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An optimization study on enhancing the vacuum distillation unit using MPC in comparison with PID controller

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Abstract

This research examines the process of choosing between the reliable proportional-integral-derivative (PID) controller and the recommended model predictive control (MPC) controller for the vacuum distillation unit (VDU) by analyzing its dynamic behavior. Aspen HYSYS V12.1 and MATLAB Simulink Environment (2021 A) software programs were used in this study to compare the performance of the PID and MPC controllers to analyze the overhead temperature response. The temperature response in the middle of the tower (stage No. 15) is both a basic factor in improving product quality and quantity through a set point (SP) step change in the mass flow rate of the feed stream, feeding temperature, and flow rate of stripping steam. In addition, to study the effect of a disturbance step change on the feed pump efficiency, as well as making a change in the overhead temperature and the temperature of stage No. 15 to clarify the performance difference between the (PID) and (MPC), The study result showed that MPC is better than PID in reaching the desired value and overcoming the turbulence effect, The overhead and (stage No.15) temperatures response time to reach steady state, it is found that the MPC response time shorter than the PID with respect to the efficiency disturbance by (81% and 293%), step change in feed flow rate by (43% and 47.2%), feed temperature by (440% and 158%), low pressure steam (LPS) (81% and 290%) and set point (86.6% and 218%), In the overshot and raising time, the MPC shows better temperature overshoot and raising time in all step change cases taken than the PID except the overhead temperature in feed temperature step change shows that PID is better in small temperature difference, and steady state error percentage for the MPC shows that it is zero or approximately zero in the inputs step change but for the PID the steady state error is not zero like in step change in feed flow rate and temperature which are 0.01 and 0.02 respectively.
This study shows how the efficiency of the distillation separation process can be increased through the prediction disturbance, overcoming it and high response time to reach the desired value, which increases the production quality, and quantity and reduces the energy associated with the production process (steam, fuel, electricity, etc.).

Keywords: *Vacuum distillation unit, model predictive control, proportional integral derivative, LPS, vacuum diesel oil, heavy vacuum gas oil, light vacuum gas oil.*

1. Introduction

The first distillation of the re-refinery, the vacuum distillation unit (VDU), is used to separate vacuum gas oil from lubricant oil. Furthermore, a refinery's secondary process unit. The atmospheric residue, the bottom product of the crude distillation unit (CDU), which has a boiling point of greater than 350°C, must be fractionated, and this unit is crucial for this [1].
One of the most important procedures in the petrochemical sector is distillation. It is a crucial step in the purification of chemical products before they are sold. One of the most popular methods for separating a mixture of components based on variations in their boiling points or relative volatilities is distillation [2].
In the distillation columns, vacuum distillation is carried out at a decreased pressure that is primarily below atmospheric pressure, allowing the liquid to boil at a temperature lower than its initial boiling point while under atmospheric conditions. The crude distillation unit (CDU) supplied it with feed, and it was used safely to recover solvents with higher boiling points. According to [2], the diameter of vacuum distillation towers is often bigger than that of atmospheric distillation towers.

The composition of the distillate and bottom product, as well as column pressure, are some of the regulated factors in the distillation column. Reflux, bottom product, and distillate flow rates are a few more factors that have been changed. A controller may meet certain required performance standards, like a robust control system, zero offset, stability, little disturbance impact, quick and seamless reaction to set point changes, moderate control action, and zero offset [2]. MIMO (multiple input, multiple output) control issues are those in which there are several controlled variables as well as numerous variables that are altered.

The proportional integral derivative (PID) control system was included in the Wataniya bitumen and oil refinery (VDU) design. This control system was chosen because of its straightforward design and strong performance attributes. PID's disadvantage, meanwhile, is that it lacks a process model for its control action. As a result, the PID control action was unable to account for process dynamic information such as dead time and nonlinearity, which made it impossible for the process to be controlled [3].

Proportional integral derivative (PID) controllers are unable to address the complexity of industrial processes or the quality requirements of their products. PIDs are often built using a feedback structure, which has some drawbacks. For example, output measurements are used to identify disturbances, meaning that control actions must be taken after they have an impact on the process. For processes that have a long latency, this is a serious issue. When a disturbance enters the process, a control action that has been delayed becomes occasionally inappropriate. There are further drawbacks to PID control, including performance compromises for resilience. It refers to achieving an advanced controller.

Since the controller's action will directly affect the distillate product, the distillation control system's performance is crucial. Advanced distillation control will improve product quality, cut waste, and boost profitability. The development of control technology has a prototype Currently one of the most popular advanced control techniques in business, predictive control is particularly useful for managing unpredictable, multivariate, and confined processes, such as those used in industrial predictive control applications [4].

In 2018, A Wahid and A P Prasetyo concluded that the MPC can enhances the control performance of the vacuum distillation unit (VDU) better than using the proportional-integral (PI) controller which they used the set point change and disturbance in feed flow rate, feed temperature, top stage pressure, bottom stage temperature and to improve the light vacuum gas oil (LVGO), middle vacuum gas oil (MVGO), heavy vacuum gas oil (HVGO) products [5].

