

# **Process Control and AI Applications**

**Course no: CHL4020**

## **Model Predictive Control**



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- Overview and Motivation of the case study:

Distillation is the separation method in the petroleum and chemical industries for purification of final products. They are used to enhance mass transfer or for transferring heat energy. In the chemical industry, distillation columns are frequently used to separate and purify liquid mixtures. In this instance, a binary combination of liquids is separated using a distillation column, which can be economically valuable in sectors including petrochemicals, pharmaceuticals, and food processing.

The main objective is to maintain the specification of the product concentration outputs  $x_B$  and  $x_D$  (controlled variables) due to disturbances  $F$  (feed flow) and  $x_F$  (feed concentration). Controlling the distillation process is done in order to increase the separation process' efficiency and effectiveness, which will improve the separated products' quality and yield. The complex nature of the distillation column process, which can be impacted by various disturbances like changes in feed flow rate, composition, and temperature, hence we may preclude the use of conventional control methods like proportional-integral-derivative (PID) control.

Motivation for each step in the case study:

Literature Review: The authors conducted a thorough literature review to identify the existing control strategies for distillation columns and the limitations of these methods. This step is important to establish the motivation for the study and to identify the research gap that the authors intend to address.

Modeling the Process: This step is essential to obtain a detailed understanding of the process dynamics and to develop a model that can be used for control design.

Controller Design: We designed a Model Predictive Controller (MPC) for the distillation column based on the mathematical model. The MPC is designed to optimize the control inputs to the process in order to achieve the desired control objectives. This step is motivated by the need to develop a control strategy that can improve the process performance in the presence of disturbances.

Simulation and Validation: We conducted simulations of the MPC controller and validated the results against experimental data. This step is important to evaluate the performance of the controller and to demonstrate the effectiveness of the proposed control strategy.

Comparison with PI Controller: We have compared the performance of the MPC controller with that of a traditional PI controller. This step is motivated by the need to demonstrate the superiority of the MPC controller over the conventional control method.

- In the paper, 'Design and development of Model Predictive Controller for Binary Distillation Column, Sivakumar and Mathew provided a brief overview of the available literature on the modeling and control of distillation columns. One of the earliest methods used for control of distillation columns is the conventional Proportional-Integral-Derivative (PID) control. However,

PID controllers may not be effective in controlling distillation columns due to the complex nature of the process, which can be affected by various disturbances such as changes in feed flow rate, composition, and temperature. To address these limitations, researchers have developed more advanced control strategies such as Model Predictive Control (MPC) for distillation columns. These advanced control methods have been shown to improve the control performance of distillation columns by considering the process dynamics and optimizing the control inputs.

In addition to control strategies, researchers have also focused on developing accurate mathematical models of distillation columns. The models are based on mass and energy balance equations and are used for process design, optimization, and control. The accuracy of the model depends on various factors such as the complexity of the process, the number of trays, and the type of separation being performed. Overall, the available literature demonstrates the importance of accurate modeling and advanced control strategies in improving the performance of distillation columns. The authors of the paper build upon the existing literature by proposing a novel MPC controller for binary distillation columns and validating its performance through simulations and experiments.

- The transfer function that we have used for the single input single output (SISO) model of the plant is :

$$\frac{y(s)}{u(s)} = \frac{1}{10\tau+1} e^{-0.8s}$$

We here use a First-Order Plus Dead Time(FOPDT) transfer function to being with. The FOPDT stands for "First-Order Plus Dead Time" and it is a type of mathematical model commonly used to represent the dynamics of many industrial processes.

The FOPDT model consists of a first-order transfer function with a time delay or dead time. The first-order transfer function has a gain (K), a time constant ( $\tau$ ), and a first-order term (s) in the denominator. The dead time (L) represents the time delay between the input and output of the process due to process dynamics or transportation lags.

The FOPDT model is often used to model processes with a slower response and time delay, such as chemical processes and transportation systems. The model assumes that the process response can be approximated by a first-order system with a dead time, which means that the output changes linearly with time after a delay in response to a step change in the input.

