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Research Article

Model Predictive Control for Efficient Process Control: A Case Study for Absorber-Stripper System With MEA in Hydrogen Plant

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Abstract: Control mechanisms are essential for all operations in chemical processing facilities, including the absorber-stripper system. This system, which is utilized for CO_2 capture, is a common feature in hydrogen plants that use steam-methane reforming technology to purify their flue gas (post-combustion). The primary objective of this system is to maximize CO_2 recovery in a cost-effective manner. Given the dynamic nature of plant operations, with frequent changes in production capacity, a robust controller is crucial for maintaining system stability. Model Predictive Control (MPC) is a widely used control method. This study focuses on developing a control simulation for an absorber-stripper system using monoethanolamine solution (MEA) and implementing it with MPC. The steady-state system is designed using Aspen Plus and integrated with MATLAB/Simulink to construct a multi-input-multi-output controller with MPC. The simulation aims to regulate the CO_2 recovery within a specific range of input disturbances while ensuring that the system operates within acceptable operating conditions. This is achieved by controlling all potential manipulated variables, such as flow of MEA solution to both absorber and stripper, flow of cooling and heating agent, and make up water. A comparison with the traditional PID control approach is also presented as part of this research. It is concluded from the result that MPC Controller is superior than PID. The MPC controller exhibits superior performance by having less settling time. This is accomplished by effectively minimizing transient deviations from the desired output.

Keywords: Carbon Capture, Process Control, Model Predictive Control (MPC), Monoethanolamine (MEA).

1. Introduction

The Control mechanisms are essential for all operations in chemical processing facilities, including the absorber-stripper system. This absorption technology of carbon dioxide using Monoethanolamine (MEA) has been utilized in steam methane reforming due to the classification of carbon dioxide as an acid gas and the corrosiveness if it combines with water [1]. This process is just one of many types of acid gas removal processes. Numerous studies on carbon dioxide capture are available due to factors such as global warming and carbon taxes [2],[3]. Existing methods such as direct separation, physical separation, and chemical materials for absorption have been researched and implemented [4]. One of hydrogen plant in Indonesia has implemented carbon dioxide capture using MEA absorbent. However, capture with absorbents requires significant energy, reducing the efficiency of energy use. This technology also does not guarantee 100% perfect carbon dioxide capture due to various factors, one of which is the fluctuating production capacity following market demand.

The evolution of control strategies in the field of carbon dioxide capture has paved the way for innovative approaches in managing the process. This research delves into the application of these strategies in the basic absorber-stripper process based on prior research. The system under control encompasses these devices, making this study fall under plantwide control [5]. The study aims to provide a comprehensive understanding of the control mechanisms involved, their advantages, and potential drawbacks. The ultimate goal is to enhance the carbon dioxide capture rate in the fluctuating production capacity, contributing to the broader objective of mitigating the impacts of global warming. The subsequent sections will further elaborate on the problem statement, research objectives, and the potential benefits derived from this study.

One of control strategies, Proportional-Integral-Derivative Controller (PID), is a control loop mechanism that uses feedback and is widely used in industrial control systems and other applications requiring continuously modulated control [6]. Control strategies for CO2 capture process based on decentralized Proportional-Integral (PID) control face certain challenges. They struggle to handle the interaction between multiple controlled and manipulated variables, as the input or control variables have a comparable effect on the outputs. Furthermore, PID control tends to increase the maximum overshot of the system and is unable to handle process constraints that represent certain limitations.

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1.1 Prior Research

Several recent studies have addressed the issue of controlling CO2 capture processes. One such contribution is the work by (Taipabu et al., 2023)[7]who presented a novel design modification for a Monoethanolamine (MEA)-based absorber-stripper system for carbon capture. Their proposed design aimed to reduce the system's energy consumption, with the best design reportedly saving up to 62% of the required heat duty. Key contributions of their work include the introduction of heat integration and optimization in the design of amine-based CO2 capture processes. However, a potential extension of this research could involve the application of more advanced control processes, such as Model Predictive Control (MPC). This could further enhance the efficiency and effectiveness of the CO2 capture process, building on the foundational work by Taipabu et al. (2023).

In the study "Plantwide Control of Carbon Dioxide Capture by Absorption and Stripping Using Monoethanolamine Solution" by (Lin et al., 2011)[8] the authors discuss control processes in absorption stripping using a single base model design. The control was implemented using Aspen Dynamics with a Proportional-Integral-Derivative (PID) controller.

While PID controllers are a fundamental tool in process control, they have certain limitations, particularly when dealing with complex systems like CO2 capture processes. They struggle to handle the interaction between multiple controlled and manipulated variables, and the input or control variables have a comparable effect on the outputs. Furthermore, PID control tends to increase the maximum overshot of the system and is unable to handle process constraints that represent certain limitations.

Given these challenges, there is a need for more advanced control strategies, such as Model Predictive Control (MPC). MPC can effectively manage these complexities and optimize process set point changes and disturbance rejections. Therefore, a potential extension of this research could involve modifying the control process from PID to MPC, which could further enhance the efficiency and effectiveness of the CO2 capture process.

1.2 Objectives

In this study, both PID and Model Predictive Control (MPC) strategies are implemented and investigated on an absorber-stripper system using monoethanolamine solution (MEA). The primary objective of this system is to maximize CO2 recovery in a cost-effective manner. Given the dynamic nature of plant operations, with frequent changes in production capacity, a robust controller is crucial for maintaining system stability.

