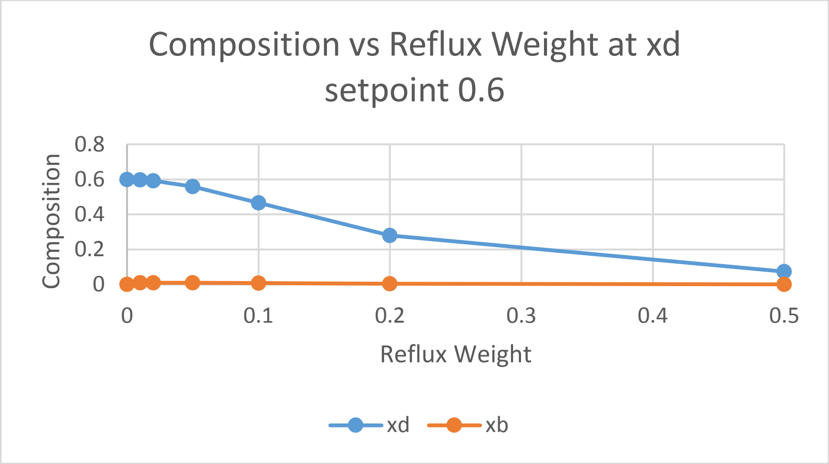


Figure 4.7: Effect of Reflux Weight on Controlled Variables for Top Composition Set Point

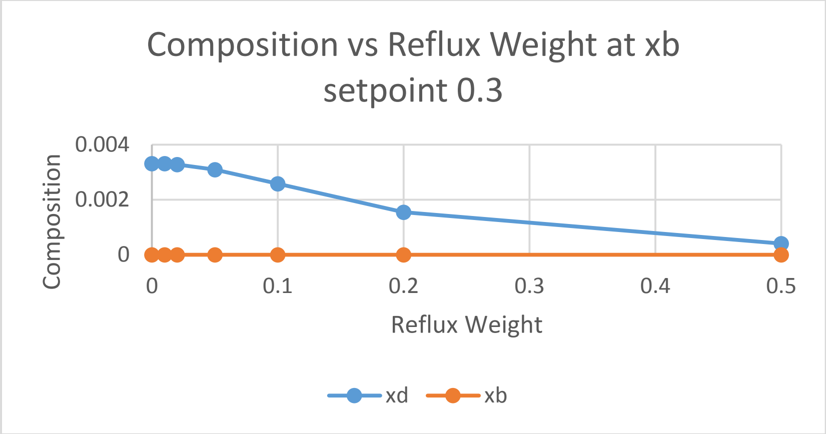


Figure 4.8: Effect of Reflux Weight on Controlled Variables for Bottom Composition Set Point

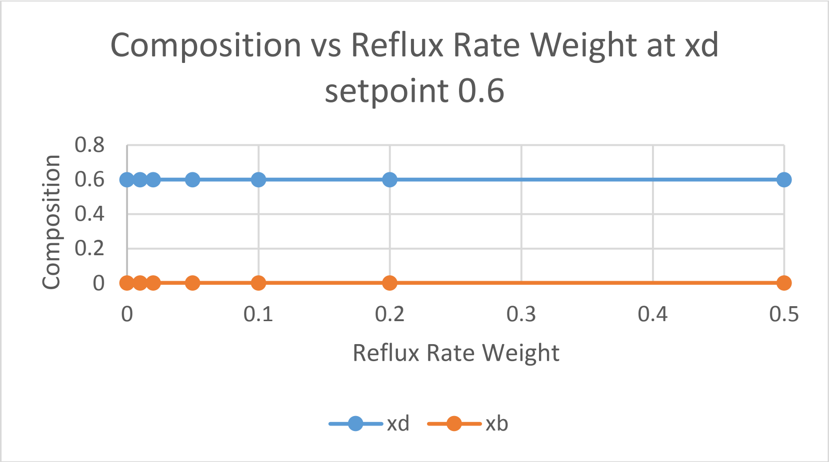


Figure 4.9: Effect of Reflux Rate Weight on Controlled Variables for Top Composition Set Point

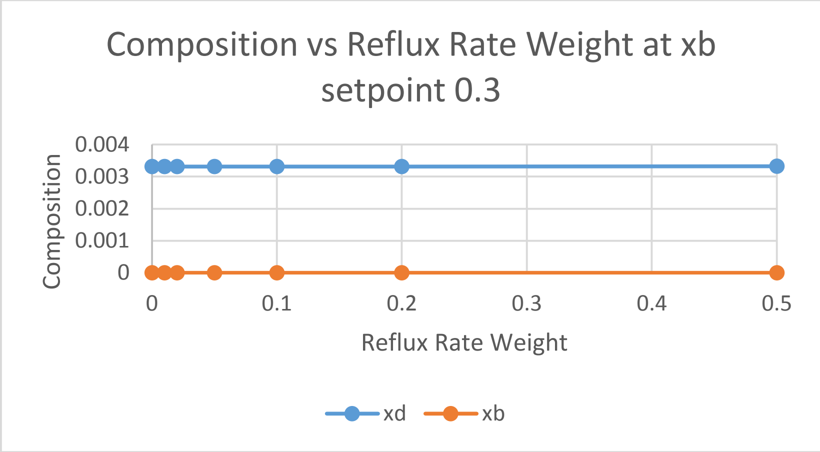


Figure 4.10: Effect of Reflux Rate Weight on Controlled Variables for Bottom Composition Set Point

The reflux weight changes were observed to have a significant impact on the controlled variables. It can be seen from the figures that an increase in reflux weight caused the controller to not be able to reach the top composition set point value. In addition, even though the bottom composition set point was not reached, the change in reflux weight had decreased the steady state value even further. On the contrary, the reflux rate weight did not affect the value of composition throughout the simulation.

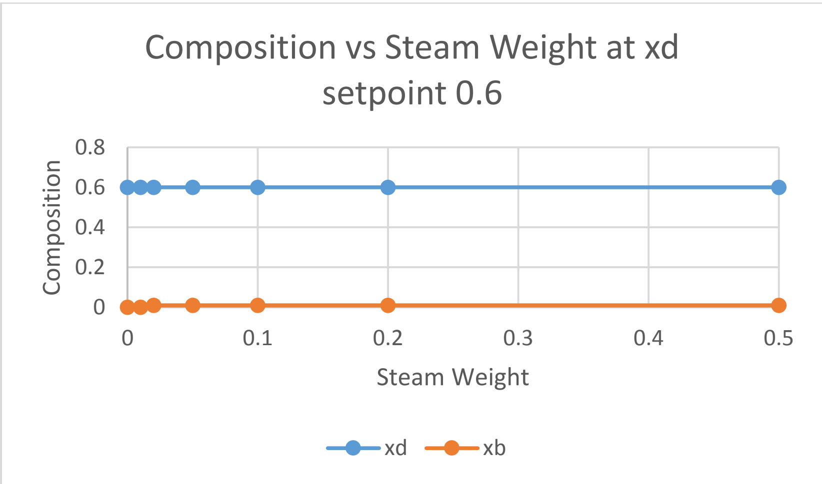


Figure 4.11: Effect of Steam Weight on Controlled Variables for Top Composition Set Point

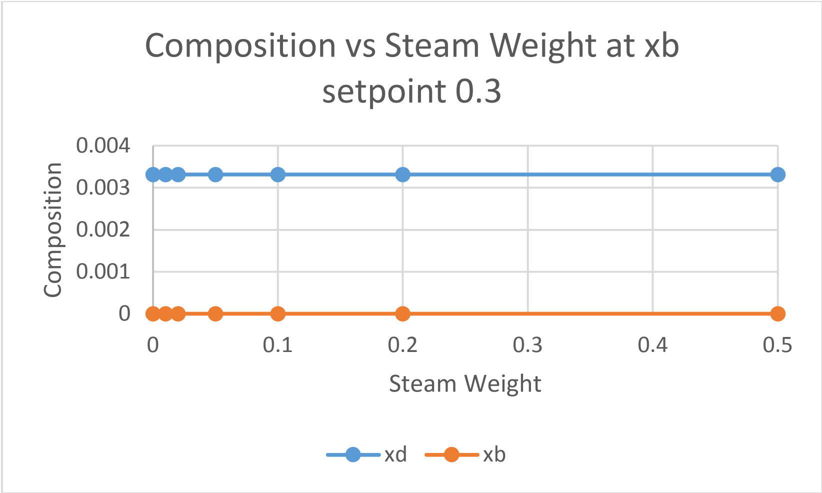


Figure 4.12: Effect of Steam Weight on Controlled Variables for Bottom Composition Set Point

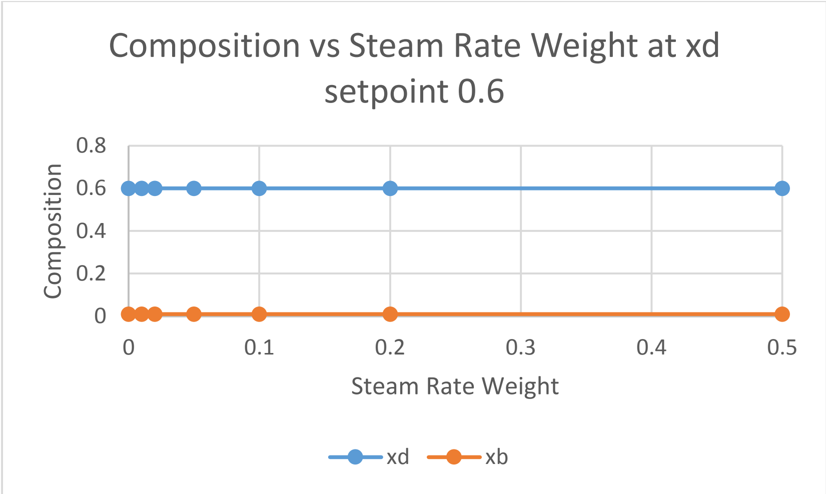


Figure 4.13: Effect of Steam Rate Weight on Controlled Variables for Top Composition Set Point

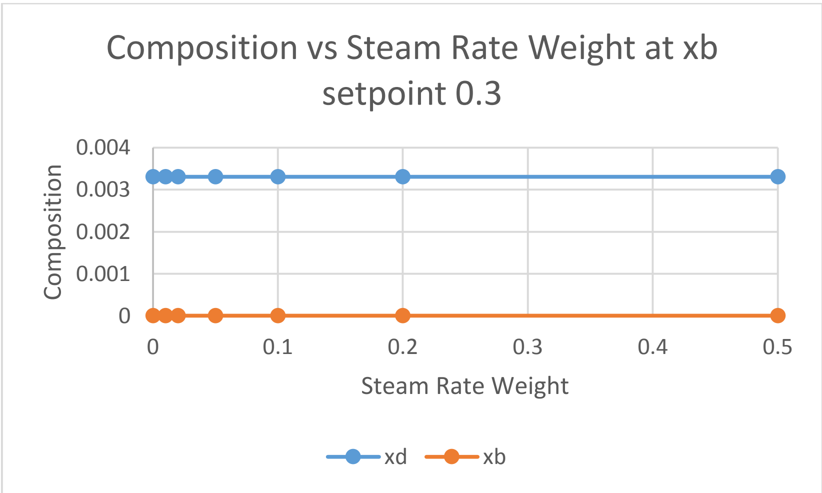


Figure 4.14: Effect of Steam Rate Weight on Controlled Variables for Bottom Composition Set Point

Steam weight and steam rate weight were observed to have no effect on the controlled variable output. For both parameters, the top composition set point value were maintained, and the bottom composition set point were still not reached even after varying the parameter values. The steam movement, on the other hand, were significantly affected. At steam weight of 0, the steam input was 103, and at 0.1, the steam value dropped to 0.

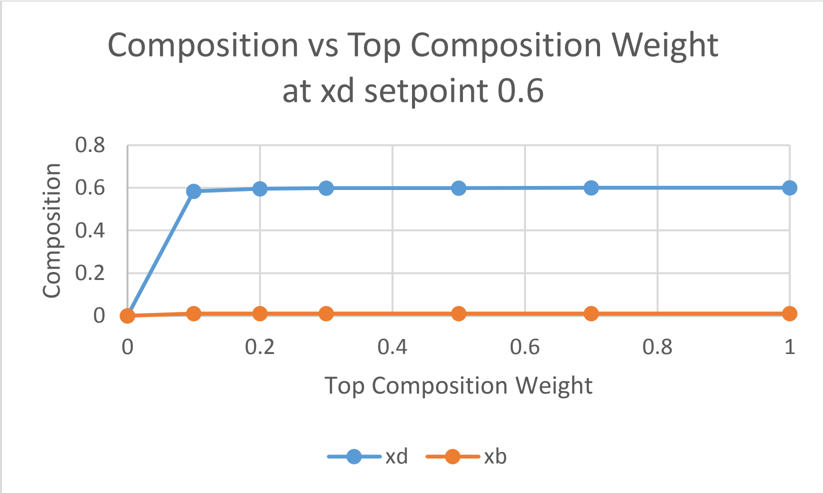


Figure 4.15: Effect of Top Composition Weight on Controlled Variables for Top Composition Set Point

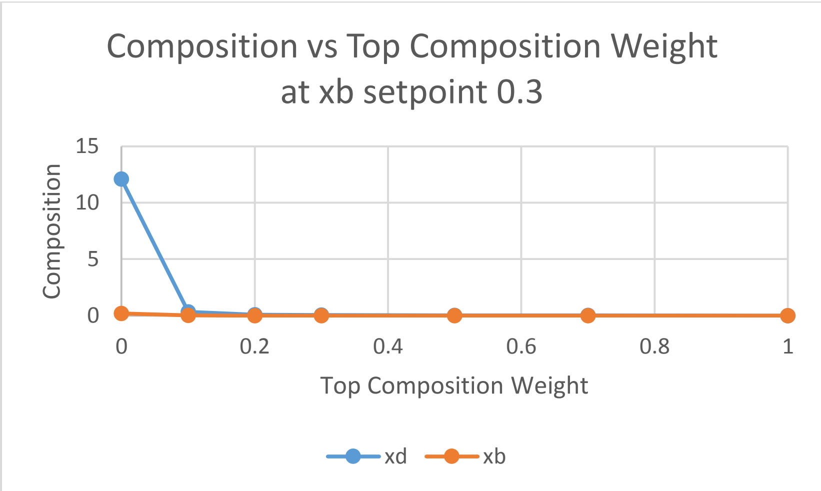


Figure 4.16: Effect of Top Composition Weight on Controlled Variables for Bottom Composition Set Point

It can be seen from the figures that the top composition weight only affects the top composition set point when it is at zero. When the top composition weight is zero, the top composition value during bottom composition set point 0.3 is a non-zero value. Therefore, any non-zero value would be possible as a parameter value. However, the relative weight against bottom composition set point also has to be taken into consideration.

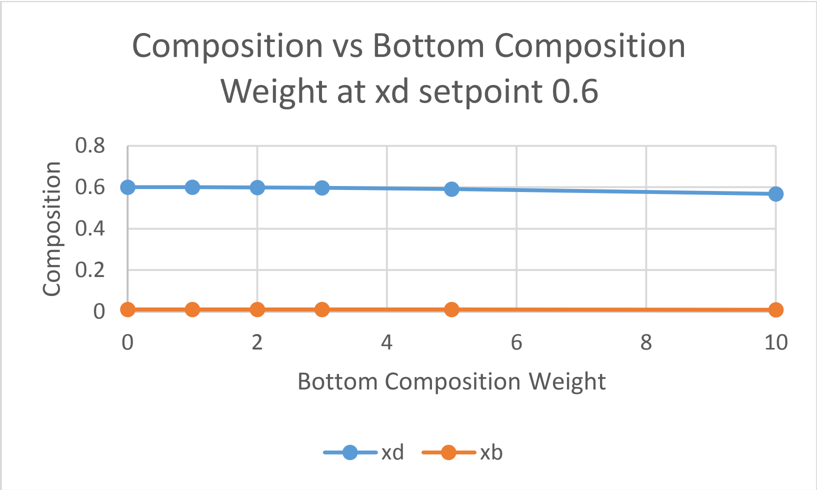


Figure 4.17: Effect of Bottom Composition Weight on Controlled Variables for Top Composition Set Point

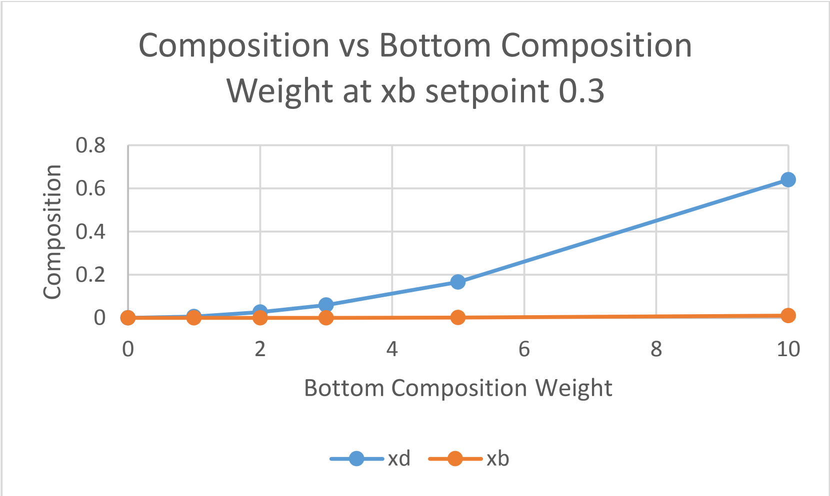


Figure 4.18: Effect of Bottom Composition Weight on Controlled Variables for Bottom Composition Set Point

The bottom composition weight parameter was also studied. In the figures above it is observed that the bottom composition did not respond to the change in its weight. Rather, the top composition seems to have been affected by large values of the parameter.

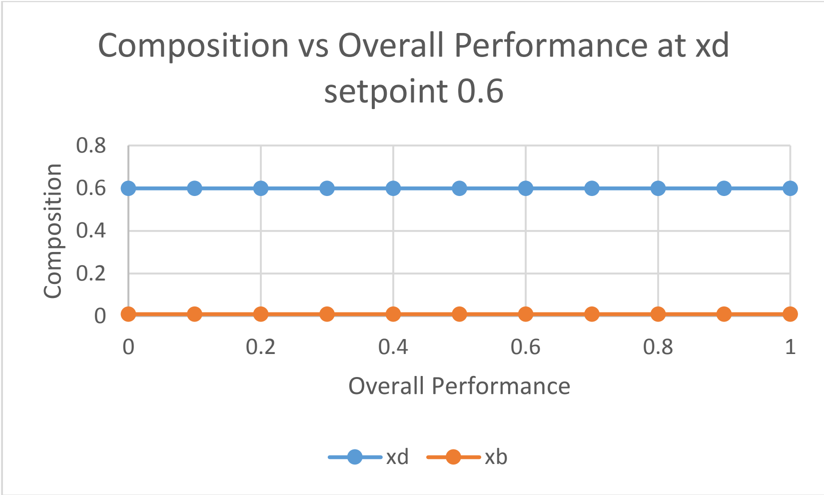


Figure 4.19: Effect of Overall Performance on Controlled Variables for Top Composition Set Point

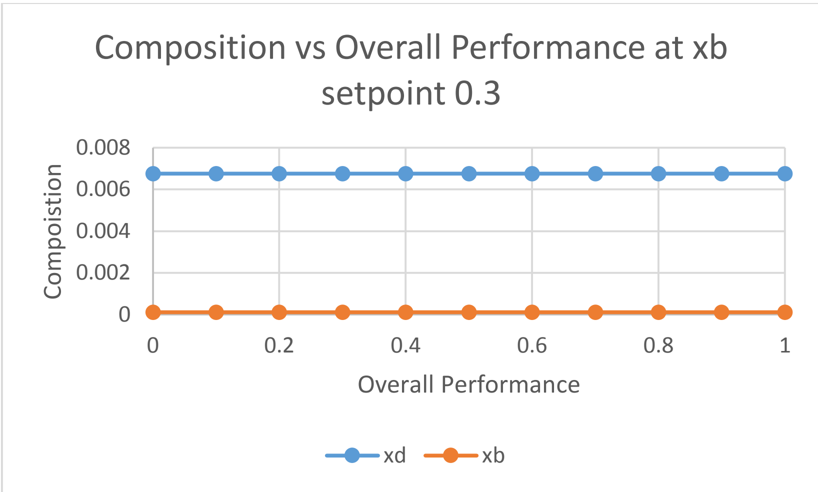


Figure 4.20: Effect of Overall Performance on Controlled Variables for Bottom Composition Set Point

The overall performance parameter was the last to be studied. After determining the values for each of the other parameters, the overall performance which can range from 0 to 1 was tested at an interval of 0.1. It was discovered that this parameter did not have any effect, positive or otherwise, towards the controlled and manipulated variables.

As a summary, the table below shows the best values of the parameters studied based on its effect towards achieving the controlled variable set point, as well as the effects on movement of the manipulated variable.

Table 4.1: Parameter Values of MPC Controller for Model 1

Trials / Parameter	1	2	3	4	5	6	7	8	9	10	11	Best Value Selected
Control Interval	0.1	0.2	0.5	1	2	5	10	-	-	-	-	5
Prediction Horizon	1	2	5	10	20	50	100	-	-	-	-	100
Control Horizon	1	2	3	5	10	50	-	-	-	-	-	2
Reflux Weight	0	0.01	0.02	0.05	0.1	0.2	0.5	-	-	-	-	0
Reflux Rate Weight	0	0.01	0.02	0.05	0.1	0.2	0.5	-	-	-	-	0
Steam Weight	0	0.01	0.02	0.05	0.1	0.2	0.5	-	-	-	-	0.1
Steam Rate Weight	0	0.01	0.02	0.05	0.1	0.2	0.5	-	-	-	-	0
xd Weight	0	0.1	0.2	0.3	0.5	0.7	-	-	-	-	-	0.7
xb Weight	0	1	2	3	5	10	-	-	-	-	-	1
Overall Performance	0	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9	1.0	0.8

These values were used to test the top and bottom composition set point as well as the controller's performance during disturbance rejection. The results of the set point test on top and bottom composition showed that the controller was able to track the top composition set point. The plant input is also reasonable. The controller was not able to achieve the desired set point for the bottom composition. A noteworthy observation is that although there is no weight on reflux and only a small weight on steam, the controller did not attempt any large movement for a long duration to achieve the set point.

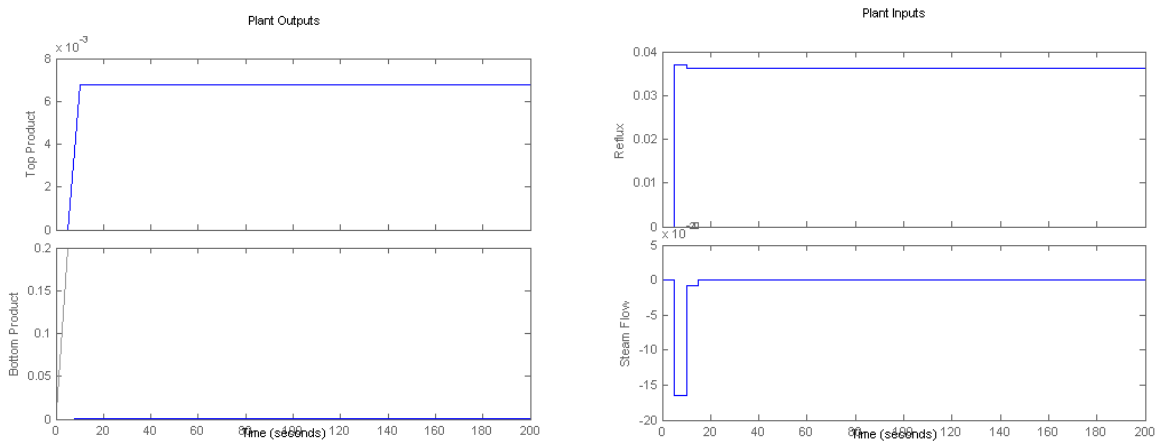


Figure 4.21: Plant Input and Output Response for Top Composition Set Point

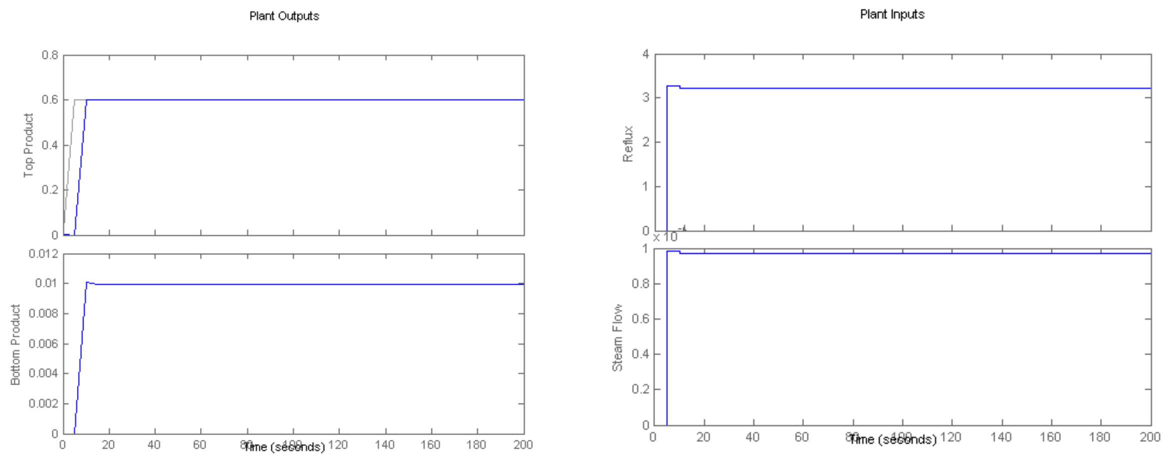


Figure 4.22: Plant Input and Output Response for Top Composition Set Point

4.2 Set Point Change on Model 2

In the development of transfer functions for model 2, the top and bottom composition acquired using the inferential model range from 0.33 to 0.58 and 0.05 to 0.26 respectively. For simulation purposes, the top and bottom composition set point values are set at 0.3 and 0.1.

