Application of Artificial Neural Network (ANN) in the Optimization of Crude Oil Refinery Process: New Port-Harcourt Refinery

M. N. Braimah[1*]

[1]*Department of Chemical Engineering, Applied Thermodynamics and Process Design Unit, Obafemi Awolowo University, Ile-Ife, Osun State, Nigeria.*

Author's contribution

The sole author designed, analysed, interpreted and prepared the manuscript.

Original Research Article

ABSTRACT

Background: Optimizing the process conditions of the crude distillation unit is a main challenge for each refinery. Optimization increases profit by producing the required range of distillates at maximum yield and at minimum cost. To achieve an acceptable control of product quality an artificial neural network (ANN) can be used. ANNs are used for engineering purposes, such as pattern recognition, forecasting, and data compression. In the petroleum refinery industry, ANN has been used as controller in for the crude distillation unit. The aim of the current study was to use ANN to optimize and achieve control of product quality of crude distillation unit of an oil refinery.

Materials: The research was carried out using the following materials; The design flowchart and the operating data of the crude distillation unit of the New Port Harcourt refinery, Simulation software (HYSYS 2006.5) and Matlab for the ANN.

Results: The ANN predicted the optimum operating conditions at which the atmospheric distillation unit (ADU) can operate with the least irreversibility and without changing the design and compromising the products quality. The corresponding exergy efficiency after optimization with

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Corresponding author: E-mail: mnerinoso1@gmail.com;

ANN for the input variable combinations was 70.6% which was a great improvement because the exergy efficiency increased as compared to the base case of 51.9%.
Conclusion: Optimization using ANN, improved the efficiency of the ADU with the least irreversibility and without changing the design and compromising the products quality.

Keywords: Atmospheric distillation unit; artificial neural network; exergy; optimization.

1. INTRODUCTION

Generally, distillation columns are the common separation units used in the chemical and refinery industry to achieve product separation and refining [1]. The crude oil distillation unit (CDU) fractionation column in the petroleum refinery industry separates the feed which is the crude oil into different products that is suitable for the different refinery processing units [2]. Currently, in other to improve fuel properties, quality of products and maximize the yield of the products, many CDU operates with different feed as compared to their original feed conditions in other to fulfil global market demand and at the same time fulfilling environmental laws [2,3]. The atmospheric distillation unit (ADU) of the CDU, have different physical properties depending on the characteristics of the crude oil [4]. Apart from the different physical interactions that occur in this unit, the unit is also extremely energy consuming and the energy requirements are strictly linked to the needed separation into the different products [1]. Minimizing the energy requirements for specific product composition can be achieved by controlling a lot of variables in the unit [1].

Optimizing the process conditions of the crude distillation unit is a main challenge for each refinery. Optimization increases profit by producing the required range of distillates at maximum yield and at minimum cost. To achieve this goal, full and real-time monitoring and control of each incoming stream and outgoing products is an unavoidable requirement. Controlling distillation column starts by identifying controlled variable (product composition, column temperatures, column pressure, and accumulator levels) which must be retained at a specific value to satisfy column objectives, manipulated variables (reflux flow, coolant flow, heating medium flow, and product flows) are those that can be altered in order to sustain the controlled variables at their values, and load variables (feed flow rate and feed composition) are those variables that cause instabilities to the column [1]. Other disturbances are steam heater pressure, feed enthalpy, environmental conditions (rain, barometric pressure, and ambient temperature), and coolant temperature [1].

Identifying which manipulated variables that can be altered in other to sustain the controlled variable, Than et al. [5] has proposed a general guideline which include: Manipulate the stream that has the greatest influence on the associated controlled variable; Manipulate the smaller stream if two streams have the same effect on the controlled variable; Manipulate the stream that has the most nearly linear correlation with the controlled variable; Manipulate the stream that is least sensitive to ambient conditions; or Manipulate the stream least likely to cause interaction problems.

