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Energy-Efficient Optimal Control of Crude Distillation Columns Using Proportional-Integral-Plus (PIP) Framework: A Simulation-Based Approach

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ABSTRACT

The objective of this research is to optimize the crude distillation unit (CDU) in oil refineries by reducing energy consumption and improving operational efficiency through the application of a Proportional-Integral-Plus (PIP) control system within a Non-Minimal State Space (NMSS) framework. Simulations of the CDU were carried out using Aspen Plus for modeling the distillation process and MATLAB for implementing the PIP control structure. The controller was tuned by an economic cost function, optimizing key parameters such as furnace duty, side-draw rates, and condenser heat removal. The PIP control system was compared to traditional control methods, with performance evaluated under various disturbances, including feed rate, temperature, and composition changes. The PIP control strategy significantly improved the CDU's performance, reducing operating costs by up to 100% compared to traditional control methods optimized by the Integral of Time-weighted Absolute Error (ITAE). The PIP system demonstrated superior disturbance handling and energy efficiency while maintaining product quality. The findings indicate that the PIP control system is a highly effective tool for optimizing energy consumption and process stability in modern refineries, especially under fluctuating operational conditions. Its application could lead to substantial cost savings and improved efficiency in CDU operations.

NOMENCLATURE

$\mathbf{A}(z^{-1})$	Denominator matrix polynomial of LMFD	$\mathbf{R}$	Matrix of LQ cost function input weightings
$\mathbf{B}(z^{-1})$	Numerator matrix polynomial of LMFD	$\mathbf{V}$	Matrix of SVF gains
$\mathbf{D}$	MIMO NMSS set-point coefficient matrix	V	Vapor flow rate
$\mathbf{F}$	NMSS system coefficient matrix	$\mathbf{x}_t$	Vector of states in NMSS
F	Feed flow rate	$\mathbf{y}_t$	Vector of outputs (MIMO)
$\mathbf{G}$	NMSS input coefficient matrix	$\mathbf{y}_t^d$	Vector of set-points in MIMO PIP
$\mathbf{H}$	NMSS output coefficient matrix	y	Output variable
$\mathbf{I}$	Identity matrix	z^{-1}	Time shift operator
J	LQ cost function	$\mathbf{z}_t$	Integral-of-error state variable
$\mathbf{K}$	Matrix of integral gains	τ	Time constant
L	Liquid flow rate	S	Side product flow rate
M	Liquid holdup	$\mathbf{u}$	Vector of inputs (MIMO)
$\mathbf{Q}$	Matrix of LQ cost function state weightings	u	Input variable

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I. Introduction

The crude distillation column is one of the most energy-intensive and crucial units in oil refineries, responsible for separating crude oil into valuable fractions. Given the significant energy consumption and the critical role it plays in product quality, optimizing control strategies for this process is essential. In modern industrial practice, there is an increasing demand for advanced control systems that ensure operational efficiency, reduce energy consumption, and maintain desired output specifications, especially as energy sustainability becomes a global priority [1].

Historically, various control methodologies have been applied to distillation columns, with conventional proportional-integral-derivative (PID) control being one of the earliest and most widely adopted strategies. Despite its simplicity and ease of implementation, PID control often falls short in dealing with multivariable interactions, nonlinearities, and the dynamic nature of the distillation process. As a result, PID-based control schemes often lead to suboptimal energy usage and reduced control over product quality, particularly when facing disturbances or changes in operating conditions [2].

To overcome these limitations, advanced control techniques, such as Model Predictive Control (MPC), have been introduced and extensively studied in recent decades. MPC excels in handling multivariable systems and has the ability to predict future system behavior using dynamic models. Numerous studies have demonstrated its effectiveness in optimizing the operation of distillation columns, particularly in reducing energy consumption and improving control precision [3-5]. However, MPC requires accurate models and can be computationally expensive, limiting its application in real-time or highly dynamic environments [6]. Furthermore, tuning MPC parameters for complex processes like crude distillation can be challenging and time-consuming [7]. Recent studies have proposed hybrid approaches that integrate multi-objective optimization with nonlinear model predictive control (NMPC) to address some of these challenges in complex processes [8].

Other notable approaches include nonlinear control strategies, adaptive control, and fuzzy logic control, each offering advantages in handling system uncertainties and nonlinearities. For instance, multi-objective MPC methods, as explored by Bemporad et al. [9], integrate multiple production objectives, providing a more robust solution for systems with variable process dynamics and multiple objectives. This approach enables decision-making strategies to balance energy efficiency and control performance in complex industrial systems, such as distillation columns. Adaptive control methods have shown promise in addressing dynamic variations in distillation columns [10], though these methods can be limited by computational complexity and implementation challenges. Recent advances have explored the use of machine learning, particularly reinforcement learning, as part of adaptive control systems to develop more autonomous and efficient process control solutions that learn from operational data [11].

Research has focused on optimizing energy consumption in crude oil distillation units, but practical application of optimal control strategies for these systems remains limited. Optimal control involves determining control actions that meet operational constraints while optimizing objectives like energy efficiency or product quality [12, 13]. Typical steps for implementing optimal control include modeling the system dynamics, identifying constraints, and defining a cost function to guide the control process.

In optimal control, physical constraints must be defined for both states and controllers. This approach aims to select a cost function that, when minimized, enhances system performance and reduces costs. Specifically, we seek an acceptable control strategy that guides the system along a desired trajectory while minimizing the cost function. In the PIP control for the crude oil distillation tower, the weight matrices Q and R were adjusted to simultaneously minimize the system cost and functional error. By fine-tuning these matrices, the control strategy is better equipped to balance energy consumption with product quality, which remains a key challenge in distillation control.

One particularly promising method is the Nonsquare Multivariable Non-Minimal State Space Proportional Integral Plus (NMSS-PIP) control, introduced by Khalilipour et al [14]. Their work demonstrated the effectiveness of NMSS-PIP control in an industrial crude distillation column, where the system exhibited ill-conditioning due to nonsquare configuration. The proposed control was based on a Singular Value Factorization (SVF) control design using the Linear Quadratic (LQ) optimal control method. The weighting matrices of the PIP control (Q and R) were optimized by minimizing the Integral of Time-weighted Absolute Error (ITAE), leading to smooth input manipulation and robust output control under several challenging scenarios. This approach outperformed conventional PI controllers, which struggled with the nonsquare nature of the system and provided suboptimal control [14]. Their findings strongly support the NMSS-PIP structure as a more robust and efficient solution for managing the complex dynamics and interactions in crude distillation columns.

The NMSS-PIP control strategy offers a balance between complexity and performance. Unlike traditional control methods, NMSS-PIP incorporates a more flexible control framework that is well-suited for multivariable systems with strong interactions [15]. Recent studies have demonstrated the potential of NMSS-PIP control in various industrial applications, showing significant improvements in both energy efficiency and process stability [16, 17]. For example, Kharaji et al. [18] applied NMSS-PIP to a tert-amyl methyl ether

(TAME) production unit using reactive distillation, which previously suffered from oscillatory behavior under conventional PI controllers. Their study revealed that NMSS-PIP completely eliminated the oscillations, providing smoother responses and better settling time than PI configurations. Furthermore, the ITAE criterion was significantly reduced by 88% using NMSS-PIP control, highlighting its potential for improving process control in multivariable systems [18].