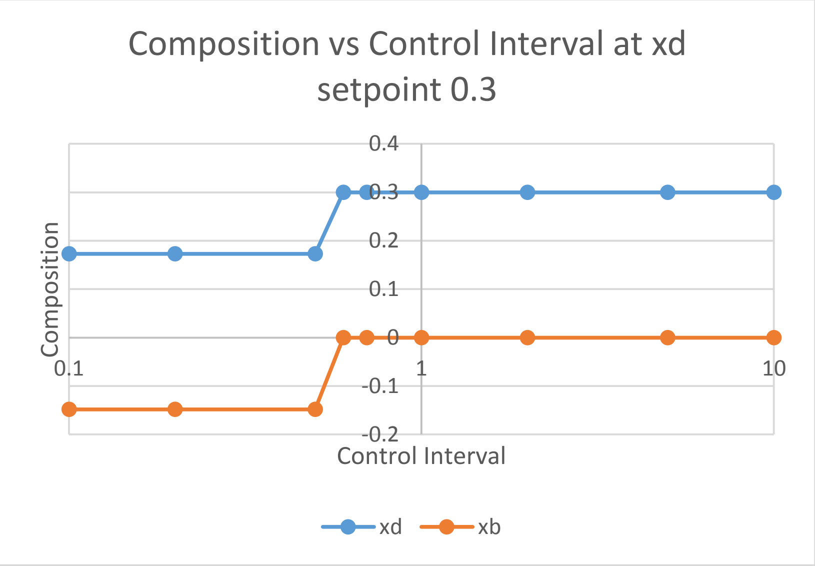


Figure 4.23: Effect of Control Interval on Controlled Variables for Top Composition Set Point in Model 2

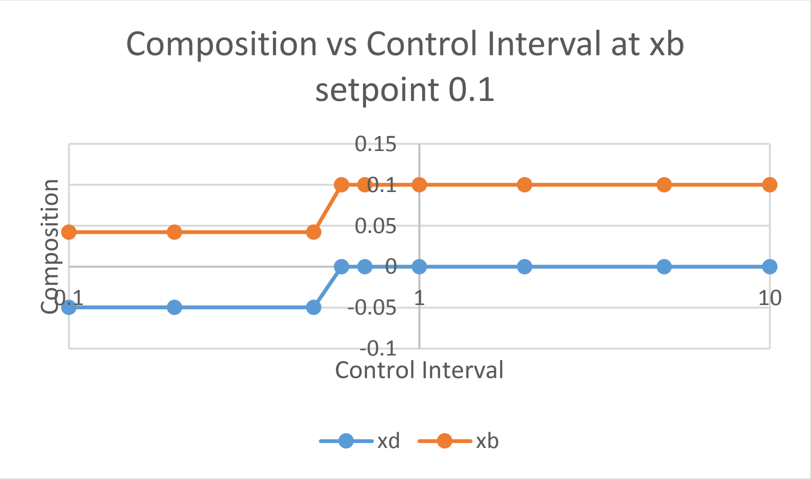


Figure 4.24: Effect of Control Interval on Controlled Variables for Bottom Composition Set Point in Model 2

For the control interval, the controlled variables were unable to reach their set point values when the control interval was set at 0.1, 0.2, and 0.3. However, from a control interval value of 0.5 onwards, it can be seen that the set point of both controlled variables were achievable.

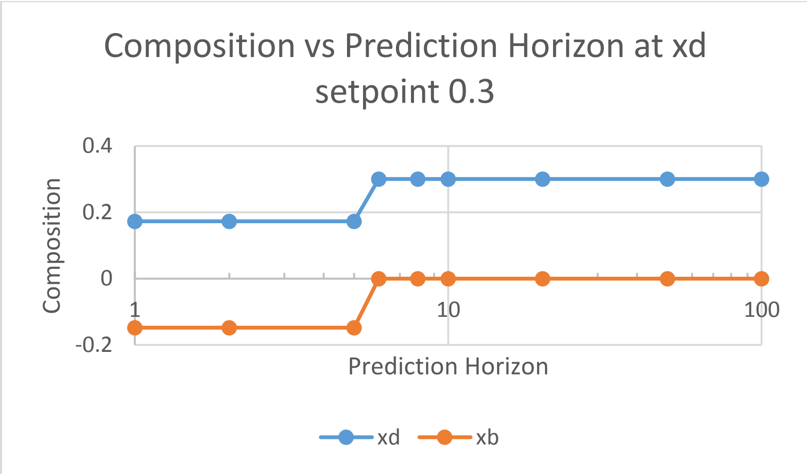


Figure 4.25: Effect of Prediction Horizon on Controlled Variables for Top Composition Set Point in Model 2

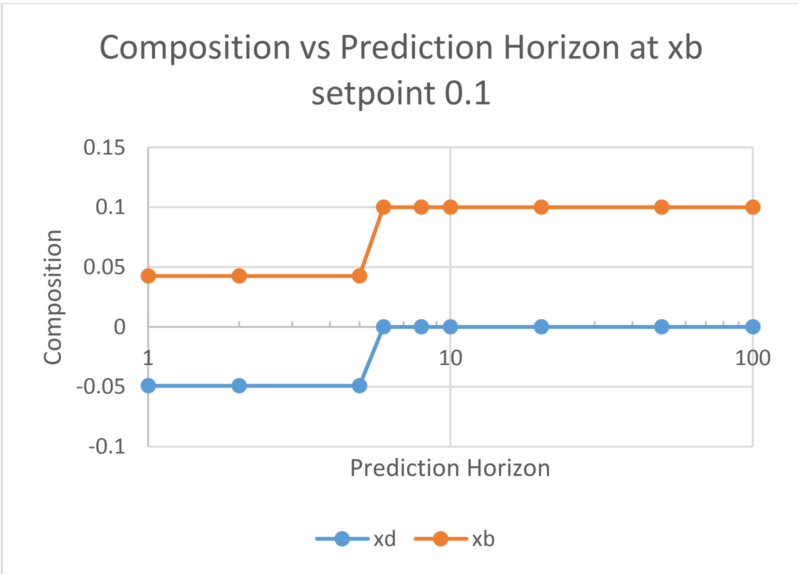


Figure 4.26: Effect of Prediction Horizon on Controlled Variables for Bottom Composition Set Point in Model 2

The prediction horizon has a similar effect on the composition values as the control interval when looking at Figures 30 and 31. For prediction horizon values of 1 to 5, the controller was unable to achieve the desired set point in both top and bottom compositions. At values of 6 and above, the set points were reached.

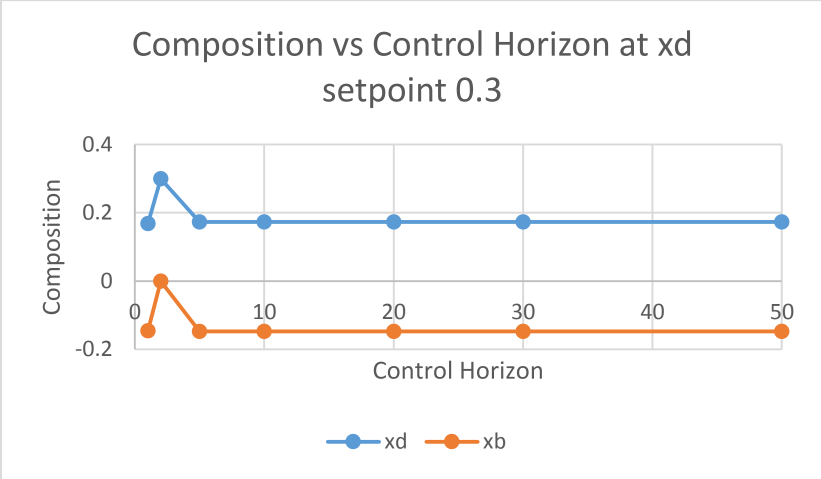


Figure 4.27: Effect of Control Horizon on Controlled Variables for Top Composition Set Point in Model 2

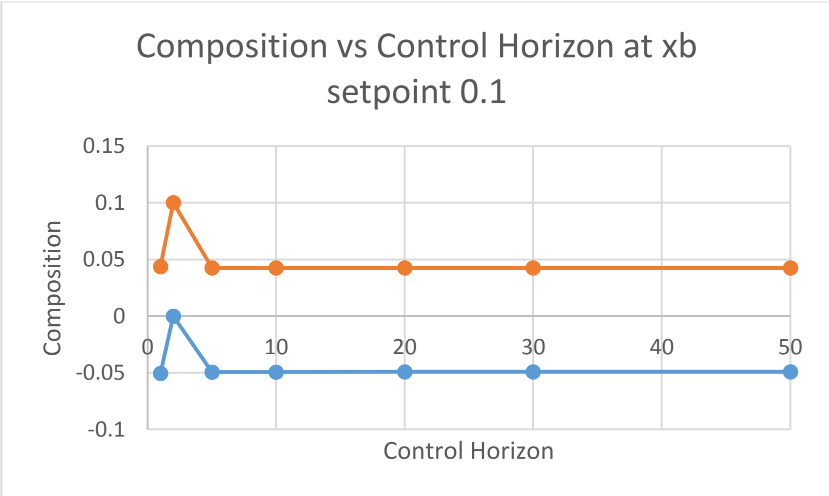


Figure 4.28: Effect of Control Horizon on Controlled Variables for Bottom Composition Set Point in Model 2

The simulation on control horizon changes result in only one of the tested values to be able to reach the set point of both top and bottom compositions. At a control horizon of 2, the composition set points were achieved. Meanwhile, for all other values of the control horizon, the composition values were unable to reach the set point.

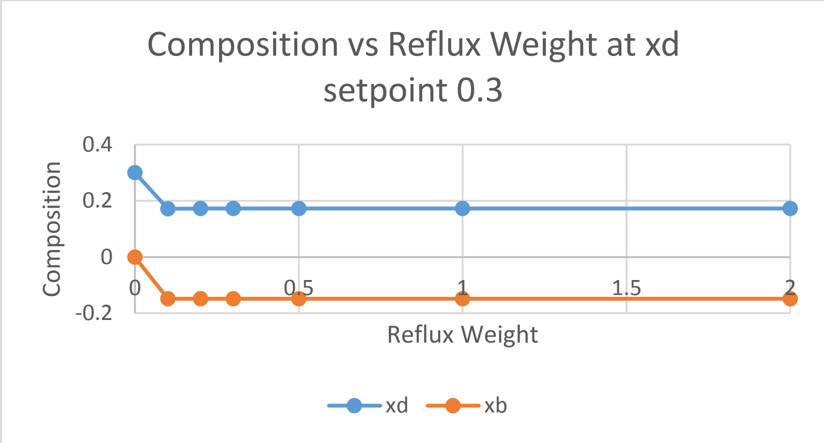


Figure 4.29: Effect of Reflux Weight on Controlled Variables for Top Composition Set Point in Model 2

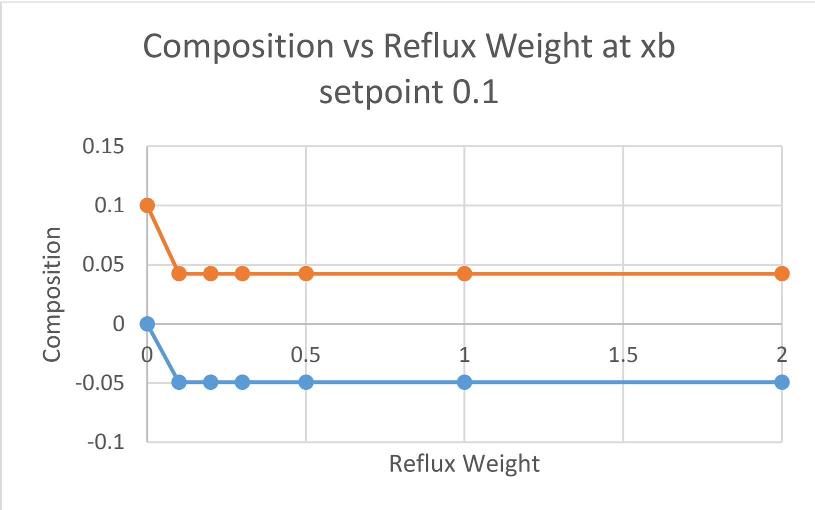


Figure 4.30: Effect of Reflux Weight on Controlled Variables for Bottom Composition Set Point in Model 2

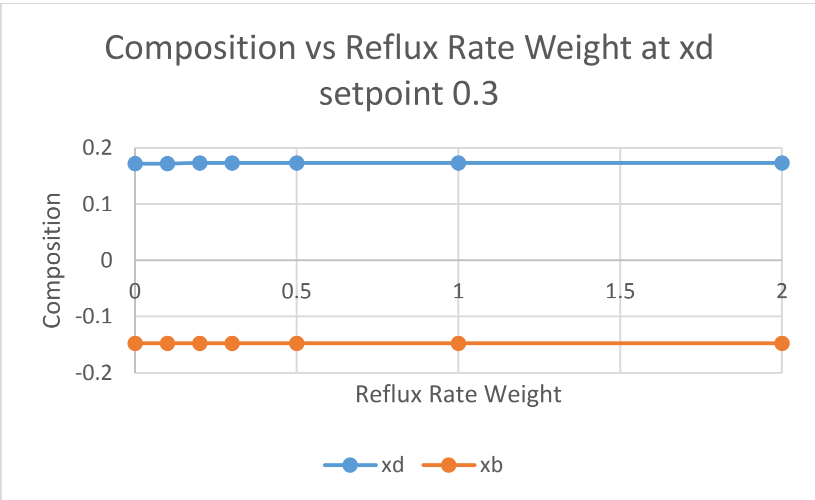


Figure 4.31: Effect of Reflux Rate Weight on Controlled Variables for Top Composition Set Point in Model 2

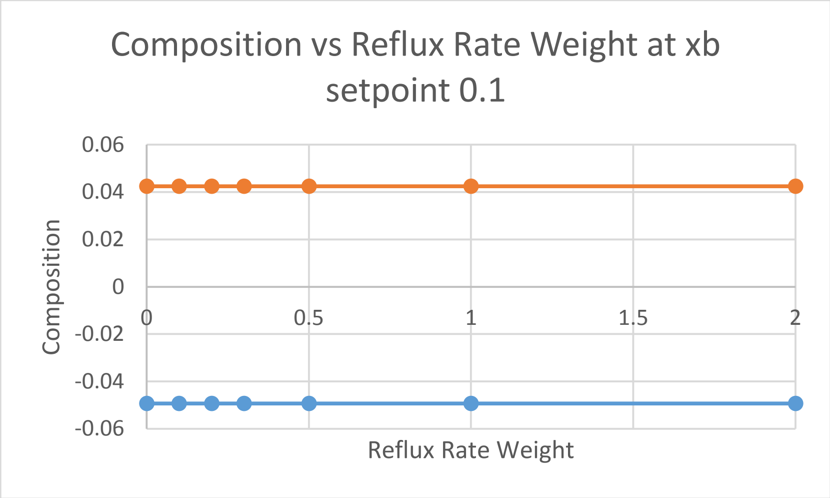


Figure 4.32: Effect of Reflux Rate Weight on Controlled Variables for Bottom Composition Set Point in Model 2

The reflux weight and reflux rate weights were not affecting the composition values in which changes in the reflux rate weight did not improve nor worsen the values. As can be seen from the reflux weight graph, only at a weight of 0 can the top and bottom compositions be reached. However, the resultant reflux and steam movement were so high that it is highly unfeasible for the controller to be able to achieve said value in real applications. Therefore, a small value of 0.1 is taken for the reflux weight, and the remaining parameters which have not been tuned will compensate for achieving the composition set points.

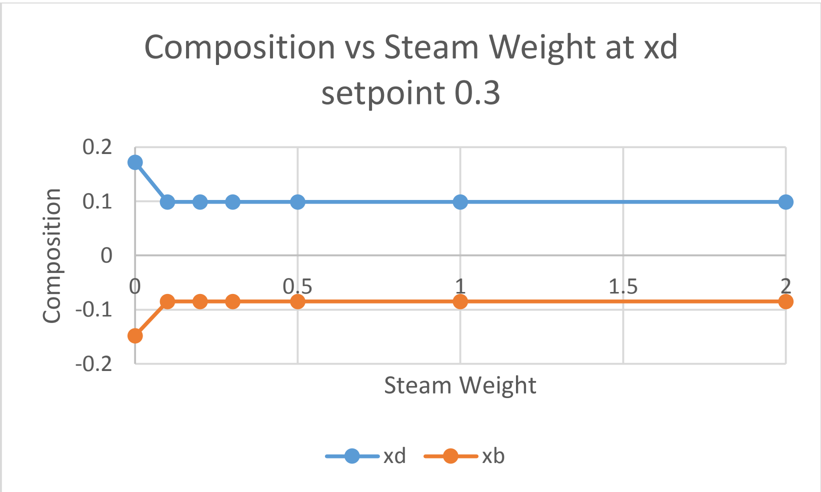


Figure 4.33: Effect of Steam Weight on Controlled Variables for Top Composition Set Point in Model 2

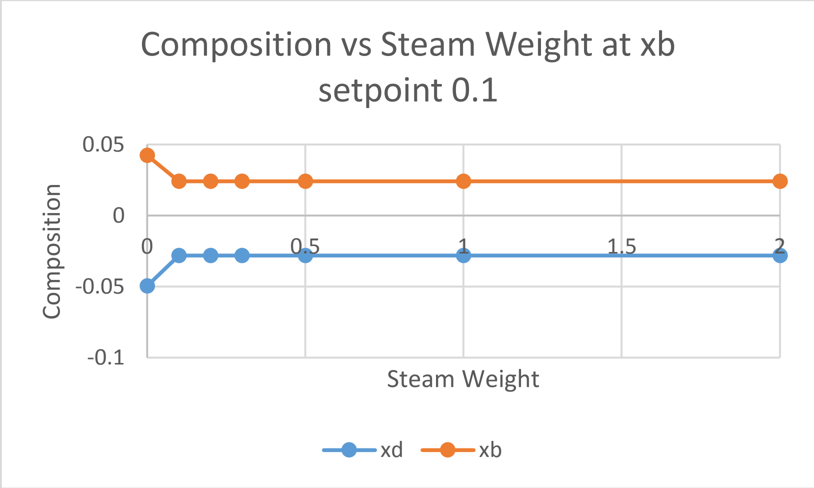


Figure 4.34: Effect of Steam Weight on Controlled Variables for Bottom Composition Set Point in Model 2

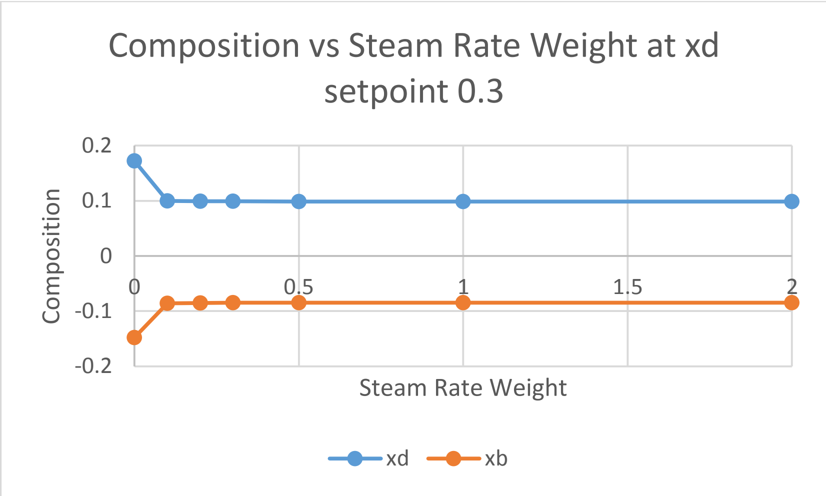


Figure 4.35: Effect of Steam Rate Weight on Controlled Variables for Top Composition Set Point in Model 2

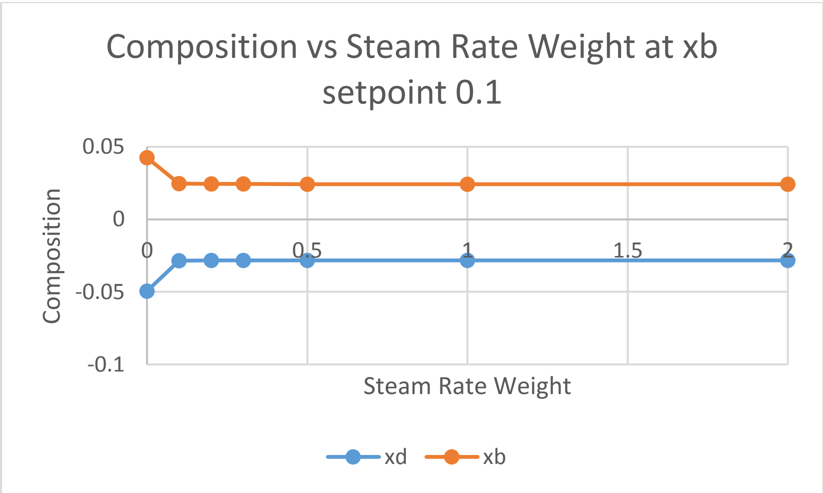


Figure 4.36: Effect of Steam Rate Weight on Controlled Variables for Bottom Composition Set Point in Model 2

The steam weight and rate weight are also seen to not affect the composition values. With the reflux weight set at 0.1, the steam weight and rate weight can be set to 0 since every other value will result in a larger deviation of composition from its set point.