In other to optimize production rate with the required product quality at low operating cost and at an optimized operating conditions of the operating variables, artificial neural network (ANN) has been proposed [1,2]. Neural networks are made up of a number of interconnected 'nodes' which contain an 'activation function' and are typically organized in layers. Patterns are presented to the network via the 'input layer', which communicates to one or more 'hidden layers' where the actual processing is done via a system of weighted 'connections'. The hidden layers then link to an 'output layer' where the answer is output as shown in Fig. 1.

ANN was defined by Robert Hecht-Nielsen as a computing system made up of a number of simple, highly interconnected processing elements, which process information by their dynamic state response to external inputs [6].

They are universal approximators, by capturing precisely associations or discovering regularities within a set of patterns; where the volume, number of variables or diversity of the data is very huge [6]. Neural network analysis often requires a large number of individual runs to determine the best solution. Once neural network is trained to attain a satisfactory level, it can be utilized as an analytical tool on other data without training runs in a forward propagation mode only [7].

New inputs are presented to the input pattern where they filter into and are processed by the middle layers as though training were taking place, however, at this point the output is retained and no back-propagation occurs. The output of a forward propagation run is the predicted model for the data which can then be used for further analysis and interpretation [7], this is illustrated in Fig. 2.

Applications of ANN in the chemical industry include; estimation of CO_2 conversion in falling film reactor using artificial neural network where it was discovered that ANN model with one hidden layer and nine neurons in the hidden layer gives a very close estimation of the CO2 conversion with high potential for absorption [8]. Also, ANN models was used to estimate contaminant composition in a xylene distillation column in a refinery in Japan [9].

Several studies have used ANN in the design of CDU [3,10,11], however, ANN use has not been very popular in the optimization of operating variables of CDU in the existing refineries. It is this void in the literature that the present study hopes to fill by studying the use of ANN in the optimization of CDU of an existing refinery.

1.1 Process Description

This research focused on the atmospheric distillation unit of crude distillation unit of the New Port Harcourt Refinery. The crude distillation unit is made up of the pre-flash unit which increases the temperature of the crude oil so as to separate into different fractions mainly liquid and vapour phase after it has passed through cleaning process and desalination process. The vapour phase is sent straight to the refluxed absorber while the liquid phase is sent to heater then to a furnace before entering the refluxed absorber which then separates it into different products Fig. 3.
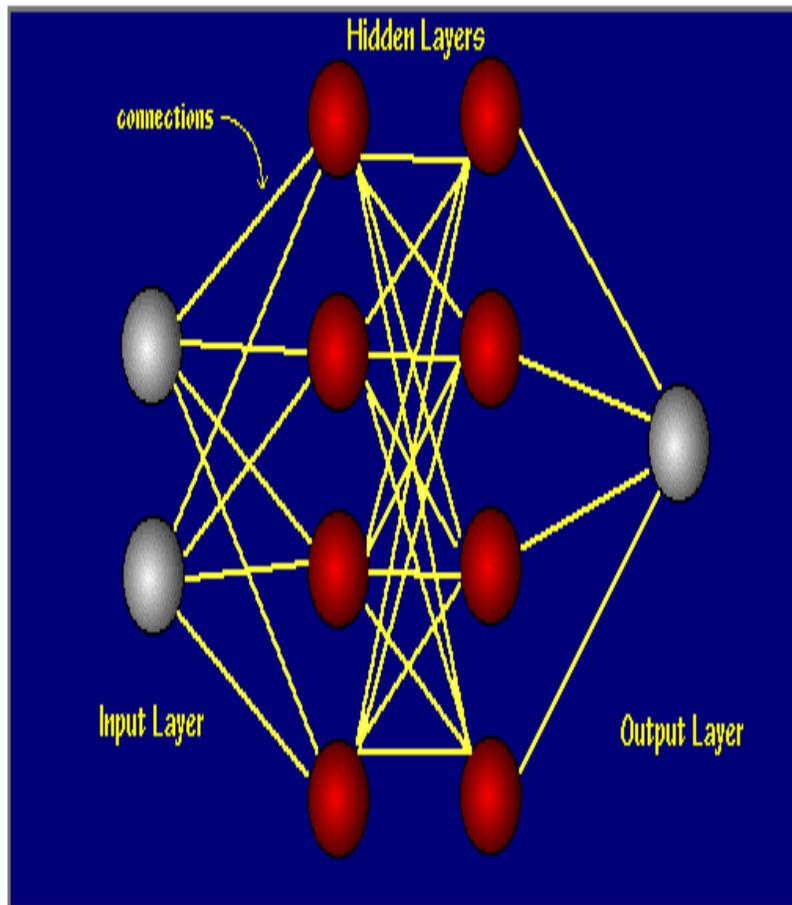