A model has been developed for the system utilizing MATLAB-Aspen Plus Dynamics interface. Both qualitative and quantitative comparisons of controller performances of the PID and MPC are conducted using quality of step responses. This study aims to assess how standard PID and MPC controllers perform in regulating the absorber-stripper system using Monoethanolamine (MEA). Specifically, it seeks to compare their effectiveness in managing step responses and minimizing residual error indices. The goal is to understand which control method PID or MPC offers superior performance in achieving accurate setpoints promptly while minimizing errors during MEA-based absorption. This research intends to provide valuable insights for selecting the most efficient control approach to optimize the chemical absorption process in the absorber-stripper system.

The novelty of this work lies in the comparative study between the efficiency of the standard PID and MPC controllers for an absorber-stripper system using MEA. This research provides valuable insights into the control strategies for CO2 capture processes, contributing to the broader objective of mitigating the impacts of global warming.

2. Materials and Methods

2.1 Process Description

The Process Flow Diagram (PFD) is in Figure 1 and it contains the Absorber-Stripper unit, where the absorption of carbon dioxide occurs in the absorber and the regeneration of carbon dioxide takes place in the stripper. The data of flow specifications, operating conditions and the equipment specifications was compared to the data simulated from prior research [7]. It will provide valuable insights into the actual operations of the industry and will serve as a basis for our analysis and further research.

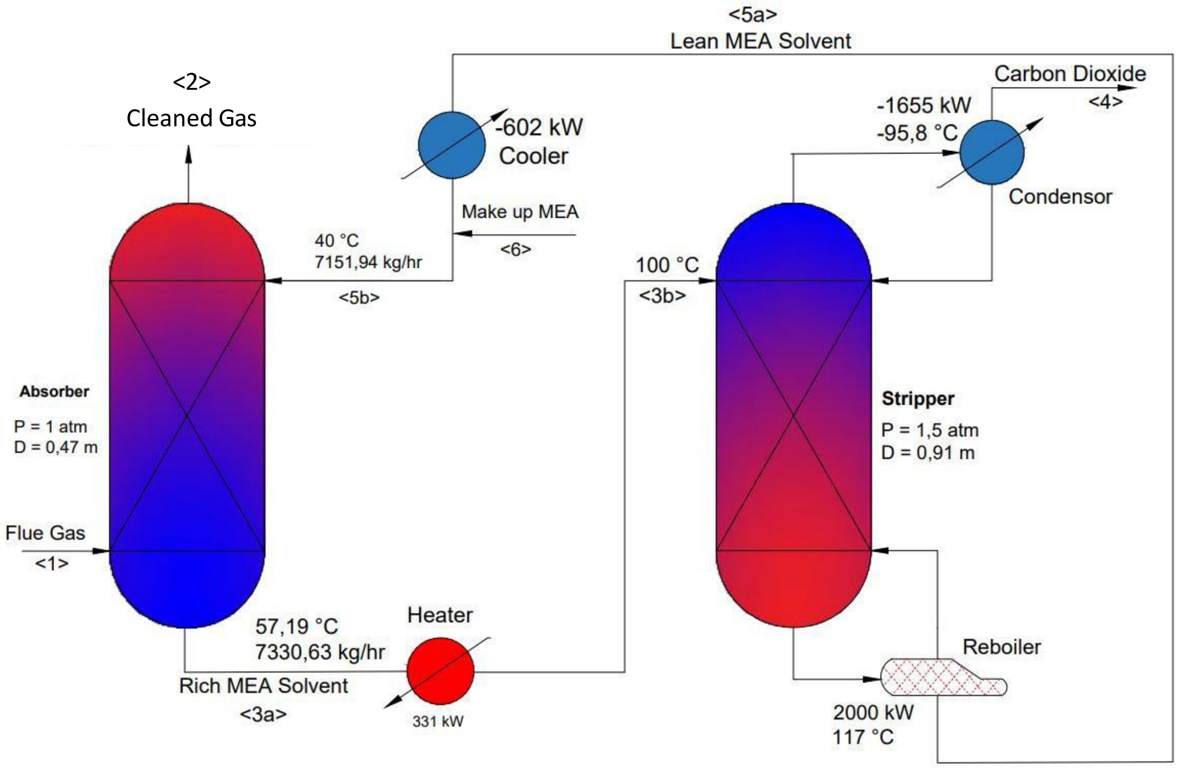

Figure 1. Schematic Diagram of Absorber-Stripper System

The data obtained from the Carbon Capture process includes feed inlet flue gas, processed flue gas output, carbon dioxide output, and steam reboiler. These data represent the conditions when the plant was newly built, as indicated in the Process Flow Diagram from the manufacturing company of the equipment. The variables that we will analyze, in line with our objectives, are the percentage recovery of existing carbon dioxide and the energy usage required by the system. Therefore, the data we will use includes the composition and operating conditions.

