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Research Article

Optimizing natural gas liquids (NGL) production process: A multi-objective approach for energy-efficient operations using genetic algorithm and artificial neural networks

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Abstract

There are various techniques for separating natural gas liquid (NGL) from natural gas, one of which is refrigeration. In this method, the temperature is reduced in the dew point adjustment stage to condense the NGLs. The purpose of this paper is to introduce a methodology for optimizing the NGLs production process by determining the optimal values for specific set-points such as temperature and pressure in various vessels and equipment. The methodology also focuses on minimizing energy consumption during the NGL production process. To do this, this research defines a multi-objective problem and presents a hybrid algorithm, including a genetic algorithm (NSGA II) and artificial neural network (ANN) system. We solve the defined multi-objective problem using NSGA II. In order to design a tool that is a decision-helper for selecting the appropriate set-points, the ability of the ANN algorithm along with multi-objective optimization is evaluated. We implement our proposed algorithm in an Iranian chemical factory, specifically the NGL plant, which separates NGL from natural gas, as a case study for this article. Finally, we demonstrate the effectiveness of our proposed algorithm using the nonparametric statistical Kruskal–Wallis test.

AMS subject classifications (2020):

Keywords: Natural gas liquid (NGL); Multi-objective optimization; Artificial neural network; NSGA II.

1 Introduction

Natural gas extracted from underground sources can contain varying amounts of heavier hydrocarbon liquids, including ethane, propane, butanes, and natural gasoline, collectively known as Natural Gas Liquids (NGL). Due to their added value and transportation requirements, NGLs are consistently separated from the treated feed gas. The utilization of NGLs has extended across different sectors, with ethane serving as a feedstock for petrochemical plants and propane and butanes being marketed as liquefied petroleum gas (LPG). Additionally, the heavier fraction of raw gas ($C5^+$) can be used as a blending stock for gasoline. NGLs are characterized as the liquid-state heavier hydrocarbons of natural gas under atmospheric conditions. In a typical natural gas refining plant, various components of NGLs are separated one by one from the natural gas stream by applying a series of fractionation columns, namely demethanizer, deethanizer, depropanizer, and debutanizer. However, process industries face significant operational challenges related to monitoring and controlling these processes. Factors such as outlet chiller temperatures, column pressures, by-pass flows, and control schemes affect the recovery rate, energy consumption, and economic benefits of different NGL extraction methods.

The majority of investigations on problems in gas processing plant focused on different kinds of controlling systems (see [3, 5]), methods of preventing product loss with special attention to the environmental aspects, and energy consumption (see [7, 20, 2]). Some studies have examined the dynamic conditions of the process (see [6, 15]), but determining optimal set-points in terms of energy consumption, and NGL quality has received less attention. It should be noted that the set-point of the the controlled variable is not a single point and can change in a certain range. Designing a tool to determine the optimal set-point is important for making operational decisions because there are numerous set-points in such processes, and even small changes in them can result in significant variations in energy consumption and product quality. On the other word, the main objective of such tools is to define the optimal set-points for the multiple control loops in the process, aiming to maximize the profits while saving energy.

Addressing this complex optimization problem, data-driven model approaches offer the ability to simplify large-scale process models and perform optimization (see [27, 14]). Among the various approaches that utilize multivariate statistics and machine learning, partial least squares [23], artificial neural network (ANN) [21], support vector regression [10], and Gaussian process regression [1] have been widely implemented in constructing surrogate models in numerous research fields. Most of these methods build predictive models using the correlations among different variables (spatial correlations).

By leveraging the computational power of ANNs, industries can achieve efficient and effective optimization, leading to improved process performance, reduced costs, and increased productivity. The application of ANNs in the

industrial sector provides a powerful tool for addressing complex optimization problems. Through their ability to simplify large-scale process models and capture relationships among variables, ANNs enable efficient optimization and predictive modeling in various research fields, ultimately contributing to improved industrial processes and outcomes. Controlling production in industrial factories to achieve optimal conditions in terms of product quality and energy consumption poses a significant challenge, given the longevity of factories. The complexity of chemical plants, characterized by numerous set-points, further exacerbates this challenge. This prompts the exploration of the possibility of designing a tool that can determine the best set-points based on the process condition, aiding operators in their decision-making. Additionally, the feasibility of specifying set-points solely using recorded data, such as process data sheets and laboratory results, is investigated. The primary objective of this paper is to assess the capability of ANNs in determining optimal set-points, considering both the quantity and quality of products as well as energy consumption. So far, there are some research based on ANN in chemical engineering (e.g., see [4, 17, 18, 19, 24, 9, 22, 25]). Also, some research works consider the optimization of NGL production based on a genetic algorithm (see [16]). In this work, for an NGL optimization process, a multi-objective model is introduced. Then, an ANN is combined with a genetic algorithm, named NSGA II, to solve it.
In the rest of the paper, first, we describe the process under investigation in section 1. Then we explain the simulation process briefly. In section 2, we will discuss the optimization methodology, and finally, the numerical results for a real case study, NGL production plant in Iran, will be presented in section 3.