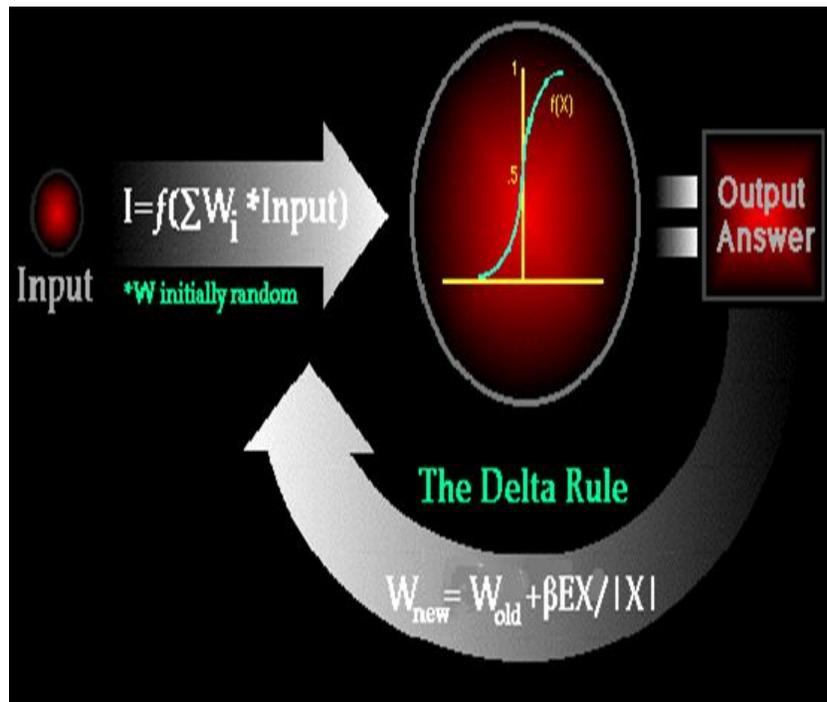**Fig. 1. A simple neural network showing nodes [6]**