As an alternative to the VDU design proportional integral derivative (PID) control system for the VDU of the Wataniya Group refinery, the Model Predictive Controller (MPC) was proposed. It can resolve issues with the conventional control system in use and is essential to process optimization because it can select the best course of action by utilizing the system model to forecast the behavior of the system in the future. MPC can also manage multi-input multi-output (MIMO) systems, which include interacting inputs and outputs. MathWorks (2023) states that MPC also manages constraints, which are necessary since violating them might have unfavorable effects.

MPC uses models in two ways: first, it utilizes a dependable model to forecast how previous control moves would affect P (prediction horizon) future outputs under the assumption that no further changes will be made; second, it uses the same model to choose the best M (control) horizon moves. For an MPC controller to function at its best, a few settings must be configured. These parameters include the following: controlled variable weights, move suppression coefficients, model horizon (N), prediction horizon (P), sampling time (T), and control horizon (M).

The objectives of the study suggest utilizing the MPC controller to assess the effectiveness of the vacuum distillation column control system at the Wataniya Group refinery in Samawah City and upgrade it. This goal will be accomplished by simulating the system using Aspen HYSYS version 12.1, a MATLAB Simulink environment (2021 A), and comparing the system's response to set point and disturbance step changes in both designed classical control proportional integral derivative (PID) and model predictive control (MPC).

2. Theoretical of PID and MPC control

2.1. Proportional-integral-derivative controller

A Proportional–integral–derivative (PID) controller has a lengthy history in the field of automatic control, dating back to the turn of the 20th century [6]. For the US Navy, Elmer Sperry created the first PID controller in 1911. The PID law was first realized as a computational mimic of the natural perception-action control principle used by experienced helmsmen in Minorsky's work in 1922. Using historical, current, and projected future error data forms the foundation of the PID law's control structure. The construction of PID controllers in two different forms is widely known: two-degree-of-freedom (2-DOF) and single-degree-of-freedom (1-DOF) PID. Since the control system's architecture can be viewed as a multi-objective optimization [7]. The field of automatic control has a long history with proportional integral derivative (PID (controllers. In 1769, James Watt created a steam engine, and the governor was acknowledged as the first negative feedback device. A control engineer must have a thorough understanding of these control systems and the ability to design and implement them, see figure 1 [8] and [6].

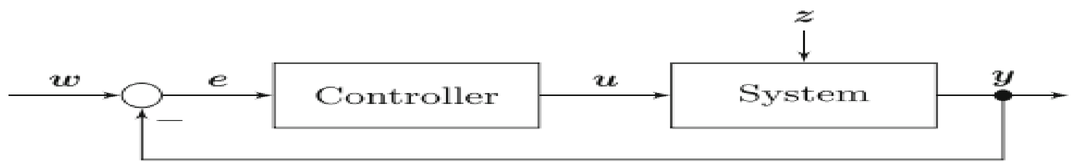

Fig. 1: A classical feedback control loop's block diagram (PID) [9].

The equation form of proportional integral derivative (PID (is produced by combining the effects of the proportional P, integral I, or derivative D actions that occur in separate equation terms. This type of parameter has independent values for each, and the corresponding control law can be expressed as follows (equation 1): -

$$u(t) = Kc\ (e(t) + 1/\ Ti\int e(t)dt + Td\ de(t)/\ dt) \quad (1)$$

where:
$kp = kc$, the proportional gain (p)
$kd = kc*Td$, the derivative gain (d)
$ki = kc*Ti$, the integral gain (i)

To attain the highest possible level of accuracy and stability in performance:

2.1.1. Plant-model-based methods

Particularly, a greater percentage of proportional integral derivative (PID) design techniques (both fixed and adaptive) that are currently available mainly depend on the comprehension of either derived mathematical model approximations from first principles or fitted mathematical model approximations of the actual underlying physical dynamical system from experimental data Considering the trade-offs between performance and robustness in modern terms.

2.1.2. Plant-model- free methods

Due to the difficulties in finding good plant models that are mathematically impossible or the time-consuming, expensive, and complex nature of plant modeling, which is associated with process identification for control. This has spurred interest in non-plant model-based design methodologies. Model-free techniques, which are essentially data-driven control design techniques, deviate from model-based conventions. In this instance, the absence of a plant mathematical model is frequently mentioned.

2.1.3. Hybrid methods

Methods that combine data-driven plant model-free approaches for tuning with a type of plant model knowledge—which need not inevitably be a plant model structure with parameters included—are referred to as hybrid methods. Methods in this category can be categorized as either using both methods that are either plant-model-based or free techniques, depending on which control techniques (adaptive control, pole placement, optimal control, and computational intelligence) are used [10].