1.1 Process description

The extraction of natural gas from wells yields a mixture of various hydrocarbons, including heavier components that tend to liquefy. Referred to as NGL, these liquids can be categorized based on their vapor pressures, such as low vapor pressure (condensate), intermediate vapor pressure (natural gasoline), and high vapor pressure (LPG). Commonly found NGL components include ethane, propane, butane, isobutene, and natural gasoline. Several methods are employed to separate NGL from natural gas, including absorption, refrigeration, and cryogenic turbo-expansion. In this study, the focus is on a specific Iranian NGL plant designed using the refrigeration method. According to this approach, the natural gas stream undergoes cooling to approximately -32°C, causing the NGL within the mixture to condense into a liquid phase and separate from the natural gas. Figure 1 illustrates the process block diagram. To prevent ice crystallization in the dew point adjustment section, the feed streams, saturated with water, require the separation of the aqueous phase from the organic phase. The dew point adjustment section facilitates temperature reduction to facilitate NGL condensation; however, it may also result in the entrapment of lean hydrocarbons in the NGL product. The stabilization section is responsible for separating these hydrocarbons from the NGL products, guided by an increase in NGL temperature.

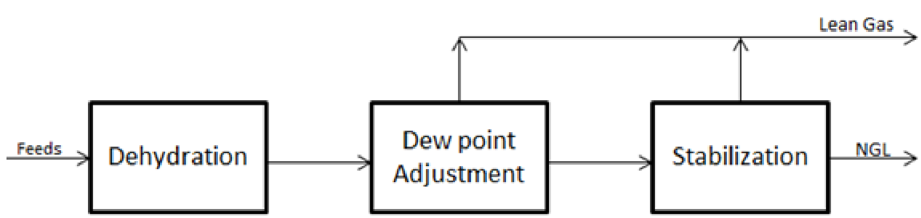

Figure 1: NGL production block diagram

1.2 Process simulation

In this section, we briefly explain the simulation process of NGL production. The process simulation will be explained based on design and operational conditions.

1.2.1 Process simulation based on design condition

This study employs an ANN algorithm, a data-driven approach, to analyze process variables; however, certain data from the plant's distribution control system (DCS) were unavailable. To overcome this limitation and avoid time-consuming data recording, a process simulation was utilized as a virtual representation of the actual process to generate the required data. The simulation incorporated design condition data such as feed and production specifications, equipment parameters, and mechanical information. To evaluate the simulation accuracy, a comparison was made between the simulated product flow values and the design values, which are presented in Tables 1 and 2. These simulation results were then utilized for both training and testing the ANN model. Subsequently, a detailed explanation of the NGL process simulation is provided. The Aspen Plus simulator was used for simulating the NGL production process (Figure 2), which includes the specification of binary parameters of various thermodynamic models. The Peng–Robinson model was specifically employed as the thermodynamic model. In Figure 2, stream (1) represents the high-pressure gas feed, while stream (2) represents the liquid feed, both of which combine in the V-1101 separator. Additionally, glycol is injected into the inlet stream of the E–1101 exchanger (stream 4).

Table 1: Design conditions for NGL plant feed and production

Parameter	Units	Inlet Gas	Inlet Liquid	Lean Gas Outlet	Lean Gas Outlet
Phase	–	Vapor	Liquid	Vapor	Liquid
Temperature	$^{\circ}C$	41	36	-40.9	22
Pressure	bara	42	42	39.5	21
Average MW	–	23	50	19	45
Mole Flows	kmol/hr	14360	409	1604	2722

Table 2: Simulation precision

Parameter	Lean Gas Outlet (kmol/hr)	NGL Outlet (kmol/hr)
Design condition	1604	2722
Simulation result	1596	2734
precision%	99.5	99.6