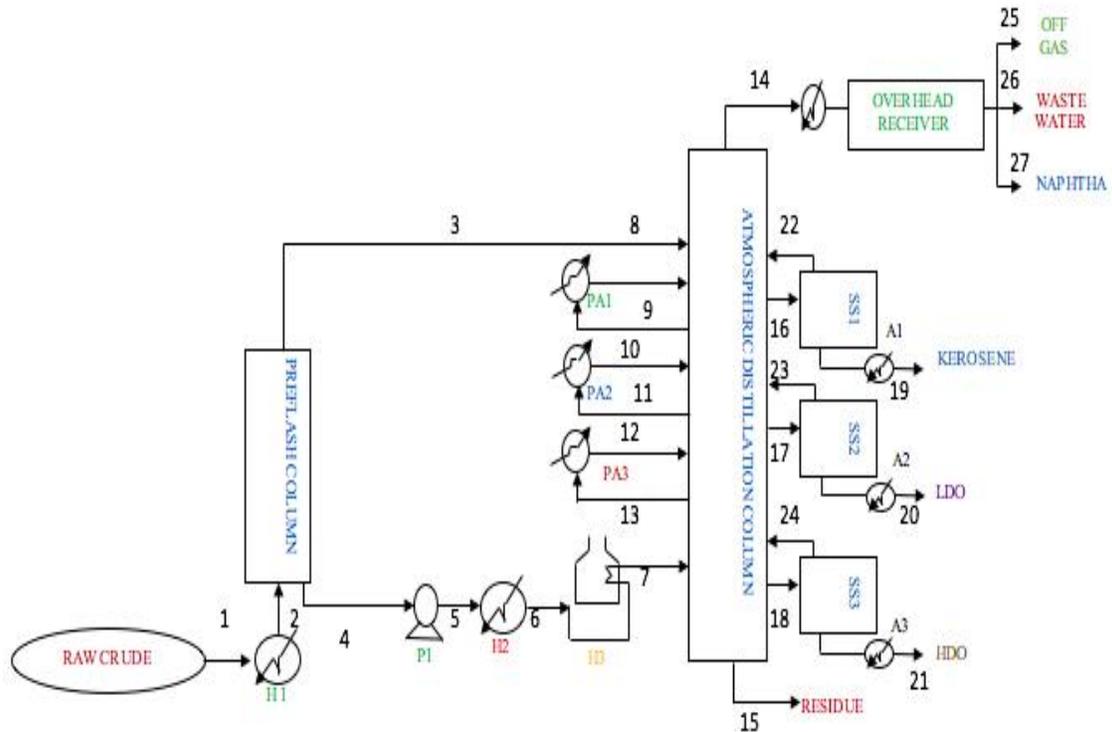**Fig. 2. A single node example [6]**

Fig. 3. Schematic diagram of the CDU for New Port Harcourt refinery

1.2 Exergy

Exergy can be defined as the maximum amount of work which can be obtained as a process which is changed reversibly from the given state to a state of equilibrium with the environment, or the maximum work that can be obtained from any quantity of energy [12]. Exergy is divided into physical and chemical components [13].

1.3 Physical Exergy

The physical exergy is the maximum useful work obtained by passing the unit of mass of a substance of the generic state (T, P) to the environmental (To, Po) state through purely physical processes [14-16]. The reference system is defined with a reference temperature of 298.15K and a reference pressure of 101.325 kPa. Thus, if kinetic and potential energy are not taken into consideration, the specific physical exergy can be determined with the enthalpy and entropy values of the stream (characterized by its composition), both at the generic state and the environmental state temperatures and pressure. The Equation 3 can be used to illustrate how to calculate physical exergy assuming steady-state steady flow conditions and assuming both potential and kinetic energy are not contributing to the system.

$$\mathrm{Ex_{ph} = Ex_i - Ex_o = (H_i - H_o) - T_o(S_i - S_o) = \Delta Ex_{phy} = \Delta H - T_o \Delta S} \qquad (1)$$

1.4 Chemical Exergy

Chemical exergy is equal to the maximum amount of work obtainable when the substance under consideration is brought form the environmental state to the reference state by processes involving heat transfer and exchange of substance only with the environment [17,18]. For a crude stream, the chemical exergy can be calculated from the standard molar chemical exergies of all identified components and pseudo-components as:

$$\Delta \mathrm{Ex_{ch}} = \sum \mathrm{x_i x_{pci}} + \sum \mathrm{x_i x_i} + RT_o \sum \mathrm{x_i ln x_i} \qquad (2)$$

Where,

$\mathrm{x_{pci}}$ is the chemical exergy for pseudo-components
$\mathrm{x_i}$ is the chemical exergy component i
$\mathrm{x_i}$ is the mole fraction of component i

1.5 Exergy Efficiency

The exergy efficiency for each process unit was calculated using Equation 3.

$$\eta = \frac{\text{Exergy out or products}}{\text{Exergy in or feed}} \qquad (3)$$