Additionally, the integration of NMSS-PIP control with data-driven soft sensors further demonstrates its versatility and effectiveness in process monitoring. In a study by Bidar et al. [19], a data-driven soft sensor using the Local Instrumental Variable (LIV) technique was developed to monitor ASTM-D86 of side products in a crude distillation unit. By implementing the NMSS-PIP control structure alongside the soft sensor model, they achieved smoother responses and better alignment with dynamic process changes when compared to conventional methods. The proposed soft sensor model, applied to an Aspen dynamic simulation of the column, showed strong predictive performance and validation against Aspen soft sensors, further establishing the merit of NMSS-PIP control in matching with soft sensors to enhance process optimization [19].

Recent advancements in process control have highlighted the potential of integrating modern techniques such as artificial neural networks (ANN) and Proportional-Integral-Plus (PIP) control into industrial applications. For instance, Shin et al. [20] developed a model predictive control (MPC) system utilizing an ANN model for a depropanizer. This study revealed that replacing traditional linear models with ANN significantly improved the optimization speed and accuracy, resulting in superior performance compared to conventional PID control. The results demonstrated a marked reduction in settling and rise times, showcasing the ANN's efficacy in enhancing operational efficiency in distillation processes.

Similarly, Li et al. [21] implemented PIP control in a high redundancy actuator for a railway track switch system. Their study emphasized the advantages of closed-loop control, which increased the reliability of the actuation system. The development of a model-based PIP controller illustrated its capability to meet actuation requirements effectively, providing valuable insights into the design of redundant control systems. This work underscores the adaptability and robustness of PIP control, further validating its relevance in various industrial contexts.

Despite these advancements, there is still a gap in the literature regarding the integration of NMSS-PIP control with energy optimization objectives in distillation processes. Most studies have focused on either improving the control precision or minimizing energy consumption, without fully addressing the simultaneous optimization of both factors. The use of a cost objective function within the NMSS-PIP framework, as proposed in this paper, aims to fill this gap by providing a method that balances energy efficiency with product quality [22, 23].

The primary contribution of this paper lies in the application of the NMSS-PIP control structure within a non-minimal state space context for the optimization of a crude distillation column. This control strategy enables centralized control pairing and utilizes a cost objective function aimed at minimizing the energy consumption of the column while maintaining high product quality. By addressing these dual objectives, this work aims to improve the operational efficiency of the distillation process, potentially offering a more sustainable and economically viable solution for the industry. The remainder of the paper is organized as follows: Section 2 provides a detailed overview of the NMSS-PIP control theory and its application to distillation processes. Section 3 outlines the non-minimal state space formulation, and Section 4 presents the simulation results and comparative analysis. Finally, Section 5 offers conclusions and recommendations for future work.

I. Methodology

A. NMSS-PIP Control Theory and Its Application to Distillation Processes

The PIP control strategy, grounded in the NMSS framework, provides an effective balance of complexity and control precision for multivariable systems like distillation columns. Originally conceptualized in the 1960s, the NMSS model extends conventional minimal state space formulations by allowing a broader representation of the system dynamics without the need for state reconstruction. This approach enables direct state measurement, facilitating the implementation of a full-state feedback controller that promotes robust and efficient control, even in high-disturbance environments. As a logical successor to conventional PI/PID controllers, the NMSS-PIP model simplifies the process design while enhancing the stability and performance of control systems. In particular, the PIP controller offers practical implementation advantages comparable to traditional PI/PID control strategies but is structured in the optimal state space, akin to General Predictive Control (GPC). As part of the SVF control design, PIP can be integrated into multiple design methods, including closed-loop pole assignment and optimal control frameworks like linear quadratic (LQ) or robust LQG/H∞ control.

The use of the NMSS-PIP approach is especially advantageous in the context of crude distillation units (CDUs), where multivariable interactions, nonlinearities, and large time delays pose challenges for conventional controllers. NMSS-PIP controllers are particularly adept at handling these complexities because they minimize both energy consumption and process deviations, optimizing energy efficiency and product quality. This study leverages these attributes by tuning the NMSS-PIP controller through an economic cost function

that targets key parameters such as furnace duty, side-draw rates, and condenser heat removal, enabling effective control under varied operational disturbances like fluctuations in feed rate, temperature, and composition.

In this work, the PIP control framework is applied to an atmospheric distillation column at Shiraz Refinery. The atmospheric distillation tower separates crude oil into various fractions, such as overhead products, naphtha, kerosene, and gas oil, through a series of complex, nonlinear operations as depicted in figure 1. This column consists of 43 trays, two mid-tower condensers (pumparounds), and three 6-stage strippers, with a maximum operating capacity of 60,000 bbl/day. Superheated stripping steam is injected from the bottom of the column to adjust the temperature profile and remove light hydrocarbons from the stripper's side products. The feed is preheated by heat recovery from the pumparounds, kerosene, and gas oil, and its temperature is increased to 690°F using a fired heater.

TABLE 1 INPUT VARIABLES [14]

Variable	Description	u_0	Unit
u_1	Side-draw of naphtha	29,748.8	lb/h
u_2	Side-draw of kerosene	12,8254.6	lb/h
u_3	Side-draw of gas oil	122,868.1	lb/h
u_4	Furnace duty	110,173,828	Btu/h
u_5	Reflux split fraction	0.61676	—
u_6	Heat removed in pumparound1	−22,428,847	Btu/h
u_7	Heat removed in pumparound2	−26,172,804	Btu/h

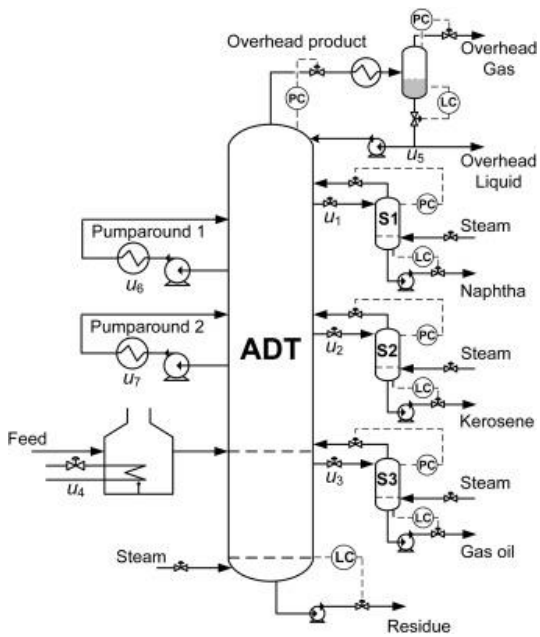


Fig. 1. Process flowsheet of atmospheric distillation column [14]

B. *Non-Minimal State Space Formulation and waiting functions*

Possible manipulated variables that influence product quality include heat removal from the mid-condensers, fired heater duty, reflux split fraction, and side-draw flows of naphtha, kerosene, and gas oil. The system is configured with 7 manipulated variables and 4 controlled variables, after addressing the pressure and level control challenges, as shown in Tables 1 and 2.