Table 1. Operating Conditions Hydrogen Plant

Flow	**Parameter**	**Value**
Flue Gas (Flow 1)	Pressure	1.1 atm
	Temperature	40.172 °C
	Flowrate	17.447 kmole/hr
	Composition	Mole Fraction
	Carbon Dioxide (CO_2)	0.295
	Oxygen (O_2)	0.076
	Nitrogen (N_2)	0.604
	Water (H_2O)	0.025
Cleaned Gas (Flow 2)	Pressure	1.1 atm
	Temperature	44.47 °C
	Flow Rate	14.5 kmol/hr
	Composition	Mole Fraction
	Carbon Dioxide (CO_2)	0.0195
	Oxygen (O_2)	0.091
	Nitrogen (N_2)	0.724
	Water (H_2O)	0.1655
Rich MEA Solvent (Flow 3a)	Flow Rate	362.52 kmol/hr
	Temperature	57.19 °C
	Pressure	1 atm
Rich MEA Solvent (Flow 3b)	Flow Rate	357.67 kmol/hr
	Temperature	100 °C
	Pressure	1.5 atm
CO_2 (Flow 4)	Temperature	95 °C
	Pressure	1.5 atm
	Composition	Mole Flow
	Carbon Dioxide (CO2)	11.46 kmol/hr
Lean MEA Solvent (Flow 5a)	Flow Rate	351.07 kmol/hr
	Temperature	117 °C
	Pressure	1.73 atm
Lean MEA Solvent (Flow 5b)	Flow Rate	359.62 kmol/hr
	Temperature	40 °C
	Pressure	1 atm
Makeup (Flow 6)	Temperature	40 °C
	Pressure	1 atm
	Composition	Mole Flow
	MEA	8.54 kmol/hr

2.2 Modeling Development

There are many various simulation softwares that can be used. Aspen Plus, as one of the simulation software, is utilized for simulating the steady state of this absorber-stripper system before control can be applied. However, Aspen Plus Dynamics, which is where we control the system, cannot accept rate-based models that closely resemble the real plant data. The only possibility is to use equilibrium-based models. Murphee efficiency is employed to approximate the real plant data, as seen in prior research [9]. In conclusion, process control can be implemented following the convergence of steady state simulation, which will be explained further below.

2.2.1 Thermodynamics Package

The thermodynamic package we will select in the Aspen Plus program is the Electrolyte Non-random-two liquid Soave Redlich Kwong (ENRTL) model. This model is suitable for carbon capture systems with Monoethanolamine (MEA) as the electrolyte. To achieve absorption equilibrium, the ENRTL property model method is used with seven reactions as outlined in Table 2. The set of reactions used are those defined by the Aspen Plus program and represent the dominant reactions. In the simulation process, reaction data for MEA and those occurring within the absorber-stripper are used. This approach ensures a comprehensive and accurate simulation of the carbon capture process. [10]

Table 2. MEA Reaction in Absorber-Stripper

No.	Stoichiometry	Reaction Type
1	$MEA + H_3O^+ \leftrightarrow MEAH^+ + H_2O$	Equilibrium
2	$CO_2 + 2H_2O \leftrightarrow H_3O^+ + HCO_3^-$	Equilibrium
3	$HCO_3^- + H_2O \leftrightarrow H_3O^+ + CO_3^{2-}$	Equilibrium
4	$MEA + HCO_3^- \leftrightarrow MEACOO^- + H_2O$	Equilibrium
5	$2H_2O \leftrightarrow H_3O^- + OH^-$	Equilibrium
6.	$CO_2 + OH^- \rightarrow HCO_3^-$	Kinetic
7.	$HCO_3^- \rightarrow CO_2 + OH^-$	Kinetic
8.	$MEA + CO_2 + H_2O \rightarrow MEACOO^- + H_3O^+$	Kinetic
9.	$MEACOO^- + H_3O^+ \rightarrow MEA + H_2O + CO_2$	Kinetic

The introduction of parameters representing constants and activation energy obtained from reference studies is essential. Precision in determining these values supports an accurate representation of the system's behavior, ensuring that the kinetic model employed aligns with observed phenomena. Furthermore, in Equations 6-8, it is evident that the kinetic parameters for the absorber-stripper are uniform, indicating a shared kinetic behavior among these components in the system. However, in Equation 9, the kinetic parameters differ, suggesting distinctions in the kinetic dynamics of specific components within the absorber-stripper system. This underscores the need for a meticulous approach in parameter estimation to comprehensively understand and delineate the kinetic properties of each component within this system. The power law equation (1) is used by the Aspen with parameters in Table 3.

$$r = kT^n \exp\left(-\frac{E}{RT}\right) \prod_{i=1}^{N} (x_i \gamma_i)^{a_i} \tag{1}$$

Table 3. Absorber-Stripper Reaction Parameter

Reaction Number	k (constant)	E (cal/mol)
6	1.33×10^{17}	13249
7	6.63×10^{16}	25656
8	3.02×10^{14}	9855.8
9 (Absorber)	5.52×10^{23}	16518
9 (Stripper)	6.50×10^{27}	22782

2.2.2 Steady State Simulation

The simulation process for the carbon capture system is conducted under steady state operating conditions. Initially, the components used in Aspen Plus are inputted, followed by the reactions obtained from references. Subsequently, a Process Flow Diagram is created based on the data obtained and the proposed design. This includes the flows entering the system and their connections to each piece of equipment.

The data and operating conditions of the equipment, as detailed in Table 1, are then inputted into the system. Following this, the simulation is run, and the results obtained are validated. This approach ensures a comprehensive and accurate simulation of the carbon capture process, providing valuable insights into its efficiency and effectiveness.

