A Technical Review on Optimization of a Natural Gas Conversion Process for Liquefied Petroleum Gas (LPG) Production

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ABSTRACT

Liquefied Petroleum Gas (LPG) production from Natural Gas Liquids (NGLs) is an energy-intensive process that relies heavily on efficient distillation operations, particularly within deethanizer, depropanizer, and debutanizer columns. This review examines recent advances in the optimization of natural gas conversion processes for LPG production, with emphasis on improving energy efficiency, reducing operational costs, and minimizing carbon dioxide (CO_2) emissions. Various optimization approaches reported in the literature are analyzed, including thermodynamic modeling, exergy analysis, Response Surface Methodology (RSM), Genetic Algorithms (GA), Artificial Neural Networks (ANN), and driving force methods. The reviewed studies commonly employed simulation tools such as MATLAB, AVEVA PRO/II, and ChemSep for modeling and optimization of distillation systems. The reviewed works demonstrate that optimization of operating variables such as reflux ratio, column pressure, and sequence configuration can significantly reduce energy consumption while maintaining product purity requirements, but little study have been made on the simultaneous optimization of debutanizer and depropanizer columns using integrated simulation platforms such as Aspen HYSYS while considering multiple interacting variables such as: Feed tray location, column Pressure and Reflux Ratio.

Keywords: Energy efficiency, Distillation column optimization, Aspen Hysys, Liquefied Petroleum Gas LPG.

INTRODUCTION

Liquefied Petroleum Gas (LPG), consisting primarily of propane (C_3H_8) and butane (C_4H_{10}), is produced from two principal sources: natural gas processing and crude oil refinery process. Natural gas processing accounts for approximately 60-62% of global LPG supply, while crude oil refining contributes the remaining 38-40%, Fig. 1 shows a Liquefied Petroleum Gas Production using natural gas processing (Son K.C., 2025 & Hahn E. et al., 2025). The dominance of gas-derived LPG has increased substantially over the past decade, driven by the shale gas revolution in the United States and expanded natural gas production in Qatar and Saudi Arabia (Hahn E. et al., 2025). With global LPG consumption reaching 347 million tonnes in 2024 and projected to grow to 370 million tonnes by 2025, the optimization of gas processing facilities has become critically important for meeting rising demand, particularly in the Asia-Pacific region which accounts for nearly half of global consumption (Hahn E. et al., 2025).

In natural gas processing, raw natural gas containing approximately 3-12% propane and butane must undergo a series of separation steps to recover natural gas liquids (NGLs) (Son K.C., 2025 & Hahn E. et al., 2025). The production process typically involves initial gas sweetening to remove hydrogen sulfide and carbon dioxide, dehydration to eliminate water vapor, and subsequent cryogenic fractionation using turboexpanders or Joule-Thomson valves to separate heavier hydrocarbons from methane (Son K.C., 2025 & Taha. et al., 2024). The recovered NGL stream then passes through a series of distillation columns—

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deethanizer, de-propanizer, and debutanizer—to produce specification-grade LPG (Taha. et al., 2024). The debutanizer column, which separates butane from heavier hydrocarbons, is particularly critical as it directly determines final LPG yield and purity (Son K.C., 2025). Natural gas liquid recovery units are among the most energy-intensive operations in the gas processing industry, requiring substantial refrigeration for cryogenic separation and significant reboiler heat duty for fractionation (Taha. et al., 2024), this consumption can reach 50% of the total energy required of a distillery and represents approximately 3% of global energy consumption (Tgarguifa et al., 2019). Process optimization studies using Aspen HYSYS simulations have shown that parametric adjustment of operating conditions—including column temperatures, pressures, reflux ratios, and feed stage locations—can significantly improve separation efficiency while reducing specific energy consumption (Bashir et al., 2025).

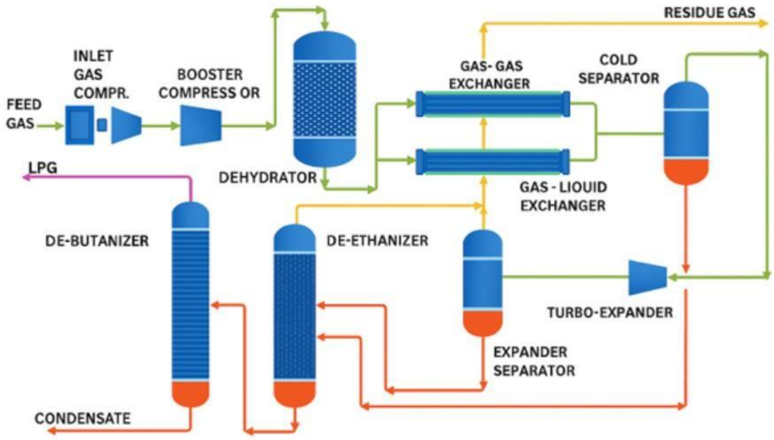

Fig. 1. Liquefied Natural Gas (LPG) production using natural gas processing (Son K.C., 2025).

THEORETICAL FRAMEWORK

Liquefied Petroleum Gas (LPG)

Liquefied Petroleum Gas (LPG) is a high-energy, low-emission fuel that is used all over the world for transportation, cooking, heating, and the production of petrochemicals. Propane (C_3H_8) and butane (C_4H_{10}) make up the majority of LPG. The two primary sources are the refining of crude oil and the processing of natural gas. LPG is essential for car fuel, as a raw material in chemical industries, and in places without electrical grids since it burns cleanly and is portable (Son K.C., 2025).. LPG is produced through several steps: 1) Gas separation — At gas plants, heavier gases (C_3–C_5) are removed out via cold distillation or absorption; 2) Refinery recovery: LPG is extracted during the distillation and cracking procedures in oil refineries; 3) Dehydration and sweetening: To make it safe to use, water, H_2S, and CO_2 are eliminated; and 4) Storage and bottling: LPG is stored in cylinders, tanks, or specialized ships after being converted into a liquid at a pressure of about 8 bar (Son K.C., 2025).

Process Optimization

Process optimization is essentially the process of making a process more efficient, less expensive, and safer. It involves modifying equipment, processes, or raw materials to either enhance the final product's quality or increase the production process's efficiency (Simulative, 2017). Plants and chemical processes can be optimized in several ways which include the following: Heat exchanger network design; Optimizing a distillation column etc. There are optimization modeling tools, such as MATLAB, as well as popular commercial chemical process simulators like ASPEN Hysys, CHEMCAD, Pro/II etc, contain integrated optimization algorithms (Armfield, 2025).