The FOPDT model can be represented by the following transfer function:

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

where K is the gain,  $\tau$  is the time constant, L is the dead time, and s is the Laplace variable. The FOPDT model is often used for controller design and optimization, as it provides a simple and accurate representation of the process dynamics. It is also used for process identification and model-based control.

- **Simulation Results and Discussion:**

The control strategies and their controller structures and parameters are as follows:

#### PI Controller

- ❖ The PI (Proportional-Integral) controller is a classic feedback control strategy widely used in industry.
- ❖ The PI controller has one input (the process variable) and one output (the control signal).
- ❖ The controller structure consists of a proportional gain ( $K_p$ ) and an integral gain ( $K_i$ ).
- ❖ The PI controller is designed with tuning parameters of  $K_p = 14.4249$  and  $K_i = 8.8268$ .

#### MPC Controller

- ❖ The MPC (Model Predictive Control) controller is a more advanced feedback control strategy that can handle more complex systems and constraints.
- ❖ The MPC controller has one or more inputs (manipulated variables) and one or more outputs (controlled variables).
- ❖ The controller structure consists of a mathematical model of the system and an optimization algorithm that calculates optimal control actions.
- ❖ The MPC controller is designed based on a tuning strategy that achieves set point tracking with minimal overshoot.
- ❖ The tuned values for the MPC controller are: Control Horizon ( $M$ ) = 5, Prediction Horizon ( $P$ ) =  $N = 53$ , Control Interval = 0.3.

Note: The output response of both the PI Controller and the MPC controller is available below.

#### Block Diagram:

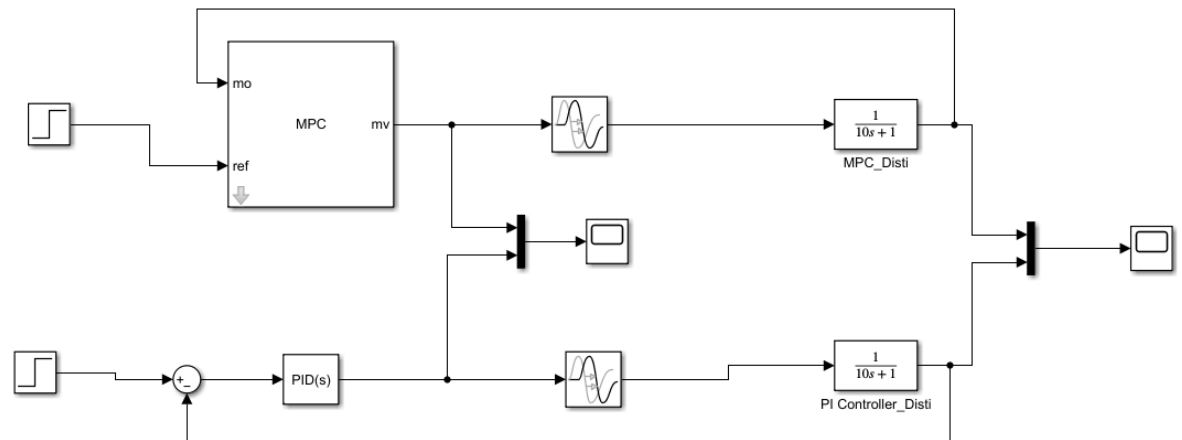


Figure 1: Block diagram of the SISO model with PI controller & MPC for comparison.