TABLE 2 OUTPUT VARIABLES [14]

Variable	Description	Set point (R)	Unit
y_1	Overhead temperature	295.7	K
y_2	95% -ASTMD86 of naphtha	385.69	K
y_3	95% -ASTMD86 of kerosene	502.23	K
y_4	95% -ASTMD86 of gas oil	622.87	K

The NMSS formulation is an essential part of the PIP control design for complex chemical processes like distillation. In this formulation, the system's transfer function is represented using the left matrix fraction description (LMFD). The state vector is a combination of present and past output values, past input values, and the integral of the error between the setpoint and the output, ensuring a robust framework for addressing process disturbances and maintaining product quality.

In NMSS representation, the transfer function is expressed as LMFD [24]:

$$\mathbf{y}_t = \left[\mathbf{A}(z^{-1})\right]^{-1}\mathbf{B}(z^{-1})\mathbf{u}_t \tag{1}$$

where $\mathbf{A}(z^{-1})$ and $\mathbf{B}(z^{-1})$ are defined by:

$$\mathbf{A}(z^{-1}) = \mathbf{I}_p + \mathbf{A}_1 z^{-1} + ... + \mathbf{A}_n z^{-n} \tag{2-a}$$

$$\mathbf{B}(z^{-1}) = \mathbf{B}_1 z^{-1} + ... + \mathbf{B}_m z^{-m} \tag{2–b}$$

Transfer function in the form of NMSS can be written as:

$$\mathbf{x}_t = \mathbf{F}\mathbf{x}_{t-1} + \mathbf{G}\mathbf{u}_{t-1} + \mathbf{D}\mathbf{y}_t^d \tag{3–a}$$

$$\mathbf{y}_t = \mathbf{H}\mathbf{x}_t \tag{3–b}$$

The state vector ($\mathbf{x}_t$) in Eq. (3) is directly related to present and past values of outputs, past values of inputs and integral of error ($\mathbf{z}_t^T$) between referenced value ($\mathbf{y}_t^d$) and output as:

$$\mathbf{x}_t = \left[\mathbf{y}_t^T \ \mathbf{y}_{t-1}^T \ldots \mathbf{y}_{t-n+1}^T \ \mathbf{u}_{t-1}^T \ .... \ \mathbf{u}_{t-1}^T \ \mathbf{u}_{t-m+1}^T \ \mathbf{z}_t^T\right]^T \tag{4–a}$$

$$\mathbf{z}_t = \mathbf{z}_{t-1} + \left[\mathbf{y}_t^d - \mathbf{y}_t\right] \tag{4–b}$$

The state matrices of Eq. (3) are defined as:

$$\mathbf{F} = \begin{bmatrix} -\mathbf{A}_1 & -\mathbf{A}_2 & \cdots & -\mathbf{A}_{n-1} & -\mathbf{A}_n & \mathbf{B}_2 & \mathbf{B}_3 & \cdots & \mathbf{B}_{m-1} & \mathbf{B}_m & \mathbf{0} \\ \mathbf{I}_p & \mathbf{0} & \cdots & \mathbf{0} & \mathbf{0} & \mathbf{0} & \mathbf{0} & \cdots & \mathbf{0} & \mathbf{0} & \mathbf{0} \\ \mathbf{0} & \mathbf{I}_p & \cdots & \mathbf{0} & \mathbf{0} & \mathbf{0} & \mathbf{0} & \cdots & \mathbf{0} & \mathbf{0} & \mathbf{0} \\ \vdots & \vdots & \ddots & \vdots & \vdots & \vdots & \vdots & \ddots & \vdots & \vdots & \vdots \\ \mathbf{0} & \mathbf{0} & \cdots & \mathbf{I}_p & \mathbf{0} & \mathbf{0} & \mathbf{0} & \cdots & \mathbf{0} & \mathbf{0} & \mathbf{0} \\ \mathbf{0} & \mathbf{0} & \cdots & \mathbf{0} & \mathbf{0} & \mathbf{0} & \mathbf{0} & \cdots & \mathbf{0} & \mathbf{0} & \mathbf{0} \\ \mathbf{0} & \mathbf{0} & \cdots & \mathbf{0} & \mathbf{0} & \mathbf{I}_r & \mathbf{0} & \cdots & \mathbf{0} & \mathbf{0} & \mathbf{0} \\ \mathbf{0} & \mathbf{0} & \cdots & \mathbf{0} & \mathbf{0} & \mathbf{0} & \mathbf{I}_r & \cdots & \mathbf{0} & \mathbf{0} & \mathbf{0} \\ \vdots & \vdots & \ddots & \vdots & \vdots & \vdots & \vdots & \ddots & \vdots & \vdots & \vdots \\ \mathbf{0} & \mathbf{0} & \cdots & \mathbf{0} & \mathbf{0} & \mathbf{0} & \mathbf{0} & \cdots & \mathbf{I}_r & \mathbf{0} & \mathbf{0} \\ \mathbf{A}_1 & \mathbf{A}_2 & \cdots & \mathbf{A}_{n-1} & \mathbf{A}_n & -\mathbf{B}_2 & -\mathbf{B}_3 & \cdots & -\mathbf{B}_{m-1} & -\mathbf{B}_m & \mathbf{I}_r \end{bmatrix} \tag{5–a}$$

$$\mathbf{G}=\begin{bmatrix}\mathbf{B}_1 & \mathbf{0} & \mathbf{0} & \cdots & \mathbf{0} & \mathbf{I}_r & \mathbf{0} & \mathbf{0} & \cdots & \mathbf{0} & -\mathbf{B}_1\end{bmatrix}^{\mathrm{T}} \quad (5\text{–b})$$

$$\mathbf{H}=\begin{bmatrix}\mathbf{I}_p & \mathbf{0} & \mathbf{0} & \cdots & \mathbf{0} & \mathbf{0} & \mathbf{0} & \cdots & \mathbf{0} & \mathbf{0}\end{bmatrix} \quad (5\text{–c})$$

$$\mathbf{D}=\begin{bmatrix}\mathbf{0} & \mathbf{0} & \mathbf{0} & \cdots & \mathbf{0} & \mathbf{0} & \mathbf{0} & \cdots & \mathbf{0} & \mathbf{I}_p\end{bmatrix}^{\mathrm{T}} \quad (5\text{–d})$$

where $\mathbf{I}_p$ and $\mathbf{I}_r$ denote $p \times p$ and $r \times r$ identity matrices, respectively and **0** is an appropriately defined matrix of zeros. The controllability of the NMSS model is discussed in Wang et al.[23]. The NMSS transformation of Eq. (3) can be formulated based on optimal LQ design. The SVF control law is written as:

$$\mathbf{u}_t = -\mathbf{V}\mathbf{x}_t \quad (6)$$

where $\mathbf{V}$ is the control gain matrix (CGM). It can be calculated from LQ optimal control by minimizing the quadratic cost function of Eq. (7) for an infinite horizon.