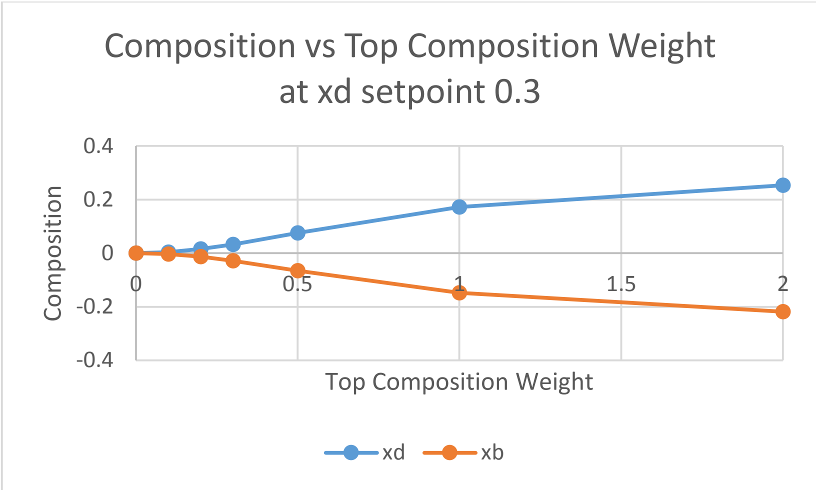


Figure 4.37: Effect of Top Composition Weight on Controlled Variables for Top Composition Set Point in Model 2

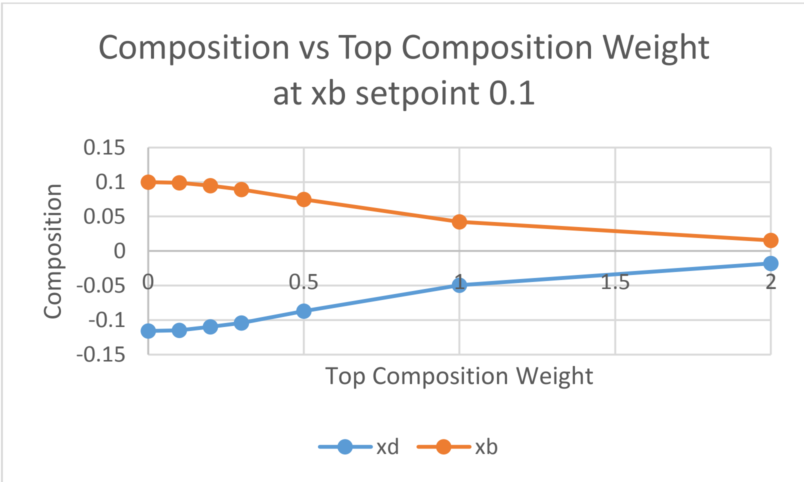


Figure 4.38: Effect of Top Composition Weight on Controlled Variables for Bottom Composition Set Point in Model 2

For the top composition weight, it was discovered that while a larger value contributes toward achieving the top composition set point, it also drives the bottom composition away from its set point value. Therefore, a balance or prioritization over which composition is more important in the process is needed to determine the appropriate value of the top composition weight. In this case, a top composition weight value of 1 was selected.

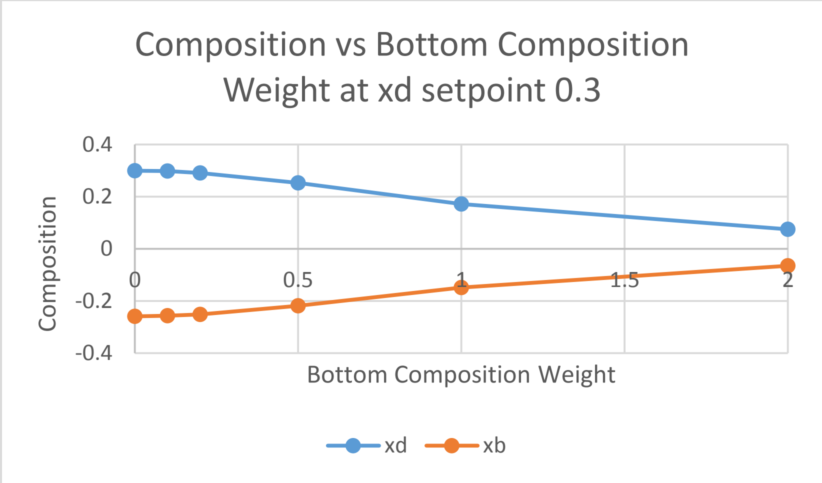


Figure 4.39: Effect of Bottom Composition Weight on Controlled Variables for Top Composition Set Point in Model 2

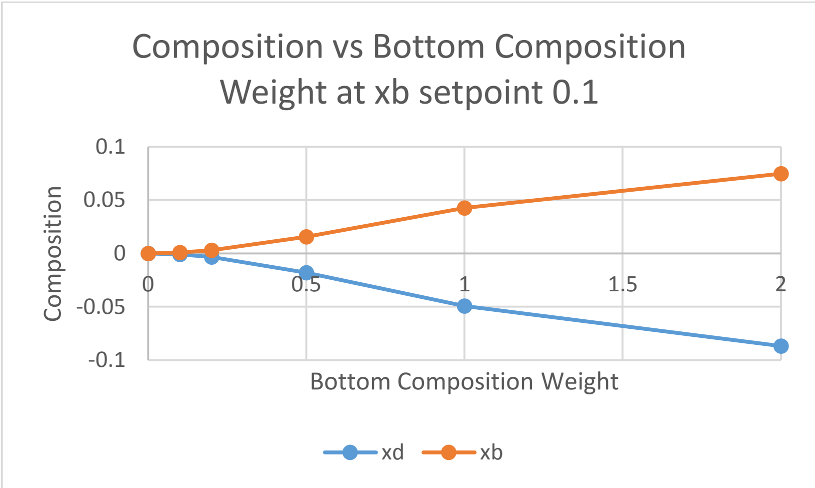


Figure 4.40: Effect of Bottom Composition Weight on Controlled Variables for Bottom Composition Set Point in Model 2

As a contrast to the top composition weight, an increase in the bottom composition weight results in a bottom composition value closer to the set point, while at the same time driving the top composition away from its set point value. Since the top composition weight was given a value of 1, a bottom composition value of less than 1 will tell the controller to prioritize the top composition, and, at value of more than 1, will prioritize the bottom composition.

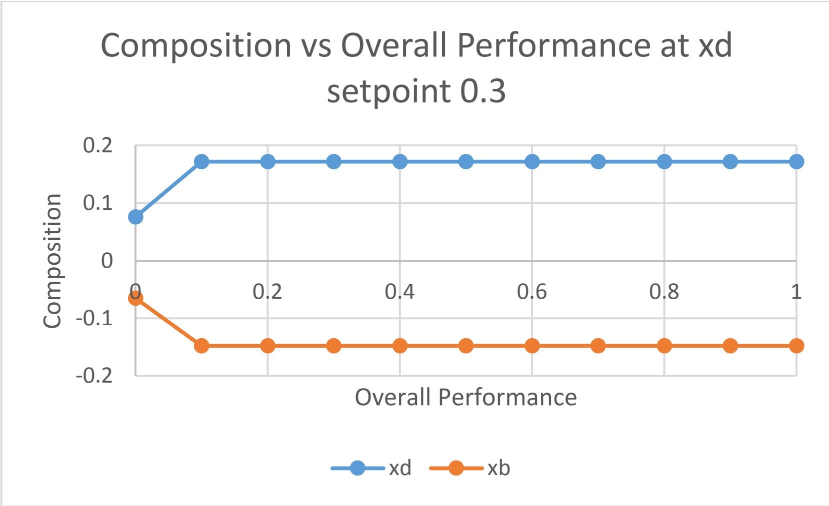


Figure 4.41: Effect of Overall Performance on Controlled Variables for Top Composition Set Point in Model 2

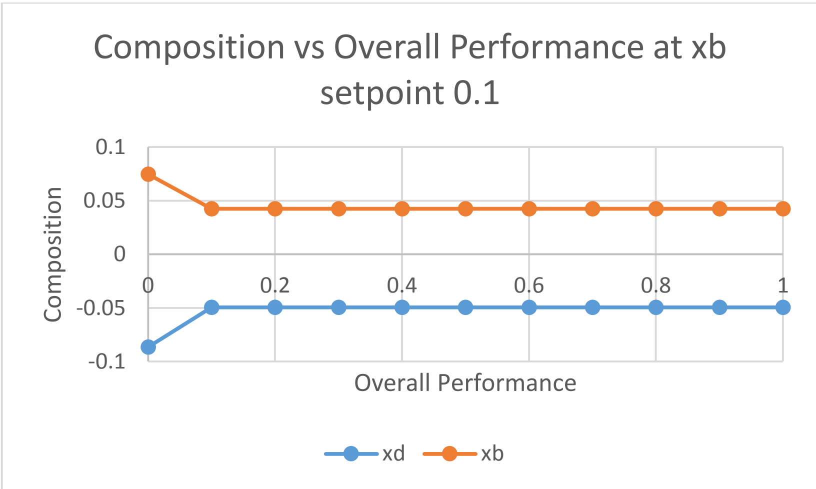


Figure 4.42: Effect of Overall Performance on Controlled Variables for Bottom Composition Set Point in Model 2

The overall performance parameter favours the bottom composition at 0, and for all other value favour the top composition. Therefore, if the top composition is given a priority, any non-zero value for the controller overall performance will give a good set point tracking on the top composition, provided all other tuning parameters were set correctly.

Table 4.2: Parameter Values of MPC Controller for Model 2

Trials / Parameter	1	2	3	4	5	6	7	8	9	10	11	Best Value Selected
Control Interval	0.1	0.2	0.5	0.6	0.7	1	2	5	10	-	-	0.7
Prediction Horizon	1	2	5	6	8	10	50	100	-	-	-	100
Control Horizon	1	2	5	10	20	30	50	-	-	-	-	2
Reflux Weight	0	0.1	0.2	0.3	0.5	1	2	-	-	-	-	1
Reflux Rate Weight	0	0.1	0.2	0.3	0.5	1	2	-	-	-	-	0.1
Steam Weight	0	0.1	0.2	0.3	0.5	1	2	-	-	-	-	0
Steam Rate Weight	0	0.1	0.2	0.3	0.5	1	2	-	-	-	-	0
xd Weight	0	0.1	0.2	0.3	0.5	1	2	-	-	-	-	1
xb Weight	0	0.1	0.2	0.3	0.5	1	2	-	-	-	-	1
Overall Performance	0	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9	1.0	1

The table above provided the summary of all the selected values for the MPC tuning parameters studied. These tuning parameters are used for both the set point change and the disturbance rejection simulations. The results of the set point change can be seen in the figures below.

For both top composition and bottom composition, the set point value was not reached. Instead, there is an offset where the process goes into steady-state well below the set point. It can also be seen that the steam input movement are sudden and very large for both cases. This could be due to model mismatch in which the model was not able to accurately describe the relationship between the steam input and the controlled variables.

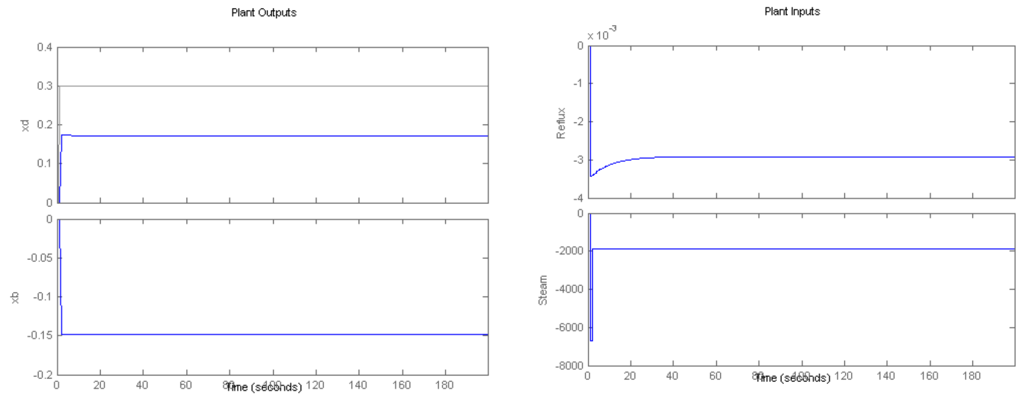


Figure 4.43: Plant Input and Output Response for Top Composition Set Point in Model 2

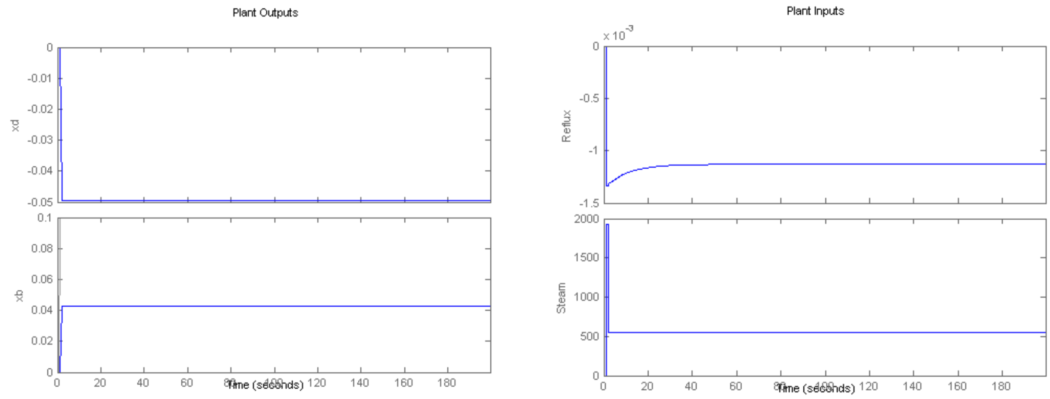


Figure 4.44: Plant Input and Output Response for Top Composition Set Point in Model 2

4.3 Disturbance Rejection on Model 1

Simulations for studying the MPC's ability in disturbance rejection are done by simulating disturbances in all variables. As can be seen in Appendix C, the controller is able to restore steady-state for both composition outputs in the process for all disturbances studied. However, there are slight variability in the time required for the controller to achieve disturbance rejection.

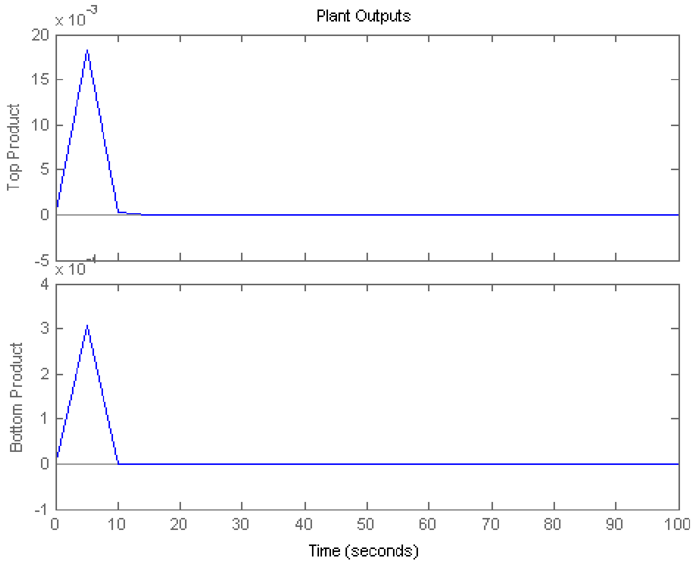


Figure 4.45: Output Response to 0.1 Reflux Disturbance in Model 1

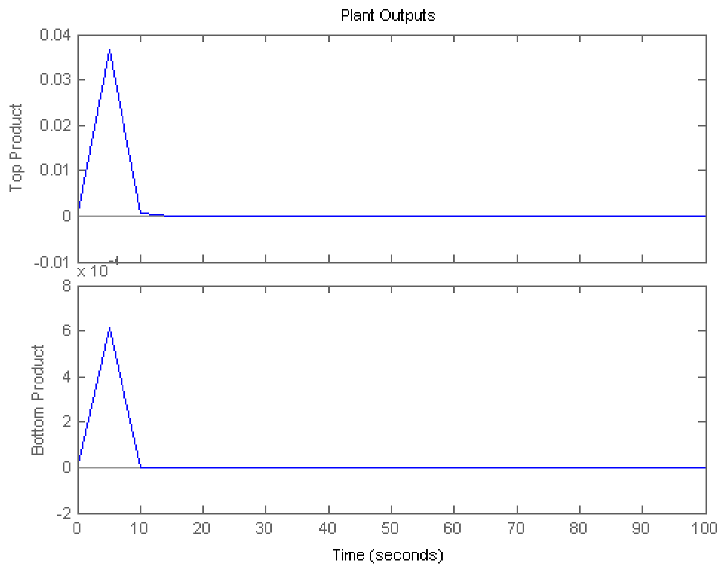


Figure 4.46: Output Response to 0.2 Reflux Disturbance in Model 1

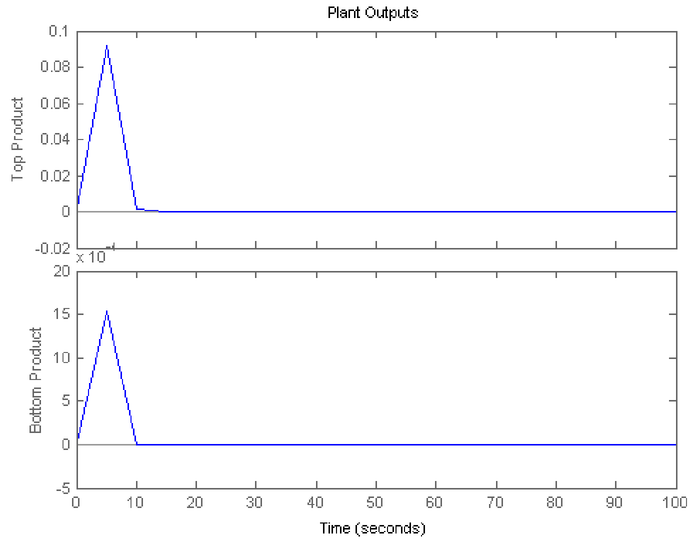


Figure 4.47: Output Response to 0.5 Reflux Disturbance in Model 1

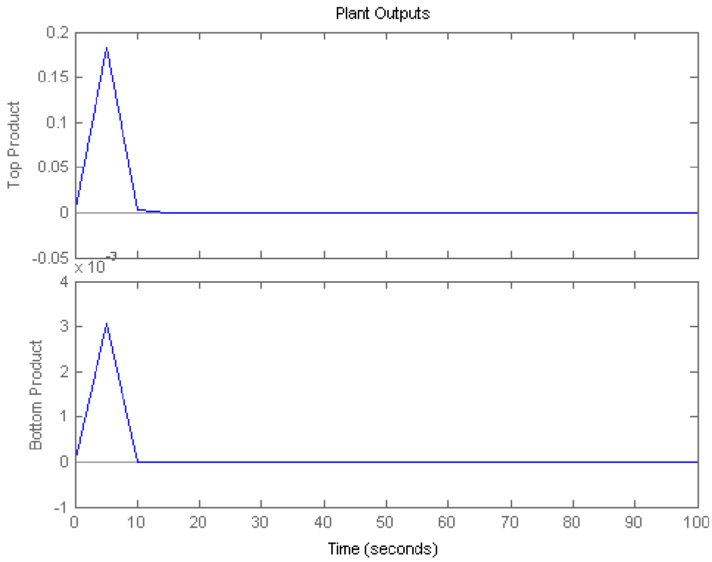


Figure 4.48: Output Response to 1.0 Reflux Disturbance in Model 1

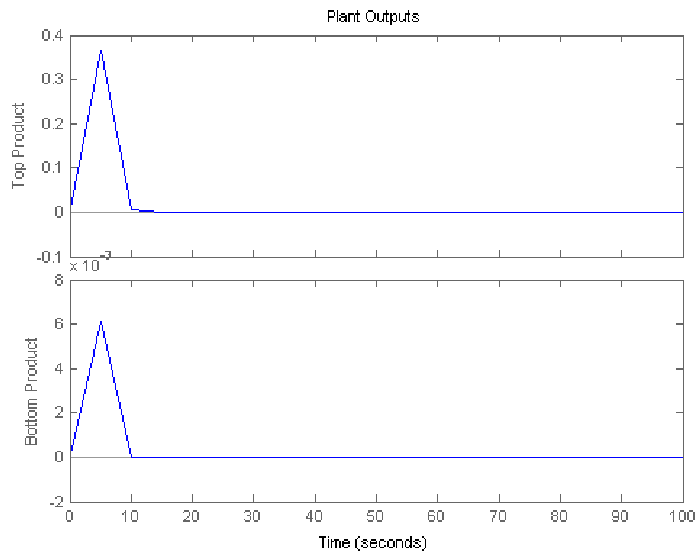


Figure 4.49: Output Response to 2.0 Reflux Disturbance in Model 1

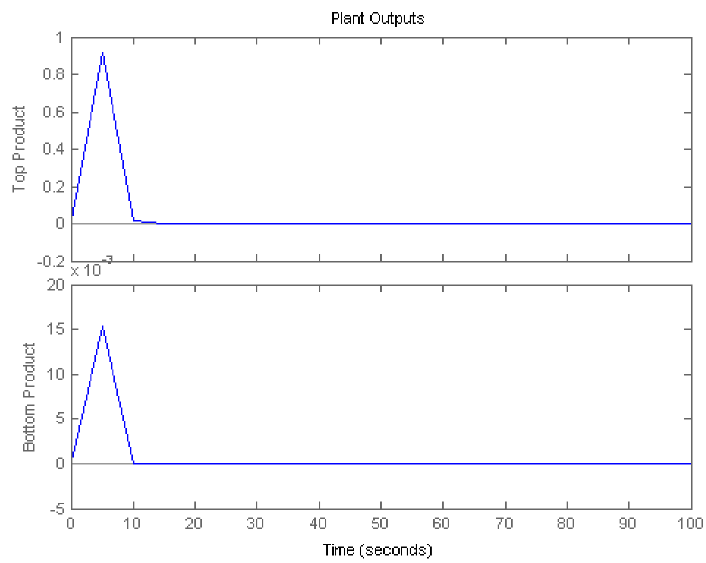


Figure 4.50: Output Response to 5.0 Reflux Disturbance in Model 1

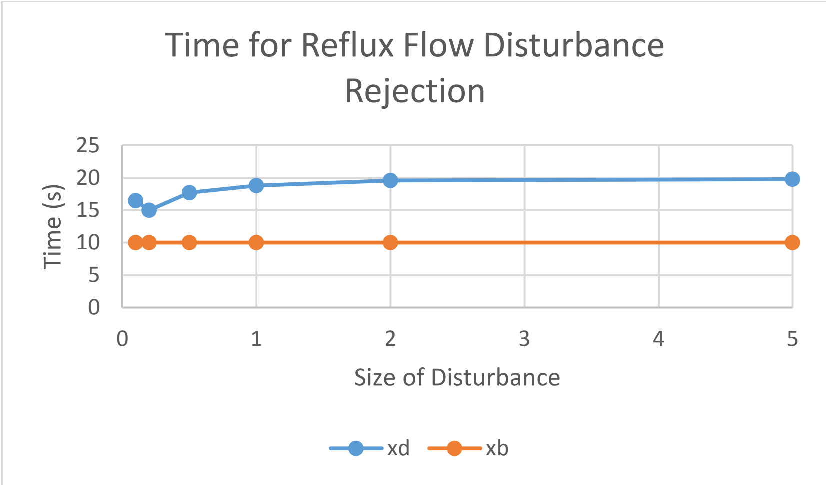


Figure 4.51: Time for Reflux Flow Disturbance Rejection in Model 1

The MPC controller's ability to restore steady state to the process after a reflux flow disturbance is constant throughout the tested values. For all the disturbance sizes, the controller was able to restore the top composition to steady state within 20 seconds, and the bottom composition at 10 seconds.