Irreversibility for each process unit was calculated using Equation 4.

$$I = \sum \mathrm{Ex_{in}} - \sum \mathrm{Ex_{out}} \qquad (4)$$

2. METHODOLOGY

The software (HYSYS 2006.5) was used for modeling and simulation of the crude distillation unit. The components that were chosen are from the refinery data includes water, methane, ethane, propane, i-butane, n-butane, i-pentane and n-pentane. The data from the simulation was exported to Microsoft Excel for exergy analysis. Parametric studies were performed by changing the operating variables (liquid inlet temperature, liquid inlet pressure, condenser temperature, condenser pressure, pump around flow rates 1, 2 and 3) to determine their effect on energy and

Table 1. Bulk crude data

Bulk crude properties	Values
API GRAVITY	34.87
REID VAPOR PRESSURE 38ºCKaf/cm^2	0.3
BS and W% VOL	0.1
POUR POINT ºC	< 0
ASH CONTENT %wt	0.00278
CONRANDSON CARBON RESIDUE %wt	1
SALT CONTENT PTB	1.04
KINEMATIC VISCOSITY at 38ºC	3.66
WATER CONTENT %VOL	<0.05
NICKEL ppm	0.022
LEAD ppm	0.027

exergy efficiencies. Data from the three most sensitive operating variables (liquid inlet temperature, liquid inlet pressure and condenser pressure) were chosen for optimization.

The fluid package chosen for this process was Peng-Robison. The crude oil was characterized using experimental assay which include API gravity, bulk crude properties, light end volume percent, TBP distillation and ASTM distillation. The assay data was fed into the data bank of HYSYS, the parameters are presented in Table 1.

The result of the characterization is a set of pseudo-components and a detailed chemical composition of the identified light end component and this is presented in Table 2.

Table 2. Light ends data

Component	Percentage (%)
Propane	0.17
Isobutane	0.55
n-butane	1.02
Isopentane	0.33
n-pentane	0.14

After the assay was calculated, the oil was cut and blended to produce hypothetical components that could be used in the simulation. This was done using the cut/blend tab on the oil manager environment. The cut was done using auto cut option which generates the hypothetical components based on the initial boiling point and the temperature ranges available. Once this was

done, the oil was installed and made ready for use in simulation. The process stream parameters used in the simulation are as shown in Table 3.

3. RESULTS AND DISCUSSION

The Simulation diagram of the crude distillation unit is shown in Fig. 4 and the simulation diagram of the atmospheric distillation unit is shown in Fig. 5.

This is the main environment where the crude distillation unit was modeled using the operating and design data from the refinery. This was done to give a prototype of the actual refinery process. The simulation environment was entered and the raw crude temperature, pressure and mass flow rate values were imputed. After converging, the simulation flow diagram of the CDU is as shown in Fig. 4, while the simulation diagram of the ADU is as shown in Fig. 5.

Table 4 shows the summarized state parameters from the simulation and the streams that were considered in the analysis. Equations 1 and 2 were used to calculate exergy analysis, equation 3 was used in calculating exergy efficiency while equation 4 was used to calculate irreversibility. The exergy efficiency result of the ADU was 51.9%. Every process has an element of irreversibility that makes it deviate from theoretical ideal performance and this is why exergy analysis of a process gives a better performance of a process than energy analysis [19,20].