$$J=\sum_{i=0}^{\infty}\mathbf{x}_i^T\mathbf{Q}\mathbf{x}_i+\mathbf{u}_i^T\mathbf{R}\mathbf{u}_i \quad (7)$$

It is worthy of that tuning of Q and R is usually limited to the diagonal weights because translation of weighting matrices are not readily convert into typical closed loop response. Further information can be found in earlier publications [27-28]. The weighting matrices and are defined as symmetric positive semi-definite and symmetric positive definite, respectively. The gain matrix which minimizes Eq. (7) can be obtained by solution of discrete algebraic riccati equation (ARE) [28]. Within the NMSS-PIP framework, the critical step involves defining the weight matrices Q and R, which dictate the performance criteria in the controller's objective function. These matrices can be configured by minimizing the economic cost function or by tuning them based on system-specific performance objectives. By using an Integral of ITAE criterion—particularly suited for systems with extended time delays—the control structure can prioritize minimizing persistent errors, leading to stable and energy-efficient operation. This tuning process was performed in MATLAB, ensuring precise configuration for application in the CDU context.

This work utilizes the NMSS-PIP framework as a pioneering approach to achieve optimal control in distillation processes. The results presented here underscore the NMSS-PIP's promise as an effective control strategy for maintaining process stability and energy efficiency in real-world scenarios, laying a foundation for further exploration and application in other critical process systems.

It's important to define the changes and limitations in optimal control regarding modes and controllers. To achieve this, the cost of modifying each input is treated as a cost function, with the change cost per variable unit established for all inputs. Since the prices of products within a quality range are generally uniform for all outputs from the distillation tower, minimizing performance error is preferred over maximizing profit. For side flows, the operational cost was represented by the pumping cost and the associated electricity usage [29].

$$E=\frac{2F}{3600\eta_{pump}} \quad (8)$$

The pump efficiency η is set at 0.96, and F represents the flow rate. Equation (9) calculates the change cost per variable unit of furnace heat rate.

$$Q_{furnace}=F_{fuel}\times(\eta_{furnace}\times Q_{fuel}) \quad (9)$$

In this regard, $\eta_{furnace}$ the efficiency of the unit furnace (equal to 0.96) and Q_{fuel} is the low heat value of the fuel used in the furnace, whose value is considered equal to Q_{fuel} = 41,816 kJkg^{-1}. The Cooling water consumption in terms of t/h for intermediate condensers is expressed in the form of equation (10):

$$F_{Cw}=\frac{Q_C}{C_{P,Cw}\Delta T_{Cw}} \quad (10)$$

In this equation, $C_{P,Cw}$ and ΔT_{Cw} are the specific heat capacity for the cooling water and the increase in the temperature difference of the cooling water, respectively while passing through the condenser. It is clear that the input cost function is equal to the sum of the mentioned costs, which is expressed in the form of the equation (11):

$$f_{cost}=\Delta C_{fuel}+\Delta C_{Cw}+\Delta C_{elec} \quad (11)$$

which ΔC_{fuel}, ΔC_{Cw} and ΔC_{elec} are increased in fuel consumption, cooling water and electricity respectively while calculated by equations (12-14):

$$\Delta C_{fuel}=P_{fuel}(F_{fuel}-F_{fuel}^0) \quad (12)$$

$$\Delta C_{Cw}=P_{Cw}(F_{Cw}-F_{Cw}^0) \quad (13)$$

$$\Delta C_{elec}=P_{elec}(F_{elec}-F_{elec}^0) \quad (14)$$

In these relationships, P denotes the costs of fuel, cooling water, and electricity, with the superscript 0 indicating their values in the system's steady state (initial values). Table (3) provides the costs for electricity, cooling water, and furnace fuel.

TABLE 3 COSTS FOR ELECTRICITY, COOLING WATER, AND FURNACE FUEL [30]

Variables	Description	Cost (USDs)
P_{fuel}	Furnace fuel (t)	673.17
P_{Cw}	Cooling water (t)	0.17
P_{elec}	Electricity(kWh)	0.19

Next, these costs should be organized by the input variable. Table (4) shows the cost for each input variable per unit change, based on the specified cost functions.

To perform a dynamic simulation of the proposed control structures under realistic conditions of the crude oil distillation tower, a conventional proportional-integral (PI) controller was initially used to benchmark the PIP controller. The PI controllers were tuned using a sequential adjustment approach, systematically refining controller parameters within a closed-loop configuration until minimal oscillations (within 10% of the set range) were achieved.

TABLE 4 THE COST OF INPUT VARIABLES PER UNIT CHANGE

Variable	Unit	Cost of input variables change*	Normalized value
u_1	\$/(lb/h)	9.7857×10^{-7}	1
u_2	\$/(lb/h)	9.7857×10^{-7}	1
u_3	\$/(lb/h)	9.7857×10^{-7}	1
u_4	\$/(Btu/h)	1.769×10^{-5}	18.0773
u_5	\$	0.367	375,530
u_6	\$/(Btu/h)	2.8×10^{-6}	2.861
u_7	\$/(Btu/h)	2.8×10^{-6}	2.861

* Such as electricity of pump and utility cost

Controller parameters were later refined using the Tyros-Leiben method, which applies smaller gains and a larger integrator constant than Ziegler-Nichols, optimizing stability for chemical processes. In the simulations, temperature control loops were assigned realistic delays: one minute at the tower top, three minutes for feed, and three minutes for side products, reflecting the slower response dynamics in furnaces relative to heat exchangers. The resulting matrices for the NMSS-PIP control structure, essential for real-time CDU management, were generated from open-loop gain tests and detailed in [14]. Finally, the distillation tower model was linked with the PIP control algorithm in ASPEN Dynamics through the SIMULINK interface, with a custom PIP controller toolbox designed in MATLAB to ensure seamless integration of control and dynamic models.