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Distillation Column Theory

A distillation column is a vessel designed to separate liquid mixtures into discrete components or fractions. The technique depends on the notion that various liquid components have varying boiling points. Distillation columns enable the extraction of a higher-purity distillate or top product through repeated cycles of vaporization and condensation, while the less volatile bottom product stream gathers at the base. Distillation systems are used across a wide range of industries like: Petrochemicals – to separate crude oil into lubricants and fuels; Pharmaceuticals – to purify solvents or active substances; Beverages – for making alcoholic beverages or distilled water etc (Armfield, 2025). Several factors affect Distillation column efficiency such as: Reflux Ratio, Column Pressure, Feed Tray Location, Number of Trays. Fig. 2 shows the distillation column separation efficiency containing these factors (Armfield, 2025).

The **Reflux Ratio** is the ratio of the liquid product removed as distillate to the liquid returned to the distillation column as reflux. It is a dimensionless number that has a big impact on a distillation column's energy consumption and separation effectiveness (Jeferson, n.d.). Reflux ratio (R) is mathematically represented as follows: R is equal to L/D Where, the reflux ratio is denoted by R. The amount of liquid that is returned to the column is known as the reflux flow rate, or L. The amount of liquid extracted as a product is known as the distillate flow rate, or D. The reflux ratio is a crucial factor in distillation that affects how many theoretical stages or trays are required to reach the required separation (Jeferson, n.d.). In general, a larger reflux ratio improves separation, but it also raises the energy needed to reboil and condense the vapor. Optimizing the reflux ratio is crucial to the design and functioning of a distillation column. Having the right reflux ratio makes the column to operate efficiently and this results to a balance between separation performance and energy consumption (Jeferson, n.d.).

The **Column Pressure** maintains the internal operating pressure within the distillation tower. It serves as a key design variable, regulating the structural vessel's thickness and diameter as well as phase equilibrium, necessary column temperatures, relative volatilities, and energy costs (William, 2016).

The **Feed Tray Location**, which separates the column into an upper enriching/rectifying part and a lower stripping segment, is the precise tray where the incoming fluid is injected into the distillation column. In order to minimize remixing, lower energy usage, and maximize condenser and reboiler tasks, it is selected where the internal liquid and vapor compositions closely match the feed (Petroskills, 2018).

The **Number of Trays** in a distillation column design refers to the actual plates inside the column needed to accomplish a particular component separation. It is divided into theoretical stages (ideal equilibrium steps) and actual trays, which are computed by dividing the tray efficiency by the theoretical stages (Tham et al., 2026).

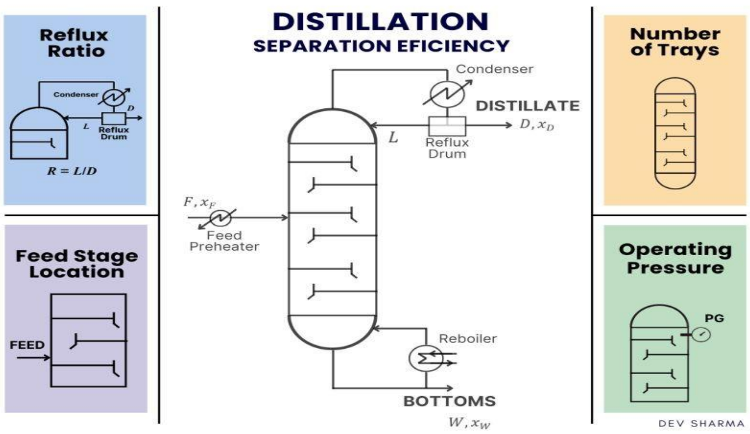

Fig. 2. Distillation Column Separation Efficiency (Dev S., n.d.).

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Vapour Liquid Equilibrium (VLE)

When a liquid and its vapor coexist at a particular temperature and pressure with equal rates of evaporation and condensation, this is known as vapor-liquid equilibrium, or VLE. Since the chemical potentials of the liquid and vapor phases are balanced in this condition, neither phase's composition changes over time. In processes like distillation, VLE is essential for comprehending phase transitions like boiling and condensation (Fivable, 2026).

Mass Balance

An application of mass conservation to the study of physical systems is a mass balance, often known as a material balance. Mass flows that would have been unknown or challenging to assess without this technique can be identified by taking into account the material entering and exiting a system. The mass that enters a system must, under conservation of mass, either leave the system or accumulate inside it, according to the general form stated for a mass balance. For a system without a chemical reaction, the mass balance is expressed mathematically as follows: Output + Accumulation = Input (Chemeurope, 2026)..

Energy Balance

It is sometimes referred to as the law of conservation of energy, which asserts that energy can only be transformed from one form to another and cannot be created or destroyed. If the system is not isolated, the change in its internal energy, ΔU, is equal to the difference between the work W that the system does on its surroundings and the heat Q that is added to the system from its surroundings; in other words, ΔU = Q – W (Ken S., 2026).

Peng Robinson EOS

Originally created by Peng and Robinson in 1976, the Peng-Robinson (PR) equation of state (EOS) is a cubic EOS that was altered in 1978 to improve the model's phase behavior predictions. A popular EOS in several petroleum and chemical engineering fields is the PR EOS (Whitson, n.d. & Petroleum Office, 2026). It is mathematically represented by:

$$P = \frac{RT}{V_m - b} - \frac{a(T)}{V_m(V_m + b) + b(V_m - b)} \quad (1)$$

Where: P is pressure; T is temperature; V_m is molar volume; R is the universal gas constant; b is Covolume parameter, represented as:

$$b = 0.07780\frac{RT_c}{P_c} \quad (2)$$

a_c is Attraction parameter at critical temperature, represented as:

$$a_c = 0.45724\frac{R^2T_c^2}{P_c} \quad (3)$$

a_c is Temperature-dependent attraction, represented as:

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$$a(T) = a_c \cdot \alpha(T) \quad (4)$$

Response surface methodology (RSM)

Response surface methodology (RSM) can be defined as an approach that uses intricate calculations for the optimization process. This method creates an appropriate experimental design that incorporates all of the independent variables and leverages the experiment's data input to ultimately provide a set of equations that can provide an output's theoretical value. The results are derived from a carefully planned regression analysis based on controlled values of the independent variables. The updated values of the independent variables can then be used to forecast the dependent variable (Khairul et al., 2015). The implementation of RSM involves three steps: (1) experiment design, such as Box Behnken and Central Composite Design (CCD); (2) statistical and regression analysis to create model equations that represent response surface modelling; and (3) model equation-based parameter/variable optimization (Khairul et al., 2015).