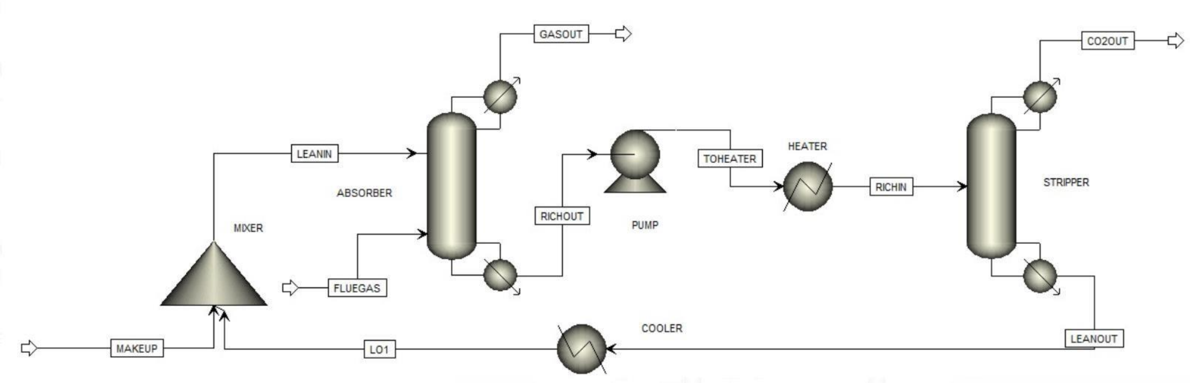

Figure 2. Process Scheme in Aspen Plus

2.3 Dynamic Approach

Aspen Dynamics is used for dynamics simulation. The steady state system that has been made in Aspen Plus is imported to Aspen Dynamics by specifying equipment sizing and using flow driven mode. After that, dynamics simulation can be controlled.

2.3.1 Equipment Sizing

After the steady state simulation, the sizing of equipment is a critical step that imparts dynamic potentiality to all installed equipment within the simulator. This process allows for the prediction of the system's realistic dynamic behavior through an accurate approximation of the gas volumes and liquid holdups in both the absorber and stripper columns.

2.3.2 Simulation in Aspen Dynamic

Aspen Dynamics offers two modes: flow-driven and pressure-driven. It was selected in Aspen Plus before importing it to Aspen Dynamics. Flow-driven sets the fluid flow rate first, then calculating subsequent parameters, while pressure-driven determines the pressure, then computing the subsequent flow rate. Mode selection is crucial. Flow-driven is preferred for its simplicity in parameterizing pressure drop, whereas pressure-driven complicates Aspen Dynamics simulation equations. It may be more accurate using pressure-driven mode because the control valves and other equipments pressure drops need to be assigned, but the lack of that particular data currently restrains the usage of this mode. Therefore, the dynamic simulation is simplified by using flow-driven mode.

2.4 Control Strategy

The development of figure 3 starts with Proportional Integral Derivatives in Aspen Plus Dynamics. After it can be controlled, the MPC control strategies for absorber-stripper are adopted.

2.4.1 Proportional Integral Derivative (PID) Control

The development of a reliable simulation model is a crucial initial step before implementing control techniques. This study presents the controlled and manipulated variables, insights derived from the process behavior, to effectively maintain the desired rate of capture while balancing the liquid gas inventory and the system's make-up water. The objective is to maintain the rate of carbon capture at around 95% and regulate the stripper bottom temperature at its optimal operating temperature to prevent solvent degradation. These measures ensure the efficiency and sustainability of the CO2 capture process.

The steady state in Aspen Dynamics is also considered with initialization of steady state before jump into process control. The control design is evaluated due to the parameter that will be controlled. The pairing of manipulated variables and control variables also PID parameter are in Table 4.

Table 4. Manipulated and Controlled Variable Pairing of PID Controller

Controlled Variable	Set Point	Manipulated Variable	P (%/%)	I (min)	D (min)
Absorber Pressure 1st Tray	0.4458 bar	Clean Gas <2> Flowrate	1.8578	2.25	0.36
Absorber Sump Level	3.1675 m	Rich MEA <3a> Flowrate	281.2337	3.75	0.6
Stripper Pressure 1st Tray	1.5199 bar	CO_2 <4> Flowrate	104.2065	2.25	0.36
Stripper Drum Level	1 m	Reflux Flowrate	482.5018	4.5	0.72

The complete process control used in this paper was depicted in Figure 3. The pairing variables were represented as dotted lines.