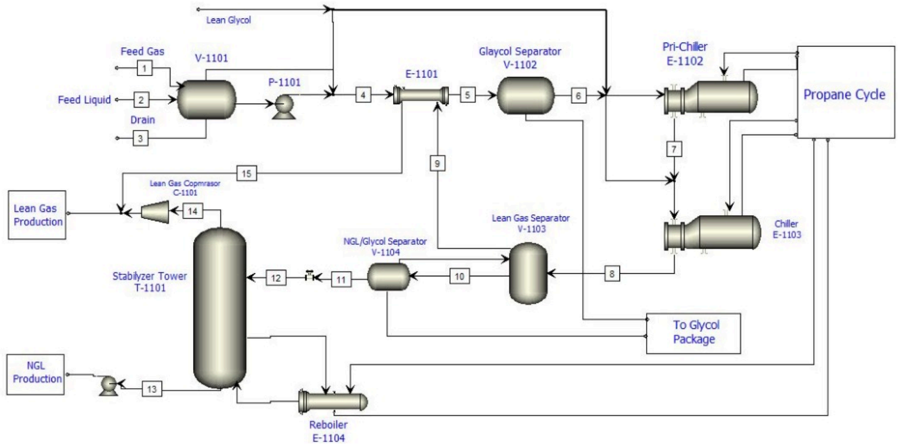

Figure 2: NGL production block diagram

This operation causes that water phase changing in E-1101 from gas to liquid occurs more quickly and prevents hydration. The V-1102 separator is employed to separate glycol solution (referred to as rich glycol) from hydrocarbons, a process commonly known as dehydration. As the hydrocarbons pass through the pre-chiller and chiller, their temperature undergoes a significant decrease of approximately -32°C. These heat exchangers enable a phase change by facilitating heat transfer between the hydrocarbons and liquid propane (used as a refrigerant). Specifically, heavy hydrocarbons transition into the liquid phase, while the liquid propane absorbs heat from the hydrocarbons and transitions into the gas phase. To prevent hydration, glycol is injected into these exchangers since the complete removal of water in the preceding stage is impractical. The outlet stream of the chiller now comprises three phases, including a gas phase. The effective operation of the pre-chiller and chiller is vital for maintaining product quality and minimizing energy consumption. The propane compression cycle incorporates three large electro-compressors, emphasizing the importance of energy efficiency through precise equipment set point tuning and operational strategies. This aspect is known as dew point adjustment. A V-1103 separator is used to separate the liquid phases (oily and aqueous) from the gas phase. Since the gaseous stream from V-1103, representing the light hydrocarbon fraction, is at a low temperature, it is directed to the E-1502 exchanger to pre-cool the hydrocarbon stream. The liquid phases are directed to V-1104, where the NGL and the aqueous solution, which includes water and glycol, are separated. To achieve the stabilization of the NGL product, it is necessary to remove the trapped light hydrocarbons in the liquid NGL at a lower pressure than the feed pressure. For this purpose, the NGL stream passes through a valve, where the pressure is reduced to half of the feed pressure. The T-1101 distillation column is responsible for the stabilization of the NGL. Distillation, a process involving selective boiling and condensation, is employed to separate the components or substances within a liquid mixture. The reboiler supplies the necessary energy for the evaporation of light hydrocarbons, such as methane and ethane. The NGL enters the top of the column and then flows down to the lowest tray, while the heat from the reboiler causes the evaporation of light hydrocarbons, ensuring the desired stabilization of the NGL product.

1.2.2 Process simulation based on operation condition

Considering the stable composition of the feeds in the plant, it is noted that while the temperature, pressure, and flow rates may undergo changes, the feed flow remains constant. In order to observe the influence of temperature and pressure variations on energy consumption patterns, it is preferable to assume a constant feed flow rate. Figures 3 and 4 illustrate the impact of pressure fluctuations on the vapor stream outlet of the V-1103 separator, specifically for methane and ethane. These figures are based on fixed values of pre-chiller and chiller set-points, as well as a feed temperature of -5°C, a pre-chiller temperature of -32°C, and a chiller temperature of 44°C. The results depicted in the figures demonstrate that an increase in pressure prompts the transition of methane into the liquid phase, consequently escalating the reboiler duty during the stabilization process. On the other hand, the desired effect of pressure variation is the transfer of other hydrocarbons such as ethane into the liquid phase, enriching the production of NGL with heavy hydrocarbons without incurring additional energy consumption. As a result, this leads to a reduction in reboiler duty.