2.2. Model predictive controller

Two innovative industrial research groups independently developed the first generation of the Model Predictive Controller (MPC) systems in the 1970s, which was developed by Clarke et al. (1987) and has also drawn a lot of interest. Industrial practice has been greatly impacted by model predictive control [11].
There are numerous significant benefits to model predictive control: -

1- Input, output, and disturbance variables interact both dynamically and statically in the process model.
2- Input and output constraints are systematically considered,
3- It is possible to synchronize the control computations with the optimal set point computation.
4- Precise model forecasts can offer preliminary alerts regarding possible issues.

The accuracy of the process model is obviously critical to the success of Model Predictive Controller (MPC) (or any other model-based approach). Rough forecasts have the potential to worsen rather than to improve the situation.
The accuracy of the process model is critical to the success of Model Predictive Controller (MPC) or any other model-based approach, rough forecasts have the potential to worsen rather than improve the situation [11].

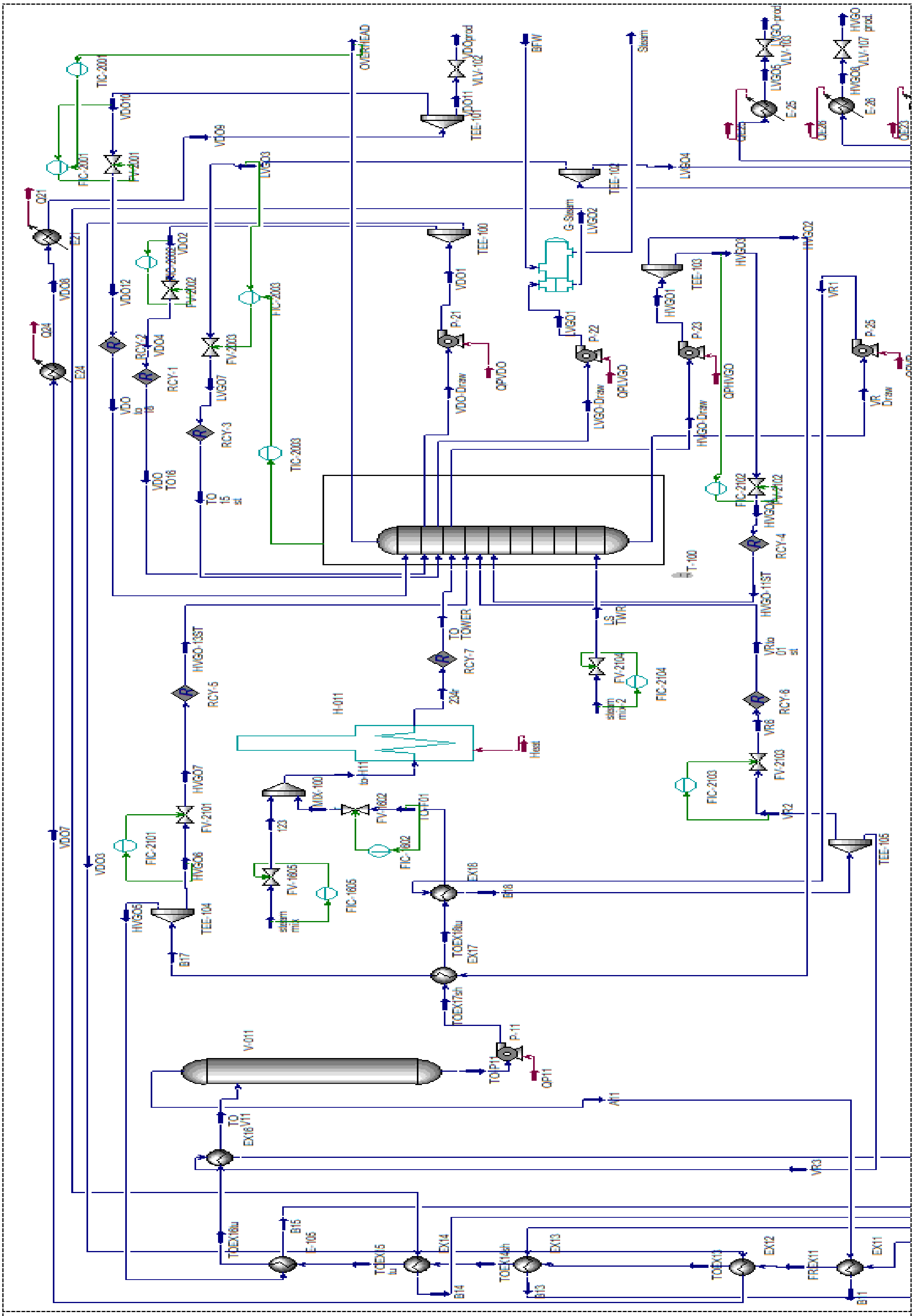

Fig. 2: VDU flowsheet using Aspen HYSYS simulated.