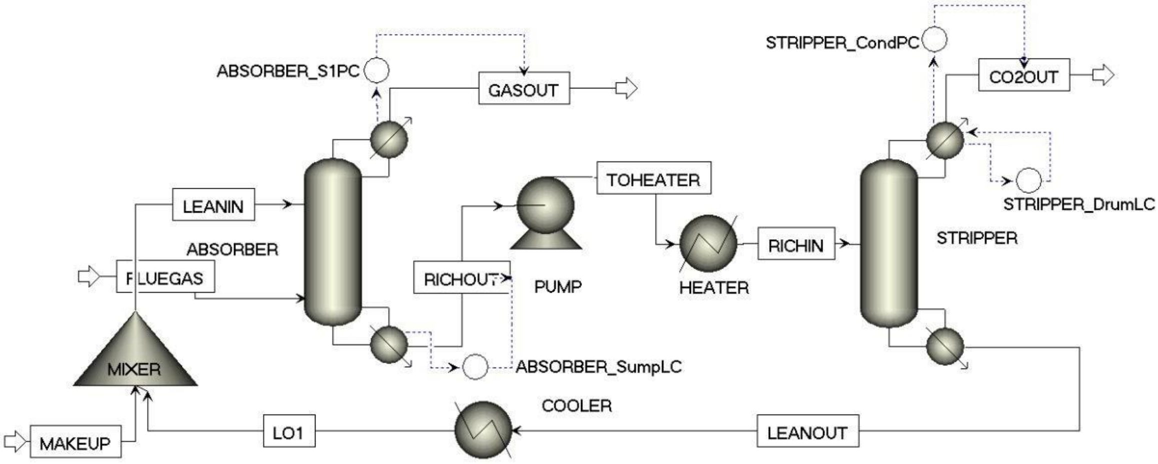

Figure 3. Assigning PID Controller to the Controlled and Manipulated Variable in Aspen Dynamics

2.4.2 Model Predictive Control (MPC) Control

Model Predictive Control (MPC) is a process control strategy that is widely used in the industry (Seborg et al., 2016). MPC offers several advantages over PID controllers, including: (1) reducing oscillations, settling time, and excessive movement of input variables [11] (2) considering constraints on inputs and outputs, (3) controlling many process variables even in the absence of sensors or actuators if possible, and (4) solving multi-input-multi-output (MIMO) control problems. This strategy calculates variables based on measurements and predictions of future output values. With the help of these two calculations, MPC is able to determine the sequence of control system movements.

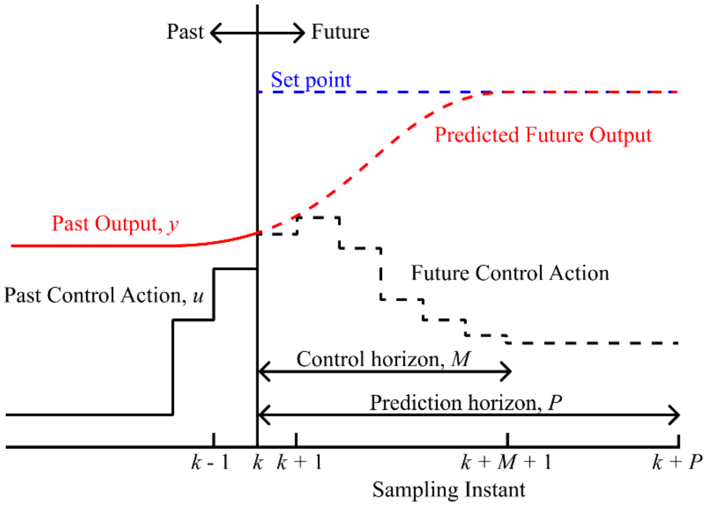

Figure 4. Basic Consept for MPC [5]

The MPC controller is first formed by incorporating the mathematical model of the system into the MPC system. After that, the weight of the controlled variable is determined based on the urgency level of an output variable to be controlled. The larger the weight, the more prioritized the variable will be. The sample time, prediction horizon, and control horizon are then set.

Another critical aspect pertains to the selection of the dynamic model employed in the computations of Model Predictive Control (MPC) algorithms. Advanced model-based controllers like MPC heavily rely on the precision and reliability of the dynamic model integrated into their algorithms [12]

3. Results and Discussion

3.1 *Steady State Analysis*

Steady state analysis is a crucial phase in validating real systems prior to their control implementation. This paper focuses on the validation process of a real system and subsequently explores the transfer of this system into Aspen Dynamics for further analysis. Initially, the study examines the importance of achieving a steady state in the model and the validation of the system's behavior. Following this, an analysis is conducted to determine the feasibility of transferring the real system data into Aspen Dynamics. It is discovered that while rate-based systems face challenges in direct transfer, implementing an equilibrium-based approach is feasible but necessitates several variations. The variations are presented in two cases:

- Case 1: Rate Based Steady State
- Case 2: Equilibrium Based with Murphee Efficiency Variation

3.1.1 Case 1 Rate Based Steady State

The rate-based simulation exhibits characteristics that closely resemble reality. This resemblance stems from the distinct rates present in each of the 20 trays within both the absorber and the stripper. Table 5 outlines the operational conditions and specifications of the absorber-stripper under investigation. Radfrac was selected for modeling in Aspen Plus, utilized for both the absorber and stripper units. This choice was made to ensure comprehensive representation and analysis of the system's behavior and performance, aligning with the intricate rate dynamics observed in the process.

Table 5. Input Parameter for Steady State Aspen Plus

Operating Condition	Data Inlet		
	Absorption Tower		Stripper Tower
Stream	Flue Gas	Lean Solvent	Rich Solvent
Composition	CO_2 39,6%	MEA 10,43%	MEA 8,95%
	N_2 51,6%	H_2O 86,26%	H_2O 86,17%
	H_2O 1,4%		$MEACO_2$ 2,3%
	O_2 7,4%		
Flowrate	218,09 m3/h	15,13 kmol/h	15,92 kmol/h
Temperature	40°C	40°C	100°C
Pressure	1.1 bar	1.1 bar	1.5 bar

The steady state simulation result was compared to the prior research [7]. The CO_2 recovery obtained was 95%. This result was different by 5% higher, and the relative error was about 5.6%. This difference can be neglected because the main focus was about building the controller.