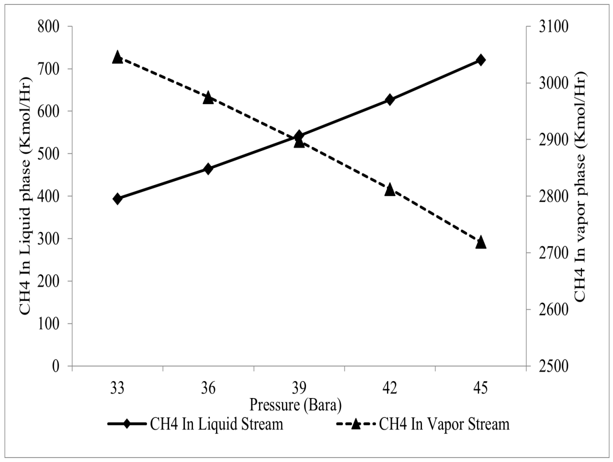

Figure 3: Methane flow rate via pressure

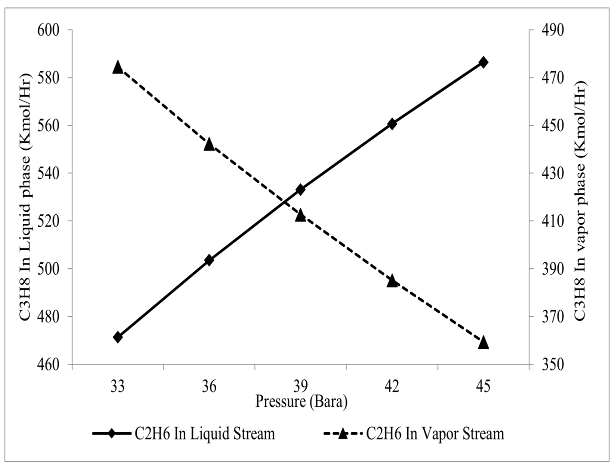

Figure 4: Ethane flow rate via pressure

As mentioned, we try to apply the ANN's ability to determine the set-points, based on which the high-quality and quantity of production with low energy consumption can be achieved. Due to this goal, according to the principles of the Monte Carlo method (see [13]) in different feed pressures and temperatures, the set-point of the pre-chiller, chiller, and the distillation column (the set-point of the tenth tray of distillation column adjust the reboiler duty), as the inputs (Table 3), are randomly changed and the variable shown in Table 4, as the output, are recorded.

Table 3: Set-point criteria ($\circ C$)

pre-chiller	$-9 \leq Temperature \leq -2$
chiller	$-36 \leq Temperature \leq -28$
tenth tray of distillation column	$-8 \leq Temperature \leq -2$

Table 4: Output variable

Output	Type	unit
NGL flow	Mass flow	kg/hr
lean gas flow	Mass flow	kg/hr
pre-chiller duty	Power	w
chiller duty	Power	w
reboiler duty	Power	w
CH4 in NGL stream	Mass fraction	-
CH4 in lean gas stream	Mass flow	-
C2H6 in NGL stream	Mass flow	-
C2H6 in lean gas stream	Mass flow	-

2 Algorithm framework

With the advancements in computer science, a wide range of software has been developed for simulation and optimization across various fields, including chemical engineering. However, most of these software programs rely on basic or "white box" models as their foundation. White box models are derived from basic knowledge and physical insight into the process. These models are primarily developed for the planning and designing of processing units and therefore describe the ideal state and steady-state of the process. While white box modeling or analytical modeling can effectively extrapolate the properties of a process, developing these models requires significant technical expertise and a considerable investment of time and effort. One of the main challenges in these types of modeling is determining the appropriate model parameters. In practice, the mechanisms underlying the system being modeled are often incomplete or imprecise, making it difficult to accurately capture the true nature of the system. Additionally, because systems can change unpredictably over time, even well-designed models may not perfectly reflect the real world.

In addition, such direct modeling is often not possible. For example, industrial processes are typically extremely complex, and accurate analytical modeling can be challenging or even infeasible. In such cases, black box modeling is often a practical solution. Black box models rely on data from the process itself to establish an input-output relationship and describe the behavior of the system. Data-driven models are particularly effective in accurately capturing the actual conditions of a process unit, as they are built using measured data. It is worth noting that with the increasing use of DCS in factories, a wealth of data is now available for potential use in developing data-driven optimization methods.

An ANN is a simplified model of the natural nervous system and has the ability to learn, like the brain, by processing experimental data [11]. In fact, by performing calculations on numerical data or examples, the grids learn general rules, and therefore, they are referred to as smart systems. The advantage of the neural network in comparison with simulation software is direct learning of data without the need to estimate their statistical characteristics. A neural network, regardless of any initial hypothesis and previous knowledge of the relationships between the parameters studied, is able to find the relationship between the set of inputs and outputs to predict any output corresponding to the desired input.

In this paper, we consider a multi-objective optimization problem and use a genetic algorithm as an optimization method.

A distinguishing feature of our approach, in comparison to similar works, is the use of an ANN to evaluate the target values.

2.1 Objective functions

Clearly, the amount of produced NGL and its quality will vary by changing the set-point of pre-chiller, chiller and tenth tray of distillation column.

Therefore, determining the appropriate set-points in a variety of feed conditions can be an optimization problem in this process. The objective functions that we consider in this paper are the NGL flow, lean gas flow, the pre-chiller duty, chiller duty, reboiler duty and the amount of methane and ethane in NGL and lean gas, which should be maximized or minimized according to Table 5.

Table 5: Problem objective functions

Maximize	NGL flow
	lean gas flow
	mass fraction of ethane in NGL flow
	mass fraction of methane in lean gas flow
Minimize	mass fraction of methane in NGL flow
	mass fraction of ethane in lean gas flow
	pre-chiller duty
	chiller duty
	reboiler duty

To evaluate the objective functions value, we use an ANN model.

2.2 Variables and constraints

The variables and their upper and lower bounds are considered in Table 3.

2.3 Genetic algorithm

Here, our optimization problem is a multi-objective problem, and we use a version of the genetic algorithm for multi-objective problems, namely NSGA II (see [8]), to obtain its solution. The specifications of the used genetic algorithm are shown in Table 6.

It should be noted that during the various implementations of the algorithm, the values reported for the parameters in Table 6 are the most appropriate values.