Models are the foundation of Model Predictive Controller (MPC) and are found in practically every field. This eliminates the need for the laborious creation of a clear control law, an assignment that is typically left to control specialists, and permits the utilization of this acquired knowledge. Instead, using a model-based optimization process, Model Predictive Controller (MPC) automatically determines the control law. Our advocacy for Maximum Part Coding Model Predictive Controller (MPC) in the engineering community stems from its primary benefits, which include its implicit formulation, flexibility, and explicit model utilization. From the perspective of application [9].

The MPC forecasts future system behavior based on this system model and takes it into account when determining the best course for the manipulated variable (u) figure (3), The input variables in MPC applications are also known as manipulated variables (MVs), and the output variables are also known as controlled variables, or feedforward variables, and are measured disturbance variables [4] and [11].

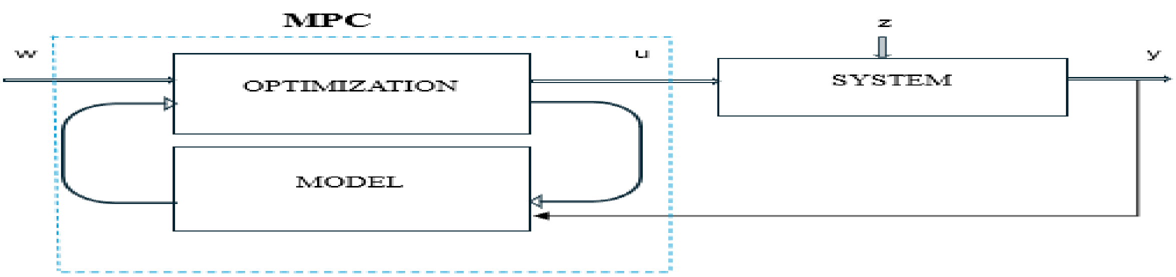

Fig. 3: An MPC-based control loop's simplified block diagram.

3. Algorithm component and principle of model predictive controller (MPC)

The Prediction Model, Objective Function, and Control Law are three mathematical models that can be used to represent the Model Predictive Controller (MPC) algorithm. With the information at hand, the Prediction Model instantly computed future responses based on the dynamics of the process. One type of actual process model that can be included in a prediction model is an impulse response model, a step response model, a transfer function model, a state space model, and many more.
Model Predictive Controller (MPC) is a class of advanced control methods that uses a model to predict the future behavior of the system. To find the optimal output U while taking this prediction into account, the MPC resolves a constrained optimization problem. It is one of the few control schemes that explicitly considers constraints. It is standard procedure to formulate the cost function such that the system output y tracks a given reference r for a given horizon N2 (see figure 4). Only the first value from the optimized output trajectory is supplied to the system. This prediction and optimization process is repeated each time. Because of this, "receding horizon" control is another name for Model Predictive Controller (MPC) control. article.

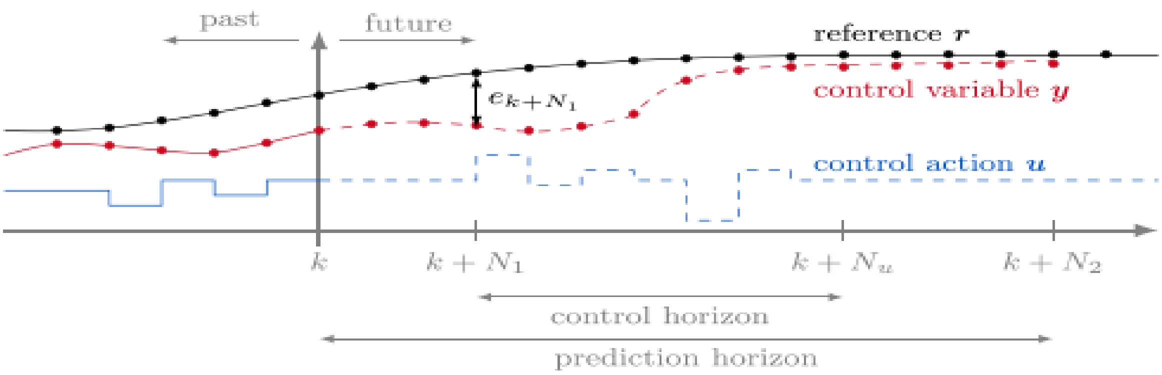

Fig. 4: A predictive model function with horizons (N2, N1, and Nu) as per [9].

To capture the impact of a change in the manipulated variable (u) on the control variable (y), the prediction horizon N2 needs to be sufficiently long. Either the lower prediction horizon N1 or the system model can take delays into account. The latter is often more intuitive, and, to account for computation time, the lower prediction horizon is set to N1 = 1. This means that while the computation is done in one-time step, the solution (u) is not implemented until the next time step.
Under the assumption of an arbitrary system (equations 2 and 3):

$$x(k+1) = f(x(k), u(k)) \tag{2}$$

$$y(k) = h(x(k)) \tag{3}$$

A modified cost function (J), such as the tracked error between the reference vector (r) and the output of the model(y) Eq. 4, is minimized by MPC, according to equations 4 and 5:

$$\min_{u} \quad \boldsymbol{J}\,(x(\boldsymbol{k}),\, \boldsymbol{u}\,(\cdot)) \tag{4}$$

$$\min_{u} \quad \sum_{i=N1}^{N2} ||\, \boldsymbol{r}\,(\boldsymbol{k} + i|\boldsymbol{k}) - \boldsymbol{y}(\boldsymbol{k} + i|\boldsymbol{k})|| \tag{5}$$

$$s.t \qquad \boldsymbol{u}_{ib} \leq \boldsymbol{u}\,(\boldsymbol{k} + j\,|\boldsymbol{k}) \leq u_{ub}$$
$$\boldsymbol{y}_{ib} \leq \boldsymbol{y}\,(\boldsymbol{k} + i|\boldsymbol{k}) \leq \boldsymbol{y}_{ub}$$
$$\forall\, i \in \{N1, \cdots, N2\} \text{ and } j \in \{(0, \cdots, Nu\}$$

An arbitrary norm · is used in this formulation. The anticipated state (k + i) at time point k will be denoted by the notation x (k + i|k). variables written in bold Higher dimensions are indicated by an asterisk (A), which can be either an uppercase or lowercase matrix or vector. A series of conditions will be represented by x (·), equations (6, 7 and 8):

$$x\,(k + i)\;\; \forall i \in (0, \cdots, N2) \Rightarrow x\,(\cdot) \tag{6}$$

$$u\,(k + i)\;\; \forall i \in (0, \cdots, Nu) \Rightarrow u\,(\cdot) \tag{7}$$

$$y\,(k + i)\;\; \forall i \in (N1, \cdots, N2) \Rightarrow y\,(\cdot) \tag{8}$$

This will allow us to shorten the constraint formulation to xib ≤ x (·) ≤ xub ⇒ x ∈ Xf, which means that the sequence x (·) is contained in the feasible set Xf. According to [9].

4. Controller tuning

The Adjustment of proportional integral derivative (PID) controls employed multiple techniques. Aspen HYSYS program's autotune method; however, the adjustment procedure did not produce satisfactory results, and some of the controllers stopped working. Also, adjusted, using the Ziegler and Nichols method, the results showed that while some of the controllers performed well, others failed and did not respond. Proportional integral derivative (PID) parameter adjustment, using the Ziegler-Nichols technique, consistently gives extremely poor performance. [12], so we will not depend on it.
Also, in the study, the two researchers [13] noticed that the proportional integral derivative (PID) controller parameters set by the auto method in MATLAB Simulink don't produce satisfactory results. The controllers were fine-tuned through the trial-and-error method. In this section, we will depend on the trial-and-error method, which shows a good result when compared with Zigler-Nichol's technique and the auto-tuner methods below.
Controllers that use Model Predictive Control (MPC), an advanced control technology used in many different applications, rely on a system model to forecast future behavior of the system. Next, based on these forecasts, the control signal that will guide the system to the intended state is determined.
There are many methods to adjust Model Predictive Control (MPC)controllers. Using trial and error is a straightforward method [14].
The following steps are part of this method:

1. Start with initial values for MPC parameters.
2. Make step changes to the input of system.
3. Monitor how the system responds.
4. Modify the MPC settings until the system responds as expected. Advantages and Disadvantages of trial-and-error Method. See table (1).

Table1: Advantages and Disadvantages of MPC Tuning by trial-and-error Method

Advantages of this method	Disadvantages of this method
Ease of implementation	May take a long time
Does not require any advanced knowledge(theory)	May not be effective with complex systems

5. Results and discussion

5.1. Closed loop dynamic simulation results with disturbance step change (regulatory loop)

The step change method and its influences as clarified Previously will be used to illustrate the conditions and analyze the disturbance dynamic in the feed pump considered as another way to comprehend system behavior and ascertain how the step changes affect process variables, Additionally, a step change in feed flowrate, temperature, and LPS flowrate to the column will be seen when studying the behavior of the system at the proportional integral derivative (PID) and Model Predictive Control (MPC) controllers as shown below:

5.1.1. Step change in feed pump efficiency (90-95%)

When controlling overhead temperature, figure 5 illustrates the preference for the Model Predictive Control (MPC) controller over the proportional integral derivative (PID) controller. In the PID, the overshot is 90.38°C in 1.8 min and stabilizes at 89.99°C in 29 min, whereas in the MPC controller, it is 90.07°C in 1.6 min and stabilizes at 89.97°C in 8.8 min. In figure 6. Notably, the overshot in the PID is 245.51°C in 0.6 min, oscillated, and stabilized at 245.24°C in 53.8 min. In contrast, the MPC controller rose to 245.38°C in 0.6 min, stabilizing at 245.3 in the time of 13min. This illustrates the advantage of the MPC controller, which has less overshot, settling time, and steady state error than the PID controller.