Sizing procedures play a pivotal role in Aspen Dynamics following the convergence of all systems. In computing the height and width of the absorber-stripper, a dataset of liquid-holdup spanning a duration of 10 minutes is utilized. The transition to dynamics is imperative to facilitate process control, the primary objective of this study. Upon completing sizing for both the absorber-stripper and reboiler within Aspen Plus, the subsequent step involves engaging in dynamic simulation, offering options such as flow-driven or pressure-driven models. Researchers opted for the flow-driven model due to its enhanced accuracy within the system. However, complications arose upon encountering a fatal error notification in Aspen Plus, revealing the inability to execute rate-based equations within Aspen Dynamics. This unforeseen obstacle presents a challenge to the seamless integration of simulation and dynamic analysis, necessitating further exploration of alternate methodologies to achieve the study's objectives.

3.1.2 Case 2 Equilibrium Based with Murphee Efficiency

Consequently, the Murphree efficiency of the stripper was fixed at unity, while the Murphree efficiency of the absorption column underwent adjustments until a satisfactory alignment between the rate-based and equilibrium models was attained. This process involved a deliberate selection of the absorption column with a Murphree efficiency set to 0.4, followed by iterative adjustments to reach a harmonious convergence between the rate-based and equilibrium models.[9]

3.2 Model Predictive Control Algorithm

The algorithm of this MPC based on the future dynamics of the system that is predicted and the the optimization problem is solved.

3.2.1 Linearisation of Non-Linear Model

The equation state space for linear discrete-time systems

$$x(k+1) = Ax(k) + B_u u(k) + B_d d(k) \tag{2}$$

$$y_c(k) = C_c x(k) \tag{3}$$

In Equation (2) and (3), the state variable is denoted as $x(k)\in\mathbb{R}^{nx}$, the control input variable as $u(k)\in\mathbb{R}^{nu}$, the controlled output variable as $yc(k)\in\mathbb{R}^{nc}$, and the measurable external interference variable as $d(k)\in\mathbb{R}^{nd}$. Specifically, $u(k)=[F_L]^T$, $yc(k)=[\eta_{CO_2}]^T$, and $d(k)=[FG]$. Here, FL represents the lean solvent flow rate, and FG represents the inlet flue gas flow rate, which serves as the primary measurable disturbance. η_{CO_2} denotes the CO2 capture rate. The parameters A, Bu, Bd, and Cc are determined through system identification. To predict the future dynamics of the system, Equation (1) and (2) are employed, utilizing the latest measurement value as the initial condition. The prediction time domain is defined as Np, the control time domain as Nm, with $Nm\leq Np$. This predictive framework enables a comprehensive understanding of the system's behavior and aids in formulating effective control strategies for post-combustion CO2 capture processes.

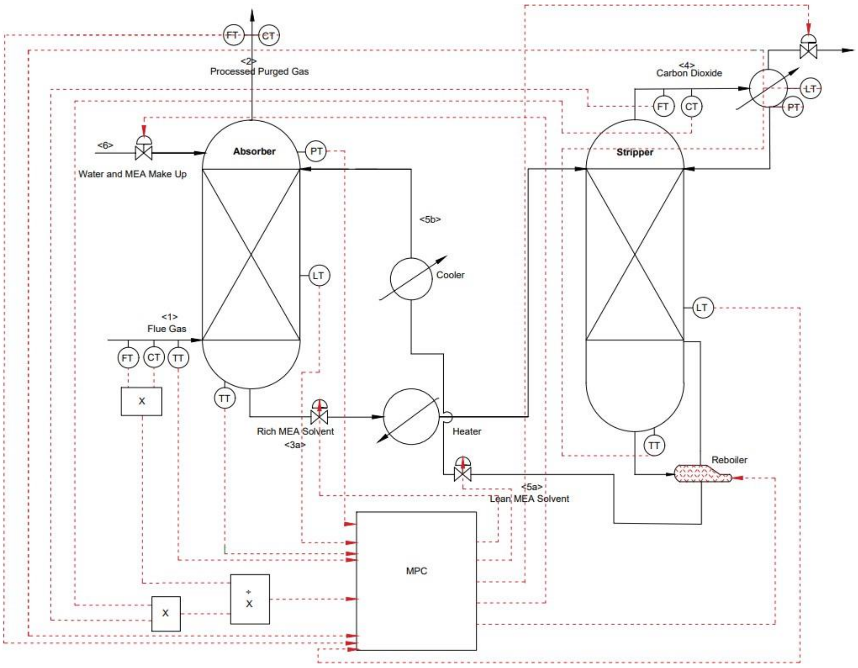

Figure 5. Schematic Diagram MPC Controller

3.2.2 MPC Tuning Parameter

The creation of an MPC controller requires consideration of the weights on the output variables, sample time, prediction horizon, and control horizon as shown in Table 6. The selection of variable weights is based on the urgency level of a variable to be controlled. The most crucial variables receive the highest weights, in this case, recovery is the main subject, while constraints for pressures and levels were given, so the system still runs in acceptable operating conditions. Table 6 becomes the final choice with these considerations. The determination of sampling time depends on the function of the MPC controller. If the MPC controller becomes the main controller, then the sampling time should be made as small as possible, with the real limit of data processing speed by the computer and actuator process. Based on references, the sample time is set at 1 minute [13]. The prediction horizon and control horizon are also determined according to the methodology. The Model Horizon (N) cannot be obtained because the open loop settling time is unobservable because it may be too long.