Table 6: the parameters of NSGA-II

Parameter	-
Population Size	50
Selection Method	Randomly
Crossover Method	Arithmetic
Probability of Crossover	0.7
Number of Crossover Points	2
Mutation Method	Gaussian
Probability of Mutation	0.4
Mutation Rate	0.02
Number of Iteration	100

2.4 Artificial neural network

In this research, in order to evaluate the objective functions (cost functions) during the NSGAII, we use an ANN [11]. The specifications of the used ANN are shown in Table 7. For convenience, the hybrid algorithm is shown in the flowchart, Figure 5.

Table 7: The parameters of ANN

Data division	Random
Training function	Levenberg-Marquardt
Performance	Mean squared error
The percentage of data used for training	80%
The number of hidden layers	5
Calculations	MATLAB

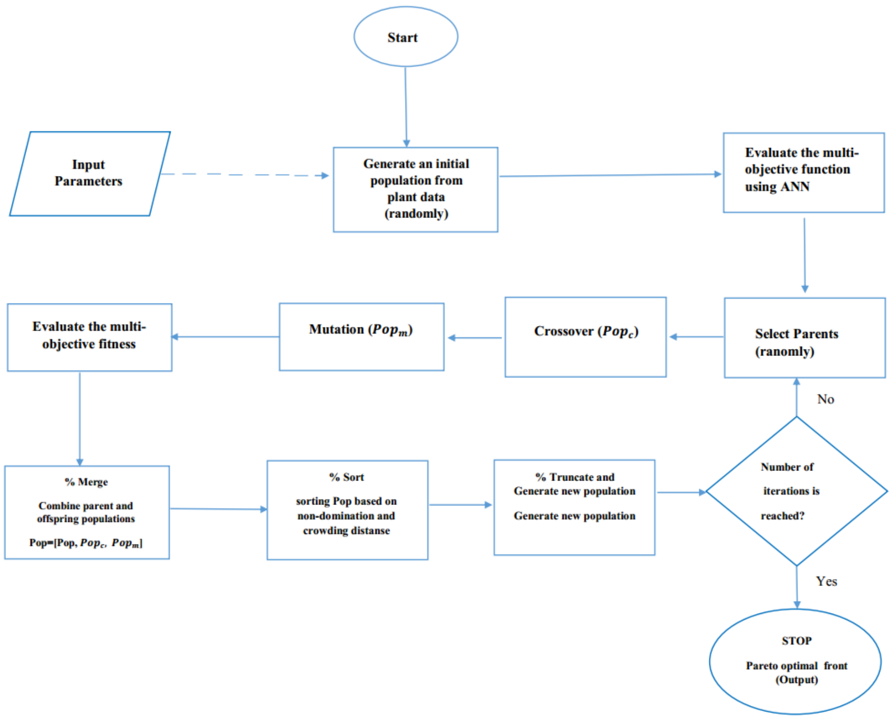

Figure 5: Diagram flow of the hybrid ANN and GA approches

3 Computational results and discussion

Our goal in this article is to evaluate the ability of ANN in determining optimal set-points for the NGL factory. No process knowledge or complex modeling is required to implement the ANN. This is a black box modeling specification. ANN has the ability to solve complex optimization problems based on a set of data. As described in Section 1.2.2, in each of the different conditions of feed, the amount of pre-chiller, chiller, and tenth tray distillation column set-points were randomly changed 100 times in Aspen Plus software, and the changes in product characteristics and energy consumption were recorded. It should be noted that in operating conditions, the temperature and pressure of the feed are always changing, but in most of the time, the set-points are constant. Based on this recorded information, the ANN was able to identify the optimal set-points for the pre-chiller, chiller, and tenth tray distillation column under various feed conditions, which are presented in Tables 8–13. Each of these tables represents a pressure change from 30 to 45 Bar at a constant temperature, consistent with the factory's design conditions.

Table 8: Results of applying hybrid algorithm when the temperature of input feed is 20 with six different values for its pressure

feed Temperature, Pressure	20, 30	20, 33	20, 36	20, 39	20, 42	20, 45
Tpch	−2.4558	−8.1039	−2.8469	−3.4545	−8.1039	−2.8469
Tch	−34.739	−28.007	−28.089	−28.324	−28.007	−28.089
Tr	−2.176	−6.973	−7.997	−4.066	−6.973	−7.997
NGL Flow(kg/hr)	51068.32	48476.67	49697.35	50486.30	51320.65	52172.75
Lean Gas Flow(kg/hr)	75581.7377	78279.2254	77061.5338	76277.0166	75440.0092	74596.1124
Pch-duty(w)	−2992828.8	−2569350.7	−1789626.3	−1940885.5	−2803750.5	−1924607.6
Ch-duty(w)	−5279878.9	−3233329	−4092233.5	−4033362	−3235192.5	−4104263.6
R-duty(w)	1628711.5	1127823.2	1198274.1	1474674.4	1440698.7	1506065.4
NGL (Methane)	0.02981	0.03417	0.03486	0.03128	0.03366	0.03443
NGL (ethane)	0.2981	0.2306	0.239	0.2466	0.2518	0.2576
Lean (Methane)	0.7099	0.6837	0.6936	0.7027	0.7085	0.7156
Lean (Methane)	0.2104	0.2205	0.2149	0.2097	0.2057	0.2011