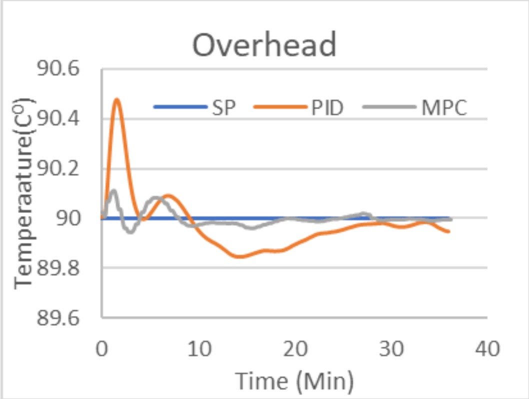

Fig. 5: Temperature response of overhead with disturbance in feed pump efficiency (90-95%).

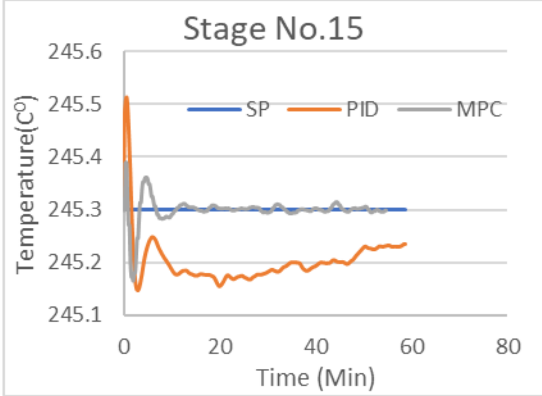

Fig. 6: Temperature response of stage (No. 15) with disturbance in feed pump efficiency (90-95%).

5.1.2. Step change in feed flowrate (74800-75088kg/h)

Figure 7 illustrates the impact of overhead temperature response with PID & MPC controllers. Specifically, utilizing a PID controller stabilizes at 89.99°C in 28.2 minutes. In MPC stabilizes at 90.07°C in the time 10 min. As notice steady state error in PID more than MPC controller. While in figure 8 The effect of distillation temperature (stage No. 15) response in PID stabilizes at 245.2°C in 250 min, and the MPC stabilizes at 245.29°C in 42.4 min. You'll see that the MPC controller has zero steady state error and the PID has a steady state error of (0.02).

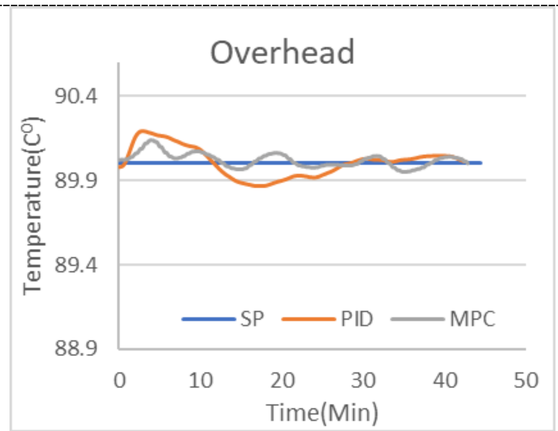

Fig. 7: Response of overhead temp. at (SP) step change in feed flow with PID & MPC controller (74800- 75088 kg/h).

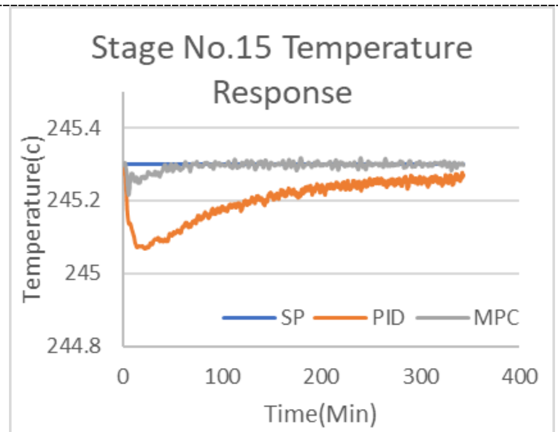

Fig. 8: Response of (Stage No.15) temp at (SP) step change in feed flow with PID & MPC controller (74800-75088kg/h).

5.1.3. Step change in feed temperature (386-394.8°C)

Figure 9 Overhead temperature response in a PID, it stabilizes at 90.7°C in period 350 min, MPC stabilizes at 90.08°C in 92 minutes. We show that the MPC controller is zero and the steady state error in PID is 0.01. In figure 10 The temperature Response of Stage (No.15), The temperature increases in the PID controller from 245.3°C to 246.42°C in 5.6min and stabilizes at 245.33°C in time 249.8min. In the MPC stabilize at 245.3°C in time 88.2min. While the steady state error in the MPC controller is zero, it is 0.01 in the PID controller.