Plot of Controller output:

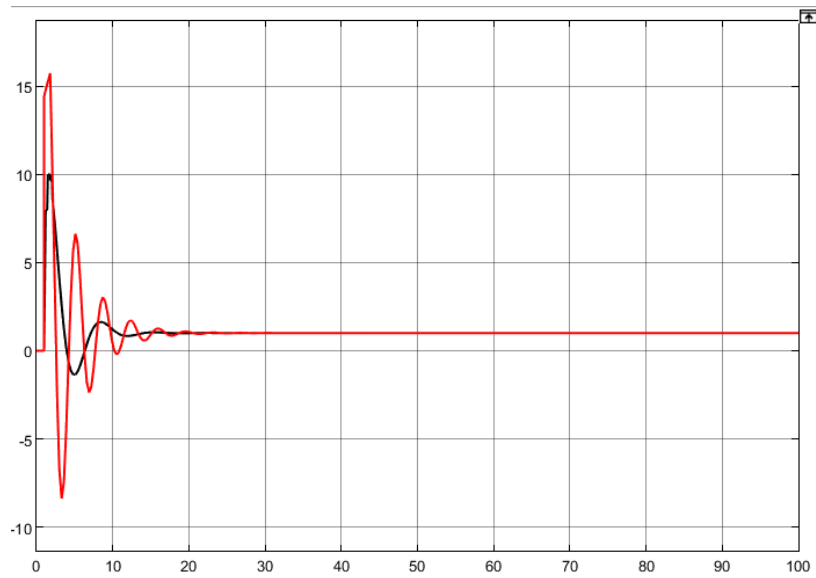


Figure 2: MPC and PI Controller output v/s time(s)

Plot of Plant Controlled Output:

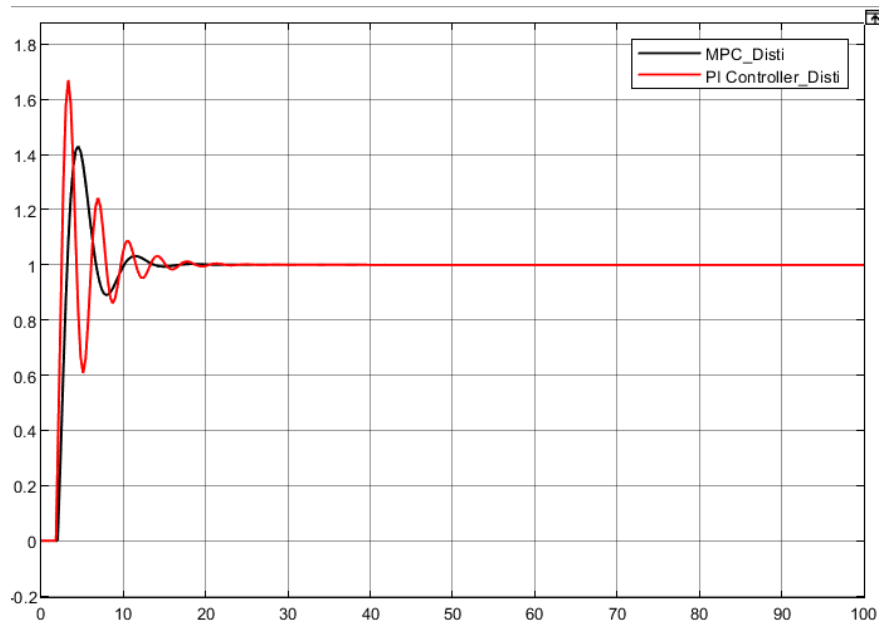


Figure 3:  $X_D$  v/s time (s)

The performance comparison between the two controllers shows that the MPC controller outperforms the PI controller in terms of settling time, overshoot, etc.

The settling time of the MPC controller is 22 sec approx, which is less than half of the settling time of the PI controller .

The overshoot of the MPC controller is 1.4 approx, which is lower than the overshoot of the PI controller (1.7 approx).

Now, coming to the SISO Unconstrained Case:

The tuned values for the MPC controller are as follows:

Control Horizon (M) = 5, Prediction Horizon (P) = N = 53, Control Interval = 0.3.