Table 9: Results of applying hybrid algorithm when the temperature of input feed is 25 with six different values for its pressure

feed Temperature, Pressure	25, 30	25, 33	25, 36	25, 39	25, 42	25, 45
Tpch	−6.18338	−8.7039	−3.4545	−8.1039	−2.8469	−6.1833
Tch	−28.137	−28.216	−28.324	−28.007	−28.089	−28.137
Tr	−5.587	−6.865	−4.066	−6.973	−7.973	−5.587
NGL Flow(kg/hr)	47212.595	48637.763	49587.753	50533.892	51478.857	52037.833
Lean Gas Flow(kg/hr)	79556.8129	78132.8698	77188.3086	76241.8668	75300.9841	74751.2638
Pch-duty(w)	−2539579.1	−3106388.4	−2362577.7	−3202990.2	−2423875.9	−2946120.6
Ch-duty(w)	−3568959.3	−3169936.6	−4032455.1	−3231098.3	−4096165.8	−3573937.9
R-duty(w)	1080486.7	1145095.2	1367966.3	1337918.5	1404682.4	1609338.3
NGL (Methane)	0.03323	0.03406	0.03148	0.03380	0.03455	0.03226
NGL (ethane)	0.2216	0.2313	0.2396	0.2456	0.2521	0.2576
Lean (Methane)	0.6739	0.6850	0.6946	0.7013	0.7092	0.7157
Lean (ethane)	0.22596	0.21999	0.2146	0.2102	0.2053	0.2011

Table 10: Results of applying hybrid algorithm when the temperature of input feed is 30 with six different values for its pressure

feed Temperature, Pressure	30, 30	30, 33	30, 36	30, 39	30, 42	30, 45
Tpch	−8.7039	−7.4553	−7.7454	−2.6906	−2.8408	−8.5214
Tch	−28.216	−35.99	−28.249	−28.037	−35.648	−35.320
Tr	−6.865	−6.865	−5.555	−4.081	−3.88	−7.59
NGL Flow(kg/hr)	47379.997	53543.9022	49673.5941	50363.0825	55608.3122	56407.8474
Lean Gas Flow(kg/hr)	79400.8129	73240.2306	77111.0292	76431.8586	71190.8946	70395.6043
Pch-duty(w)	−3201496.2	−2970380.75	−3363020.30	−2684177.7	−2642137.9	−3601514.4
Ch-duty(w)	−3174206.3	−4637885.7	−3327603.1	−4108695.4	−5345604.1	−4393631.2
R-duty(w)	1037903.7	1656311.4	1305177.2	1455658.1	2139106	2072962.8
NGL (Methane)	0.0343	0.0334	0.0327	0.0313	0.0302	0.0335
NGL (ethane)	0.2220	0.2586	0.2394	0.2455	0.2766	0.2807
Lean (Methane)	0.6745	0.7289	0.6945	0.7013	0.7515	0.7570
Lean (ethane)	0.2257	0.1993	0.2146	0.2103	0.1834	0.1791

Table 11: Results of applying hybrid algorithm when the temperature of input feed is 35 with six different values for its pressure

feed Temperature, Pressure	35, 30	35, 33	35, 36	35, 39	35, 42	35, 45
Tpch	−8.1564	−2.3367	−2.7848	−4.375	−3.9652	−4.4152
Tch	−28.147	−35.39	−33.948	−28.470	−35.809	−28.974
Tr	−5.019	−3.748	−2.199	−2.146	−4.550	−2.586
NGL Flow(kg/hr)	47237.1015	52964.270	52951.511	50512.7140	55776.8986	52361.6583
Lean Gas Flow(kg/hr)	79560.0112	73835.9236	73847.042	76293.1329	71037.8673	70395.6043
Pch-duty(w)	−3370471	−2424978.4	−2689324	−3219069.8	−3104113.9	−3369385.6
Ch-duty(w)	−3251258.3	−5364446.5	−5056929.11	−3907831.5	−5190935.7	−3996550.7
R-duty(w)	1103174	1745392.4	1832591.2	1562914.2	2122881.6	1794971
NGL (Methane)	0.0327	0.0307	0.0293	0.0296	0.0308	0.0296
NGL (ethane)	0.2216	0.2563	0.2588	0.2468	0.2771	0.2620
Lean (Methane)	0.6741	0.7253	0.7262	0.7036	0.7526	0.7203
Lean (ethane)	0.2259	0.2013	0.1995	0.2093	0.1828	0.1989