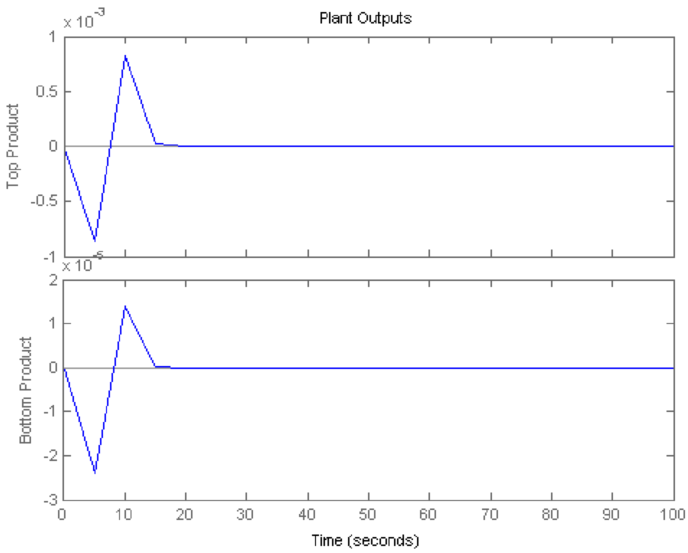


Figure 4.52: Output Response to 0.1 Steam Disturbance in Model 1

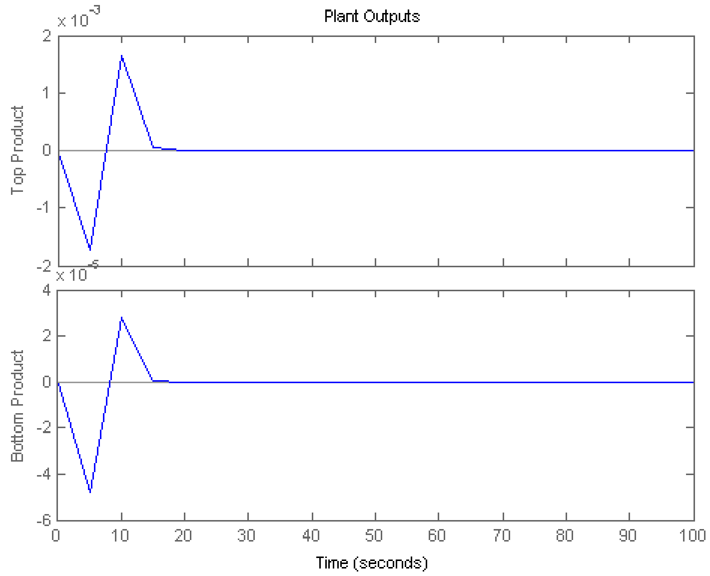


Figure 4.53: Output Response to 0.2 Steam Disturbance in Model 1

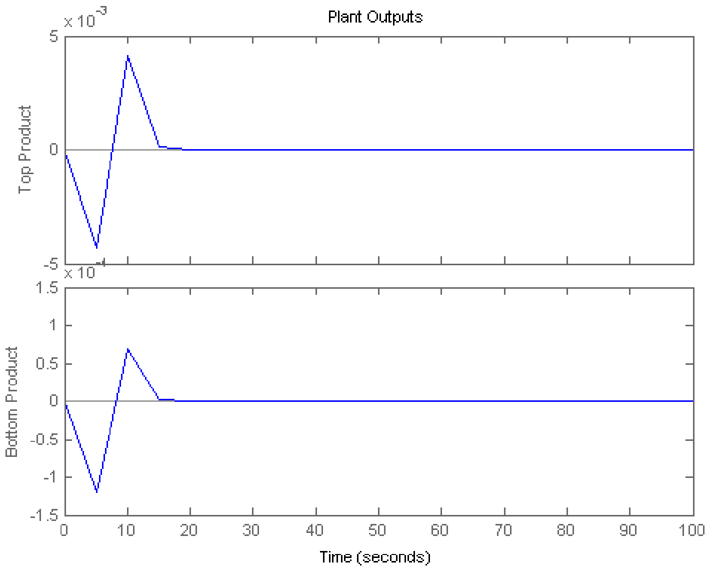


Figure 4.54: Output Response to 0.5 Steam Disturbance in Model 1

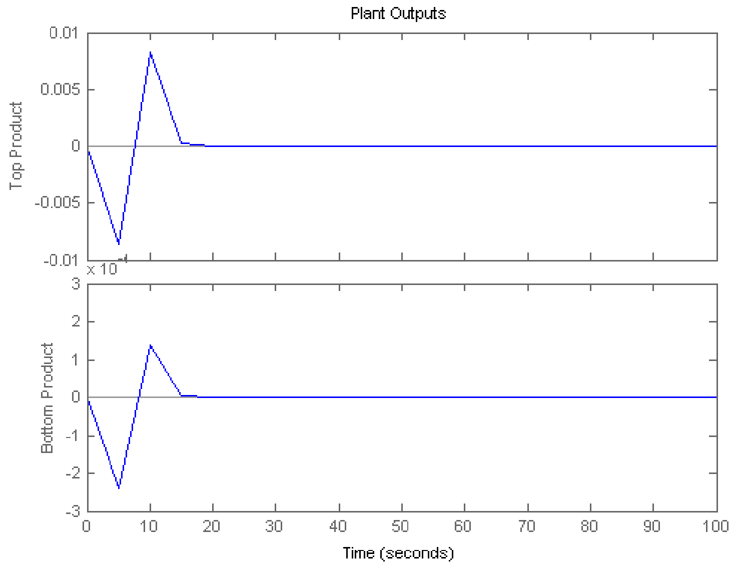


Figure 4.55: Output Response to 1.0 Steam Disturbance in Model 1

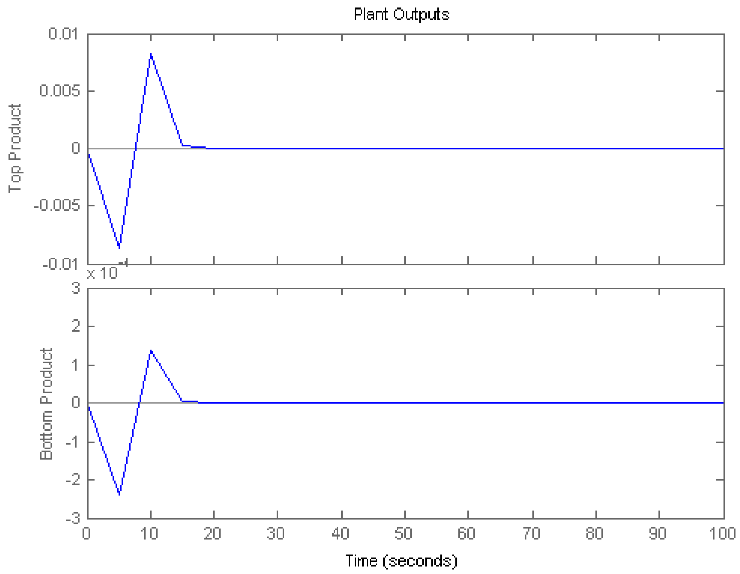


Figure 4.56: Output Response to 2.0 Steam Disturbance in Model 1

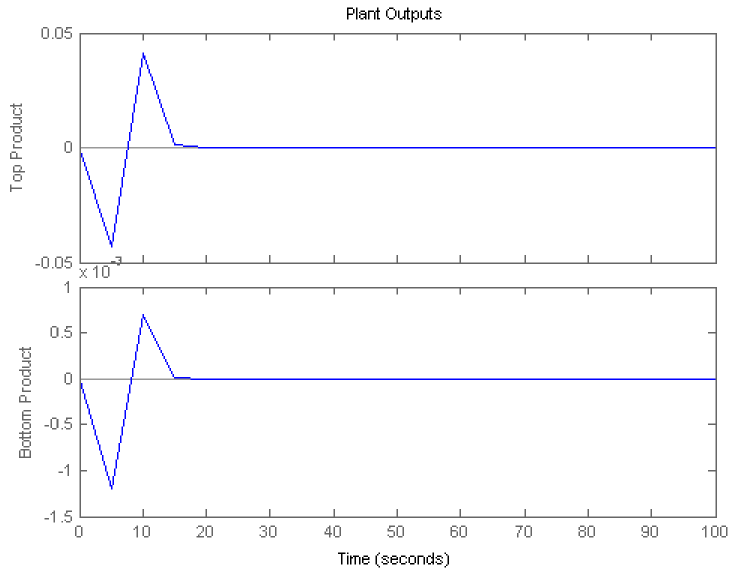


Figure 4.57: Output Response to 5.0 Steam Disturbance in Model 1

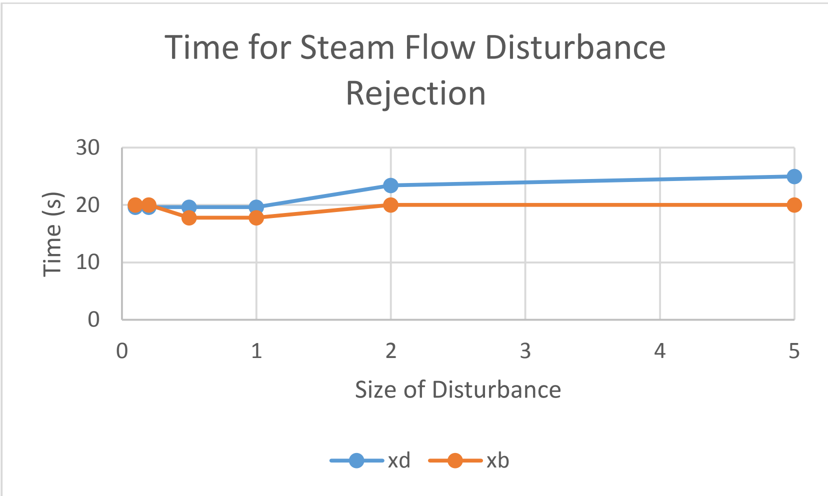


Figure 4.58: Time for Steam Flow Disturbance Rejection in Model 1

The MPC controller was also tested for its performance during a steam flow disturbance. For all the disturbance sizes, the top and bottom compositions were restored to their steady state conditions within 24 seconds after the introduction of the disturbance.

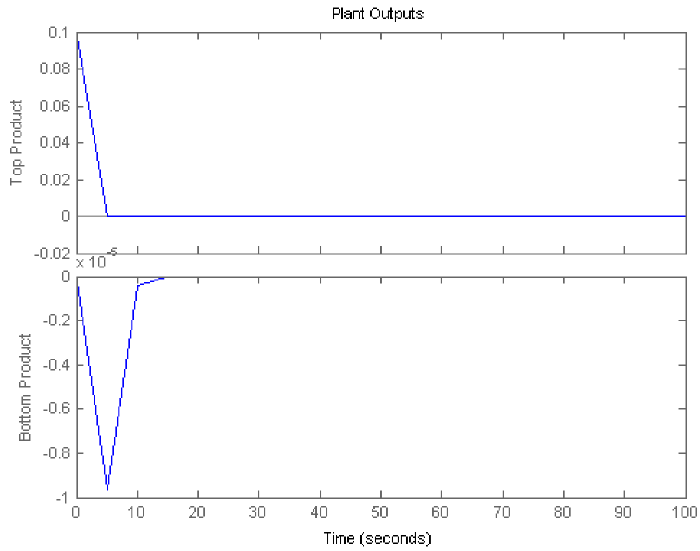


Figure 4.59: Output Response to 0.1 Top Composition Disturbance in Model 1

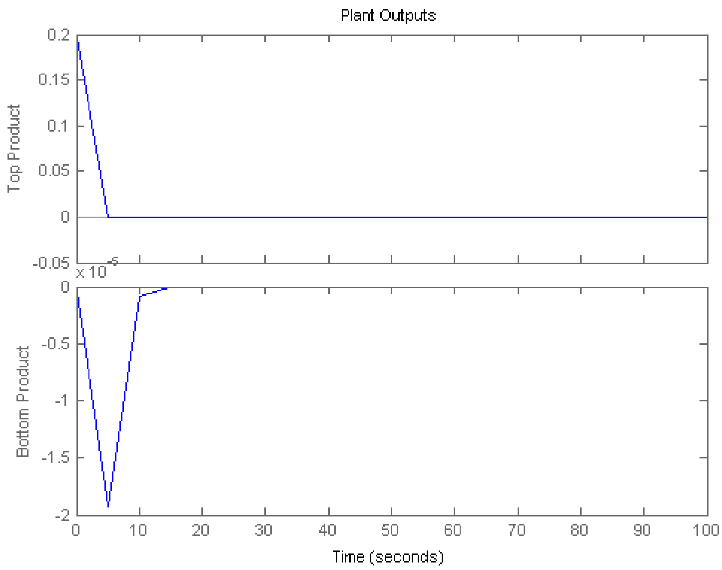


Figure 4.60: Output Response to 0.2 Top Composition Disturbance in Model 1

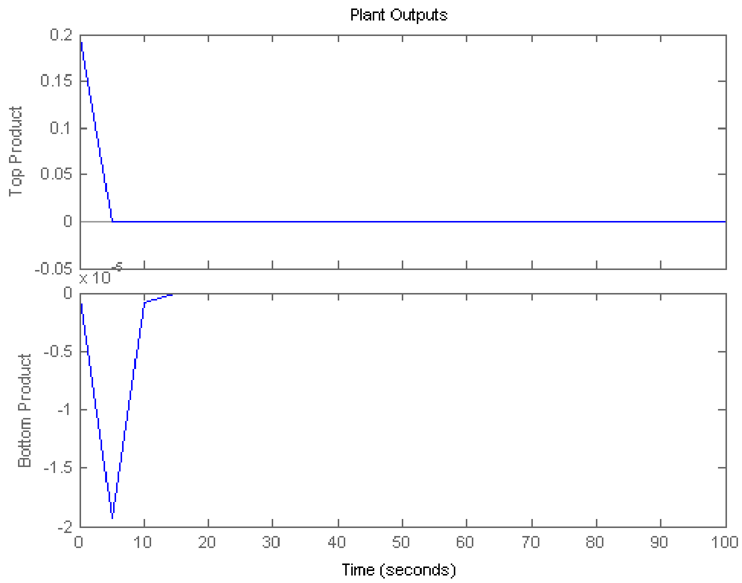


Figure 4.61: Output Response to 0.3 Top Composition Disturbance in Model 1

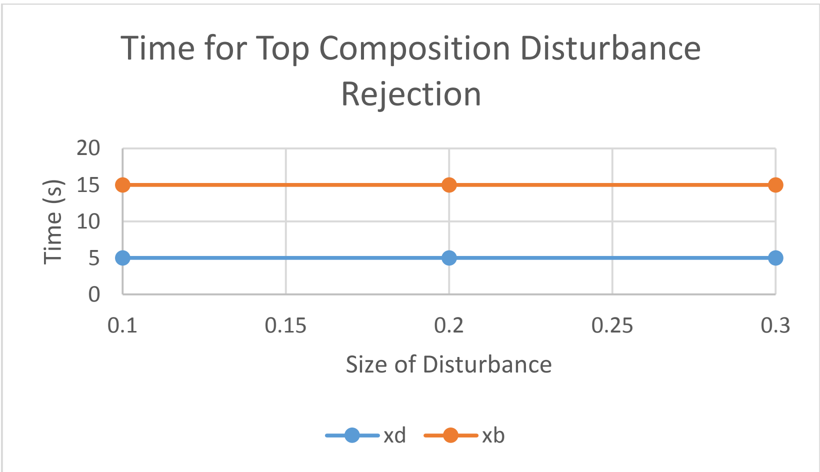


Figure 4.62: Time for Top Composition Disturbance Rejection in Model 1

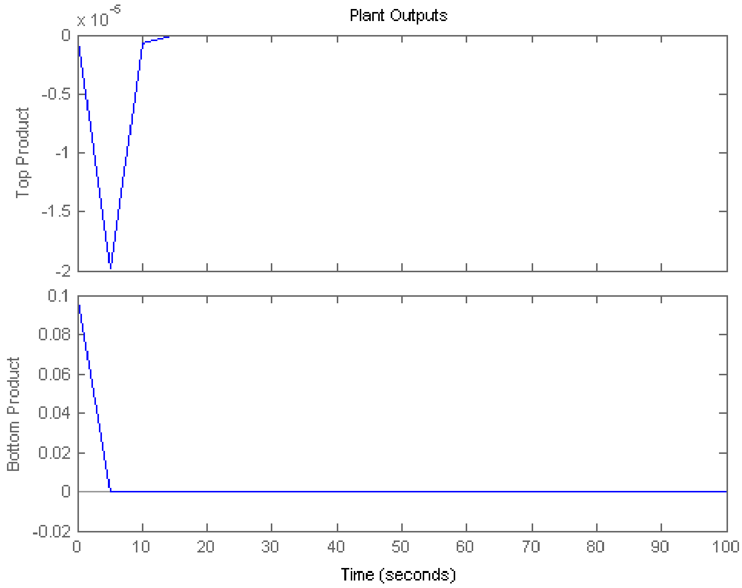


Figure 4.63: Output Response to 0.1 Bottom Composition Disturbance in Model 1

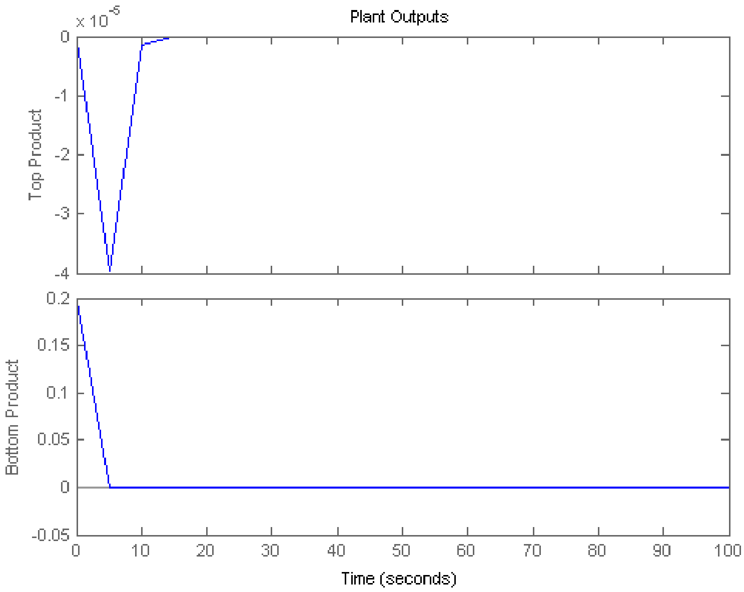


Figure 4.64: Output Response to 0.2 Bottom Composition Disturbance in Model 1

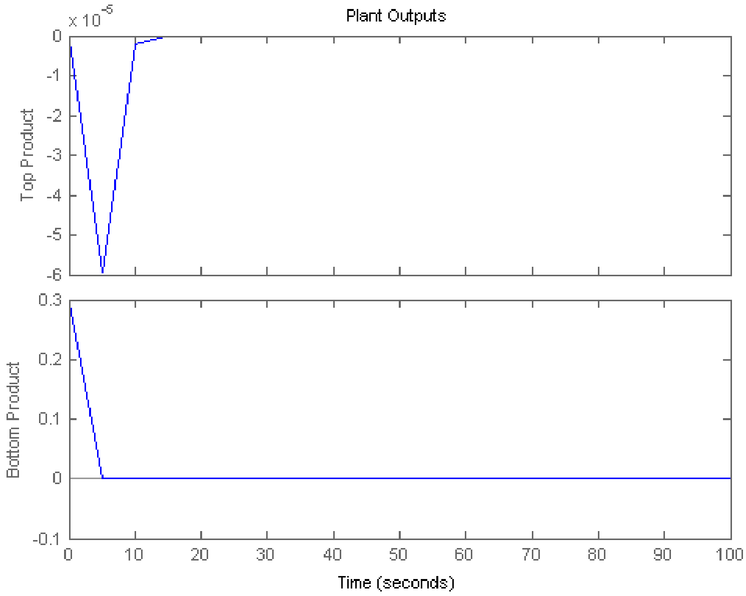


Figure 4.65: Output Response to 0.3 Bottom Composition Disturbance in Model 1

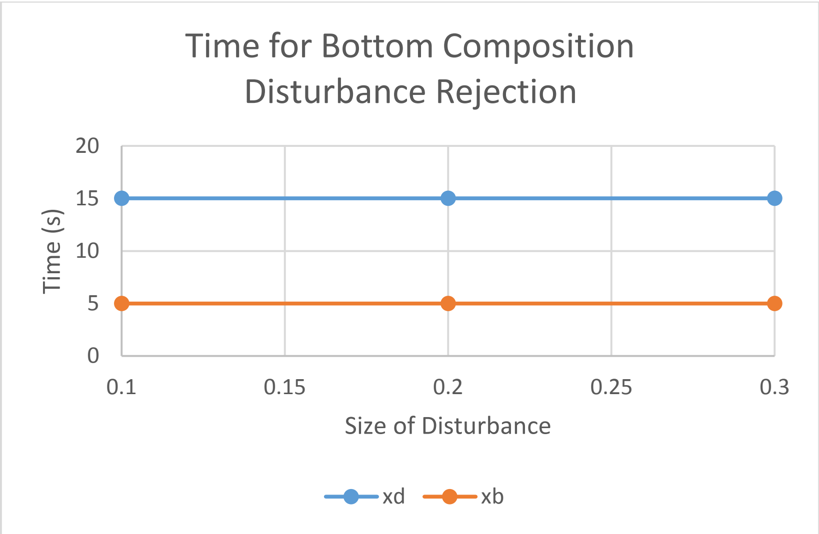


Figure 4.66: Time for Bottom Composition Disturbance Rejection in Model 1

Based on Figure 4.62 and 4.66, it can be seen that the controller was able to restore steady state on the top composition in 5 seconds when a disturbance in the top composition was introduced. Meanwhile, with a disturbance in the bottom composition, the top composition took 15 seconds to return to steady state.

In reverse, the bottom composition took 15 seconds to return to steady state when a disturbance in the top composition was introduced, and 5 seconds on the introduction of bottom composition disturbance.

4.4 Disturbance Rejection on Model 2

Similar to the results presented for model 1, the MPC controller for this model also showed that it is able to restore steady-state conditions to the process after a disturbance was introduced. The data obtained during simulation is available in Appendix C.