To streamline the optimization process, the cost per variable change has been normalized, as shown in the third column of table (4). Profit reduction from specific quality intervals and product storage relates solely to decreased production output. Since the profit reduction costs for all products are nearly identical due to similar pricing, the normalized output values have been set to one. Additionally, the optimization requires adjusting one of the integrators. The optimization scenario mirrored the previous case, featuring a 5% step change in the input feed rate. Based on the normalized values in table (4), the optimal values for weight matrices Q and R, are derived from relations (15).

$$\mathbf{Q} = \mathrm{diag}\left[q_1(1 \quad 1 \quad 1 \quad 1) \quad 1 \quad q_2 \quad q_3 \quad q_4\right] \tag{15–a}$$

$$\mathbf{R} = \mathrm{diag}\left(r_1\left[1 \quad 1 \quad 1 \quad 18.0773 \quad 375{,}530 \quad 2.861 \quad 2.861\right]^2\right) \tag{15–b}$$

In equation (15-a), the first four elements of the matrix represent the four outputs in the weight matrix, while the last four values correspond to the available integrators. Since chemical processes have significant time delays between inputs and outputs. Among the integral of error methods, ITAE places greater emphasis on long-lasting errors. Our optimization goal is to minimize the performance error of the PIP controller, using the weight functions Q and R from equations (15-a) and (15-b) based on ITAE (equation 16). The optimization algorithm employed in MATLAB is the Nelder-Mead simplex method. The optimal values of Q and R are provided in table (5).

$$\mathrm{ITAE} = \int_0^\infty t\left|e(t)\right|dt \tag{16}$$

TABLE 5 OPTIMAL VALUES OF PARAMETERS OF WEIGHT MATRICES

PARAMETERS OF WEIGHT MATRICES	OPTIMAL VALUE
q_1	6.7741
q_2	0.0621
q_3	0.9993
q_4	0.9959
r_1	1.1×10^{-5}

The weight matrices were computed using the proposed algorithm:

$$\mathbf{Q} = \mathrm{diag}\left[(6.7741 \quad 6.7741 \quad 6.7741 \quad 6.7741 \quad 1 \quad 0.0621 \quad 0.9993 \quad 0.9959\right] \tag{17–a}$$

$$\mathbf{R} = \mathrm{diag}\left[1.1\times10^{-5} \quad 1.1\times10^{-5} \quad 1.1\times10^{-5} \quad 0.0036 \quad 1.55\times10^{6} \quad 9.03\times10^{-5} \quad 9.03\times10^{-5}\right] \tag{17–b}$$

Based on the results from equation (17-a), it can be concluded that only one integrator was effective for optimal control performance.

While the NMSS-PIP approach offers substantial advantages over traditional plant-wide control methods, several limitations and challenges exist in practical applications. Unlike conventional control strategies that often require variable pairing, the NMSS-PIP framework facilitates comprehensive dynamic interaction without needing such pairing, allowing for a more streamlined setup. Additionally, as compared to centralized control systems, NMSS-PIP can directly measure state variables without reconstruction algorithms, like observers or predictors, thereby simplifying implementation. This simplicity makes NMSS-PIP particularly accessible for field engineers, allowing them to effectively manage and adjust the system in real-world operations.

However, NMSS-PIP control is most effective in regulatory and continuous processes, where it consistently maintains performance. In batch processes, frequent setpoint changes can necessitate recalculations of the weight matrices Q and *R*, potentially requiring additional estimations to maintain optimal performance. Moreover, tuning these matrices for

dynamic, high-variability environments may demand further adjustments to the control algorithm. Despite these limitations, the NMSS-PIP control structure continues to perform effectively in the TAME process for crude distillation units, demonstrating improved oscillation suppression, faster settling times, and lower ITAE values when compared to conventional PI control structures, even under cost-based function optimization.

II. Test Results

The performance of the NMSS-PIP control strategy in the CDU was evaluated using simulations carried out in Aspen Plus for the distillation process and MATLAB for the control implementation. The primary objectives of this study were to optimize energy consumption while maintaining product quality and to examine the robustness of the control strategy against disturbances, such as changes in feed rate, temperature, and composition.

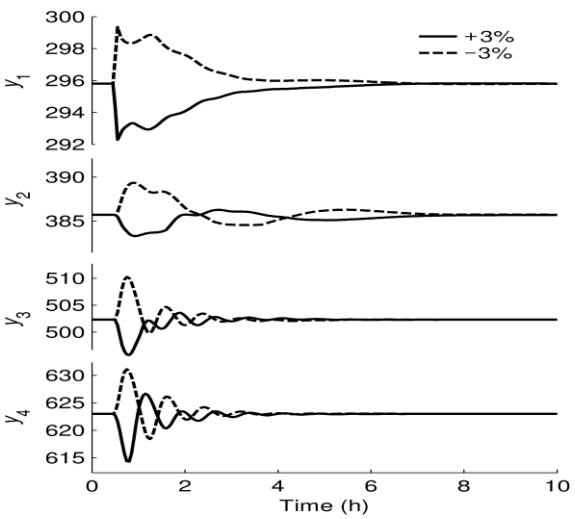


Fig. 2. Output response to ±3% changes in input feed, NMSS-PIP controller for economic weight functions

Figures 2 and 3 illustrate the output response and input changes when a ±3% step change was applied to the feed rate.

The NMSS-PIP controller, with weight matrices derived from the economic cost function, effectively dampens the disturbances. As seen in Figure 2, the system's output response is smooth, and the overshoot remains within an acceptable range, indicating that the controller effectively maintains product quality despite the input variation. Notably, the economic weighting functions allow for efficient control actions without introducing large oscillations, which can be detrimental in industrial operations. The input changes, shown in Figure 3, demonstrate that the control efforts are minimized, keeping the system inputs well-regulated while avoiding abrupt control actions that could lead to inefficiencies.

The results suggest that the NMSS-PIP controller, tuned using economic weight functions, offers superior disturbance rejection. For instance, in the crude oil distillation process, where even small changes in feed rate can significantly impact the separation of crude oil into different fractions, this level of control precision is crucial. By minimizing both energy consumption and deviation from product setpoints, the NMSS-PIP control structure enhances process stability, making it ideal for energy-intensive systems like the CDU.

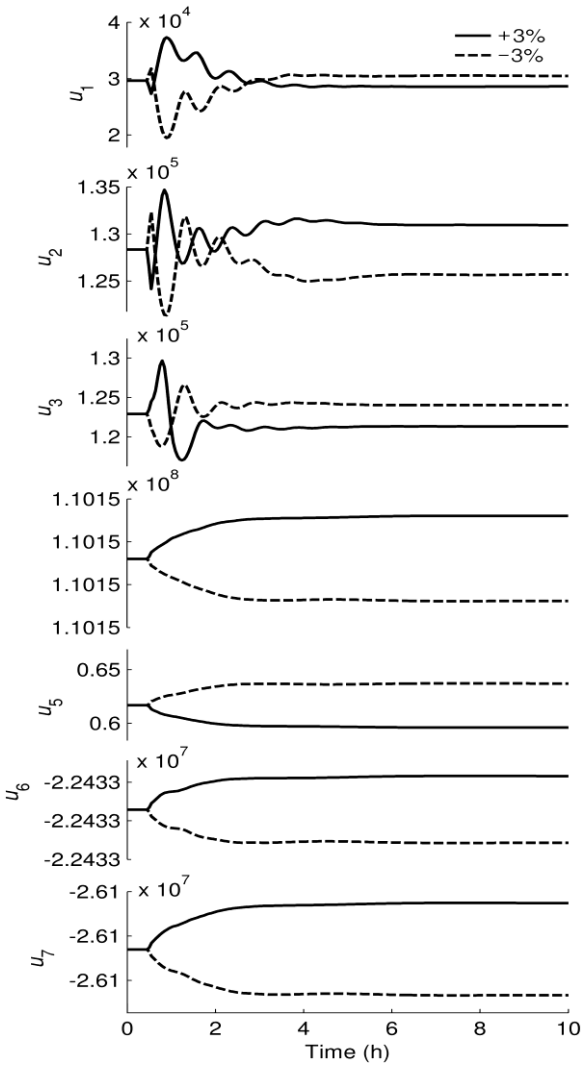


Fig. 3. Input changes to ±3% changes in input feed, NMSS-PIP controller for economic weight functions