Tabel 6. MPC Parameter Controller

Variable:	Constraints:
Abs. Pressure	90% - 110%
Abs. Sump Level	95% - 105%
Stp. Sump Level	95% - 105%
Stp. Drum Level	95% - 105%
Stp. Pressure	95% - 105%
Variable:	Weight:
Recovery	1
Sample Time Δt, hr	0.0167
Prediction Horizon (P), hr	40
Control Horizon (M), hr	20

3.3 *Dynamic Result*

In this study, a dynamic characteristic model of post-combustion CO2 capture in a power plant was established using MATLAB/Simulink. The model uses lean solvent flow and rich solvent flow as the manipulated variable, carbon dioxide recovery rate as the controlled output, and flue gas flow as the disturbance variable. The principles of small overshoot, fast response speed, and good tracking of a set value were taken into account in the design of the model. The output response of the system after the program has finished running was verified through prior research. The results were then compared to those obtained using a traditional PID controller. The key parameters of the MPC controller tuning are presented in Table 6. This approach provides a comprehensive understanding of the dynamic characteristics of CO2 capture in power plants, which could be beneficial for optimizing the operation and control of such systems.

3.4 *Controller Results and Analysis*

Figure 6 illustrates the integration of Simulink software for recording simulations conducted in Aspen Dynamics, incorporating a PID controller. The input variable was a step test from disturbance variables. The output variables were controlled variables and manipulated variables that were paired. The utilization of Simulink in this context serves as a comprehensive tool for capturing and analyzing the dynamic behavior of the system under study. The Aspen Dynamics simulation software, renowned for its good performance in process simulation, interfaces seamlessly with Simulink to enable the incorporation of a PID controller, a fundamental component in control system design. This integration facilitates the creation of graphical representations derived from the simulation, allowing for a visual assessment of the system's response to the PID controller. Furthermore, the subsequent comparison of these results with those obtained using an MPC (Model Predictive Control) controller provides valuable insights into the relative efficacy and performance of different control strategies within the dynamic simulation framework. This interdisciplinary approach enhances the understanding of control system dynamics and contributes to the ongoing discourse on optimizing control strategies for complex processes.

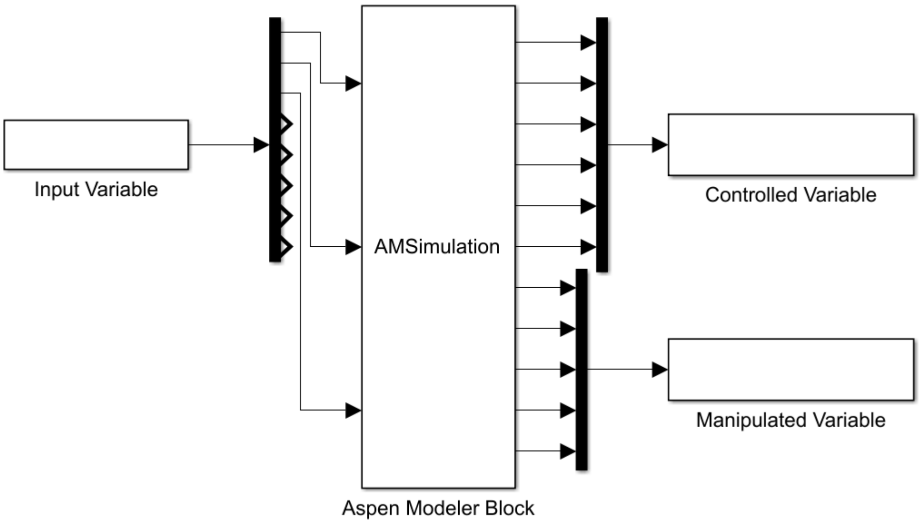

Figure 6. Disturbance Rejection Test on Simulink

The simulation of load disturbances +5% flue gas feed flowrate was obtained through Aspen Dynamics and Matlab Program.The results of both controllers, MPC and PID, can be depicted as a graph in Matlab, and a comparison of them can be seen in figure 7. The time span was 1 hour to see the detailed differences between MPC and PID in reaching the steady state value.