Generic Algorithm

Genetic Algorithm (GA) is a population-based evolutionary optimization method that draws inspiration from genetics and natural selection. It finds optimal or nearly optimal solutions to complicated problems where conventional optimization approaches fail by iteratively evolving a population of candidate solutions utilizing biologically driven operators like selection, crossover, and mutation (Geeksforgeeks, 2026).

Aspen Hysys

Aspen HYSYS is a popular process modelling program in the chemical, oil & gas, and refining sectors. It enables engineers to design, optimize, and troubleshoot process facilities by simulating the behaviour of chemical processes. Process design, plant performance monitoring, and operational optimization are typical applications (Khairul et al., 2015).

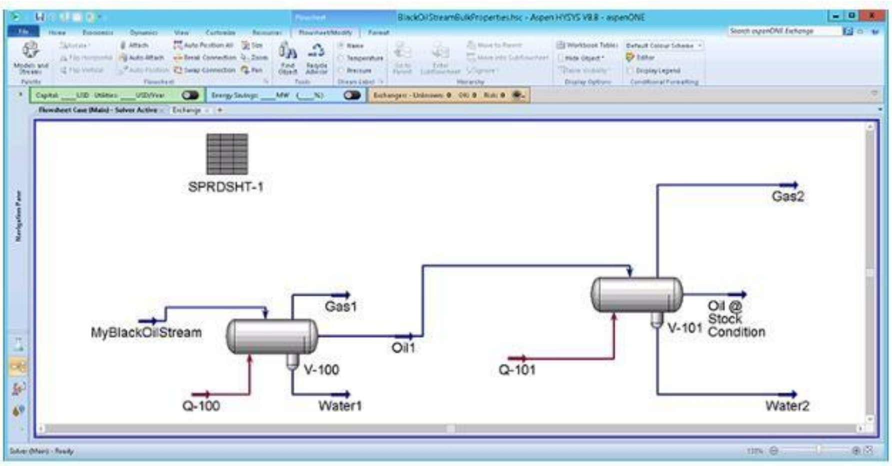

Fig. 3. Distillation column in NGL separation (Chemengguy, 2019).

Review of Previous Studies

Energy efficiency and reducing CO2 emissions was optimized during the separation of Natural Gas Liquid (NGL) fractions, specifically within the deethanizer and depropanizer distillation columns (Brahim et al., 2016). Fig. 4 shows the distillation columns of consideration. The model of the distillation columns was developed using material and energy balance equations and Vapor-Liquid Equilibrium (VLE) conditions for each stage. Peng-Robinson thermodynamic model and Aveva Pro/II software were utilized to perform

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these calculations; by using this software predictions were generated for heat duty, temperature and purity of ethane and propane and compared it with experimental data from literature as shown in Table 1 (Brahim et al., 2016).

By adjusting variables such as column pressure and reflux ratios, Ideal operating conditions were identified which maximized productivity while minimizing resource use. The findings demonstrate that fine-tuning these parameters significantly lowers energy consumption, which directly results in a substantial reduction of carbon dioxide emissions. Ultimately, the conclusion was that these technical improvements offer both environmental benefits and economic savings for industrial refinery operations (Brahim et al., 2016).

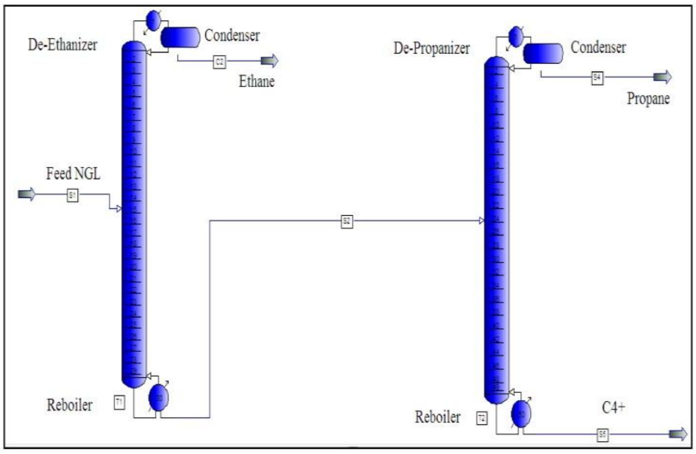

Fig. 4. Distillation column in NGL separation (Brahim et al., 2016)

Table 1. Comparison of reference and calculated data for NGL separation (Brahim et al., 2016)

Column	Parameter	V_r	V_c	E (%)
Deethanizer	Q_r (kW)	2108	2085	0.043
	Q_c (kW)	1734	1700	0.019
	Purity	0.9706	0.974	0.003
Depropanizer	Q_r (kW)	1611	1600	0.006
	Q_c (kW)	1656	1600	0.030
	Purity	0.9875	0.995	0.070

Energy efficiency of the debutanizer column was enhanced and used in the separation of Natural Gas Liquids. A mathematical model of the debutanizer column was developed using mass and energy balances and the Peng-Robinson Equation of State for vapor-liquid equilibrium calculations. This model was simulated using COCO flowsheeting and Chemsep LITE and validated against industrial refinery data as shown in Table 2, here the temperatures and pressures at the bottom and head of the column, the energy of condenser and reboiler, and purity of butane were carried out using the software and showed a high reliability with a mean absolute error of only 0.87% (Brahim et al., 2021).

Response Surface Methodology and a desirability function were utilized to identify the most efficient balance between reflux ratio and operating pressure. By applying these mathematical models, the study successfully determined optimal settings that simultaneously maximize butane purity and minimize heat duty in the reboiler and condenser as shown in Fig. 5. The findings demonstrate that this optimization can lower operating costs by 37% and reduce carbon dioxide emissions by 38%. Ultimately, the paper provides

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a reliable framework for industrial refineries to improve sustainability and economic performance without requiring expensive new equipment (Brahim et al., 2021).

Table 2. Comparison of experimental and calculated parameters values, of NGL separation for the Debutanizer column (Brahim et al., 2021).