The NMSS-PIP controller was further tested against step changes in feed temperature, as shown in Figures 4 and 5, where a ±5°F step change was applied. The results indicate that the controller maintained steady outputs within the desired range, with minimal oscillation. The ability of the NMSS-PIP controller to maintain tight control over the product temperature demonstrates its robustness, even in the presence of feed temperature disturbances. In practical terms, this can help prevent undesirable changes in the output product's quality, especially when the crude oil feedstock's properties fluctuate.

Given the stringent temperature requirements for the fractionation process, particularly for fractions like naphtha and gas oil, the NMSS-PIP controller's performance is significant. Maintaining optimal temperatures directly correlates with energy savings, as excessive heating or cooling is avoided. Furthermore, the controller adapts to changing conditions quickly, ensuring smooth transitions without a loss in product quality.

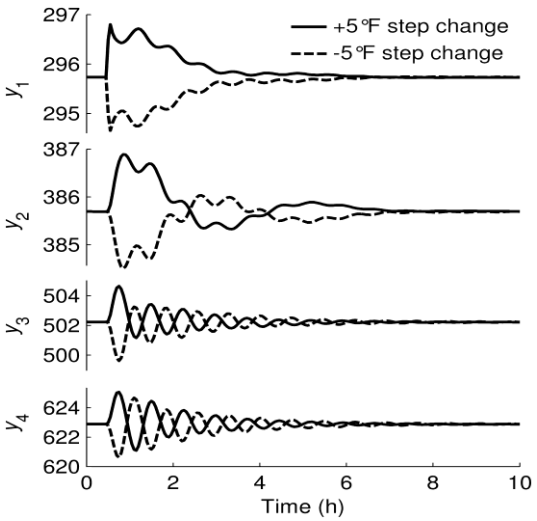


Fig. 4. Output response to ±5°F step change in input feed temperature for economic weighting functions

To assess the effectiveness of the NMSS-PIP control strategy in handling disturbances, a change in the feed composition was introduced. Specifically, after a set time, 95% of the input feed was mixed with 5% of the upstream flow, while keeping the volumetric flow rate constant. This allowed for the evaluation of the controller's performance when faced with composition variations, independent of volumetric disturbances. The true boiling point (TBP) specifications for the primary feed, the overhead product, and the combined feed are provided in Table 6, offering a detailed breakdown of the thermodynamic properties of the feed mixtures.

True Boiling Point (TBP) specifications for various feedstock volumes and the corresponding overhead product, including values for the combined feed in the distillation tower are elucidate in Table 6. This table highlights the TBP differences between crude, overhead, and combined feeds, illustrating the control requirements for maintaining product quality under variable feed compositions.

II. As depicted in Table 6, the TBP specifications vary across different volumetric fractions, highlighting the complexity of the composition change. For instance, the TBP of the combined feed reaches 1,328°F at 100% volume, whereas the overhead product shows a more controlled range, indicating the separation effectiveness. The ability to maintain such distinct separation profiles, despite the composition shift, is essential for achieving high product quality and efficient energy use.

TABLE 6 TRUE BOILING POINT (TBP) SPECIFICATIONS FOR FEEDS AND OVERHEAD PRODUCT

Volume percentage of distillated product %	TBP of crude (°F)	TBP of overhead product (°F)	TBP of combined feed (°F)
0	25	-12	26
10	120	52	110
5	188	88	180
30	399	185	362
50	594	236	573
70	806	282	791
90	1088	321	1075
95	1221	339	1214
100	1330	368	1328

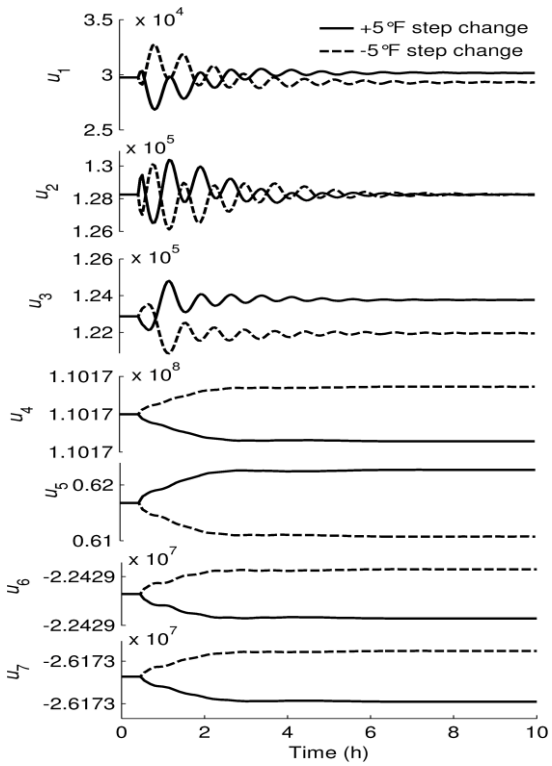


Fig. 5. Input changes for ±5°F Step change in input feed temperature for economic weighting functions

Figures 6 and 7 show the system's response to these disturbances. The NMSS-PIP controller managed the feed composition change smoothly, ensuring only minor deviations in the controlled outputs. These deviations were quickly corrected as the system returned to its setpoints, demonstrating the controller's ability to adapt to varying feedstock compositions. Notably, even with the introduction of an upstream flow and the alteration in the TBP characteristics, the system maintained stable operation, underscoring the robustness of the NMSS-PIP control strategy.

This result is critical in industrial scenarios where crude oil feedstocks often exhibit varying properties due to differences in sourcing. The refinery's ability to process crude from multiple origins without significant process disruptions or the

need for continuous manual intervention is crucial for maintaining consistent product quality. By responding swiftly and efficiently to changes in feed composition, the NMSS-PIP controller ensures that the distillation column operates within desired specifications, reducing the likelihood of costly off-spec products or energy wastage. Furthermore, the smooth control actions prevent overcompensation in input variables, thereby optimizing the energy consumption of critical subsystems, such as the furnace and intermediate condensers.