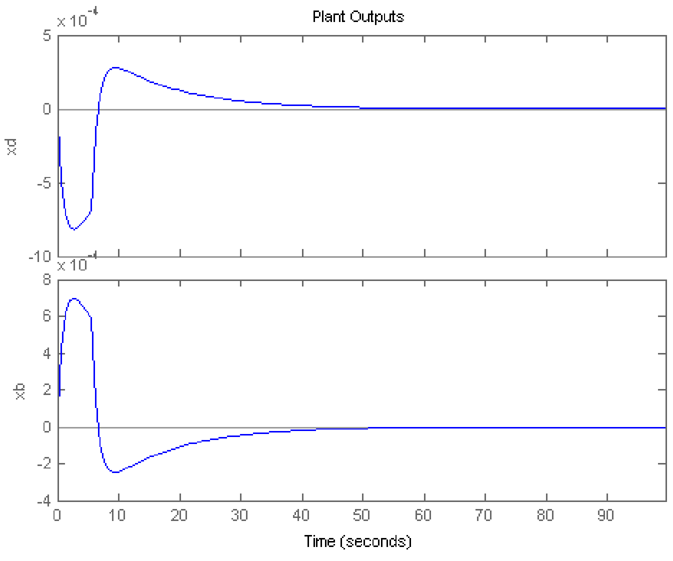


Figure 4.67: Output Response to 0.1 Reflux Disturbance in Model 2

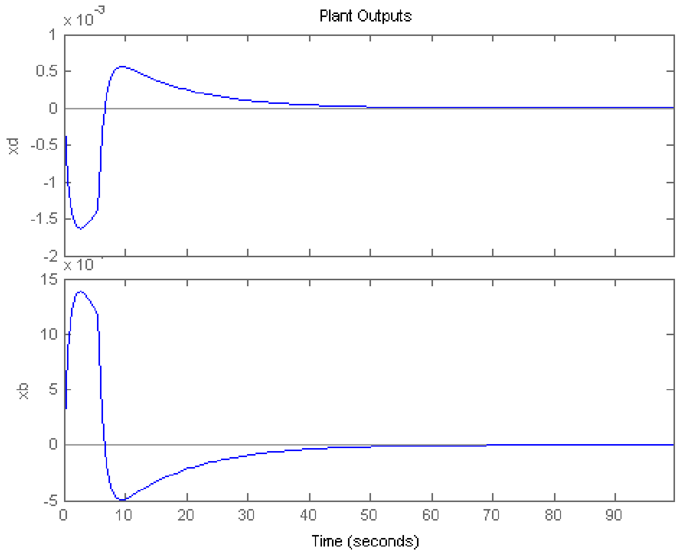


Figure 4.68: Output Response to 0.2 Reflux Disturbance in Model 2

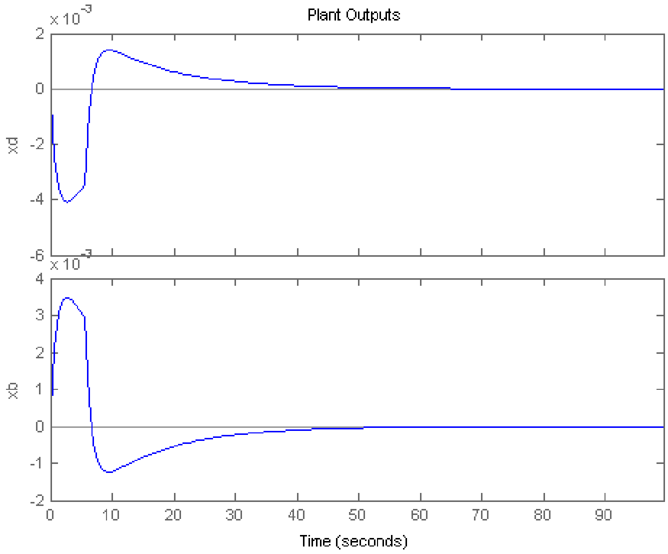


Figure 4.69: Output Response to 0.5 Reflux Disturbance in Model 2

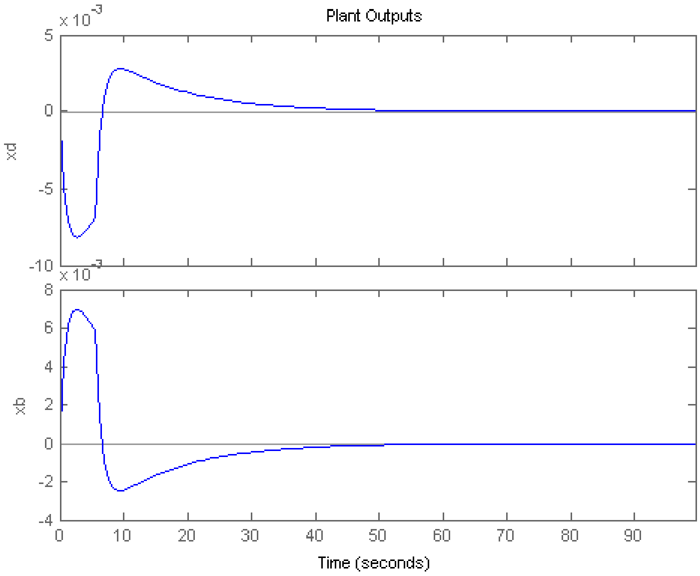


Figure 4.70: Output Response to 1.0 Reflux Disturbance in Model 2

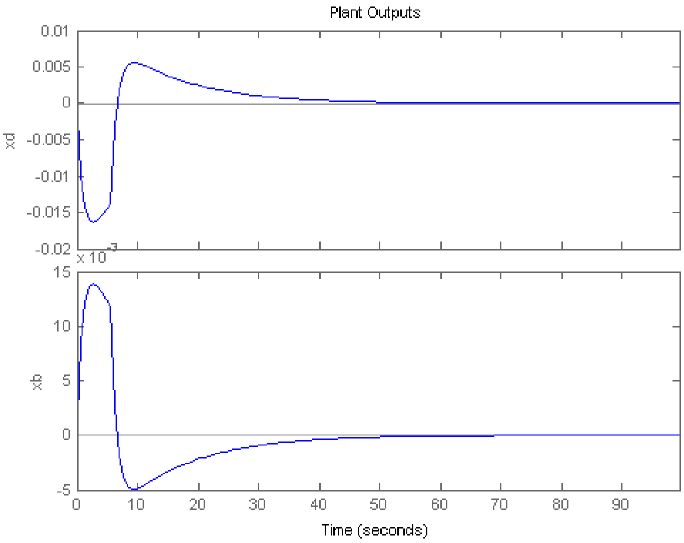


Figure 4.71: Output Response to 2.0 Reflux Disturbance in Model 2

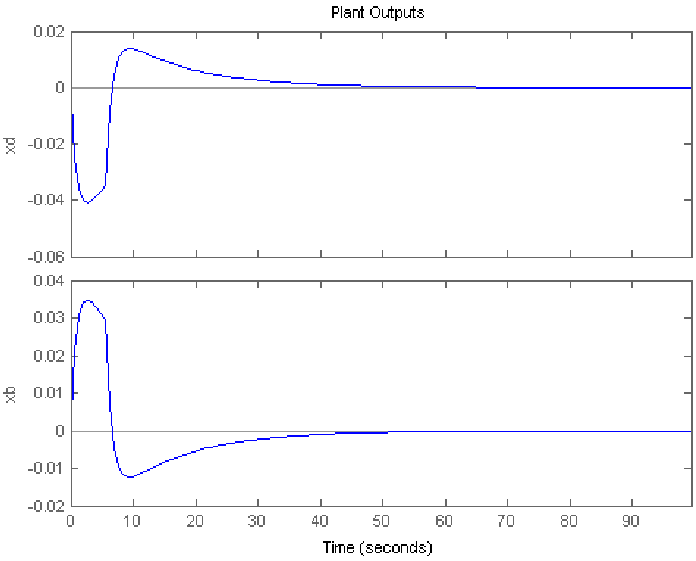


Figure 4.72: Output Response to 5.0 Reflux Disturbance in Model 2

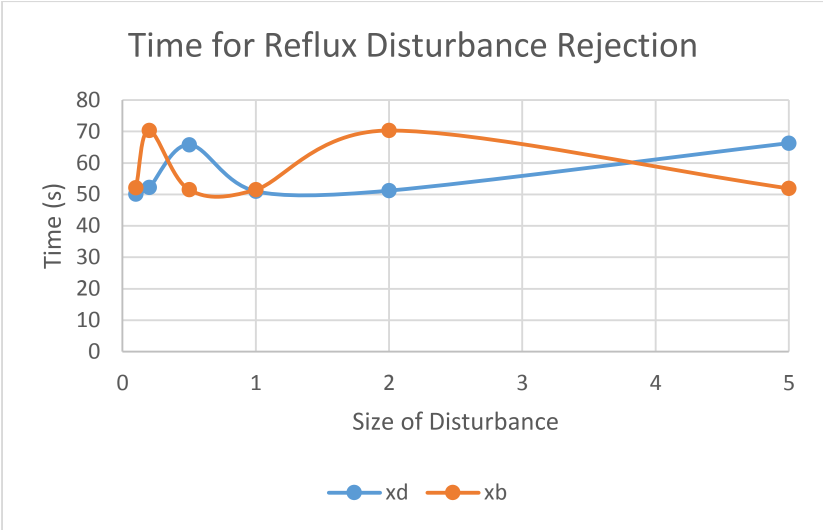


Figure 4.73: Time for Reflux Flow Disturbance Rejection in Model 2

During the reflux flow disturbance test, the time taken for both compositions to be eliminated from disturbance vary for as much as 20 seconds from one disturbance size to the other. It was also observed that during all trial values, except at 0.1 and 1, the difference between the time the top composition reached steady state and the bottom composition reaching its steady state is 20 seconds.

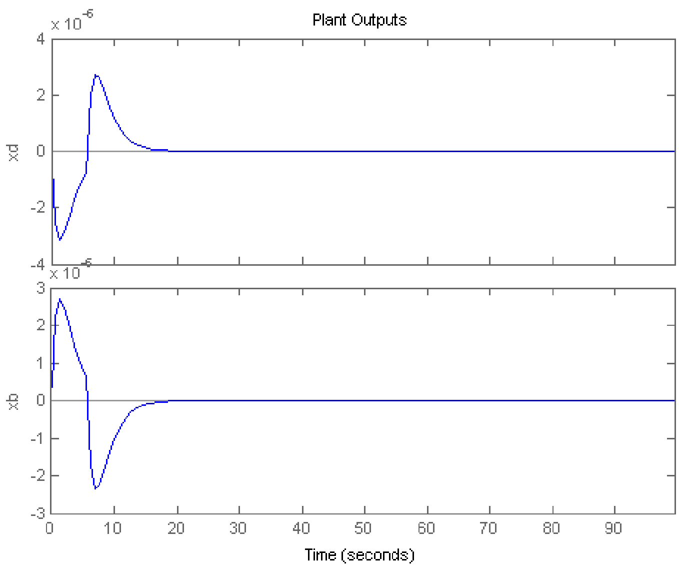


Figure 4.74: Output Response to 0.1 Steam Disturbance in Model 2

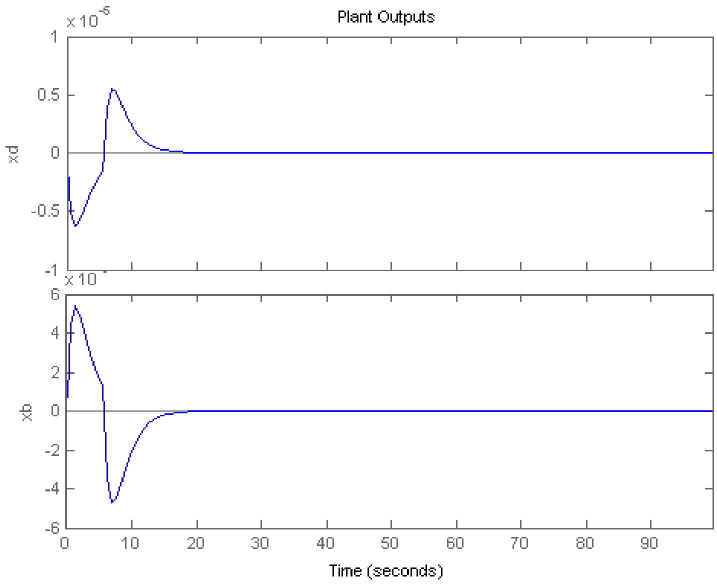


Figure 4.75: Output Response to 0.2 Steam Disturbance in Model 2

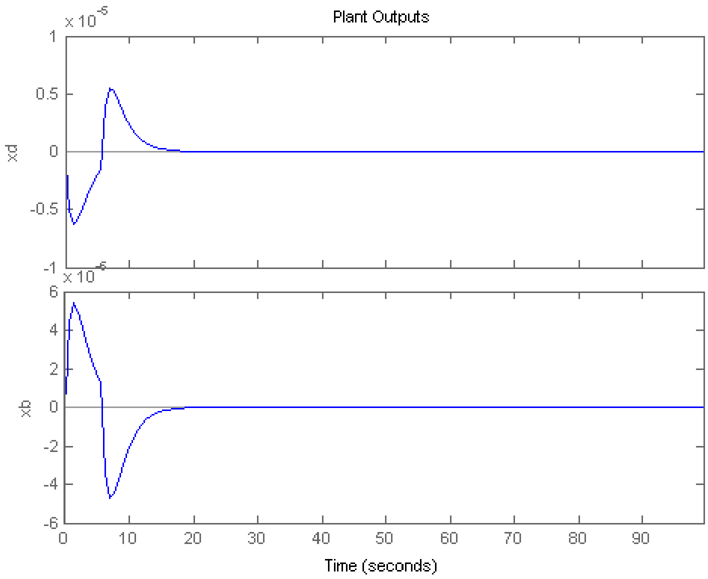


Figure 4.76: Output Response to 0.5 Steam Disturbance in Model 2

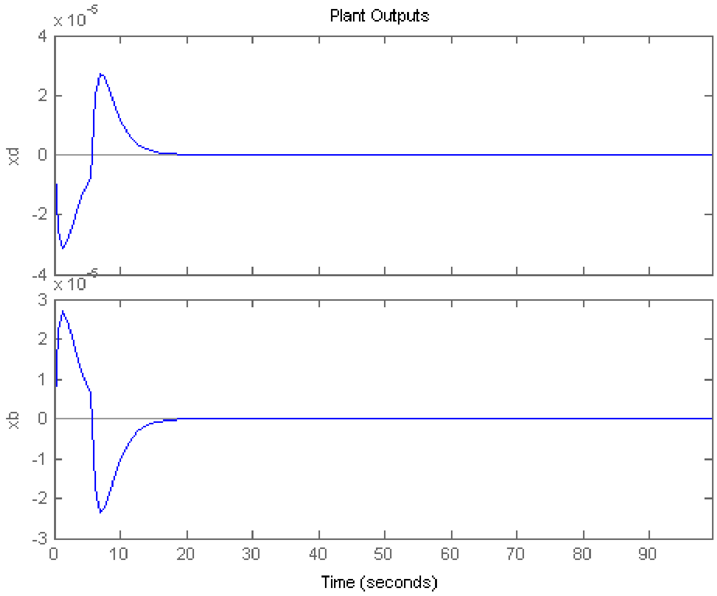


Figure 4.77: Output Response to 1.0 Steam Disturbance in Model 2

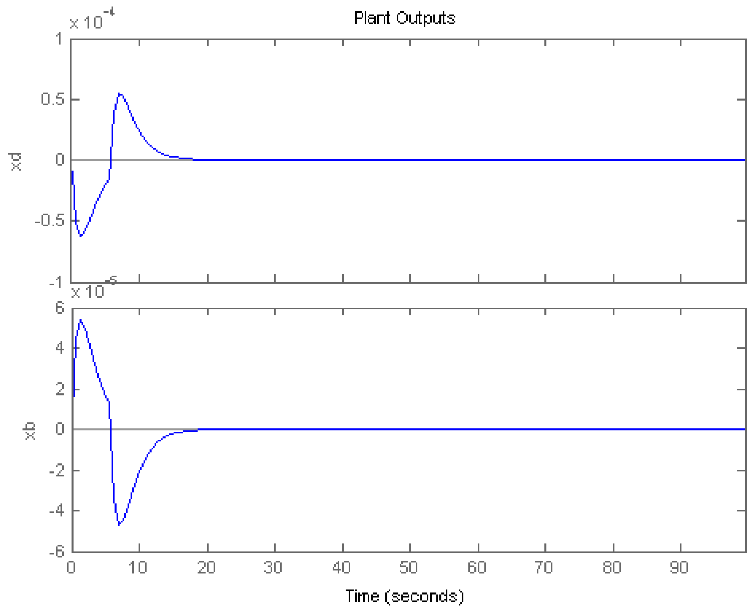


Figure 4.78: Output Response to 2.0 Steam Disturbance in Model 2

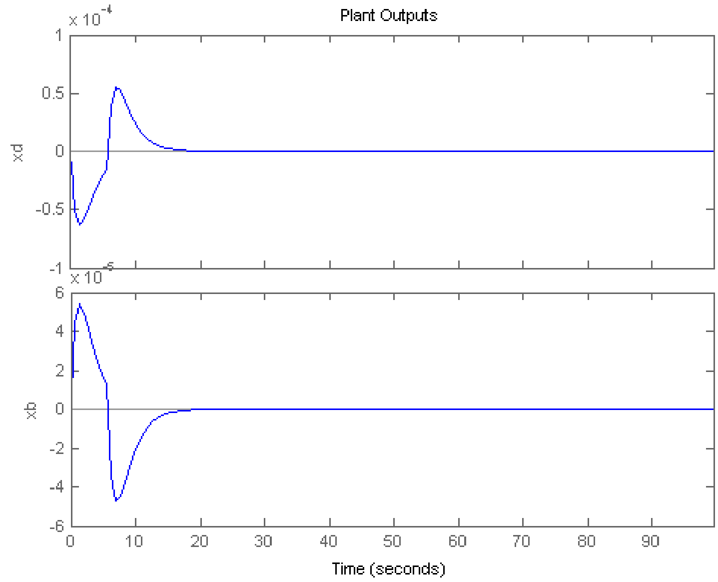


Figure 4.79: Output Response to 5.0 Steam Disturbance in Model 2

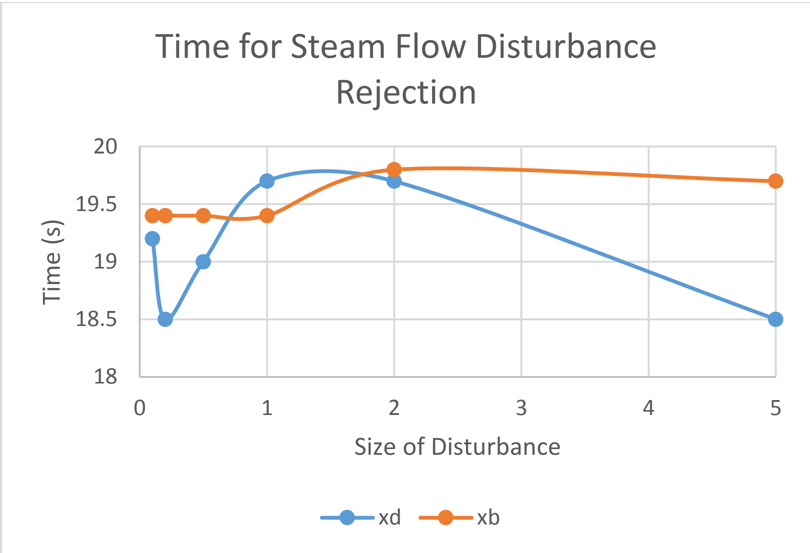


Figure 4.80: Time for Steam Flow Disturbance Rejection in Model 2

When the controller was tested for disturbance in the steam flow, the bottom composition took between 19.4 and 19.8 seconds to return to steady state. On the other hand, the top composition took between 18.5 to 19.7 seconds, signifying that the top composition is more affected by disturbances in the steam flow as compared to reflux flow.