	V_e	V_c	E (%)
T_{Bottom}(K)	394.6	394.77	0.04
T_{Head}(K)	322.0	331.00	2.80
P_{Bottom}(atm)	7.400	7.3760	0.32
P_{Head}(atm)	7.100	7.1000	0.00
Purity (C4, iC4)	0.9959	0.9937	0.22
E_r (kW)	1020	1000	1.96
E_c (kW)	1301	1300	0.08

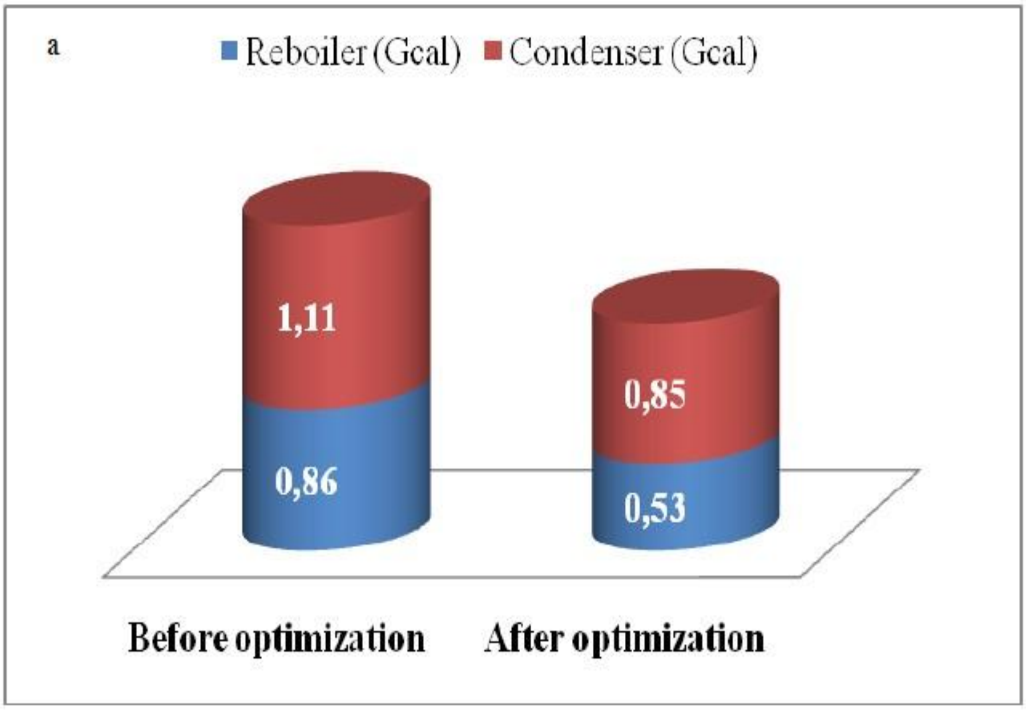

Fig. 5. Energy consumption for the debutanizer,before and after optimization (Brahim et al., 2021),

Energy consumption of a debutanizer column was optimized within a natural gas liquid (NGL) separation process and the primary goal was to find the specific operating parameters that would minimize the heat required by the column's reboiler and condenser while ensuring the final product (butane) met a purity requirement of 0.99. A statistical model of the debutanizer column was developed using the PengRobinson (PR) thermodynamic model and the simulation was validated by comparing its results against experimental data as shown in Table 3. The low relative error confirmed the model was reliable for further optimization. Aveva Pro/II simulation software was used to model the debutanizer column's operation (Brahim et al., 2023)

MATLAB software was used thereby applying a Genetic Algorithm to the simulation data, and the most efficient reflux ratios and pressure settings were identified and used to maintain product purity while minimizing waste, the Generic Algorithm procedure is shown in Fig. 6. The findings demonstrate that this optimization approach can significantly reduce operating costs and greenhouse gas emissions by over

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20%. Ultimately, the source advocates for these advanced modeling techniques to enhance the environmental sustainability and economic performance of industrial refineries (Brahim et al., 2023).

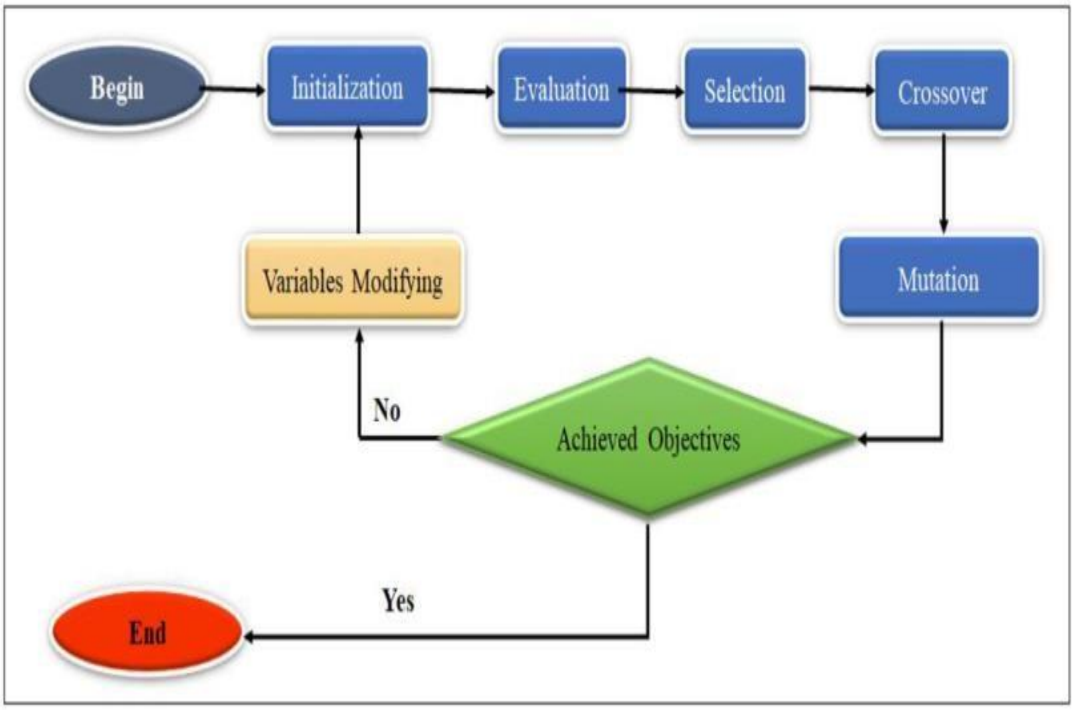

Fig. 6. Genetic algorithm procedure (Brahim et al., 2023).

Table 3. Comparison of reference and calculated data for NGL separation (Brahim et al., 2023).