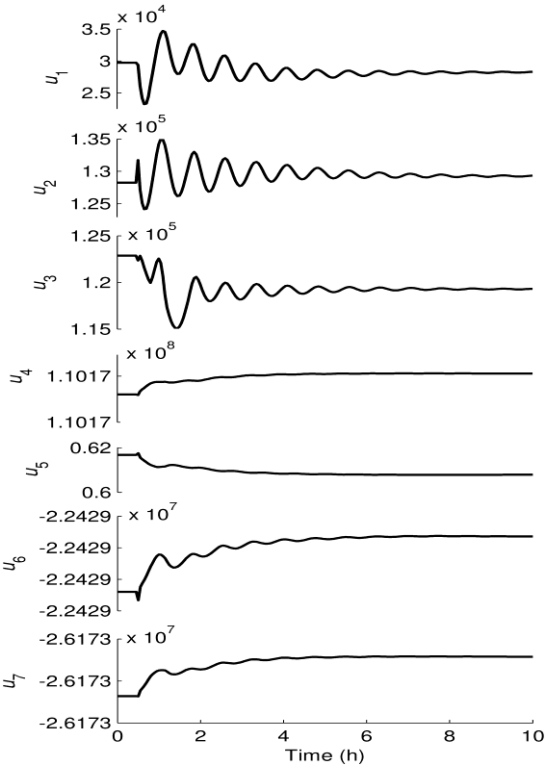


Fig. 6. Input changes affecting the percentage composition of input feed for economic weighting functions

Figure 8 shows the output response of the NMSS-PIP controller to ±1°F setpoint changes, demonstrating that the controller maintained system stability without inducing significant oscillations. The slight overshoot observed during the +1°F step change is well within operational tolerances. The control actions, depicted in Figure 9, show smooth and gradual input adjustments, further confirming the effectiveness of the NMSS-PIP controller.

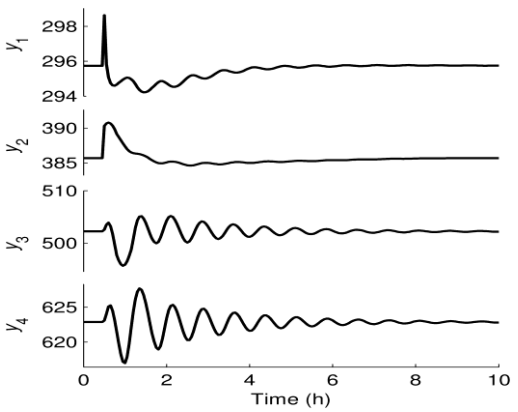


Fig. 7. Output response to change in input feed percentage composition for economic weight functions

The setpoint control performance is particularly relevant for optimizing production in response to market demands. Refineries may need to adjust product specifications to meet customer requirements, and the ability to make such adjustments dynamically, without energy penalties or compromising product quality, is a valuable asset for process optimization.

The comparison of energy consumption between two tuning methods, namely the economic cost function and ITAE minimization, is summarized in Table 7.

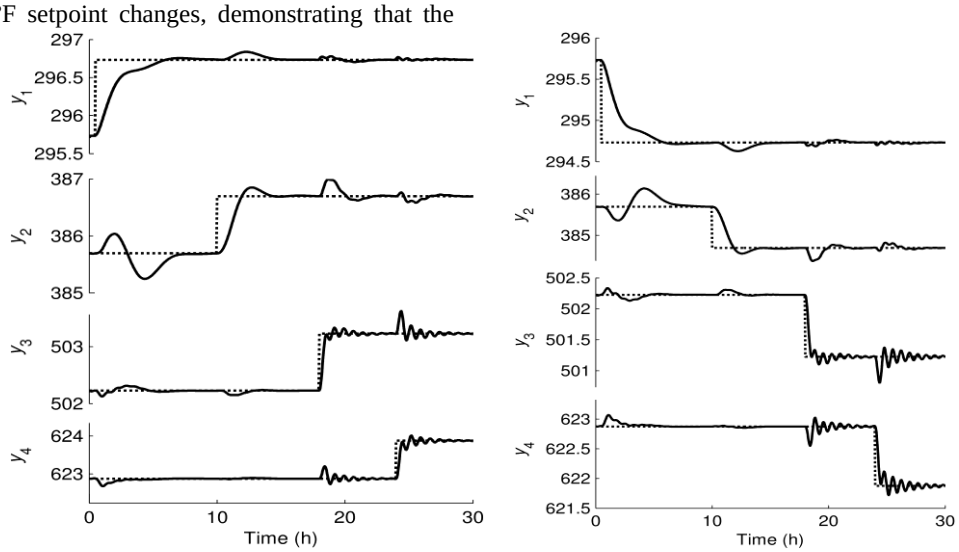


Fig.8. Input changes affecting the percentage composition of input feed for economic weighting functions

TABLE 7 . COMPARISON OF OPERATING COSTS USING ECONOMIC WEIGHTING FUNCTIONS AND ITAE TUNING

Scenario	$C_{furnace}$ ($/h)		$C_{pumparounds}$ ($/h)		C_{pumps} ($/h)		C_{total} ($/h)	
	Case a	Case b	Case a	Case b	Case a	Case b	Case a	Case b
Change in feed rate	117.5	0	0.2	0.005	0.0001	0	118	0.006
Change in feed temperature	34.5	0	0.03	0	0	0.015	34.5	0.015
Change in Feed composition	56.5	0	0.009	0	0.003	0.006	57	0.006
Change in setpoint	18.5	0	0.1	0	0	0.001	19	0.001

Scenario (a): Weighting matrices based on minimizing ITAE; Scenario (b): Weighting matrices based on economic cost functions.

This table presents an operating cost comparison between the NMSS-PIP control strategy with economic weighting functions and the ITAE tuning scenario. It breaks down furnace, pumparounds, and pumping costs under various disturbances (feed rate, temperature, composition, and setpoint changes), highlighting the NMSS-PIP controller's cost-saving advantages in energy management. In Table 7, furnace cost refers to the operating cost per input variation in the furnace by the end of each scenario, pumparounds cost indicates the operating cost for intermediate condensers per input variation, pumping cost represents the cost associated with pump operation per input variation, and total operating cost is the sum of all input variable variations. Additionally, Scenario (a) represents NMSS-PIP control tuned using ITAE minimization weighting functions, while Scenario (b) corresponds to tuning based on economic weighting functions. Across all scenarios, the NMSS-PIP control based on the economic cost function led to significant cost savings, reducing operating costs by nearly 100% relative to the ITAE-based scenario. This improvement is particularly evident in the furnace's operating costs and cooling water usage, both of which saw substantial reductions. In terms of practical implications, these cost reductions can translate into considerable economic benefits for refineries. For example, the study shows that an increase in feed rate by 1800 barrels per day over one month could result in cost savings of approximately $84,700. These findings underscore the importance of using a control method that not only optimizes product quality but also minimizes energy consumption, making the process more sustainable and economically viable.