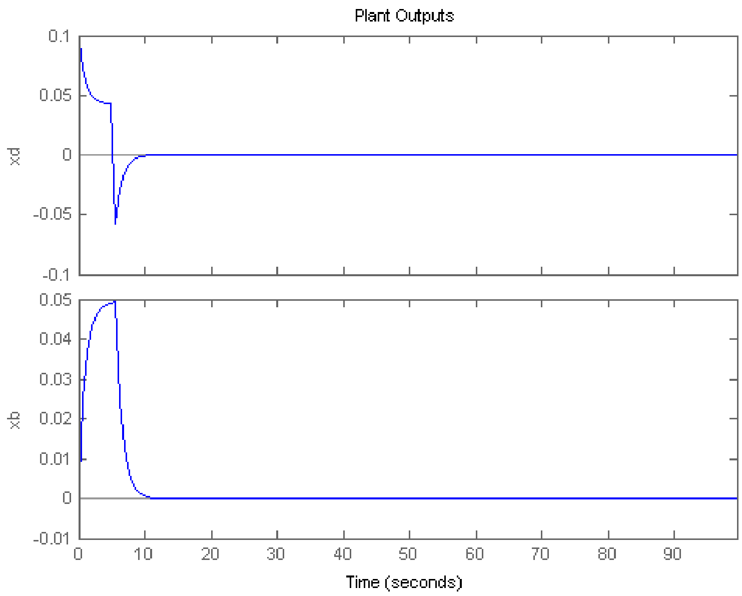


Figure 4.81: Output Response to 0.1 Top Composition Disturbance in Model 2

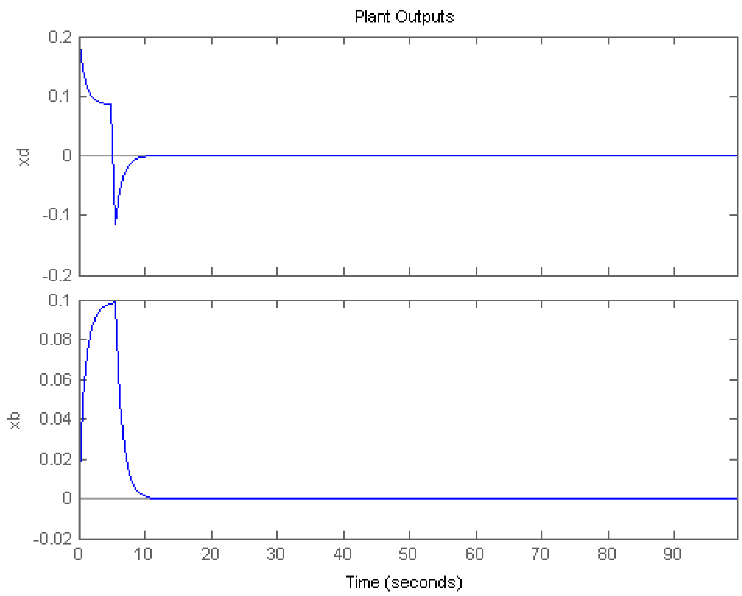


Figure 4.82: Output Response to 0.2 Top Composition Disturbance in Model 2

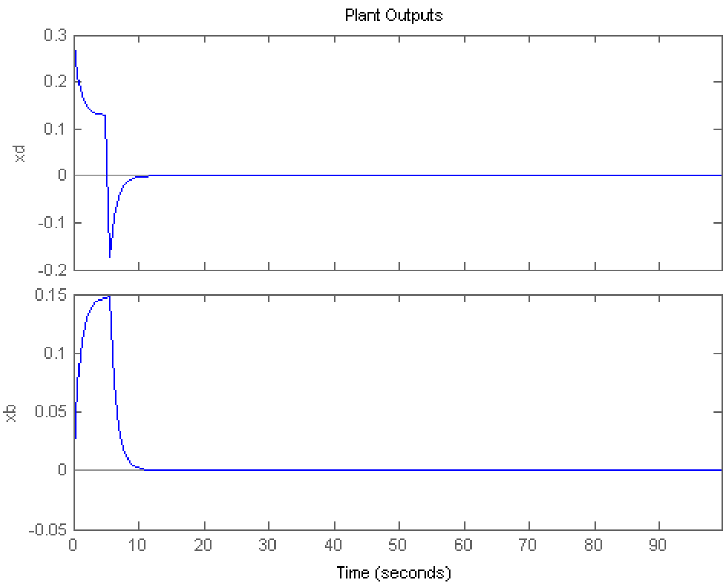


Figure 4.83: Output Response to 0.3 Top Composition Disturbance in Model 2

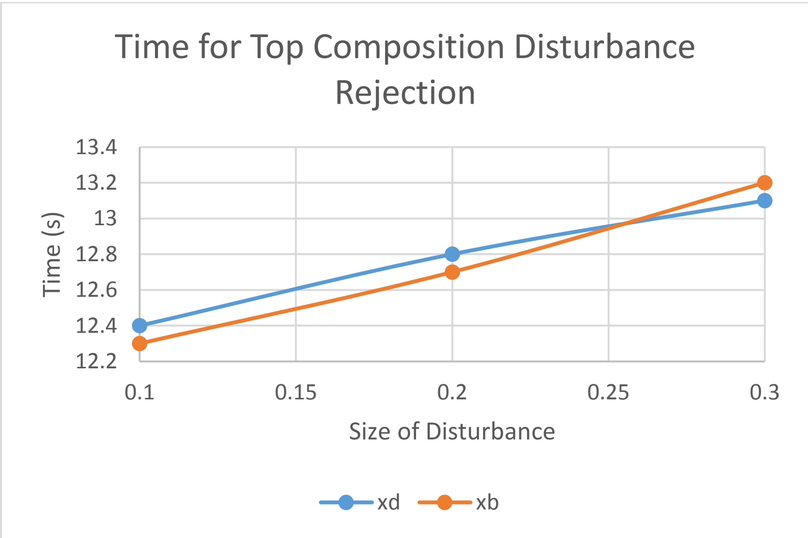


Figure 4.84: Time for Top Composition Disturbance Rejection in Model 2

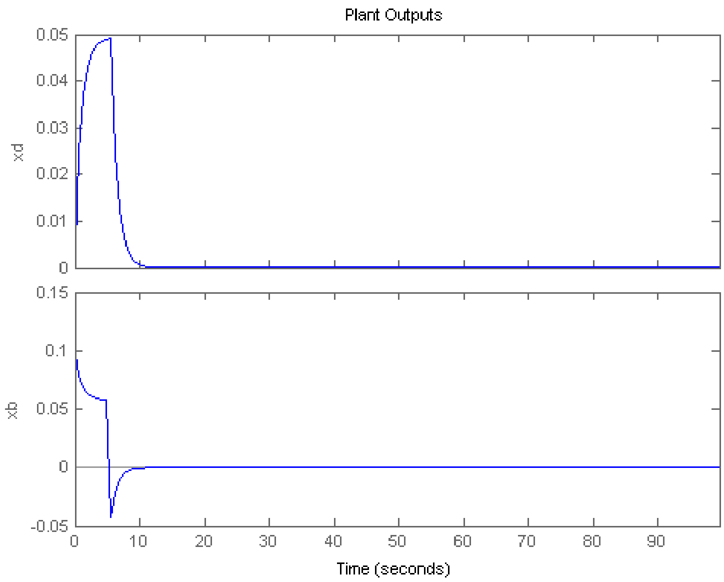


Figure 4.85: Output Response to 0.1 Bottom Composition Disturbance in Model 2

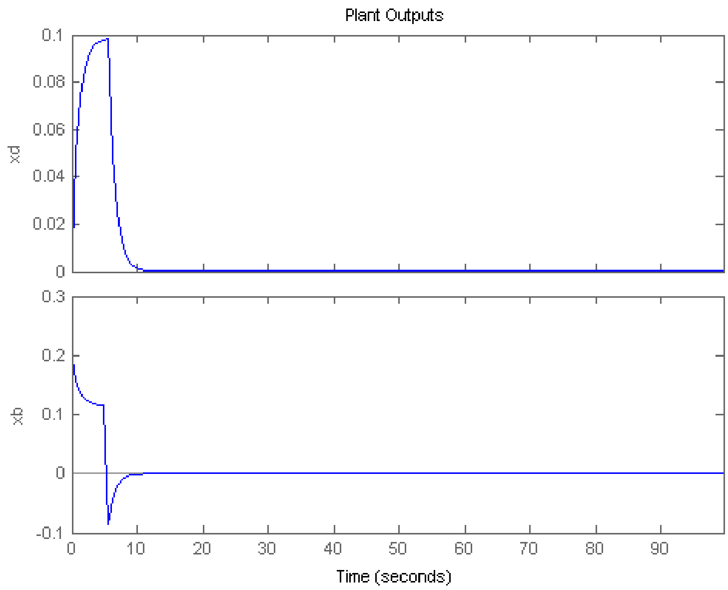


Figure 4.86: Output Response to 0.2 Bottom Composition Disturbance in Model 2

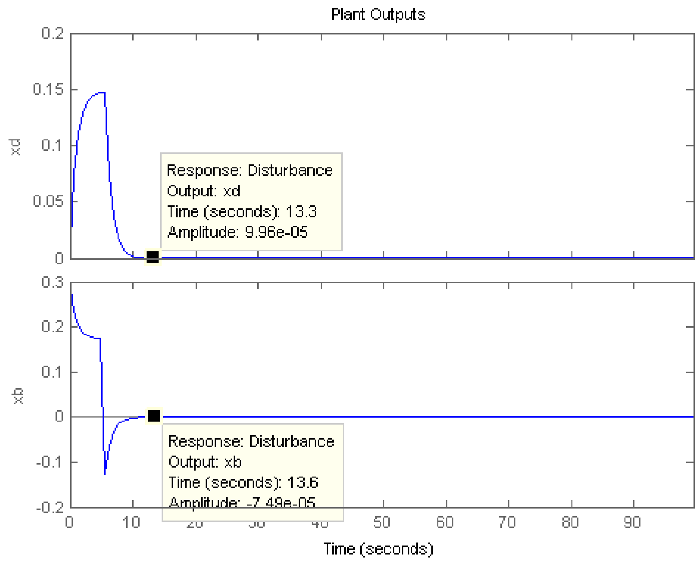


Figure 4.87: Output Response to 0.3 Bottom Composition Disturbance in Model 2

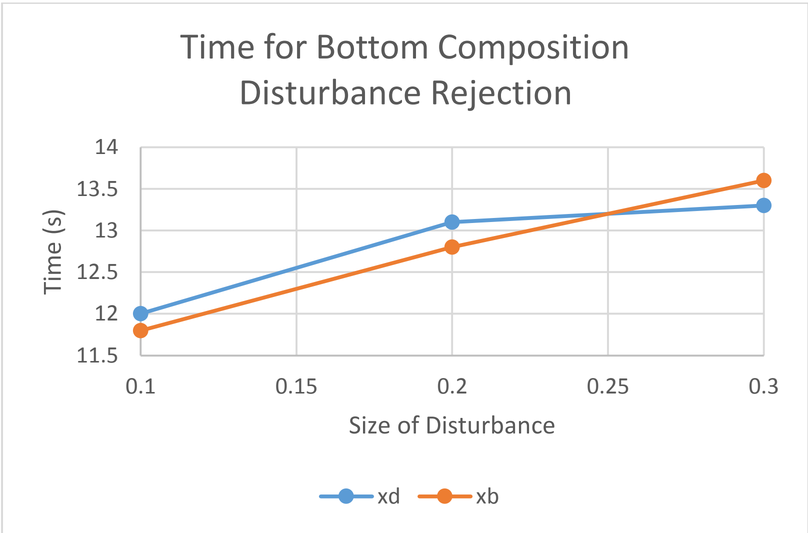
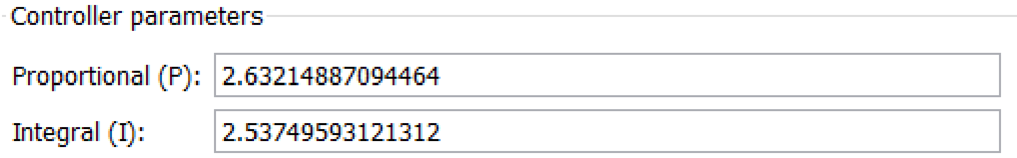


Figure 4.88: Time for Bottom Composition Disturbance Rejection in Model 2

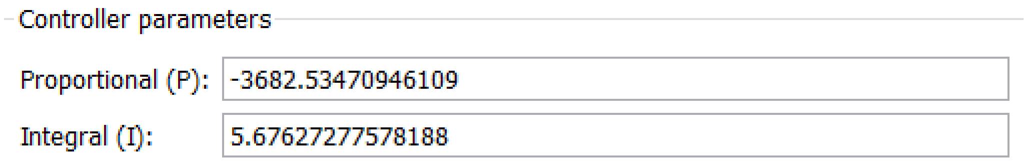
For both top and bottom composition disturbances, the time taken for both controlled variables to return to steady state increased with the increase in size of disturbance. However, when comparing between the two types of disturbance, it can be seen that the increase in time taken to return to steady state during a bottom composition disturbance is more than during a top composition disturbance.

4.5 Comparison with PID control

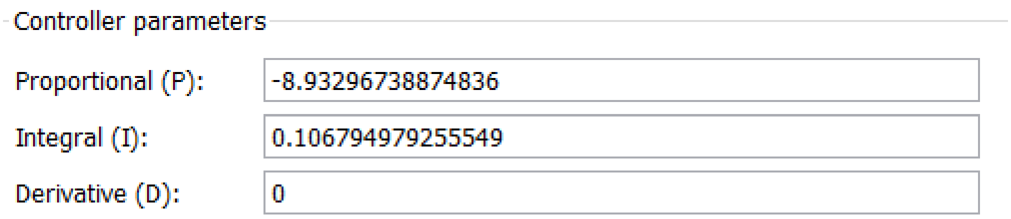
To perform comparison with a PID controller, a 1-1/2-2 PID controller pairing was done for both models as described in the methodology. The tuning of the PID controllers were done by MATLAB. The resultant controller tuning are as shown below.



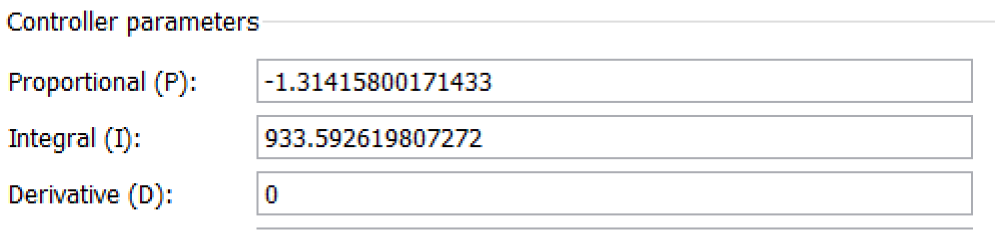
(a)



(b)



(c)



(d)

Figure 4.89: Tuning of (a) first and (b) second PID controller for model 1 and (c) first and (d) second PID controller for model 2

4.5.1 Model 1

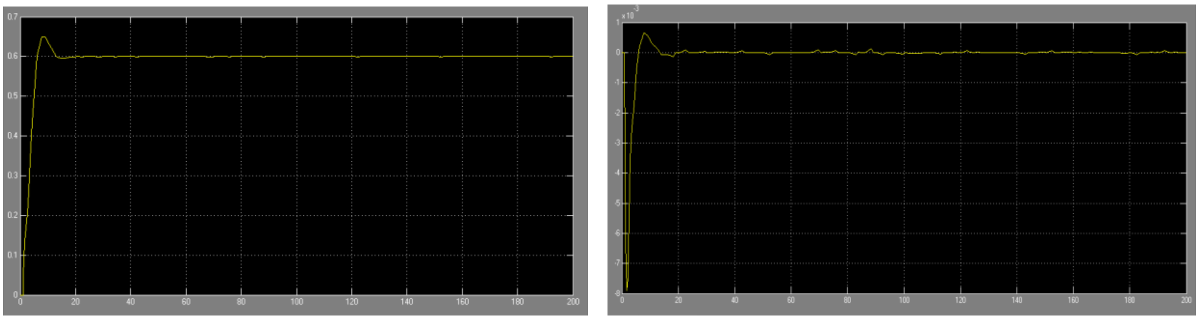


Figure 4.90: Top and Bottom Composition at Top Composition Set Point using PID in Model 1

For the top composition set point at 0.6, the PID controller was able to reach the set point within 20 seconds with a small overshoot. The bottom composition was slightly affected but was restored within the same time the top composition set point was reached. This performance is comparable to the MPC controller, where it also managed to achieve the set point within 20 seconds. In addition, the MPC controller did not have any overshoot.

However, when comparing the effects of the top composition set point on the bottom composition, the MPC controller had upset the bottom composition and did not attempt to restore it. However, the bottom composition upset is a small value of 0.01.

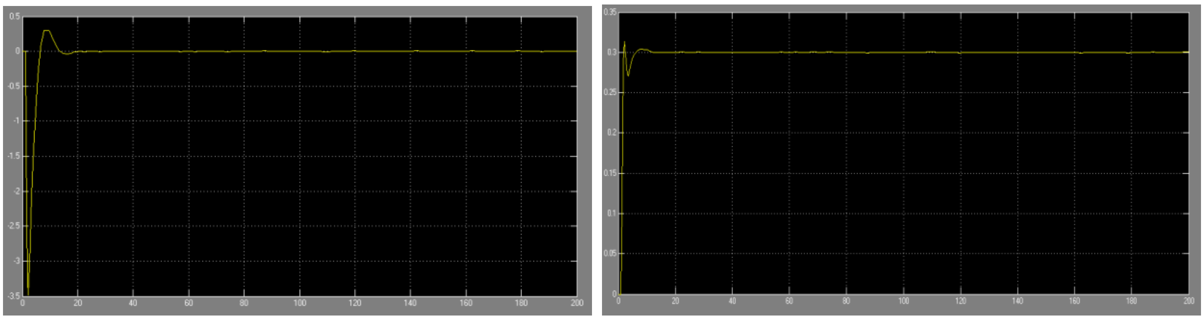


Figure 4.91: Top and Bottom Composition at Bottom Composition Set Point using PID in Model 1

The bottom composition set point was achieved by the PID controller within 15 seconds of the simulation. It was also able to restore the disturbance caused on the top composition within 20 seconds. This is a better performance as compared to the MPC controller which was not able to reach the bottom composition.

4.5.2 Model 2

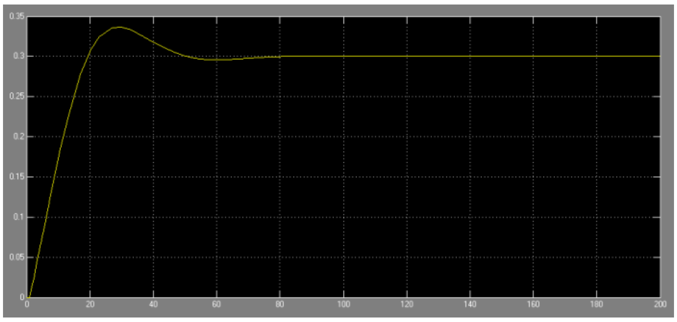


Figure 4.92: Top Composition at Top Composition Set Point using PID in Model 2

The PID controller for model 2 showed that it was able to achieve the top composition set point of 0.3 in 80 seconds. When compared with the MPC controller, the PID controller performed better in which it was able to reach the set point value.

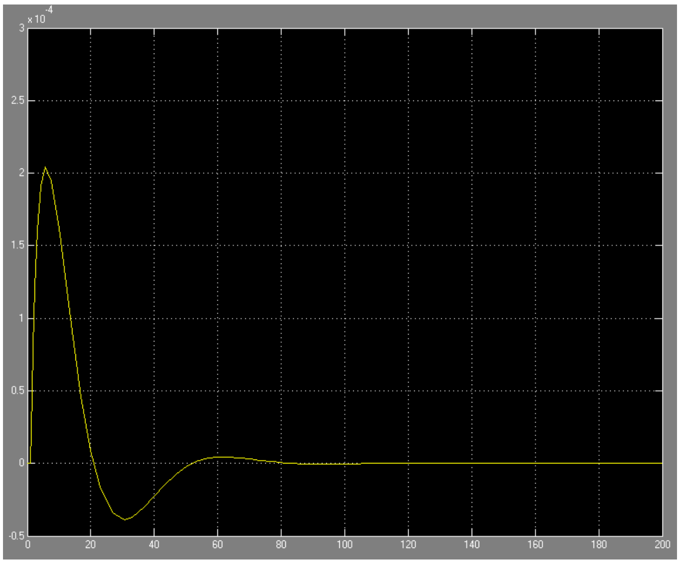


Figure 4.93: Bottom Composition at Top Composition Set Point using PID in Model 2

The PID controller was also able to restore the bottom composition to 0 within the same time for the top composition to achieve its set point. This is comparably better than the MPC controller which did not manage to restore the bottom composition.

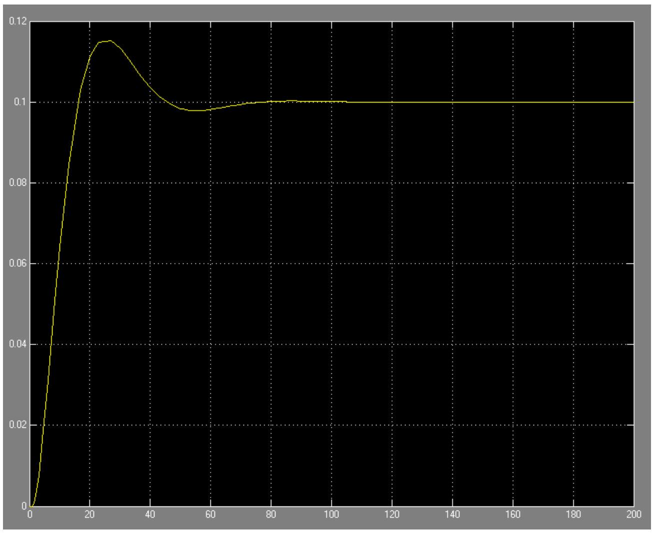


Figure 4.94: Bottom Composition at Bottom Composition Set Point using PID in Model 2

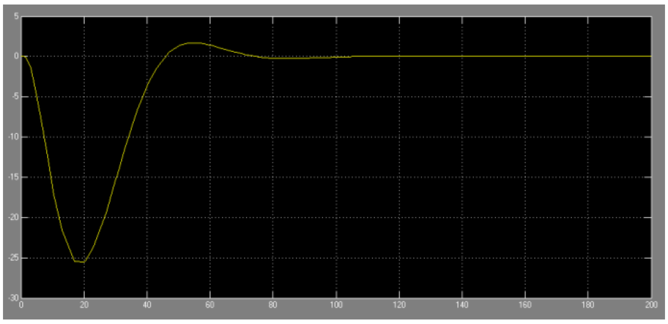


Figure 4.95: Top Composition at Bottom Composition Set Point using PID in Model 2

When tested for the bottom composition set point, it was discovered that the PID controller was able to bring the process to the desired value in 80 seconds. However, the effects on top composition was significant. There is a big movement of top composition away from 0 during the first 20 seconds before returning to steady state. This is not favourable since a small change in the bottom composition would affect the top composition greatly.

In comparison, the MPC controller was not able to reach the bottom set point value of 0.1. Instead, there is an offset of more than 50% of the desired set point. Nevertheless, the MPC controller did not affect the top composition as severely as the PID controller. The top composition remained at a small value in steady state instead of 0.

CHAPTER 5

CONCLUSION AND RECOMMENDATION

5.1 Conclusion

In the beginning of this project, it was intended to develop MPC controllers for two models, one of them is a 2x2 Wood and Berry model, and the other an inferential model. The first model was used as is, while the second model was used to develop a new set of transfer functions based on available data.

The MPC controller developed for model 1 was able to control the process when the top composition set point was changed. However, it was unable to do so with a change in the bottom composition. The disturbance rejection performance, nevertheless, showed that it was able to restore the process to its initial condition in a short period.

In comparison, the MPC controller developed for model 2 did not manage to perform as expected. Neither the top composition nor bottom composition set point was reached. This could be due to model mismatch or an error in tuning. Despite that, the controller was able to perform well during disturbance rejection.

Both controllers were also compared to PID controllers for each process model. It was conclusive that the PID controller was able to perform better for model 1. For model 2, however, it was able to achieve the desired bottom composition set point with a large movement in the top composition.

5.2 Recommendation

Several recommendations can be given for future works. Among them are:

1. Revise the models used to create an MPC controller

For an MPC controller to be developed, the model describing the process has to be as accurate as possible. To do this, a large number of data is required to account for the process dynamics. Since the models used were developed using a limited amount of data, it is recommended that the models be improved with more data.

2. Expand the number of simulation runs to fit in different set point values

In this project, the simulation is limited to one set point value per controlled variable. To be able to measure the performance of an MPC controller, it must be tested over a range of set point values. This will give a better representation of the true ability of the MPC controller.

3. Use a simulation of the distillation column to develop the MPC controller

Other software which can simulate the distillation column as well as have an MPC controller tool can be used to develop the controller. Using this method, the distillation column parameters can be changed as well, giving a more realistic result.

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APPENDIX

Appendix A: Tuning of MPC for Model 1

I. Changes to Control Interval

Horizon	Control Interval		0.1	0.2	0.5	1	2	5	10
	Prediction Horizon		10	10	10	10	10	10	10
	Control Horizon		2	2	2	2	2	2	2
Weights	Overall		0.8	0.8	0.8	0.8	0.8	0.8	0.8
	Reflux	Weight	0	0	0	0	0	0	0
		Rate Weight	0	0	0	0	0	0	0
	Steam	Weight	0	0	0	0	0	0	0
		Rate Weight	0	0	0	0	0	0	0
	xd	Weight	1	1	1	1	1	1	1
	xb	Weight	1	1	1	1	1	1	1
xd=0.6	xd	Max	0.6	0.6	0.6	0.6	0.6	0.6	0.6
		Min	0	0	0	0	0	0	0
		Steady	0.6	0.6	0.6	0.6	0.6	0.6	0.6
	xb	Max	0.00843	0.00901	0.00815	0.00612	0.00313	0.00028	0
		Min	0	0	0	0	0	0	0
		Steady	0	0	0	0	0	0	0
	Reflux	Max	180	72.7	27.1	15.3	10.2	8.14	7.91
		Min	0	0	0	0	0	0	0
		Steady	7.9	7.9	7.9	7.9	7.9	7.9	7.9
	Steam	Max	1740	656	241	147	109	104	102
		Min	0	0	0	0	0	0	0
		Steady	102	102	102	102	102	102	102
xb=0.3	xd	Max	0.00367	0.00332	0.00316	0.00325	0.0033	0.00331	0.00331
		Min	0	0	0	0	0	0	0
		Steady	0.00367	0.00332	0.00316	0.00325	0.0033	0.00331	0.00331
	xb	Max	0	0	0	0	0	0	0
		Min	0	0	0	0	0	0	0
		Steady	0	0	0	0	0	0	0
	Reflux	Max	0.263	0.124	0.0525	0.0322	0.0217	0.0181	0.0177
		Min	0	0	0	0	0	0	0
		Steady	0.0196	0.0178	0.0169	0.0174	0.0177	0.0177	0.0177
	Steam	Max	0	0	0	0	0	0	0
		Min	0	0	0	0	0	0	0
		Steady	0	0	0	0	0	0	0

II. Changes in Prediction Horizon

Horizon	Control Interval		5	5	5	5	5	5	5
	Prediction Horizon		1	2	5	10	50	100	200
	Control Horizon		2	2	2	2	2	2	2
Weights	Overall		0.8	0.8	0.8	0.8	0.8	0.8	0.8
	Reflux	Weight	0	0	0	0	0	0	0
		Rate Weight	0	0	0	0	0	0	0
	Steam	Weight	0	0	0	0	0	0	0
		Rate Weight	0	0	0	0	0	0	0
	xd	Weight	1	1	1	1	1	1	1
	xb	Weight	1	1	1	1	1	1	1
xd=0.6	xd	Max	0.6	0.6	0.6	0.6	0.6	0.6	0.6
		Min	0	0	0	0	0	0	0
		Steady	0.6	0.6	0.6	0.6	0.6	0.6	0.6
	xb	Max	0	0	0.000254	0.000288	0.000313	0.000316	0.000318
		Min	0	0	0	0	0	0	0
		Steady	0	0	0	0	0	0	0
	Reflux	Max	8.28	8.28	8.15	8.14	8.12	8.12	8.12
		Min	0	0	0	0	0	0	0
		Steady	7.9	7.9	7.9	7.9	7.9	7.9	7.9
	Steam	Max	107	107	104	104	103	103	103
		Min	0	0	0	0	0	0	0
		Steady	102	102	102	102	102	102	102
xb=0.3	xd	Max	0.00337	0.00331	0.00331	0.00331	0.00331	0.00331	0.00331
		Min	0	0	0	0	0	0	0
		Steady	0.00337	0.00331	0.00331	0.00331	0.00331	0.00331	0.00331
	xb	Max	0	0	0	0	0	0	0
		Min	0	0	0	0	0	0	0
		Steady	0	0	0	0	0	0	0
	Reflux	Max	0.0184	0.0181	0.0181	0.0181	0.0181	0.0181	0.0181
		Min	0	0	0	0	0	0	0
		Steady	0.018	0.0177	0.0177	0.0177	0.0177	0.0177	0.0177
	Steam	Max	0	0	0	0	0	0	0
		Min	0	0	0	0	0	0	0
		Steady	0	0	0	0	0	0	0

III. Changes in Control Horizon

Horizon	Control Interval		5	5	5	5	5	5
	Prediction Horizon		100	100	100	100	100	100
	Control Horizon		1	2	3	5	10	50
Weights	Overall		0.8	0.8	0.8	0.8	0.8	0.8
	Reflux	Weight	0	0	0	0	0	0
		Rate Weight	0	0	0	0	0	0
	Steam	Weight	0	0	0	0	0	0
		Rate Weight	0	0	0	0	0	0
	xd	Weight	1	1	1	1	1	1
	xb	Weight	1	1	1	1	1	1
xd=0.6	xd	Max	0.6	0.6	0.6	0.6	0.6	0.6
		Min	0	0	0	0	0	0
		Steady	0.6	0.6	0.6	0.6	0.6	0.6
	xb	Max	0.000428	0.000316	0	0	0	0
		Min	0	0	0	0	0	0
		Steady	0	0	0	0	0	0
	Reflux	Max	7.9	8.12	8.28	8.28	8.28	8.28
		Min	0	0	0	0	0	0
		Steady	7.9	7.9	7.9	7.9	7.9	7.9
	Steam	Max	102	103	103	107	107	107
		Min	0	0	0	0	0	0
		Steady	102	102	102	102	102	102
xb=0.3	xd	Max	0.00332	0.00331	0.00331	0.00331	0.00331	0.00331
		Min	0	0	0	0	0	0
		Steady	0.00332	0.00331	0.00331	0.00331	0.00331	0.00331
	xb	Max	0	0	0	0	0	0
		Min	0	0	0	0	0	0
		Steady	0	0	0	0	0	0
	Reflux	Max	0.0177	0.0181	0.0181	0.0181	0.0181	0.0181
		Min	0	0	0	0	0	0
		Steady	0.0177	0.0177	0.0177	0.0177	0.0177	0.0177
	Steam	Max	0	0	0	0	0	0
		Min	0	0	0	0	0	0
		Steady	0	0	0	0	0	0