	Déethanizeur			Dépropanizeur			Débutaniseur		
	V_e	V_c	E (%)	V_e	V_c	E(%)	V_e	V_c	E(%)
E_r (MW)	2,108	2,20	4,3	1,611	1,600	0,6	1,02	1,00	1,96
E_c (MW)	1,734	1,7	1,9	1,656	1,600	3	1,301	1,30	0,08
Pureté	0,970	0,974	0,3	0,987	0,995	7	0,9959	0,9937	0,002
	Ethane			Propane			Butane		

Thermodynamic optimization of a propane-propylene distillation splitter was explored and used to enhance energy efficiency and lower production costs, a Schematic of propane-propylene distillation splitter is shown in Fig. 7. Exergy analysis and the Column Grand Composite Curve (CGCC) were utilized to identify areas of energy dissipation and establish targets for process modification. The propanepropylene splitter was modelled using Aspen Plus (Version 11.1) with the Peng-Robinson (PR) property package. Exergy Analysis was used to quantify the "lost work"—the energy dissipated due to irreversibility—and to calculate the overall thermodynamic efficiency of the system (Umo et al., 2017).

The study optimized three key variables: reflux ratio, column pressure, and feed stage location using Response Surface Optimization to achieve better energy performance. These variables were adjusted to reduce the condenser and reboiler load without requiring additional capital investment. By adjusting those critical variables, the study demonstrates how to reduce wasted work within the system. The findings reveal that these strategic operational changes increased the column's thermodynamic efficiency by 2.2% while significantly lowering exergy loss. Ultimately, the paper provides a practical guide for improving energy utilization in industrial separation systems without requiring expensive capital investments (Umo et al., 2017).

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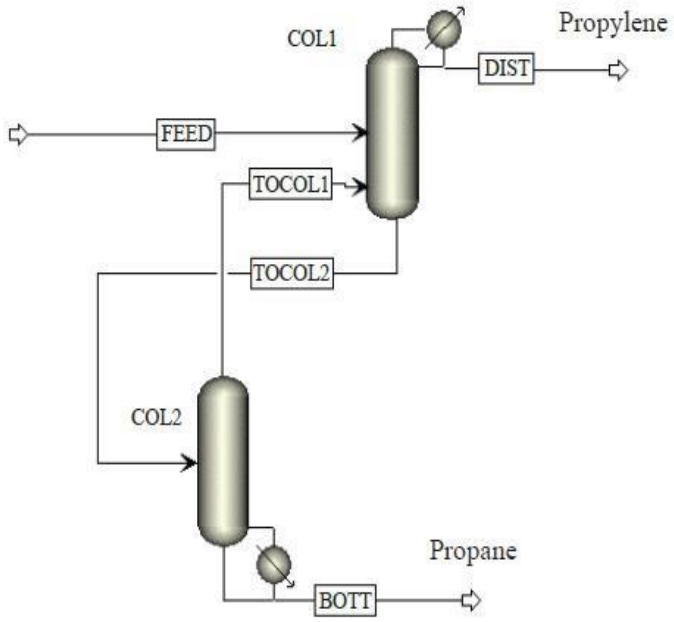

Fig. 7. Schematic of propane-propylene distillation splitter (Umo et al., 2017).

Artificial neural networks (ANN) was explored to enhance the energy efficiency and control of distillation columns. Traditional mechanistic models are often too complex and computationally slow for real-time optimization, but data-driven ANN models provide a faster, more reliable alternative. By applying the second law of thermodynamics, exergy analysis was applied to minimize energy waste and internal entropy production. The study successfully uses bootstrap aggregated neural networks to predict exergy efficiency and product composition for methanol-water and benzene-toluene systems (Osuolade et al., 2014)

Ultimately, this approach allows engineers to maximize operational performance without compromising product quality constraints. Table 4 shows the summary of the optimisation results. Table 4. Summary of optimization results (Osuolade et al., 2014)

	Methanol-water		Benzene-Toluene	
	Base case	Optimum case	Base case	Optimum case
Feed rate (kmol/h)	216.8	260	350	450
Feed temperature(^{o}C)	53	60	95	90
Feed composition(methanol)	0.4	0.3		
Feed composition(benzene)			0.4402	0.35
Reboiler duty(kJ/h)	6.156e6	6.156e6	7.5e6	7.5e6
Distillate composition	0.95	0.95	0.95	0.95
Bottom composition	0.08	0.05	0.19	0.21
Exergy efficiency (%)	42.43	48.9	47.29	56. 56
ANN predicted Exergy efficiency (%)		48.63		57. 65

Artificial neural network (ANN) strategy was used to enhance the energy efficiency of distillation columns by applying the second law of thermodynamics. Traditional mechanistic models are too computationally expensive for real-time optimization, whereas data-driven ANN models provide rapid and accurate predictions. To ensure higher reliability, the study utilizes bootstrap aggregated neural networks (BANN) as shown in Fig 9, which combine multiple models to improve generalization and provide confidence bounds (Osuolade et al., 2016).

These models were tested on binary systems as shown in Fig 8, such as methanol-water and benzenetoluene, as well as multi-component separation units. The results demonstrate that optimizing exergy efficiency through this method significantly lowers utility consumption and reduces internal

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entropy generation. Ultimately, the paper provides a practical framework for maintaining product quality while achieving substantial energy savings in chemical processing (Osuolade et al., 2016).

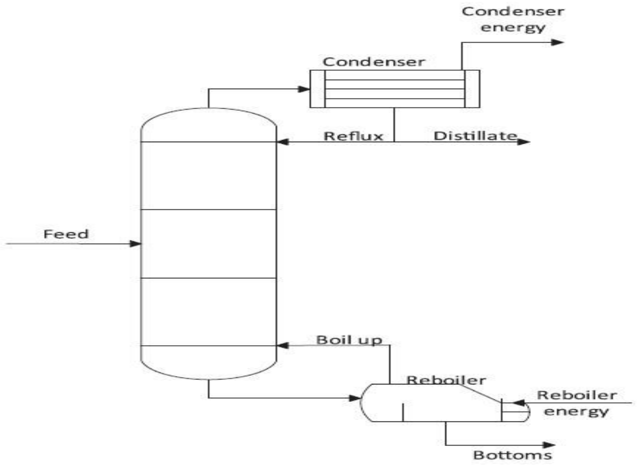

Fig. 8. A typical binary distillation column with the in and out streams and the exergy analysis boundary (Osuolade et al., 2016).