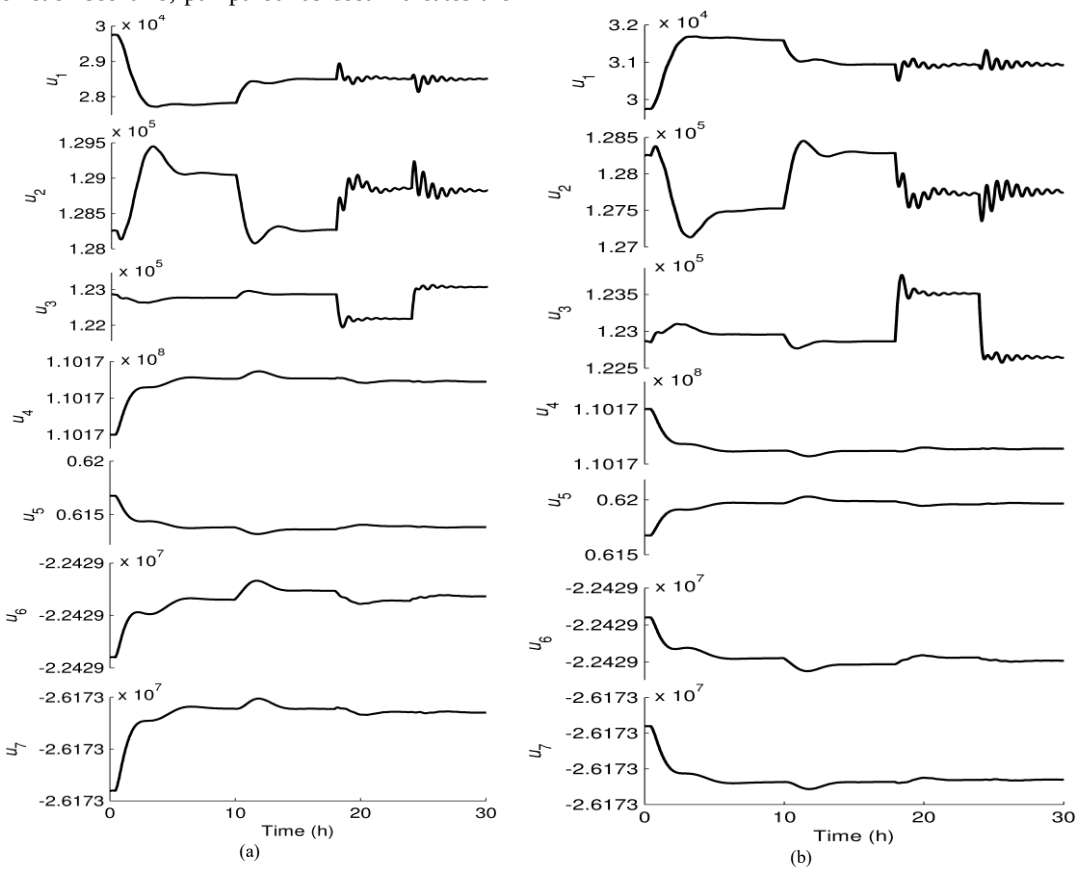


Fig. 9. Input changes in response to setpoint variations for the NMSS-PIP controller under the application of economic weighting functions: (a) +1°F step change; (b) -1°F step change.

The results from this study highlight the effectiveness of the NMSS-PIP control strategy for managing complex, multivariable processes in crude distillation columns. The economic cost function approach used to tune the controller

demonstrates clear advantages in reducing energy consumption and maintaining product quality across different operating conditions. Compared to traditional control methods like PID and even advanced strategies like MPC, the NMSS-PIP controller offers a balanced solution, providing robustness and efficiency with fewer computational demands.

Moreover, the flexibility of the NMSS-PIP controller allows for easy integration with existing refinery infrastructure, making it a practical choice for operators looking to improve their process control without investing in entirely new systems.

In terms of closed-loop stability, the robustness of the NMSS-PIP control structure has been validated in previous research by Taylor et al. [27], who developed and tested robust PIP controllers within the non-minimal state space (NMSS) framework. Their work demonstrated that the PIP control strategy maintains stable closed-loop performance even under challenging conditions, such as model uncertainties and significant disturbance inputs. Specifically, Taylor et al. evaluated this control structure on multivariable systems, including laboratory-scale materials handling and stochastic benchmark simulations, underscoring its capability to handle variability and 'worst-case' disturbance scenarios. Therefore, this study relies on Taylor et al.'s findings as a foundational stability assessment for the NMSS-PIP controller, focusing here on its optimization for energy efficiency and cost functions.

The NMSS-PIP control method demonstrates marked advantages in optimizing energy consumption, maintaining product quality, and managing disturbances within the CDU framework, effectively addressing the limitations encountered with traditional PI control. As illustrated in the results, the NMSS-PIP controller not only minimized operating costs by nearly 100% through economically weighted tuning but also maintained consistent product quality across varied operational conditions. For instance, in scenarios of ±5°F step changes in input feed temperature, the NMSS-PIP controller ensured product output stability with minimal oscillation, a notable improvement over PI, which often struggled to stabilize under similar disturbances. Moreover, with its centralized nature, the NMSS-PIP can be tuned based on cost objective functions, making it particularly suited to address the energy efficiency demands of Industry 4.0 as global energy shortages intensify. The NMSS-PIP's adaptable structure and direct compatibility with industry-standard software position it as a viable next-generation industrial controller, providing a practical alternative to the PI controller for large-scale processes. This combination of robustness, cost optimization, and practical scalability underscores the potential of NMSS-PIP to evolve as an advanced, energy-conscious control solution in modern industrial applications.

III. Conclusions

This study demonstrates the effectiveness of the NMSS-PIP control strategy in optimizing the operation of crude distillation units (CDUs). By implementing the PIP control system within a Non-Minimal State Space (NMSS) framework, the controller achieved substantial energy savings while maintaining product quality under disturbance scenarios, such as changes in feed rate, temperature, and composition. The economic cost function approach used to tune the controller's weight matrices led to significant reductions in operating costs, particularly in furnace duty and cooling water usage, highlighting its energy-saving potential. Results indicate that the NMSS-PIP strategy outperforms traditional PID and ITAE-tuned controllers in both energy efficiency and control precision, offering robust disturbance rejection with smooth control actions.

However, the NMSS-PIP control strategy may be most effective in continuous, steady-state processes, such as regulatory control in CDUs, rather than in highly variable or batch processes, where frequent recalibration of weighting matrices could be required. Additionally, while the NMSS-PIP method shows promise for enhancing operational efficiency in energy-intensive environments like refineries, further research is needed to validate its performance across different refinery units and under varying feed compositions over extended periods.

In conclusion, the NMSS-PIP control framework presents a powerful tool for optimizing crude distillation processes, with significant potential to improve energy savings, operational efficiency, and process stability. Future work could explore real-time implementations and assess the adaptability of NMSS-PIP control in broader refinery applications, contributing to more sustainable process control in the oil and gas industry.

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