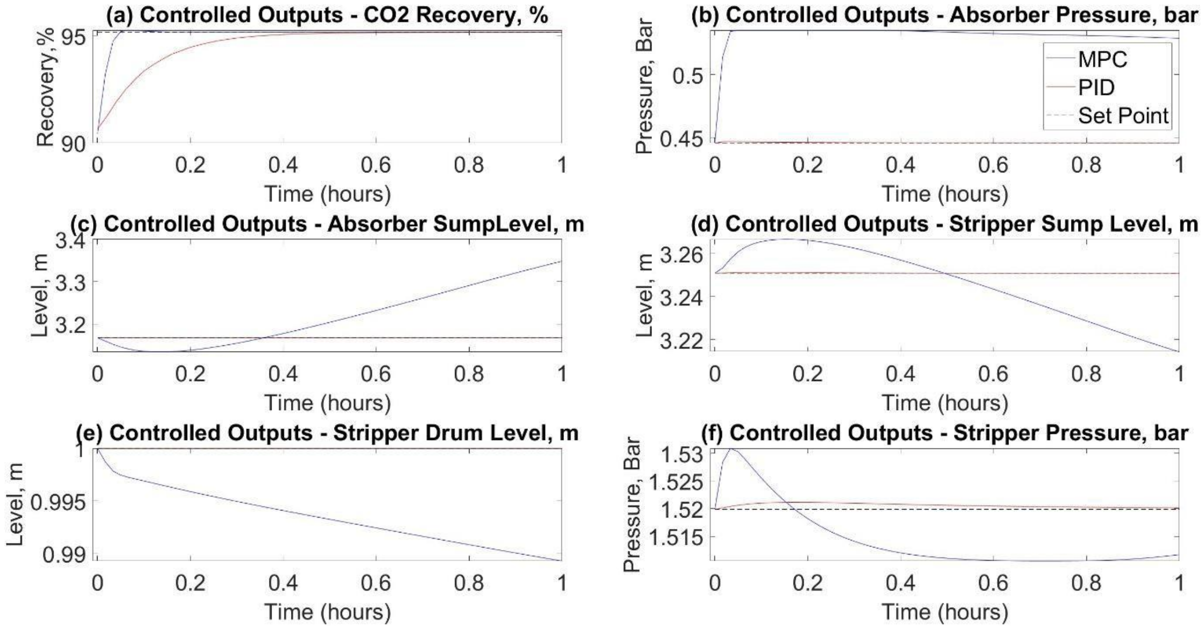

Figure 7. Controlled Output Comparison of PID and MPC for Disturbance Rejection Test +5% Feed Flowrate

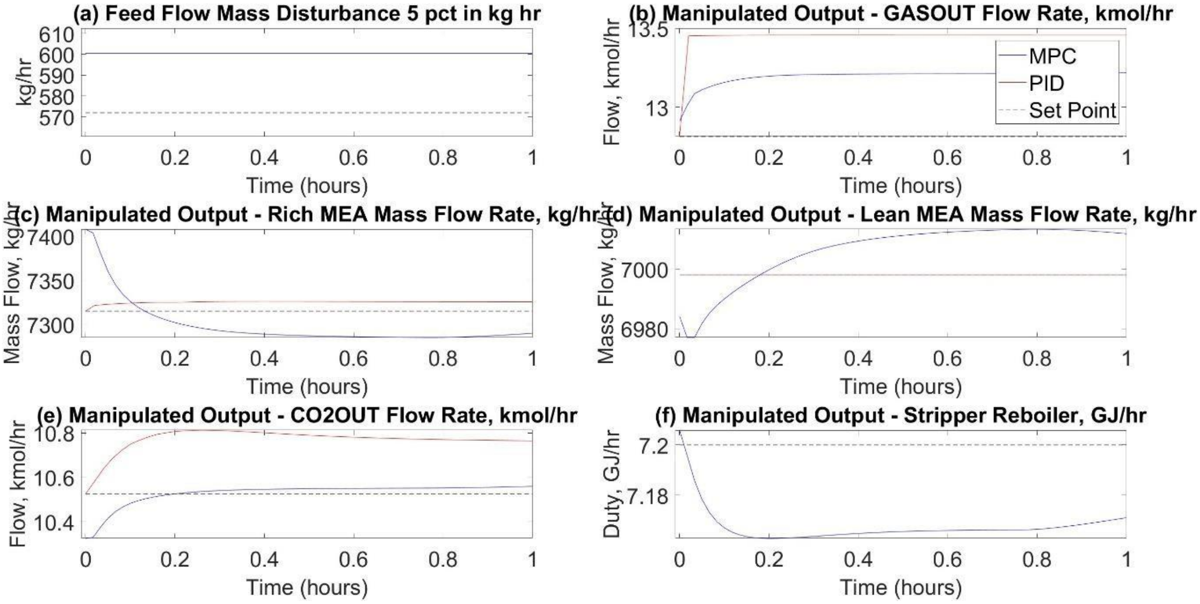

Figure 8. Manipulated Output Comparison of PID and MPC for Disturbance Rejection Test +5% Feed Flowrate

The analysis of the results indicates that the MPC controller exhibits a higher degree of responsiveness compared to its PID counterpart. No overshoot observed in PID-controlled system and little overshoot observed in MPC-controlled system, suggesting robust and controlled response for both. Additionally, when scrutinizing the time taken to reach steady-state conditions, the MPC controller demonstrates a superior performance by achieving faster convergence. This outcome underscores the efficacy of MPC in minimizing transient deviations and accelerating the attainment of a stable operating state.

4. Conclusions

This paper studies about the comparative analysis between PID controller and the more sophisticated Model Predictive Control (MPC) systems in regulating the capture rate of carbon dioxide (CO2) from burning natural gas streams with an emphasis on achieving around 95% capture efficiency. Employing a 32 wt% monoethanolamine (MEA) solution at 1 atm pressure for CO2 absorption, the simulation of the absorber column was implemented on the hydrogen plant data, specifically designed based on a hydrogen plant setup.

Results showcased that the MPC's perceived advancement over the decentralized PID controller. This suggests that within standard operational parameters, MPC controllers can rival the vast usage of PID controllers. The cost-intensive nature of advanced model-based controllers necessitates a thorough cost-benefit analysis before investment.

Future research trajectories should be: (i) Using the recent ongoing artificial intelligence for the MPC for a potentially high performance, (ii) Evaluating the robustness of MPC performance for other plant that emit a lot of carbon dioxide, and (iii) conducting dynamic in rate base condition with other software to control with model predictive control. This research seeks to further optimize control strategies for enhanced CO2 capture efficiency within industrial contexts, promoting both economic viability and environmental sustainability.

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