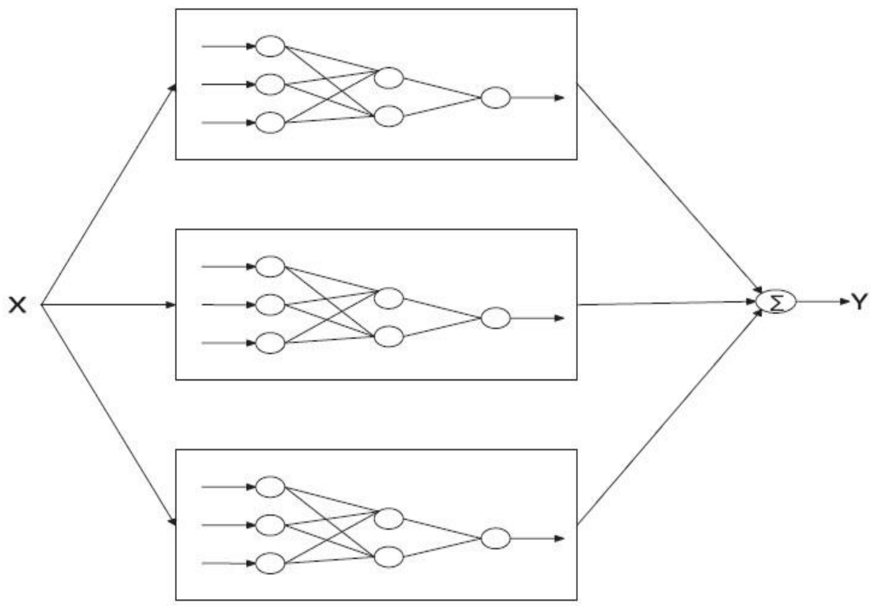

Fig. 9. A bootstrap aggregated neural network (BANN) (Osuolade et al., 2016).

A numerical approach was introduced for the design and optimization of distillation columns by converting discrete structural variables into continuous parameters. To avoid the mathematical difficulties of mixed-integer programming, distributed streams and Gaussian distribution functions were utilized to model a flexible number of separation stages. A core contribution is the development of stage-to-stage calculations that simplify the complex MESH equations into a sequence of one-dimensional problems, ensuring stable convergence without the need for specialized initialization (Seidel et al., 2025)

The methodology was validated through numerical experiments, demonstrating high accuracy compared to traditional enumeration methods and significant energy savings in complex flowsheets. Ultimately, the study applied this robust framework to two main scenarios: the design of a single distillation column and

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the optimization of a multi-column flowsheet for azeotropic separation via pressure swing distillation as shown in Fig 10 (Seidel et al., 2025).

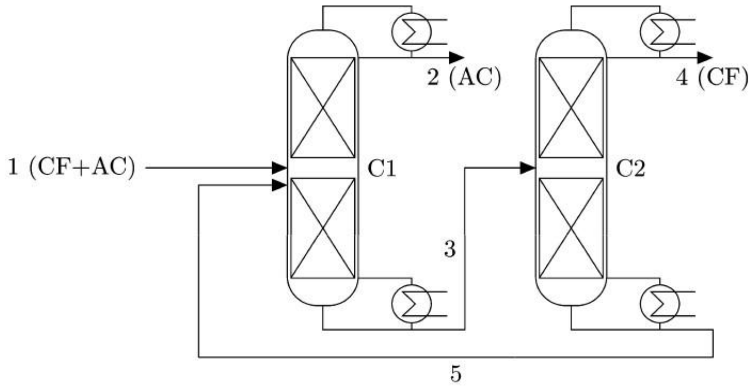

Fig. 10. Flowsheet of the pressure-swing distillation process for separating ace-tone (AC) and chloroform (CF) (Seidel et al., 2025)

A structural and operational retrofit of an industrial deethanizer column was investigated within an Iranian gas refinery. By eliminating the condenser and its expensive refrigerant, the process design was modified to prioritize increased production capacity during peak demand periods like the cold season. Aspen HYSYS was utilized for simulation and employs response surface methodology (RSM) to determine the optimal balance of reboiler temperature, operating pressure, and feed inlet location. Their findings indicate that this reconfiguration can boost output by 18% while simultaneously reducing energy demands and operational costs (Tavan et al., 2016).

Ultimately, a mathematical model and economic analysis was provided to prove that a medium reboiler temperature and specific pressure settings yield the most efficient results. Fig 11 shows the deethanizer without a condenser.[8]

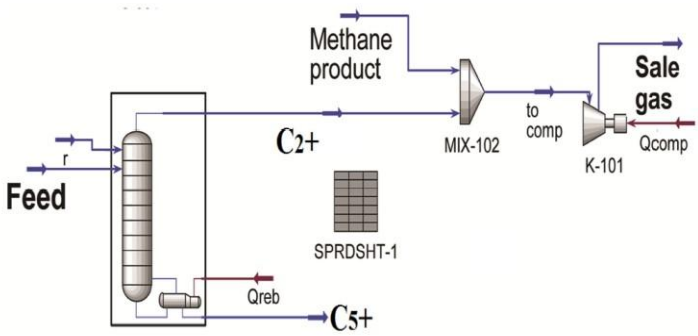

Fig. 11. Deethenizer without a condenser (Tavan et al., 2016).

Energy efficiency was improved within a natural gas liquids (NGLs) fractionation unit by optimizing the sequence of its distillation columns. The primary objective was to demonstrate that significant energy savings could be achieved through innovative configurations without requiring major modifications to the separation units themselves. Energy efficient NGLs fractionation plant methodology was developed and applied consisting of four hierarchical steps: 1) Existing Sequence Energy Analysis; 2) Optimal Sequence Determination; 3) Optimal Sequence Energy Analysis; and 4) Energy Comparison (Rahimi et al., 2015)

The sequence determined by the driving force method achieved a 21.19% reduction in total energy consumption compared to the existing sequence, reducing requirements from 155.95 MW to 122.9 MW as shown in Table 5. The researchers highlighted that this methodology provides an easy, practical, and

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systematic manner for designing energy-efficient distillation columns for NGL fractionation (Rahimi et al., 2015)

Fig. 12 shows Driving force curves for a set of binary components at uniform pressure. Fig 14 and Fig. 13 show the Flow sheet illustrating the existing direct sequence of NGLs fractionation process using driving force method and without using driving force method respectively (Rahimi et al., 2015).