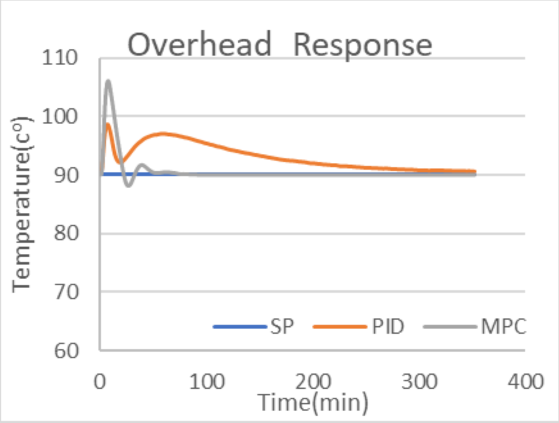

Fig. 9: Overhead temperature at (SP) step change in feed temp. (386-394.8°C).

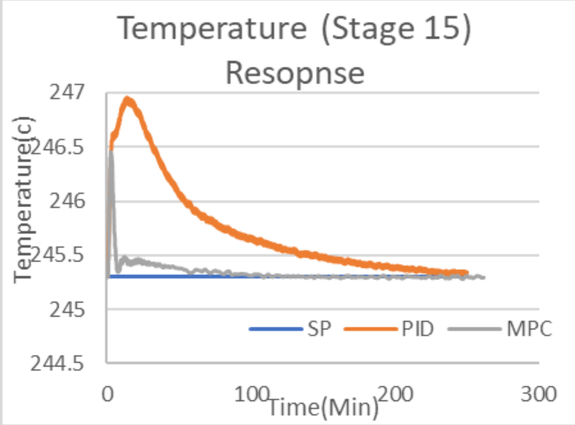

Fig. 10: (Stage No.15) temperature at (SP) step change in feed temp. (386-394.8°C).

5.1.4. Step change in stripping steam mass flowrate(190-200kg/h)

Figure 11 Overhead temperature response in a PID increases from 100°C to 100.43°C, then oscillation and stabilize at 99.99°C in 60 minutes. In MPC the temperature rises from 100°C to 100.17°C then stabilizes at 100.02°C in the time 26.6 min. As notice steady state error in PID more than MPC controller. While in figure 12, The response of distillation temperature (stage No. 15) The PID controller's temperature decreases from 245.3°C to 244.84°C in a period of 0 to 2.8 minutes, then rises and stabilizes at 245.2°C in 39.4 minutes. in the MPC drops and stabilizes at 245.29°C in 17.4 min, the PID controller exhibits a higher steady state error than the MPC controller.

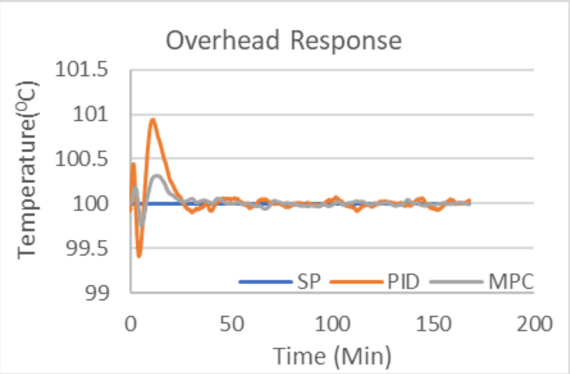

Fig. 11: Overhead temperature at (SP) change in LPS (190 - 200 kg/h).

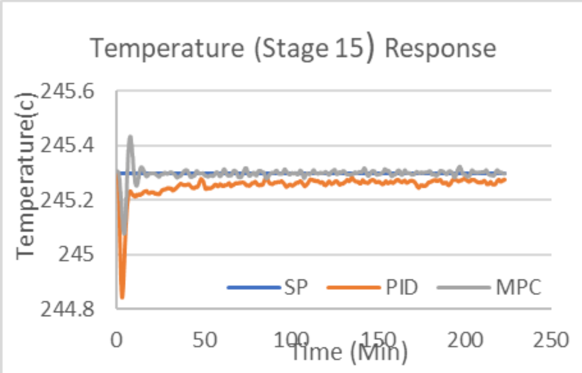

Fig. 12: (Stage No.15) temperature at (SP) step change in feed temp. (386-394.8°C).

5.2. Closed loop dynamic simulation results with set point step change (Servo loop)

5.2.1. Set point step change in overhead (90-95 °C)

Figure 13 illustrates the impact of overhead temperature response with set point step change (90-95°C) overhead in the PID controller rises from 90°C to 96.4°C and oscillation before stabilizing at the set point in 30.2 min. While in MPC controller, it rises to 95.35°C then reaches the set point in 14.95 min. MPC, a result, MPC's response time is shorter than that of the PID controller.

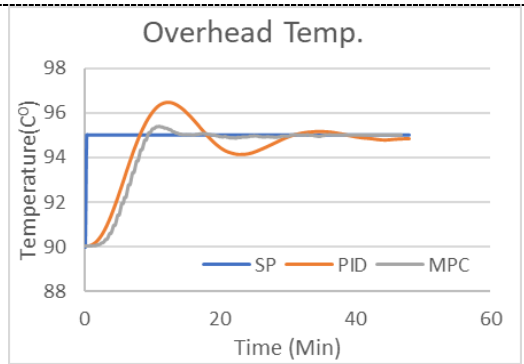

Fig. 13: Response of overhead Temp with (SP) step change (90-95°C).