IV. Changes in Reflux Weight

Horizon	Control Interval		5	5	5	5	5	5	5
	Prediction Horizon		100	100	100	100	100	100	100
	Control Horizon		2	2	2	2	2	2	2
Weights	Overall		0.8	0.8	0.8	0.8	0.8	0.8	0.8
	Reflux	Weight	0	0.01	0.02	0.05	0.1	0.2	0.5
		Rate Weight	0	0	0	0	0	0	0
	Steam	Weight	0	0	0	0	0	0	0
		Rate Weight	0	0	0	0	0	0	0
	xd	Weight	1	1	1	1	1	1	1
	xb	Weight	1	1	1	1	1	1	1
xd=0.6	xd	Max	0.6	0.598	0.593	0.56	0.466	0.28	0.0736
		Min	0	0	0	0	0	0	0
		Steady	0.6	0.598	0.593	0.56	0.466	0.28	0.0736
	xb	Max	0.000316	0.0101	0.00998	0.00941	0.00782	0.00466	0.00122
		Min	0	0	0	0	0	0	0
		Steady	0.000316	0.00992	0.00983	0.00928	0.00773	0.00464	0.00122
	Reflux	Max	8.12	3.27	3.24	3.05	2.54	1.51	0.395
		Min	0	0	0	0	0	0	0
		Steady	7.9	3.2	3.17	2.99	2.49	1.5	0.394
	Steam	Max	103	0	0	0	0	0	0
		Min	0	0	0	0	0	0	0
		Steady	102	0	0	0	0	0	0
xb=0.3	xd	Max	0.00331	0.00331	0.00328	0.00309	0.00258	0.00155	0.000404
		Min	0	0	0	0	0	0	0
		Steady	0.00331	0.00331	0.00328	0.00309	0.00258	0.00155	0.000404
	xb	Max	0	0	0	0	0	0	0
		Min	0	0	0	0	0	0	0
		Steady	0	0	0	0	0	0	0
	Reflux	Max	0.0181	0.018	0.0179	0.0169	0.014	0.00835	0.00218
		Min	0	0	0	0	0	0	0
		Steady	0.0177	0.0177	0.0175	0.0165	0.0138	0.00827	0.00218
	Steam	Max	0	0	0	0	0	0	0
		Min	0	0	0	0	0	0	0
		Steady	0	0	0	0	0	0	0

V. Changes in Reflux Rate Weight

Horizon	Control Interval		5	5	5	5	5	5	5
	Prediction Horizon		100	100	100	100	100	100	100
	Control Horizon		2	2	2	2	2	2	2
Weights	Overall		0.8	0.8	0.8	0.8	0.8	0.8	0.8
	Reflux	Weight	0	0	0	0	0	0	0
		Rate Weight	0	0.01	0.02	0.05	0.1	0.2	0.5
	Steam	Weight	0	0	0	0	0	0	0
		Rate Weight	0	0	0	0	0	0	0
	xd	Weight	1	1	1	1	1	1	1
	xb	Weight	1	1	1	1	1	1	1
							sim time=1000s		
xd=0.6	xd	Max	0.6	0.6	0.6	0.6	0.6	0.6	0.6
		Min	0	0	0	0	0	0	0
		Steady	0.6	0.6	0.6	0.6	0.6	0.6	0.6
	xb	Max	0.000316	0.00894	0.0101	0.0101	0.0097	0.00971	0.00994
		Min	0	0	0	0	0	0	0
		Steady	0.000316	0	0	0	0	0	N/A
	Reflux	Max	8.12	7.9	7.9	7.9	7.9	7.9	4.56
		Min	0	0	0	0	0	0	0
		Steady	7.9	7.9	7.9	7.9	7.9	7.9	N/A
	Steam	Max	103	102	102	102	102	102	29.5
		Min	0	0	0	0	0	0	0
		Steady	102	102	102	102	102	102	N/A
xb=0.3	xd	Max	0.00331	0.00331	0.00331	0.00331	0.00331	0.00331	0.00332
		Min	0	0	0	0	0	0	0
		Steady	0.00331	0.00331	0.00331	0.00331	0.00331	0.00331	0.00332
	xb	Max	0	0	0	0	0	0	0
		Min	0	0	0	0	0	0	0
		Steady	0	0	0	0	0	0	0
	Reflux	Max	0.0181	0.018	0.0179	0.0179	0.0177	0.0177	0.0177
		Min	0		0	0	0	0	0
		Steady	0.0177	0.0177	0.0177	0.0177	0.0177	0.0177	0.0177
	Steam	Max	0	0	0	0	0	0	0
		Min	0	0	0	0	0	0	0
		Steady	0	0	0	0	0	0	0

VI. Changes to Steam Weight

Horizon	Control Interval		5	5	5	5	5	5	5
	Prediction Horizon		100	100	100	100	100	100	100
	Control Horizon		2	2	2	2	2	2	2
Weights	Overall		0.8	0.8	0.8	0.8	0.8	0.8	0.8
	Reflux	Weight	0	0	0	0	0	0	0
		Rate Weight	0	0	0	0	0	0	0
	Steam	Weight	0	0.01	0.02	0.05	0.1	0.2	0.5
		Rate Weight	0	0	0	0	0	0	0
	xd	Weight	1	1	1	1	1	1	1
	xb	Weight	1	1	1	1	1	1	1
xd=0.6	xd	Max	0.6	0.6	0.6	0.6	0.6	0.6	0.6
		Min	0	0	0	0	0	0	0
		Steady	0.6	0.6	0.6	0.6	0.6	0.6	0.6
	xb	Max	0.000316	0.000316	0.0101	0.0101	0.0101	0.0101	0.0101
		Min	0	0	0	0	0	0	0
		Steady	0.000316	0.000316	0.00994	0.00994	0.00994	0.00994	0.00994
	Reflux	Max	8.12	8.12	3.28	3.28	3.28	3.28	3.28
		Min	0	0	0	0	0	0	0
		Steady	7.9	7.9	3.21	3.21	3.21	3.21	3.21
	Steam	Max	103	103	0.00246	0.000393	0	0	0
		Min	0	0	0	0	0	0	0
		Steady	102	102	0.00242	0.000388	0	0	0
xb=0.3	xd	Max	0.00331	0.00331	0.00331	0.00331	0.00331	0.00331	0.00331
		Min	0	0	0	0	0	0	0
		Steady	0.00331	0.00331	0.00331	0.00331	0.00331	0.00331	0.00331
	xb	Max	0	0	0	0	0	0	0
		Min	0	0	0	0	0	0	0
		Steady	0	0	0	0	0	0	0
	Reflux	Max	0.0181	0.0181	0.0181	0.0181	0.0181	0.0181	0.0181
		Min	0	0	0	0	0	0	0
		Steady	0.0177	0.0177	0.0177	0.0177	0.0177	0.0177	0.0177
	Steam	Max	0	0	0	0	0	0	0
		Min	0	0	0	0	0	0	0
		Steady	0	0	0	0	0	0	0

VII. Changes to Steam Rate Weight

Horizon	Control Interval		5	5	5	5	5	5	5
	Prediction Horizon		100	100	100	100	100	100	100
	Control Horizon		2	2	2	2	2	2	2
Weights	Overall		0.8	0.8	0.8	0.8	0.8	0.8	0.8
	Reflux	Weight	0	0	0	0	0	0	0
		Rate Weight	0	0	0	0	0	0	0
	Steam	Weight	0.1	0.1	0.1	0.1	0.1	0.1	0.1
		Rate Weight	0	0.01	0.02	0.05	0.1	0.2	0.5
	xd	Weight	1	1	1	1	1	1	1
	xb	Weight	1	1	1	1	1	1	1
xd=0.6	xd	Max	0.6	0.6	0.6	0.6	0.6	0.6	0.6
		Min	0	0	0	0	0	0	0
		Steady	0.6	0.6	0.6	0.6	0.6	0.6	0.6
	xb	Max	0.0101	0.0101	0.0101	0.0101	0.0101	0.0101	0.0101
		Min	0	0	0	0	0	0	0
		Steady	0.00994	0.00994	0.00994	0.00994	0.00994	0.00994	0.00994
	Reflux	Max	3.28	3.28	3.28	3.28	3.28	3.28	3.28
		Min	0	0	0	0	0	0	0
		Steady	3.21	3.21	3.21	3.21	3.21	3.21	3.21
	Steam	Max	0	0	0	0	0	0	0
		Min	0	0	0	0	0	0	0
		Steady	0	0	0	0	0	0	0
xb=0.3	xd	Max	0.00331	0.00331	0.00331	0.00331	0.00331	0.00331	0.00331
		Min	0	0	0	0	0	0	0
		Steady	0.00331	0.00331	0.00331	0.00331	0.00331	0.00331	0.00331
	xb	Max	0	0	0	0	0	0	0
		Min	0	0	0	0	0	0	0
		Steady	0	0	0	0	0	0	0
	Reflux	Max	0.0181	0.0181	0.0181	0.0181	0.0181	0.0181	0.0181
		Min	0	0	0	0	0	0	0
		Steady	0.0177	0.0177	0.0177	0.0177	0.0177	0.0177	0.0177
	Steam	Max	0	0	0	0	0	0	0
		Min	0	0	0	0	0	0	0
		Steady	0	0	0	0	0	0	0

VIII. Changes to Top Composition Weight

Horizon	Control Interval		5	5	5	5	5	5	5
	Prediction Horizon		100	100	100	100	100	100	100
	Control Horizon		2	2	2	2	2	2	2
Weights	Overall		0.8	0.8	0.8	0.8	0.8	0.8	0.8
	Reflux	Weight	0	0	0	0	0	0	0
		Rate Weight	0	0	0	0	0	0	0
	Steam	Weight	0.1	0.1	0.1	0.1	0.1	0.1	0.1
		Rate Weight	0	0	0	0	0	0	0
	xd	Weight	0	0.1	0.2	0.3	0.5	0.7	1
	xb	Weight	1	1	1	1	1	1	1
xd=0.6	xd	Max	0	0.584	0.596	0.598	0.599	0.6	0.6
		Min	0	0	0	0	0	0	0
		Steady	0	0.584	0.596	0.598	0.599	0.6	0.6
	xb	Max	0	0.00983	0.01	0.0101	0.0101	0.0101	0.0101
		Min	0	0	0	0	0	0	0
		Steady	0	0.00968	0.00988	0.0101	0.0101	0.00994	0.00994
	Reflux	Max	0	3.19	3.25	3.27	3.27	3.27	3.28
		Min	0	0	0	0	0	0	0
		Steady	0	3.12	3.19	3.2	3.21	3.21	3.21
	Steam	Max	0	0	0	0	0	0	0
		Min	0	0	0	0	0	0	0
		Steady	0	0	0	0	0	0	0
xb=0.3	xd	Max	12.1	0.323	0.0823	0.0367	0.0132	0.00676	0.00331
		Min	0	0	0	0	0	0	0
		Steady	12.1	0.323	0.0823	0.0367	0.0132	0.00676	0.00331
	xb	Max	0.2	0.00543	0.00139	0.000609	0.00022	0.000112	0
		Min	0	0	0	0	0	0	0
		Steady	0.2	0.00535	0.00136	0.000609	0.00022	0.000112	0
	Reflux	Max	64.9	1.76	0.449	0.201	0.0732	0.0369	0.0181
		Min	0	0	0	0	0	0	0
		Steady	64.5	1.73	0.44	0.196	0.0708	0.0362	0.0177
	Steam	Max	0	0	0	0	0	0	0
		Min	0	0	0	0	0	0	0
		Steady	0	0	0	0	0	0	0

IX. Changes to Bottom Composition Weight

Horizon	Control Interval		5	5	5	5	5	5
	Prediction Horizon		100	100	100	100	100	100
	Control Horizon		2	2	2	2	2	2
Weights	Overall		0.8	0.8	0.8	0.8	0.8	0.8
	Reflux	Weight	0	0	0	0	0	0
		Rate Weight	0	0	0	0	0	0
	Steam	Weight	0.1	0.1	0.1	0.1	0.1	0.1
		Rate Weight	0	0	0	0	0	0
	xd	Weight	0.7	0.7	0.7	0.7	0.7	0.7
	xb	Weight	0	1	2	3	5	10
xd=0.6	xd	Max	0.6	0.6	0.599	0.597	0.592	0.568
		Min	0	0	0	0	0	0
		Steady	0.6	0.6	0.599	0.597	0.592	0.568
	xb	Max	0.01	0.0101	0.0101	0.01	0.00996	0.00956
		Min	0	0	0	0	0	0
		Steady	0.00995	0.00994	0.00992	0.0099	0.00981	0.00942
	Reflux	Max	3.28	3.27	3.27	3.26	3.23	3.1
		Min	0	0	0	0	0	0
		Steady	3.21	3.21	3.2	3.19	3.16	3.04
	Steam	Max	0	0	0.000393	0.000881	0.00242	0.00931
		Min	0	0	0	0	0	0
		Steady	0	0	0.000387	0.000868	0.00239	0.00918
xb=0.3	xd	Max	0	0.00676	0.027	0.0606	0.167	0.64
		Min	0	0	0	0	0	0
		Steady	0	0.00676	0.027	0.0606	0.167	0.64
	xb	Max	0	0.000112	0.000448	0.00102	0.00281	0.0108
		Min	0	0	0	0	0	0
		Steady	0	0.000112	0.000448	0.001	0.00277	0.0106
	Reflux	Max	0	0.0369	0.147	0.331	0.991	3.5
		Min	0	0	0	0	0	0
		Steady	0	0.0362	0.144	0.324	0.892	3.43
	Steam	Max	0	0	0	0	0	0
		Min	0	0	0	0	0	0
		Steady	0	0	0	0	0	0

X. Changes to Overall Performance

Horizon	Control Interval		5	5	5	5	5	5	5	5	5	5	5
	Prediction Horizon		100	100	100	100	100	100	100	100	100	100	100
	Control Horizon		2	2	2	2	2	2	2	2	2	2	2
Weights	Overall		0	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9	1
	Reflux	Weight	0	0	0	0	0	0	0	0	0	0	0
		Rate Weight	0	0	0	0	0	0	0	0	0	0	0
	Steam	Weight	0.1	0.1	0.1	0.1	0.1	0.1	0.1	0.1	0.1	0.1	0.1
		Rate Weight	0	0	0	0	0	0	0	0	0	0	0
	xd	Weight	0.7	0.7	0.7	0.7	0.7	0.7	0.7	0.7	0.7	0.7	0.7
	xb	Weight	1	1	1	1	1	1	1	1	1	1	1
xd=0.6	xd	Max	0.6	0.6	0.6	0.6	0.6	0.6	0.6	0.6	0.6	0.6	0.6
		Min	0	0	0	0	0	0	0	0	0	0	0
		Steady	0.6	0.6	0.6	0.6	0.6	0.6	0.6	0.6	0.6	0.6	0.6
	xb	Max	0.0101	0.0101	0.0101	0.0101	0.0101	0.0101	0.0101	0.0101	0.0101	0.0101	0.0101
		Min	0	0	0	0	0	0	0	0	0	0	0
		Steady	0.00994	0.00994	0.00994	0.00994	0.00994	0.00994	0.00994	0.00994	0.00994	0.00994	0.00994
	Reflux	Max	3.27	3.27	3.27	3.27	3.27	3.27	3.27	3.27	3.27	3.27	3.27
		Min	0	0	0	0	0	0	0	0	0	0	0
		Steady	3.21	3.21	3.21	3.21	3.21	3.21	3.21	3.21	3.21	3.21	3.21
	Steam	Max	0	0	0	0	0	0	0	0	0	0	0
		Min	0	0	0	0	0	0	0	0	0	0	0
		Steady	0	0	0	0	0	0	0	0	0	0	0
xb=0.3	xd	Max	0.00676	0.00676	0.00676	0.00676	0.00676	0.00676	0.00676	0.00676	0.00676	0.00676	0.00676
		Min	0	0	0	0	0	0	0	0	0	0	0
		Steady	0.00676	0.00676	0.00676	0.00676	0.00676	0.00676	0.00676	0.00676	0.00676	0.00676	0.00676
	xb	Max	0.000112	0.000112	0.000112	0.000112	0.000112	0.000112	0.000112	0.000112	0.000112	0.000112	0.000112
		Min	0	0	0	0	0	0	0	0	0	0	0
		Steady	0.000112	0.000112	0.000112	0.000112	0.000112	0.000112	0.000112	0.000112	0.000112	0.000112	0.000112
	Reflux	Max	0.0369	0.0369	0.0369	0.0369	0.0369	0.0369	0.0369	0.0369	0.0369	0.0369	0.0369
		Min	0	0	0	0	0	0	0	0	0	0	0
		Steady	0.0362	0.0362	0.0362	0.0362	0.0362	0.0362	0.0362	0.0362	0.0362	0.0362	0.0362
	Steam	Max	0	0	0	0	0	0	0	0	0	0	0
		Min	0	0	0	0	0	0	0	0	0	0	0
		Steady	0	0	0	0	0	0	0	0	0	0	0

Appendix B: Tuning of MPC for Model 2

I. Changes to Control Interval

Horizon	Control Interval		0.1	0.2	0.5	0.6	0.7	1	2	5	10
	Prediction Horizon		10	10	10	10	10	10	10	10	10
	Control Horizon		2	2	2	2	2	2	2	2	2
Weights	Overall		0.8	0.8	0.8	0.8	0.8	0.8	0.8	0.8	0.8
	Reflux	Weight	0	0	0	0	0	0	0	0	0
		Rate Weight	0	0	0	0	0	0	0	0	0
	Steam	Weight	0	0	0	0	0	0	0	0	0
		Rate Weight	0	0	0	0	0	0	0	0	0
	xd	Weight	1	1	1	1	1	1	1	1	1
	xb	Weight	1	1	1	1	1	1	1	1	1
xd=0.3	xd	Max	0.179	0.173	0.173	0.3	0.3	0.3	0.3	0.3	0.3
		Min	0	0	0	0	0	0	0	0	0
		Steady	0.173	0.173	0.173	0.3	0.3	0.3	0.3	0.3	0.3
	xb	Max	0	0	0	0	0	0	0	0	0
		Min	-0.153	-0.15	-0.148	0	0	0	0	0	0
		Steady	-0.148	-0.148	-0.148	0	0	0	0	0	0
	Reflux	Max	0	0	0	0	0	0	0	0	0
		Min	-213	-116	-48.3	-2.54E+04	-2.19E+04	-1.55E+04	-8.09E+03	-3.65E+03	-2.21E+03
		Steady	-3.08	-2.47	-2.42	-1.27E+03	-1.27E+03	-1.27E+03	-1.27E+03	-1.27E+03	-1.27E+03
	Steam	Max	954	822	560	4.79E+06	4.20E+06	3.14E+06	1.94E+06	1.31E+06	1.20E+06
		Min	0	0	0	0	0	0	0	0	0
		Steady	N/A	N/A	N/A	1.19E+06	1.19E+06	1.19E+06	1.19E+06	1.19E+06	1.19E+06
xb=0.1	xd	Max	0	0	0	0	0	0	0	0	0
		Min	-0.051	-0.05	-0.0494	0	0	0	0	0	0
		Steady	-0.0494	-0.0494	-0.0494	0	0	0	0	0	0
	xb	Max	0.0438	0.0429	0.0424	0.1	0.1	0.1	0.1	0.1	0.1
		Min	0	0	0	0	0	0	0	0	0
		Steady	0.0424	0.0424	0.0424	0.1	0.1	0.1	0.1	0.1	0.1
	Reflux	Max	60.8	33.2	13.8	0	0	0.00E+00	0	0	0
		Min	-0.923	0.235	0.339	-9.85E+03	-8.48E+03	-6010	-3.14E+03	-1.42E+03	-858
		Steady	0.244	N/A	N/A	-494	-494	-494	-494	-494	-494
	Steam	Max	371	320	218	1.86E+06	1.63E+06	1.22E+06	7.35E+05	5.10E+05	4.67E+05
		Min	0	0	0	0	0	0	0.00E+00	0	0
		Steady	N/A	N/A	N/A	4.63E+05	4.63E+05	4.63E+05	4.63E+05	4.63E+05	4.63E+05

II. Changes to Prediction Horizon

Horizon	Control Interval		0.7	0.7	0.7	0.7	0.7	0.7	0.7	0.7	0.7
	Prediction Horizon		1	2	5	6	8	10	20	50	100
	Control Horizon		2	2	2	2	2	2	2	2	2
Weights	Overall		0.8	0.8	0.8	0.8	0.8	0.8	0.8	0.8	0.8
	Reflux	Weight	0	0	0	0	0	0	0	0	0
		Rate Weight	0	0	0	0	0	0	0	0	0
	Steam	Weight	0	0	0	0	0	0	0	0	0
		Rate Weight	0	0	0	0	0	0	0	0	0
	xd	Weight	1	1	1	1	1	1	1	1	1
	xb	Weight	1	1	1	1	1	1	1	1	1
xd=0.3	xd	Max	0.173	0.173	0.173	0.3	0.3	0.3	0.3	0.3	0.3
		Min	0	0	0	0	0	0	0	0	0
		Steady	0.173	0.173	0.173	0.3	0.3	0.3	0.3	0.3	0.3
	xb	Max	0	0	0	0	0	0	0	0	0
		Min	-0.149	-0.149	-0.149	0	0	0	0	0	0
		Steady	-0.148	-0.148	-0.148	0	0	0	0	0	0
	Reflux	Max	0	0	0	0	0	0	0	0	0
		Min	-34.9	-34.7	-34.8	-2.19E+04	-2.19E+04	-2.19E+04	-2.19E+04	-2.19E+04	-2.19E+04
		Steady	-2.05	-2.06	-2.24	-1.27E+03	-1.27E+03	-1.27E+03	-1.27E+03	-1.27E+03	-1.27E+03
	Steam	Max	17.3	47	180	4.20E+06	4.20E+06	4.20E+06	4.20E+06	4.20E+06	4.20E+06
		Min	0	0	0	0	0	0	0	0	0
		Steady	N/A	N/A	N/A	1.19E+06	1.19E+06	1.19E+06	1.19E+06	1.19E+06	1.19E+06
xb=0.1	xd	Max	0	0	0	0.1	0.1	0	0	0	0
		Min	-0.0494	-0.0496	-0.0495	0	0	0	0	0	0
		Steady	-0.0494	-0.0494	-0.0494	0.1	0.1	0	0	0	0
	xb	Max	0.0424	0.0424	0.0424	0	0	0.1	0.1	0.1	0.1
		Min	0	0	0	0	0	0	0	0	0
		Steady	0.0424	0.0424	0.0424	0	0	0.1	0.1	0.1	0.1
	Reflux	Max	9.96	9.9	9.95	0	0	0	0	0	0
		Min	0	0	0	-8.48E+03	-8.48E+03	-8.48E+03	-8.48E+03	-8.48E+03	-8.48E+03
		Steady	0.582	0.568	0.553	-494	-494	-494	-494	-494	-494
	Steam	Max	6.73	18.3	69.9	1.63E+06	1.63E+06	1.63E+06	1.63E+06	1.63E+06	1.63E+06
		Min	0	0	0	0	0	0	0	0	0
		Steady	N/A	N/A	N/A	4.63E+05	4.63E+05	4.63E+05	4.63E+05	4.63E+05	4.63E+05

III. Changes to Control Horizon

Horizon	Control Interval		0.7	0.7	0.7	0.7	0.7	0.7	0.7
	Prediction Horizon		100	100	100	100	100	100	100
	Control Horizon		1	2	5	10	20	30	50
Weights	Overall		0.8	0.8	0.8	0.8	0.8	0.8	0.8
	Reflux	Weight	0	0	0	0	0	0	0
		Rate Weight	0	0	0	0	0	0	0
	Steam	Weight	0	0	0	0	0	0	0
		Rate Weight	0	0	0	0	0	0	0
	xd	Weight	1	1	1	1	1	1	1
	xb	Weight	1	1	1	1	1	1	1
xd=0.3	xd	Max	0.169	0.3	0.173	0.173	0.173	0.173	0.173
		Min	0	0	0	0	0	0	0
		Steady	0.169	0.3	0.173	0.173	0.173	0.173	0.173
	xb	Max	0	0	0	0	0	0	0
		Min	-0.146	0	-0.148	-0.148	-0.148	-0.148	-0.148
		Steady	-0.146	0	-0.148	-0.148	-0.148	-0.148	-0.148
	Reflux	Max	0.479	0	0	0	0	0	0
		Min	-0.878	-2.19E+04	-34.8	-34.8	-34.8	-34.8	-34.8
		Steady	N/A	-1.27E+03	N/A	N/A	N/A	N/A	N/A
	Steam	Max	0	4.20E+06	5.55E+03	5.87E+03	5.93E+03	5.94E+03	5.94E+03
		Min	-2.32E+03	0	0	0	0	0	0
		Steady	N/A	1.19E+06	N/A	N/A	N/A	N/A	N/A
xb=0.1	xd	Max	0	0	0	0	0	0	0
		Min	-0.0506	0	-0.0493	-0.0493	-0.0496	-0.0496	-0.0496
		Steady	-0.0506	0	-0.0493	-0.0493	-0.0492	-0.0492	-0.0492
	xb	Max	0.0436	0.1	0.0425	0.0424	0.0426	0.0426	0.0426
		Min	0	0	0	0	0	0	0
		Steady	0.0436	0.1	0.0425	0.0424	0.0426	0.0426	0.0426
	Reflux	Max	0	0	9.86	9.86	9.86	9.86	9.86
		Min	-0.403	-8.48E+03	-1.83	.1.97	-2	-2	-2
		Steady	N/A	-494	N/A	N/A	N/A	N/A	N/A
	Steam	Max	920	1.63E+06	2.16E+03	2.28E+03	2.31E+03	2.31E+03	2.31E+03
		Min	0	0	0	0	0	0	0
		Steady	N/A	4.63E+05	N/A	N/A	N/A	N/A	N/A