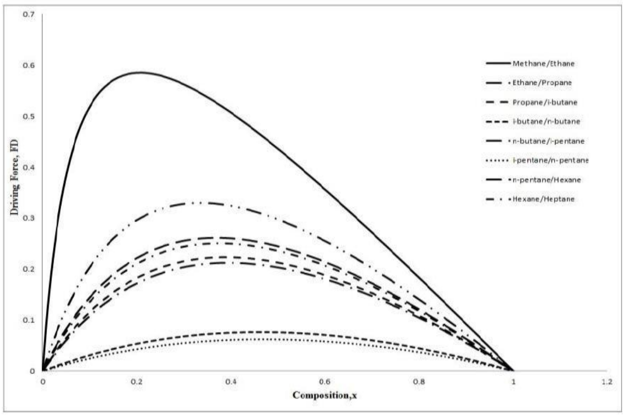

Fig. 12. Driving force curves for a set of binary components at uniform pressure (Rahimi et al., 2015)

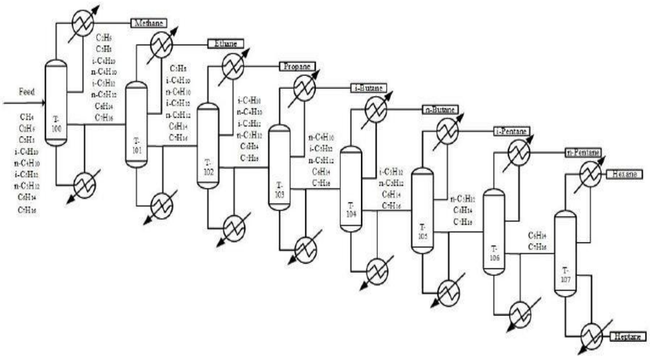

Fig. 13. Flowsheet illustrating the existing direct sequence of NGLs fractionation process (Rahimi et al., 2015)

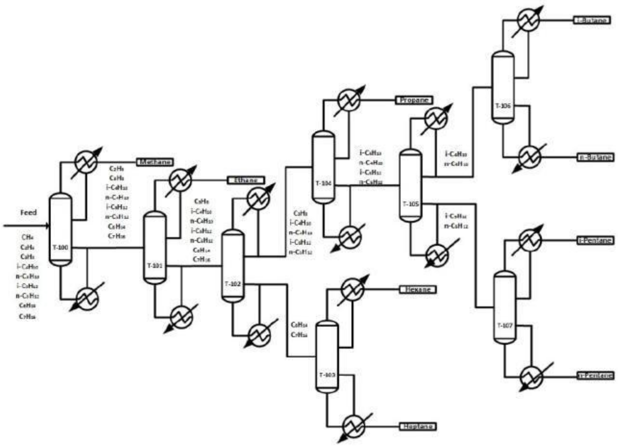

Fig. 14. Flowsheet illustrating the optimal driving force sequence of NGLs fractionation process (Rahimi et al., 2015)

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Table 5. Energy comparison between direct sequence and driving force sequence for NGLs fractionation process (Rahimi et al., 2015)

Distillation Column Unit	Direct Sequence (MW)	Driving Force Sequence	Percentage Difference (%)
Total Condenser Duty (MW)	75.10	58.58	22.01
Total Reboiler Duty (MW)	80.85	64.32	20.44
Total Energy (MW)	155.95	122.9	21.19

A systematic four-step methodology designed to enhance energy efficiency in natural gas liquids (NGLs) fractionation units. By utilizing the driving force method, which analyzes the differences in composition between vapor and liquid phases, engineers can determine the optimal sequence of distillation columns. Rearranging these sequences according to the maximum driving force results in easier separation tasks and lower utility requirements. Implementing this approach achieved a significant 10.62% reduction in energy consumption compared to traditional direct-splitter-direct configurations as shown in Table 6 (Rahimi et al., 2016).

Ultimately, a practical framework for reducing industrial operating costs was provided without necessitating major mechanical modifications to existing separation equipment. Fig 16 and Fig. 15 show the Flow sheet illustrating the existing direct-splitter-direct sequence of NGLs fractionation process using driving force method and without using driving force method respectively (Rahimi et al., 2016).

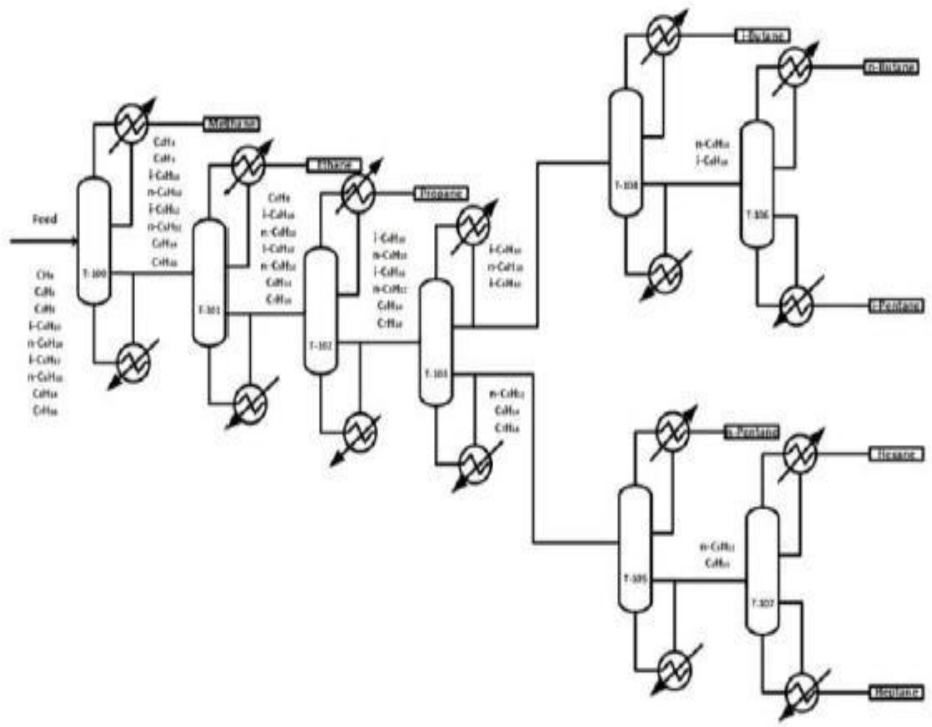

Fig. 15. Flow sheet illustrating the existing direct-splitter-direct sequence of NGLs fractionation process (Rahimi et al., 2016)