For our comparisons, in different temperatures, we used the Kruskal–Wallis nonparametric statistical hypothesis test [26]. We considered the null and alternative hypotheses as follows:

$$\begin{cases} H_0 : \mu_{20} = \mu_{25} = \mu_{30} = \mu_{35} = \mu_{40} = \mu_{45}, \\ H_1 : \mu_{20} \neq \mu_{25} \neq \mu_{30} \neq \mu_{35} \neq \mu_{40} \neq \mu_{45}, \end{cases} \tag{1}$$

where μ_i $(i = 20, 25, 30, 35, 40, 45)$ is the mean value of the results due to NSGA II in different temperature of the input feed. According to the Kruskal–Wallis, since the p-value (p-value is defined as probability under the assumption of the null hypothesis; see the detail on p-value in [12]) is bigger

Table 12: Results of applying hybrid algorithm when the temperature of input feed is 40 with six different values for its pressure

feed Temperature, Pressure	40, 30	40, 33	40, 36	40, 39	40, 42	40, 45
Tpch	−7.4888	−3.9254	−2.3948	−2.0129	−8.6673	−8.9663
Tch	−35.992	−34.847	−28.417	−34.945	−28.043	−31.298
Tr	−2.560	−4.184	−5.282	−2.272	−6.759	−3.335
NGL Flow(kg/hr)	52157.4104	52706.1927	49822.8637	54399.9901	51437.3716	53811.6187
Lean Gas Flow(kg/hr)	74661.0344	74113.3967	77001.8408	72426.5602	75392.4430	73018.6954
Pch-duty(w)	−3318042.2	−2955805.4	−3029352.5	−2956612.1	−4321120	−4337468.1
Ch-duty(w)	−4636169.8	−5019948.5	−4216945.8	−5349044.9	−3148542.7	−3646772.6
R-duty(w)	1706350.2	1689083.7	1327406.6	2029210.2	1452874.3	193927.7
NGL (Methane)	0.0299	0.0312	0.0325	0.0290	0.0334	0.03
NGL (ethane)	0.2498	0.2545	0.2399	0.2686	0.2518	0.2678
Lean (Methane)	0.7182	0.7224	0.6956	0.7401	0.7091	0.7336
Lean (ethane)	0.2064	0.2028	0.2141	0.191	0.2054	0.1922

Table 13: Results of applying hybrid algorithm when the temperature of input feed is 45 with six different values for its pressure

feed Temperature, Pressure	45, 30	45, 33	45, 36	45, 39	45, 42	45, 45
Tpch	−2.4418	−3.4545	−8.1039	−3.4545	−8.1039	−2.2458
Tch	−35.745	−28.324	−28.007	−28.324	−28.007	−34.739
Tr	−4.438	−4.066	−6.973	−4.066	−6.973	−2.176
NGL Flow(kg/hr)	52171.1324	48612.0988	49693.756	50603.0594	51429.8852	55661.4816
Lean Gas Flow(kg/hr)	74662.7311	78212.3323	77134.2149	76226.8468	75394.6536	71170.3579
Pch-duty(w)	−2740606.2	−3288061.8	−4223594.7	−3614717.7	−4506176.1	−3466013.3
Ch-duty(w)	−5408302.9	−4033571.1	−3229535.1	−4031765.8	−3233724.1	−5306934
R-duty(w)	1612112.6	1260970.7	1235050.4	1476449.4	1441966.1	2265692.4
NGL (Methane)	0.0315	0.0317	0.0339	0.0312	0.0336	0.0286
NGL (ethane)	0.2490	0.2314	0.2386	0.2465	0.2517	0.2778
Lean (Methane)	0.7170	0.6858	0.6935	0.7031	0.7089	0.753
Lean (ethane)	0.2069	0.2198	0.2150	0.2095	0.2055	0.1816

than 0.05, H_0 is accepted. Thus, at the $\alpha = 0.05$ level of significance, there is evidence to conclude that the mean value of our proposed algorithm is equal in different temperatures.

NGL and lean gas are the factory productions that sales to the Petrochemical and Gas Company. Each of these customers has quality restrictions when purchasing products. In this article, considering that the selected set-points are in the operational range of the factory, the quality restrictions of the products are satisfied.

Table 14 shows the comparison between the factories fixed set-points ($-5°C$ for pre-chiller and reboiler and $-30°C$ for chiller) and the optimal

Table 14: The comparison between the current operating set-points and the optimal set-points

Production Stream	Variables	plant setpoint	Optimal Setpoint	Difference (%)
NGL	NGL flow (kg/hr)	49767	47380	4.80
	Methane Mass Fraction	0.03	0.03	-5.86
	Ethane Mass Fraction	0.24	0.22	5.77
Lean Gas	lean flow (kg/hr)	77014	79401	-3.10
	Methane Mass Fraction	0.70	0.67	3.03
	ethane Mass Fraction	0.22	0.23	-3.99
Total Energy (mw)		8.23	7.41	9.92

set-points in terms of production rate, product quality, and energy consumption in feed conditions with temperature 30 and pressure 30. The amount of difference in this table is calculated relative to the plant set-point values. In this comparison, about 9.9% less energy is used for optimal set-points. This is equivalent to 0.817 MW and also equivalent to 13.8 tons per day of carbon dioxide emissions. However, under optimal conditions, the amount of NGL production is lower (about 4.8%) compared to the current operating set-points, which is the opposite for light gas (about -3.1%). As mentioned above, the purpose of this paper is to evaluate the ability of ANN to determine the optimal set-points in terms of quantity and quality of products and energy consumption so this study can be the basis for the next study at a higher level (managerial perspective) to determine the set-points in terms of profitability and reduce production costs.