IV. Changes to Reflux Weight

Horizon	Control Interval		0.7	0.7	0.7	0.7	0.7	0.7	0.7
	Prediction Horizon		100	100	100	100	100	100	100
	Control Horizon		2	2	2	2	2	2	2
Weights	Overall		0.8	0.8	0.8	0.8	0.8	0.8	0.8
	Reflux	Weight	0	0.1	0.2	0.3	0.5	1	2
		Rate Weight	0	0	0	0	0	0	0
	Steam	Weight	0	0	0	0	0	0	0
		Rate Weight	0	0	0	0	0	0	0
	xd	Weight	1	1	1	1	1	1	1
	xb	Weight	1	1	1	1	1	1	1
xd=0.3	xd	Max	0.3	0.173	0.173	0.173	0.173	0.173	0.173
		Min	0	0	0	0	0	0	0
		Steady	0.3	0.172	0.173	0.173	0.173	0.173	0.173
	xb	Max	0	0	0	0	0	0	0
		Min	0	-0.148	-0.148	-0.148	-0.148	-0.148	-0.148
		Steady	0	-0.148	-0.148	-0.148	-0.148	-0.148	-0.148
	Reflux	Max	0	0	0	0	0	0	0
		Min	-2.19E+04	-0.00344	-0.00078	-0.00034	-0.00012	0	0
		Steady	-1.27E+03	-0.00292	-0.00074	-0.00033	-0.00012	0	0
	Steam	Max	4.20E+06	0	0	0	0	0	0
		Min	0.00E+00	-6.72E+03	-6.72E+03	-6.72E+03	-6.72E+03	-6.72E+03	-6.72E+03
		Steady	1.19E+06	-1.90E+03	-1.90E+03	-1.90E+03	-1.90E+03	-1.90E+03	-1.90E+03
xb=0.1	xd	Max	0	0	0	0	0	0	0
		Min	0	-0.0494	-0.0494	-0.0494	-0.0494	-0.0494	-0.0494
		Steady	0	-0.0494	-0.0494	-0.0494	-0.0494	-0.0494	-0.0494
	xb	Max	0.1	0.0425	0.0425	0.0425	0.0425	0.0425	0.0425
		Min	0	0	0	0	0	0	0
		Steady	0.1	0.0425	0.0425	0.0425	0.0425	0.0425	0.0425
	Reflux	Max	0	0	0	0	0	0	0
		Min	-8.48E+03	-0.00133	-0.0003	-0.00013	0	0	0
		Steady	-494	-0.00113	-0.00029	-0.00013	0	0	0
	Steam	Max	1.63E+06	1.92E+03	1.92E+03	1.92E+03	1.92E+03	1.93E+03	1.93E+03
		Min	0	0	0	0	0	0	0
		Steady	4.63E+05	547	546	546	546	546	546

V. Changes to Reflux Rate Weight

Horizon	Control Interval		0.7	0.7	0.7	0.7	0.7	0.7	0.7
	Prediction Horizon		100	100	100	100	100	100	100
	Control Horizon		2	2	2	2	2	2	2
Weights	Overall		0.8	0.8	0.8	0.8	0.8	0.8	0.8
	Reflux	Weight	0.1	0.1	0.1	0.1	0.1	0.1	0.1
		Rate Weight	0	0.1	0.2	0.3	0.5	1	2
	Steam	Weight	0	0	0	0	0	0	0
		Rate Weight	0	0	0	0	0	0	0
	xd	Weight	1	1	1	1	1	1	1
	xb	Weight	1	1	1	1	1	1	1
xd=0.3	xd	Max	0.173	0.173	0.173	0.173	0.173	0.173	0.173
		Min	0	0	0	0	0	0	0
		Steady	0.172	0.172	0.173	0.173	0.173	0.173	0.173
	xb	Max	0	0	0	0	0	0	0
		Min	-0.148	-0.148	-0.148	-0.148	-0.148	-0.148	-0.148
		Steady	-0.148	-0.148	-0.148	-0.148	-0.148	-0.148	-0.148
	Reflux	Max	0	0	0	0	0	0	0
		Min	-0.00344	-0.00288	-0.00263	-0.00256	-0.00254	-0.00252	-0.00252
		Steady	-0.00292	-0.00274	-0.00261	-0.00256	-0.00254	-0.00252	-0.00252
	Steam	Max	0	0	0	0	0	0	0
		Min	-6.72E+03	-6.72E+03	-6.72E+03	-6.72E+03	-6.72E+03	-6.72E+03	-6.72E+03
		Steady	-1.90E+03	-1.90E+03	-1.90E+03	-1.90E+03	-1.90E+03	-1.90E+03	-1.90E+03
xb=0.1	xd	Max	0	0	0	0	0	0	0
		Min	-0.0494	-0.0494	-0.0494	-0.0494	-0.0494	-0.0494	-0.0494
		Steady	-0.0494	-0.0494	-0.0494	-0.0494	-0.0494	-0.0494	-0.0494
	xb	Max	0.0425	0.0425	0.0425	0.0425	0.0425	0.0425	0.0425
		Min	0	0	0	0	0	0	0
		Steady	0.0425	0.0425	0.0425	0.0425	0.0425	0.0425	0.0425
	Reflux	Max	0	0	0	0	0	0	0
		Min	-0.00133	-0.00112	-0.00102	-0.00099	-0.00098	-0.00098	-0.00098
		Steady	-0.00113	-0.00106	-0.00101	-0.00099	-0.00098	-0.00098	-0.00098
	Steam	Max	1.92E+03	1.92E+03	1.92E+03	1.92E+03	1.92E+03	1.92E+03	1.89E+03
		Min	0	0	0	0	0	0	0
		Steady	547	547	547	547	547	547	547

VI. Changes to Steam Weight

Horizon	Control Interval		0.7	0.7	0.7	0.7	0.7	0.7	0.7
	Prediction Horizon		100	100	100	100	100	100	100
	Control Horizon		2	2	2	2	2	2	2
Weights	Overall		0.8	0.8	0.8	0.8	0.8	0.8	0.8
	Reflux	Weight	0.1	0.1	0.1	0.1	0.1	0.1	0.1
		Rate Weight	0	0	0	0	0	0	0
	Steam	Weight	0	0.1	0.2	0.3	0.5	1	2
		Rate Weight	0	0	0	0	0	0	0
	xd	Weight	1	1	1	1	1	1	1
	xb	Weight	1	1	1	1	1	1	1

xd=0.3	xd	Max	0.173	0.0988	0.0988	0.0988	0.0988	0.0988	0.0988
		Min	0	0	0	0	0	0	0
		Steady	0.172	0.0988	0.0988	0.0988	0.0988	0.0988	0.0988
	xb	Max	0	0	0	0	0	0	0
		Min	-0.148	-0.0847	-0.0847	-0.0847	-0.0847	-0.0847	-0.0847
		Steady	-0.148	-0.0847	-0.0847	-0.0847	-0.0847	-0.0847	-0.0847
	Reflux	Max	0	0	0	0	0	0	0
		Min	-0.00344	-1.81	-1.81	-1.81	-1.81	-1.81	-1.81
		Steady	-0.00292	-1.17	-1.17	-1.17	-1.17	-1.17	-1.17
	Steam	Max	0	0	0	0	0	0	0
		Min	-6.72E+03	-0.00241	-0.0006	-0.00027	0	0	0
		Steady	-1.90E+03	-0.00118	-0.0003	-0.00013	0	0	0

xb=0.1	xd	Max	0	0	0	0	0	0	0
		Min	-0.0494	-0.0282	-0.0282	-0.0282	-0.0282	-0.0282	-0.0282
		Steady	-0.0494	-0.0282	-0.0282	-0.0282	-0.0282	-0.0282	-0.0282
	xb	Max	0.0425	0.0242	0.0242	0.0242	0.0242	0.0242	0.0242
		Min	0	0	0	0	0	0	0
		Steady	0.0425	0.0242	0.0242	0.0242	0.0242	0.0242	0.0242
	Reflux	Max	0	0.518	0.494	0.518	0.518	0.518	0.518
		Min	-0.00133	0	0	0	0	0	0
		Steady	-0.00113	0.333	0.333	0.333	0.333	0.333	0.333
	Steam	Max	1.92E+03	0.00069	0.000168	0	0	0	0
		Min	0	0	0	0	0	0	0
		Steady	547	0.000341	0	0	0	0	0

VII. Changes to Steam Rate Weight

Horizon	Control Interval		0.7	0.7	0.7	0.7	0.7	0.7	0.7
	Prediction Horizon		100	100	100	100	100	100	100
	Control Horizon		2	2	2	2	2	2	2
Weights	Overall		0.8	0.8	0.8	0.8	0.8	0.8	0.8
	Reflux	Weight	0.1	0.1	0.1	0.1	0.1	0.1	0.1
		Rate Weight	0	0	0	0	0	0	0
	Steam	Weight	0	0	0	0	0	0	0
		Rate Weight	0	0.1	0.2	0.3	0.5	1	2
	xd	Weight	1	1	1	1	1	1	1
	xb	Weight	1	1	1	1	1	1	1
xd=0.3	xd	Max	0.173	0.1	0.0992	0.099	0.0989	0.0989	0.0988
		Min	0	0	0	0	0	0	0
		Steady	0.172	0.1	0.0992	0.099	0.0989	0.0989	0.0988
	xb	Max	0	0	0	0	0	0	0
		Min	-0.148	-0.086	-0.0851	-0.0849	-0.0848	-0.0848	-0.0847
		Steady	-0.148	-0.086	-0.0851	-0.0849	-0.0848	-0.0848	-0.0847
	Reflux	Max	0	-1.81	-1.81	-1.81	-1.81	-1.81	-1.81
		Min	-0.00344	-1.14	-1.16	-1.16	-1.16	-1.17	-1.17
		Steady	-0.00292	-1.14	-1.16	-1.16	-1.16	-1.17	-1.17
	Steam	Max	0	0	0	0	0	0	0
		Min	-6.72E+03	-36.1	-9.08	-4.04	-1.46	-0.364	-0.0911
		Steady	-1.90E+03	N/A	N/A	N/A	N/A	N/A	N/A
xb=0.1	xd	Max	0	0	0	0	0	0	0
		Min	-0.0494	-0.0285	-0.0283	-0.0283	-0.0283	-0.0283	-0.0283
		Steady	-0.0494	-0.0285	-0.0283	-0.0283	-0.0283	-0.0283	-0.0283
	xb	Max	0.0425	0.0245	0.0243	0.0243	0.0242	0.0242	0.0242
		Min	0	0	0	0	0	0	0
		Steady	0.0425	0.0245	0.0243	0.0243	0.0242	0.0242	0.0242
	Reflux	Max	0	0.518	0.518	0.518	0.518	0.518	0.518
		Min	-0.00133	0	0	0	0	0	0
		Steady	-0.00113	0.327	0.332	0.332	0.333	0.333	0.333
	Steam	Max	1.92E+03	10.4	2.61	1.16	0.419	0.105	0.0262
		Min	0	0	0	0	0	0	0
		Steady	547	N/A	N/A	N/A	N/A	N/A	N/A

VIII. Changes to Top Composition Weight

Horizon	Control Interval		0.7	0.7	0.7	0.7	0.7	0.7	0.7
	Prediction Horizon		100	100	100	100	100	100	100
	Control Horizon		2	2	2	2	2	2	2
Weights	Overall		0.8	0.8	0.8	0.8	0.8	0.8	0.8
	Reflux	Weight	0.1	0.1	0.1	0.1	0.1	0.1	0.1
		Rate Weight	0	0	0	0	0	0	0
	Steam	Weight	0	0	0	0	0	0	0
		Rate Weight	0	0	0	0	0	0	0
	xd	Weight	0	0.1	0.2	0.3	0.5	1	2
	xb	Weight	1	1	1	1	1	1	1
xd=0.3	xd	Max	0	0.00401	0.0154	0.0326	0.0759	0.173	0.253
		Min	0	0	0	0	0	0	0
		Steady	0	0.00401	0.0154	0.0326	0.0758	0.172	0.253
	xb	Max	0	0	0	0	0	0	0
		Min	0	-0.00344	-0.0132	-0.028	-0.0652	-0.148	-0.218
		Steady	0	-0.00344	-0.0132	-0.028	-0.0652	-0.148	-0.218
	Reflux	Max	0	0	0	0	0	0	0
		Min	0	0	-0.00029	-0.00061	-0.00143	-0.00344	-0.00605
		Steady	0	0	-0.00026	-0.00056	-0.00129	-0.00292	-0.00416
	Steam	Max	0	0	0	0	0	0	0
		Min	0	-156	-600	-1.27E+03	-2.95E+03	-6.72E+03	-9.86E+03
		Steady	0	-44.1	-170	-359	-836	-1.90E+03	-2.79E+03
xb=0.1	xd	Max	0	0	0	0	0	0	0
		Min	-0.116	-0.115	-0.11	-0.104	-0.0869	-0.0494	-0.0181
		Steady	-0.116	-0.115	-0.11	-0.104	-0.0869	-0.0494	-0.0181
	xb	Max	0.1	0.0987	0.0949	0.0891	0.0747	0.0425	0.0156
		Min	0	0	0	0	0	0	0
		Steady	0.1	0.0987	0.0949	0.0891	0.0747	0.0425	0.0156
	Reflux	Max	0	0	0	0	0	0	0
		Min	0	0	-0.00011	-0.00024	-0.00055	-0.00133	-0.00235
		Steady	0	0	-0.0001	-0.00022	-0.0005	-0.00113	-0.00161
	Steam	Max	4.53E+03	4.47E+03	4.30E+03	4.04E+03	3.38E+03	1.92E+03	705
		Min	0	0	0	0	0	0	0
		Steady	1.28E+03	1.27E+03	1.22E+03	1.14E+03	960	547	202

IX. Changes to Bottom Composition Weight

Horizon	Control Interval		0.7	0.7	0.7	0.7	0.7	0.7
	Prediction Horizon		100	100	100	100	100	100
	Control Horizon		2	2	2	2	2	2
Weights	Overall		0.8	0.8	0.8	0.8	0.8	0.8
	Reflux	Weight	0.1	0.1	0.1	0.1	0.1	0.1
		Rate Weight	0	0	0	0	0	0
	Steam	Weight	0	0	0	0	0	0
		Rate Weight	0	0	0	0	0	0
	xd	Weight	1	1	1	1	1	1
	xb	Weight	0	0.1	0.2	0.5	1	2
xd=0.3	xd	Max	0.3	0.298	0.291	0.253	0.173	0.076
		Min	0	0	0	0	0	0
		Steady	0.3	0.298	0.291	0.253	0.172	0.0758
	xb	Max	0	0	0	0	0	0
		Min	-0.258	-0.256	-0.251	-0.218	-0.148	-0.0652
		Steady	-0.258	-0.256	-0.251	-0.218	-0.148	-0.0652
	Reflux	Max	0	0	0	0	0	0
		Min	0	0	-0.00022	-0.00121	-0.00344	-0.00695
		Steady	0	0	-0.0002	-0.00108	-0.00292	-0.00501
	Steam	Max	0	0	0	0	0	0
		Min	-1.17E+04	-1.16E+04	-1.13E+04	-9.86E+03	-6.72E+03	-2.96E+03
		Steady	-3.31E+03	-3.29E+03	-3.22E+03	-2.79E+03	-1.90E+03	-832
xb=0.1	xd	Max	0	0	0	0	0	0
		Min	0	-0.00085	-0.00334	-0.0181	-0.0494	-0.0869
		Steady	0	-0.00085	-0.00334	-0.0181	-0.0494	-0.0869
	xb	Max	0	0.000734	0.00287	0.0156	0.0425	0.0747
		Min	0	0	0	0	0	0
		Steady	0	0.000734	0.00287	0.0156	0.0425	0.0747
	Reflux	Max	0	0	0	0	0	0
		Min	0	0	0	-0.00047	-0.00133	-0.00269
		Steady	0	0	0	-0.00042	-0.00113	-0.00194
	Steam	Max	0	33.2	130	706	1.92E+03	3.38E+03
		Min	0	0	0	0	0	0
		Steady	0	9.44	36.9	201	547	961

X. Changes to Overall Performance

Horizon	Control Interval		0.7	0.7	0.7	0.7	0.7	0.7	0.7	0.7	0.7	0.7	0.7
	Prediction Horizon		100	100	100	100	100	100	100	100	100	100	100
	Control Horizon		2	2	2	2	2	2	2	2	2	2	2
Weights	Overall		0	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9	1
	Reflux	Weight	0.1	0.1	0.1	0.1	0.1	0.1	0.1	0.1	0.1	0.1	0.1
		Rate Weight	0	0	0	0	0	0	0	0	0	0	0
	Steam	Weight	0	0	0	0	0	0	0	0	0	0	0
		Rate Weight	0	0	0	0	0	0	0	0	0	0	0
	xd	Weight	1	1	1	1	1	1	1	1	1	1	1
	xb	Weight	1	1	1	1	1	1	1	1	1	1	1
xd=0.3	xd	Max	0.076	0.173	0.173	0.173	0.173	0.173	0.173	0.173	0.173	0.173	0.173
		Min	0	0	0	0	0	0	0	0	0	0	0
		Steady	0.0758	0.172	0.172	0.172	0.172	0.172	0.172	0.172	0.172	0.172	0.172
	xb	Max	0	0	0	0	0	0	0	0	0	0	0
		Min	-0.0653	-0.148	-0.148	-0.148	-0.148	-0.148	-0.148	-0.148	-0.148	-0.148	-0.148
		Steady	-0.0652	-0.148	-0.148	-0.148	-0.148	-0.148	-0.148	-0.148	-0.148	-0.148	-0.148
	Reflux	Max	0	0	0	0	0	0	0	0	0	0	0
		Min	-0.00695	-0.00344	-0.00344	-0.00344	-0.00344	-0.00344	-0.00344	-0.00344	-0.00344	-0.00344	-0.00344
		Steady	-0.00501	-0.00292	-0.00292	-0.00292	-0.00292	-0.00292	-0.00292	-0.00292	-0.00292	-0.00292	-0.00292
	Steam	Max	0	0	0	0	0	0	0	0	0	0	0
		Min	-2.96E+03	-6.72E+03	-6.72E+03	-6.72E+03	-6.72E+03	-6.72E+03	-6.72E+03	-6.72E+03	-6.72E+03	-6.72E+03	-6.72E+03
		Steady	-832	-1.90E+03	-1.90E+03	-1.90E+03	-1.90E+03	-1.90E+03	-1.90E+03	-1.90E+03	-1.90E+03	-1.90E+03	-1.90E+03
xb=0.1	xd	Max	0	0	0	0	0	0	0	0	0	0	0
		Min	-0.0869	-0.0494	-0.0494	-0.0494	-0.0494	-0.0494	-0.0494	-0.0494	-0.0494	-0.0494	-0.0494
		Steady	-0.08669	-0.0494	-0.0494	-0.0494	-0.0494	-0.0494	-0.0494	-0.0494	-0.0494	-0.0494	-0.0494
	xb	Max	0.0747	0.0425	0.0425	0.0425	0.0425	0.0425	0.0425	0.0425	0.0425	0.0425	0.0425
		Min		0	0	0	0	0	0	0	0	0	0
		Steady	0.0747	0.0425	0.0425	0.0425	0.0425	0.0425	0.0425	0.0425	0.0425	0.0425	0.0425
	Reflux	Max	0	0	0	0	0	0	0	0	0	0	0
		Min	-0.00269	-0.00133	-0.00133	-0.00133	-0.00133	-0.00133	-0.00133	-0.00133	-0.00133	-0.00133	-0.00133
		Steady	-0.00194	-0.00113	-0.00113	-0.00113	-0.00113	-0.00113	-0.00113	-0.00113	-0.00113	-0.00113	-0.00113
	Steam	Max	3.38E+03	1.92E+03	1.92E+03	1.92E+03	1.92E+03	1.92E+03	1.92E+03	1.92E+03	1.92E+03	1.92E+03	1.92E+03
		Min	0	0	0	0	0	0	0	0	0	0	0
		Steady	961	547	547	547	547	547	547	547	547	547	547

Appendix C: Test for Disturbance Rejection on MPC

I. Reflux as Disturbance in Model I

Trial	1	2	3	4	5	6
Type	Pulse	Pulse	Pulse	Pulse	Pulse	Pulse
Size	0.1	0.2	0.5	1	2	5
Period (s)	5	5	5	5	5	5
xd time to steady state (s)	16.5	15	17.7	18.8	19.6	19.8
xd value at steady state	0	0	0	0	0	0
xb time to steady state (s)	10	10	10	10	10	10
xb value at steady state	0	0	0	0	0	0

II. Steam Flow as Disturbance in Model I

Trial	1	2	3	4	5	6
Type	Pulse	Pulse	Pulse	Pulse	Pulse	Pulse
Size	0.1	0.2	0.5	1	2	5
Period (s)	5	5	5	5	5	5
xd time to steady state (s)	19.6	19.6	19.6	19.6	23.4	25
xd value at steady state	0	0	0	0	0	0
xb time to steady state (s)	20	20	17.8	17.8	20	20
xb value at steady state	0	0	0	0	0	0

III. Top Composition as Disturbance in Model I

Trial	1	2	3
Type	Pulse	Pulse	Pulse
Size	0.1	0.2	0.3
Period (s)	5	5	5
xd time to steady state (s)	5	5	5
xd value at steady state	-0.00035	-0.00069	-0.00104
xb time to steady state (s)	15	15	15
xb value at steady state	0	0	0

IV. Bottom Composition as Disturbance in Model I

Trial	1	2	3
Type	Pulse	Pulse	Pulse
Size	0.1	0.2	0.3
Period (s)	5	5	5
xd time to steady state (s)	15	15	15
xd value at steady state	0	0	0
xb time to steady state (s)	5	5	5
xb value at steady state	0	0	0

V. Reflux as Disturbance in Model 2

Trial	1	2	3	4	5	6
Type	Pulse	Pulse	Pulse	Pulse	Pulse	Pulse
Size	0.1	0.2	0.5	1	2	5
Period (s)	5	5	5	5	5	5
xd time to steady state (s)	50.1	52.2	65.8	51	51.2	66.3
xd value at steady state	0	0	0	0	0	0
xb time to steady state (s)	52.1	70.3	51.5	51.5	70.3	51.9
xb value at steady state	0	0	0	0	0	0

VI. Steam Flow as Disturbance in Model 2

Trial	1	2	3	4	5	6
Type	Pulse	Pulse	Pulse	Pulse	Pulse	Pulse
Size	0.1	0.2	0.5	1	2	5
Period (s)	5	5	5	5	5	5
xd time to steady state (s)	19.2	18.5	19	19.7	19.7	18.5
xd value at steady state	0	0	0	0	0	0
xb time to steady state (s)	19.4	19.4	19.4	19.4	19.8	19.7
xb value at steady state	0	0	0	0	0	0

VII. Top Composition as Disturbance in Model 2

Trial	1	2	3
Type	Pulse	Pulse	Pulse
Size	0.1	0.2	0.3
Period (s)	5	5	5
xd time to steady state (s)	12.4	12.8	13.1
xd value at steady state	0	0	0
xb time to steady state (s)	12.3	12.7	13.2
xb value at steady state	0	0	0

VIII. Bottom Composition as Disturbance in Model 2

Trial	1	2	3
Type	Pulse	Pulse	Pulse
Size	0.1	0.2	0.3
Period (s)	5	5	5
xd time to steady state (s)	12	13.1	13.3
xd value at steady state	0	0	0
xb time to steady state (s)	11.8	12.8	13.6
xb value at steady state	0	0	0