Block diagram:

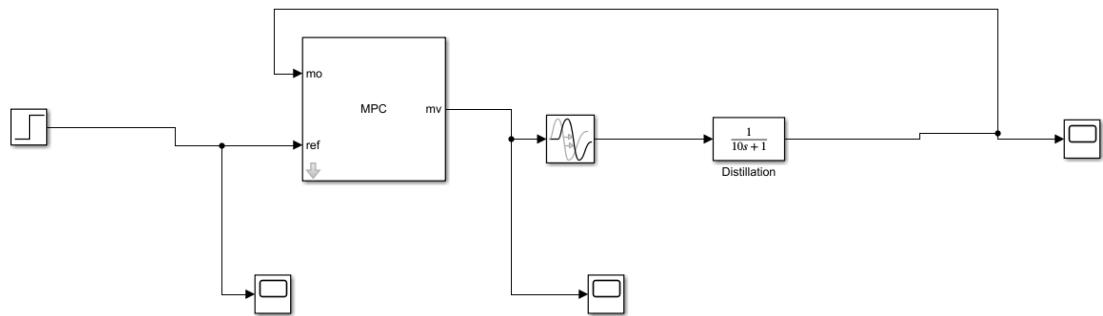


Figure 4: block diagram of the SISO unconstrained case with MPC.

Plot for Plant Controlled Variable ( $X_D$ ):

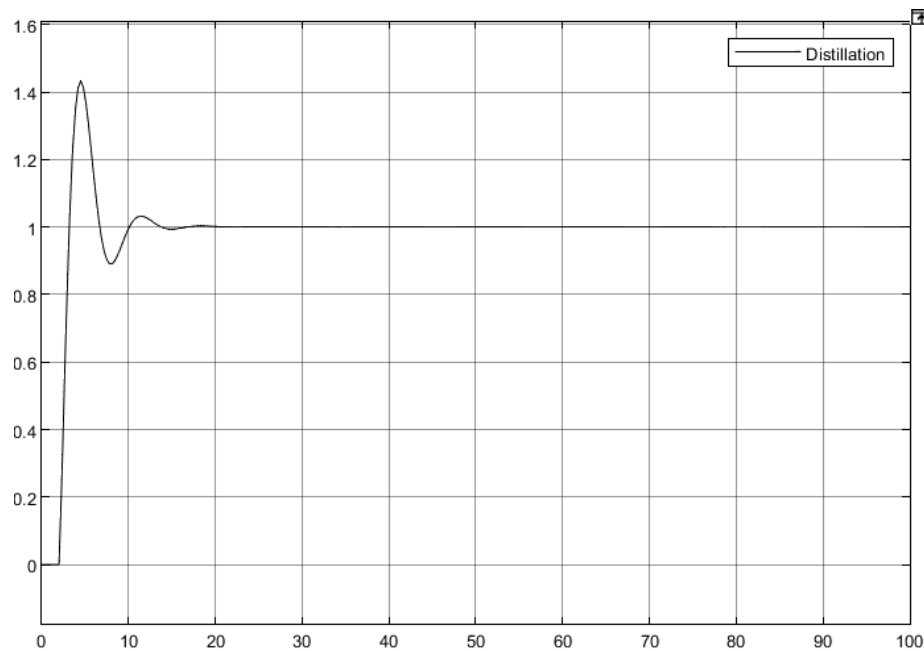


Figure 5:  $X_D$  v/s time(s)