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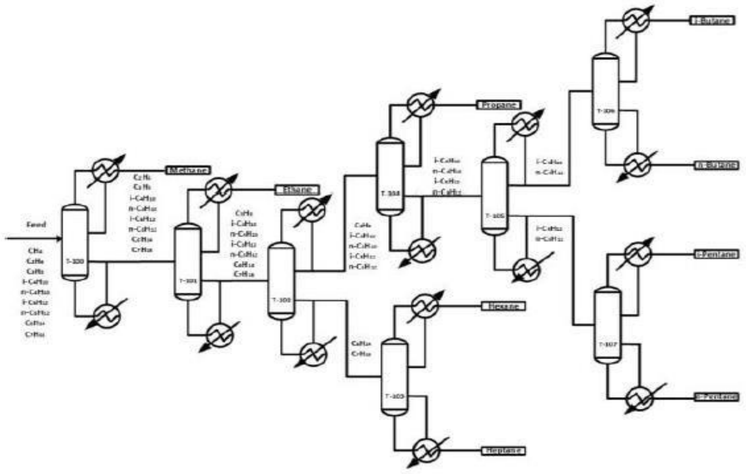

Fig. 16. Flow sheet illustrating the existing direct-splitter-direct sequence of NGLs fractionation process using driving force method (Rahimi et al., 2016)

Table 6. Energy Comparison between Direct-Splitter-Direct sequence and Driving Force sequence for NGLs fractionation process (Rahimi et al., 2016).

Distillation Column Unit	Direct-Splitter-Direct Sequence (MW)	Driving Force Sequence (MW)	Percentage Difference (%)
Total Condenser Duty (MW)	65.88	58.58	11.09
Total Reboiler Duty (MW)	71.62	64.32	10.19
Total Energy (MW)	137.50	122.9	10.62

Study Limitations

The Deethanizer and Depropanizer columns were considered for study and left out the Debutanizer column and limited the study focus almost exclusively on only two variables: reflux ratio and column pressure—to test their effects on energy consumption. Other variables like feed tray location and feed temperature were not considered. The modelling assumes the pressure remains constant throughout the column, which may not account for real pressure drops across trays. The models assume all distillation trays are in perfect equilibrium, which ignores the physical reality of tray efficiencies in actual industrial columns. Aspen Hysys was not used which is an oil and gas industry standard software for process simulation but went ahead to use “Pro II” software (Brabim et al., 2016.)

Only the Debutanizer was studied and the Depropanizer column was left and limited the study focus exclusively on only two variables: reflux ratio and column pressure—to test their effects on energy consumption. Variable like feed tray location were not considered. Aspen Hysys was not used which is an oil and gas industry standard software for process simulation but went ahead to use “COCO/ChemSep” software. Response surface methodology (RSM) was used as an optimization technique for reflux ratio and column pressure which relies on simplified "statistical guess" or polynomial approximation of your data (Brabim et al., 2021).

The Debutanizer was considered only but left out the Depropanizer column and limited the study focus exclusively on only two variables: reflux ratio and column pressure—to test their effects on energy consumption. Variable like feed tray location were not considered. Aspen Hysys which is an oil and gas industry standard software for process simulation but went ahead to use “Pro II” software. Genetic

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Algorithm (GA) was used as an optimization technique for reflux ratio and column pressure which is slow and requires thousands of computational runs to converge (Brabim et al., 2023).

Propane-propylene splitter was the focus in a particular polypropylene plant designed for 35,000 metric tonnes per year. Since the analysis was highly specific to these components (propylene and propane) and this specific plant configuration, the results may not be directly generalizable to other types of distillation columns or different chemical mixtures, also, Column Grand Composite Curves (CGCCs) are not used more frequently because of the difficulty in constructing them. This is because a column operating at the minimum thermodynamic condition (the ideal benchmark) theoretically requires infinite stages and an infinite number of side condensers and reboilers (Umo et al., 2017).

Artificial Neural Network (ANN) approach was employed for energy efficiency Optimization for binary distillation systems, both studies generated their training and validation data using Aspen HYSYS simulations rather than actual industrial plant data. This methodology could be generic and applied to real plant data, the models in these studies were not tested against the unpredictable noise, sensor errors, or fluctuations typical of a physical operating environment (Osuolade et al., 2016 & Seidel et al., 2025).

A Bootstrap Aggregated Neural Network (BANN) model developed for a particular system might not work for another. This means that the models lack universality; each individual distillation column in a refinery or chemical plant would require its own extensive data collection and training process, the studies also focused mainly on Methanol-Water and Benzene-Toluene systems and did not explore Debutanizer and Depropanizer columns (Osuolade et al., 2016 & Seidel et al., 2025).

Simulation of the deethanizer column was the focus here and did not consider the depropanizer and debutanizer columns, also, because the condenser was removed, the top temperature of the deethanizer column cannot be carefully controlled. This lack of control is significant because any increase in the inlet temperature of the compressor leads to considerable energy consumption. The increase in capacity comes at the cost of product quality; the sale gas is diluted with ethane and parts of the LPG. The researchers noted that this dilution might reduce plant revenue despite the higher production flow rate (Tavan et al., 2016).

Analysis of the energy efficiency for the natural gas liquids (NGLs) fractionation sequence was the primary focus by using driving force method but the research utilized "simple and reliable shortcut methods" in Aspen HYSYS to simulate both the existing and optimal sequences. While useful for initial screening and design, shortcut methods are generally less precise than rigorous stage-by-stage simulations (Rahimi et al., 2015 & Rahimi et al., 2016).

CONCLUSIONS

This review has examined recent developments in the optimization of natural gas conversion processes for LPG production, with particular focus on the performance of NGL fractionation units such as deethanizer, depropanizer, and debutanizer distillation columns. The reviewed studies demonstrate that process optimization plays a critical role in improving energy efficiency, reducing utility consumption, minimizing greenhouse gas emissions, and enhancing overall economic performance in gas processing industries. Various optimization techniques, including thermodynamic analysis, exergy analysis, Response Surface Methodology (RSM), Desirability Function, Genetic Algorithms (GA), Artificial Neural Networks (ANN), and driving force methods, have proven effective in identifying optimal operating conditions for distillation systems. The literature further reveals that key operational parameters such as reflux ratio, operating pressure, feed tray location, and column sequencing significantly influence separation efficiency and energy demand. Advanced simulation and modeling tools such as Aspen HYSYS, Aspen Plus, MATLAB, and AVEVA PRO/II have enabled researchers to accurately predict

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process behaviour and evaluate optimization strategies before industrial implementation. Reported improvements include substantial reductions in reboiler and condenser duties, lower CO_2 emissions, increased thermodynamic efficiency, and significant operating cost savings without major equipment modifications. However, despite the progress achieved, gaps still exist in the simultaneous optimization of debutanizer and depropanizer columns using integrated simulation platforms such as Aspen HYSYS while considering multiple interacting variables such as: Feed tray location, column Pressure and Reflux Ratio.

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