5.2.2. Set point step change in stage No.15 temperature (241.3-245.3°C)

Figure 14, the temperature response of (Stage No.15) in PID stabilizing at the set point (245.3°C) through 100 min and the MPC, it corresponds to the set point 245.3°C in the time13.8 min Therefore, the response of MPC is short compared to the PID controller with steady state error is zero. The comparative between PID & MPC controller at Overhead Temperature and Stage No.15 Temperature, see table (2) below.

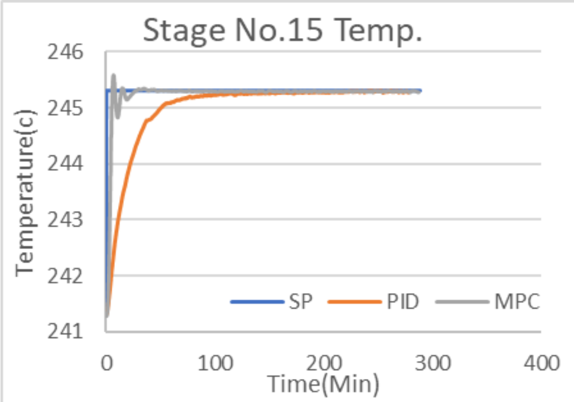

Fig. 14: Response of (Stage No.15) with (SP) step change (241.3-245.3°C).

Table 2: Response of overhead temperature and (stage No. 15) temperature with one step change

Step change case	Overheat PID (min)	Temp. response MPC (min)	Stage No.15 PID (min)	Temp. response MPC (min)
Pump eff.	29	8.8	53.8	13
Feed flowrate	28.2	10	250	42.4
Feed Temp.	350	92	249.8	88.2
LPS Flowrate	60	26.6	39.4	17.4
Set point	30.2	14.95	100	13.8

The comparison of plant data and Aspen HYSYS-simulated data for temperature and volumetric flow rare is displayed in table 3.

Table 3: Mass flowrate and Temperature comparison between simulation and plant data in steady state mode

Stream Name	Mass flowrate (kg/h)			Temperature (°C)		
	Simulation	Design	Error%	Simulation	Design	Error %
Overhead	528.6	528	0.113	89	75	18
VDO prod.	14240	14242	0.014	46	50	8
LVGO prod.	17330	17327	0.017	90.19	90	0.11
HVGO prod.	8048	8048	zero	90.17	90	0.11
VR prod.	35151	35151	zero	150.3	150	0.2
Feed Flow	75300	75095	0.27	395	395	zero
LPS (Tower)	200	200	zero	220	220	zero
LPS Furnace	150	150	zero	220	220	zero

6. Conclusion

The major goal of this research is to control the distillation tower's dynamic behavior to achieve optimal operation. In addition to raising production levels or upholding specifications, achieving economic viability also heavily depends on the energy used in the process. When we compared the MPC's performance to the PID, we were able to observe that it had a continuous production capacity which is achieved by reaching the desired value and rejecting disturbances. The high response speed of the MPC controller during dynamic operation was observed compared to the PID, and the error rate between design data and simulation data was found to be very small. When the PID controller was applied to start the simulation, it was observed that the stability time of the product specifications was approximately 6 hours longer than the MPC, when determining the economic feasibility of using the MPC controller suggestion alternative to the PID controller, we estimated that the production difference for VDO was approximately 85.4 tons, LVGO was 103.3 tons, HVGO was 48.2 tons, and VR was 210.9 tons, Lastly it is found that the MPC response time shorter than the PID with respect to the efficiency disturbance by (81% and 293%), step change in feed flow rate by (43% and 47.2%), feed temperature by (440%

and 158%), low pressure steam (LPS) (81% and 290%) and set point (86.6% and 218%), In the overshot and raising time, the MPC shows better temperature overshoot and raising time in all step change cases taken than the PID except the overhead temperature in feed temperature step change shows that PID is better in small temperature difference, and steady state error percentage for the MPC shows that it is zero or approximately zero in the inputs step change but for the PID the steady state error is not zero like in step change in feed flow rate and temperature which are 0.01 and 0.02 respectively.

When compared with predictive control (MPC), the specific limitations of proportional integral derivative (PID) are shown that the steady state error in MPC is zero or near to zero while in the used PID is not zero, the overshoot and rising time in MPC is much than that of the used PID.

Depending on the simulation result compared with designed plant data, it has shown that the error percentage for the simulation and designed plant data are overhead temperature 18%, VDO production 8%, LVGO and HVGO 0.11, VR product 0.2 and feed flow rate with LPS 0%.

It is recommended in the future to apply some advanced control techniques like fuzzy control, neural network, and adaptive neuro- fuzzy or use intelligent algorithms like genetic algorithms or particle swarm optimization as tuning methods to enhance the MPC performance.

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