## Model Predictive Controller Output Plot :

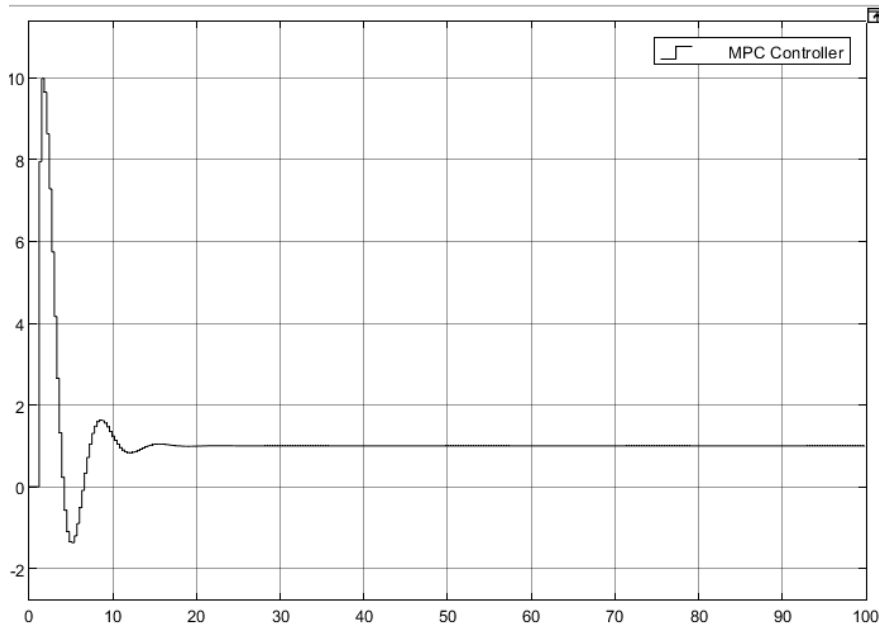


Figure 6: MPC and PI output v/s time(s)

### • MIMO System

Model Predictive Control (MPC) has been used as the control strategy for the Wood and Berry distillation column model.

Transfer Function Matrix:

$$\begin{bmatrix} X_D(s) \\ X_B(s) \end{bmatrix} = \begin{bmatrix} \frac{12.8e^{-s}}{16.7s + 1} & \frac{-18.9e^{-2s}}{21s + 1} \\ \frac{6.6e^{-2s}}{10.9s + 1} & \frac{-19.4e^{-2s}}{14.4s + 1} \end{bmatrix} \begin{bmatrix} R(s) \\ S(s) \end{bmatrix}$$

The controller structure and parameters are as follows:

- Controller Structure:
  - ❖ The MPC controller is a multiple-input, multiple-output (MIMO) system.
  - ❖ The manipulated variables (MVs) are the reflux flow rate (R) and the steam flow rate (S).
  - ❖ The controlled variables (CVs) are the distillate composition (xD) and the bottoms composition (xB).
  - ❖ The MPC controller receives measurements of the CVs and the current values of the MVs as inputs.
  - ❖ Based on the current measurements and the model of the system, the MPC controller calculates optimal values for the MVs over a future time horizon.

- ❖ The optimal values of the MVs are then applied to the system to achieve the desired values of the CVs.
- Controller Parameters:
  - ❖ Control Horizon (M) = 4: This parameter determines how far into the future the controller will optimize the MVs. A Control Horizon of 4 means the controller will optimize MVs for the next 4 time steps.
  - ❖ Prediction Horizon (P) = N = 96: This parameter determines the length of the future prediction for the CVs. A Prediction Horizon of 96 means the controller will predict the values of the CVs for the next 96 time steps.
  - ❖ Control Interval = 0.485: This parameter determines the time interval between each control action. A Control Interval of 0.485 means the controller will calculate and apply control actions every 0.485 seconds.
  - ❖ The MPC controller uses a linear constrained optimization algorithm to calculate optimal values for the MVs. The constraints are based on the physical limits of the system, such as maximum and minimum values for the reflux and steam flow rates.