In the used neural network, we considered five neurons in the hidden layer and based on that, the results of Tables 8–13 were obtained. The performance of the designed network for all cases is desirable. The neural network performance and regression diagrams for the data, when the input feed temperature is 44, are shown in Figures 6 and 7, respectively. It should be noted that by changing the number of neurons in the hidden layer and even changing the number of layers, the performance of the network did not change much. The same was true for the other cases.

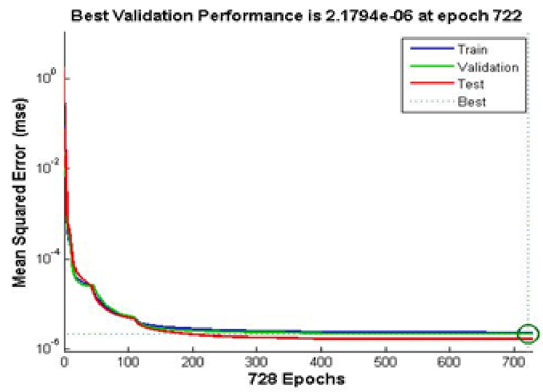

Figure 6: ANN Performance diagram

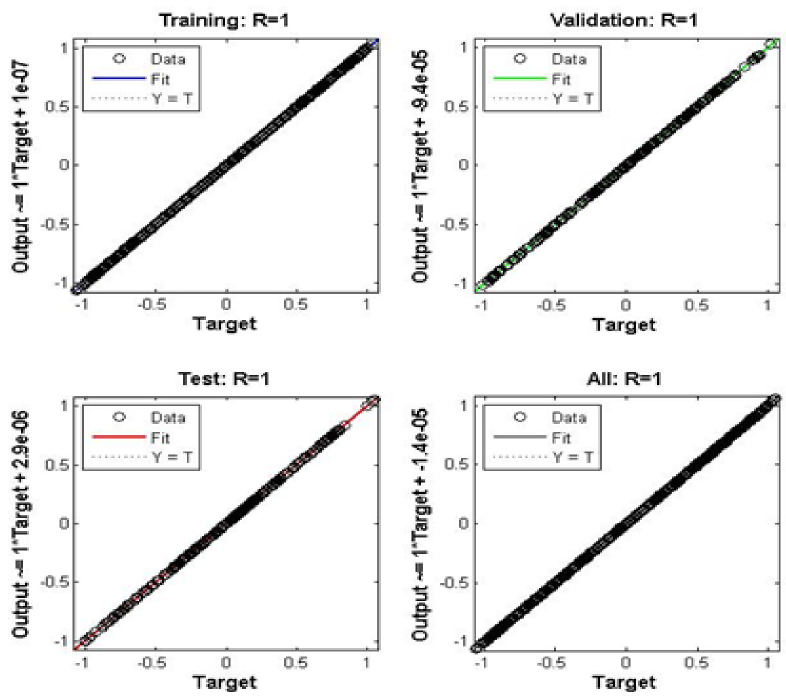

Figure 7: ANN Regression diagram

4 Conclusions and future suggestions

In this paper, we have tried to determine the best amount of set-points in the NGL production process by considering several objective functions, including the amount of NGL, lean gas, the energy consumption of pre-chiller, chiller, and reboiler, and the amount of ethane and methane in NGL and lean gas. This is done using the NSGA-II algorithm and an ANN. The contribution of the presented method is its ability to adapt to any process, its capacity for upgrades, and its utilization of available plant data for machine learning. If there are no sufficient data in the plant, then we can use a simulation just for generating data to train and test the ANN. We used the non-parametric statistical Kruskal–Wallis test to analyze the performance of our algorithm. The obtained results showed that the mean value of our proposed algorithm is equal at different temperatures.

The purpose of this paper is to assess the capability of ANN in identifying the optimal set-points that result in high-quality products, reduced energy consumption, and increased efficiency. This study lays the foundation for further research at a managerial level, which will determine the set-points based on profitability and cost-effectiveness. Additionally, there are two crucial materials used in the process, namely propane and ethylene glycol. Propane is utilized to cool the gas in the pre-chiller and chiller, while ethylene glycol is used to prevent the hydrate phenomenon. Future studies should investigate the factors that contribute to propane wastage and optimize its usage, as well as explore ways to minimize the use of ethylene glycol, thereby providing further opportunities for optimization and can be considered in future research.

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