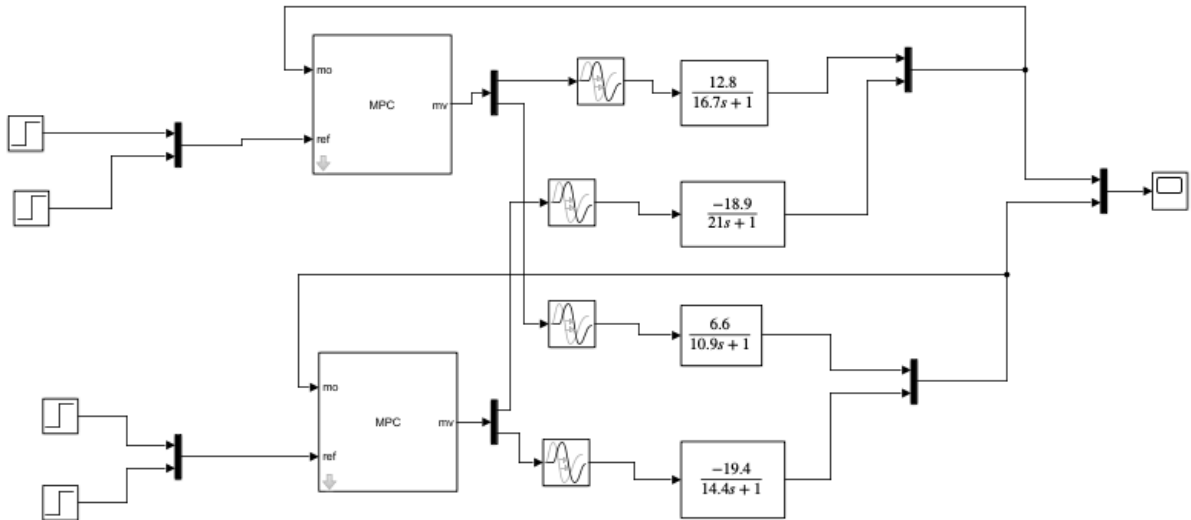


Figure 7: Block diagram of MPC for MIMO system.

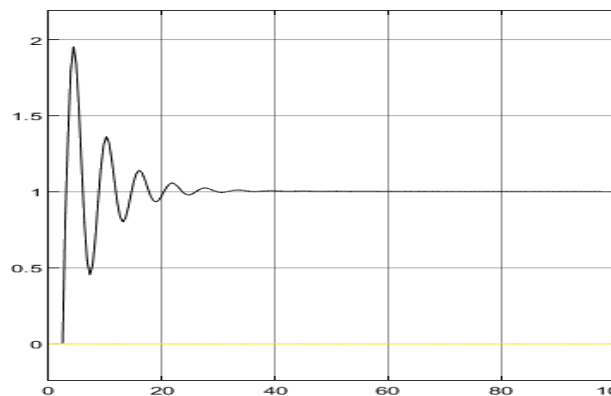




Figure 8:  $X_D$  &  $X_w$  v/s time(s) [yellow: bottom( $X_w$ ), black: distillate( $X_D$ )]

- **Conclusions:**

- ❖ At first the simulations were performed for the SISO system and the controller was used to control the purity of the distillate having the manipulating variable as reflux ratio. PI and MPC controllers are used in this case.
- ❖ The second simulation was performed for the MIMO(Multiple input Multiple output) system and the model used was Wood and Berry model that was used to control the purity of distillate and bottom product having the manipulating variable as reflux ratio and steam flow rate. PI and MPC controllers are used in this case.
- ❖ The results showed that MPC is superior to the conventional multi-loop PID controller in all aspects. MPC provides smooth reference tracking, reduced peak overshoot, and better closed-loop performance.
- ❖ The closed-loop MPC simulation was carried out using MATLAB and the Model Predictive Control Toolbox.
- ❖ The MATLAB simulations are performed for unconstrained MPC.
- ❖ The prediction and the control horizon are tuned for better performance.
- ❖ The larger control horizon value compared to the prediction horizon leads to aggressive use of input and an unstable system.
- ❖ Along with the tuning parameters, control interval, weights, and gain also play a significant role in the performance of the system.
- ❖ Overall, these results suggest that the MPC controller is a better choice than the PI controller for the SISO FOPDT system, as it achieves faster and more accurate set point tracking with less overshoot.

- **References:**

- Design and Development of Model Predictive Controller for Binary Distillation Column.  
[https://www.researchgate.net/publication/268079241\\_Design\\_and\\_Development\\_of\\_Model\\_Predictive\\_Controller\\_for\\_Binary\\_Distillation\\_Column](https://www.researchgate.net/publication/268079241_Design_and_Development_of_Model_Predictive_Controller_for_Binary_Distillation_Column)