Table 3. Process stream data

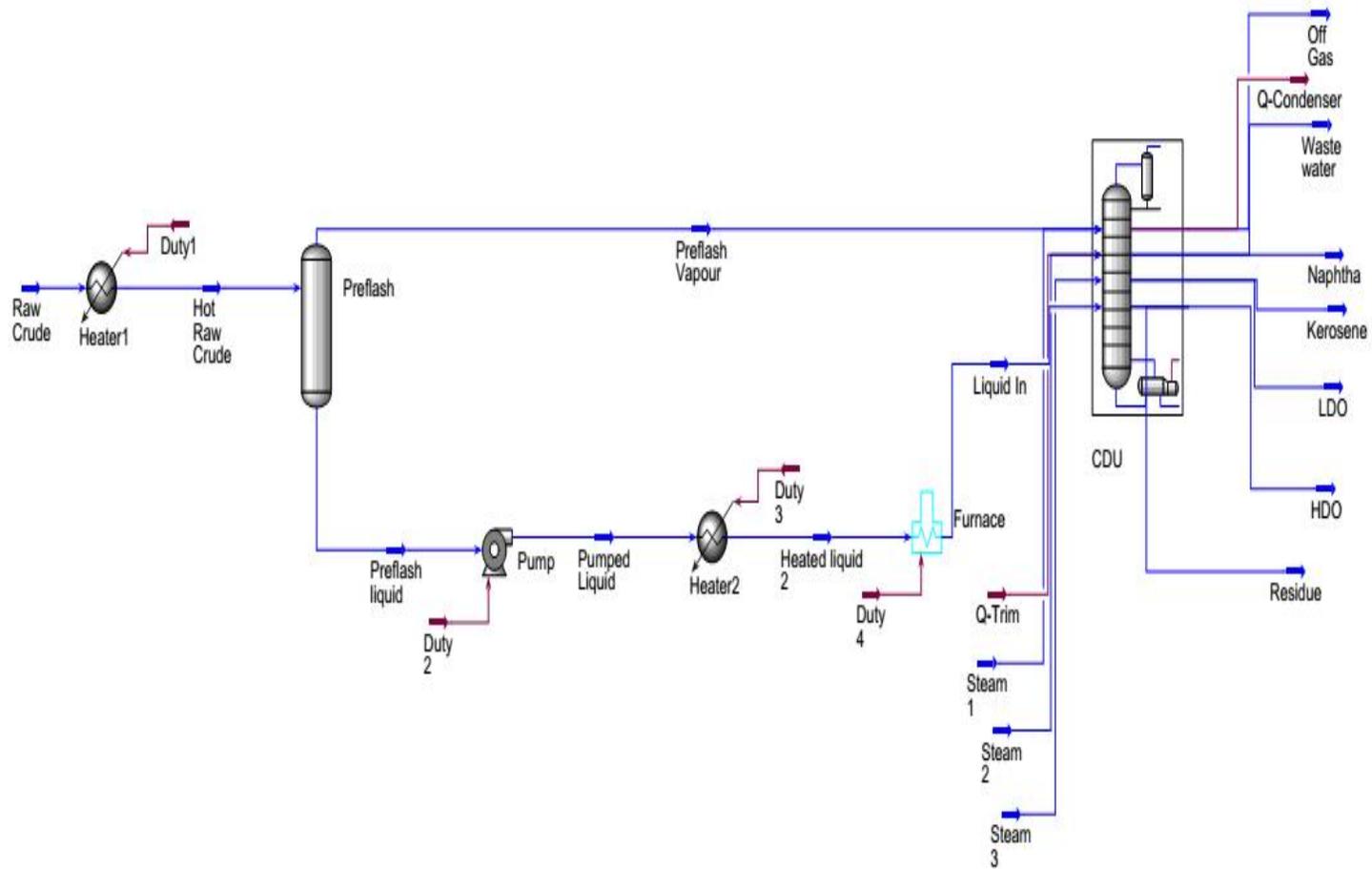| Streams	Temperature [K]	Pressure [kPa]	Molar flow [kgmole/h]
Raw Crude	396.15	2210	4846.267
Hot Raw Crude	475.15	493.4323	4846.267
Preflash Vapour	475.15	493.4323	270.0916
Preflash liquid	475.15	493.4323	4576.176
Pumped Liquid	475.7579	1915.55	4576.176
Heated liquid 2	510.15	1719.4	4576.176
Liquid IN	626.15	395.5	4576.176
Steam 1	530.15	210	310.8503
Steam 2	581.15	202.33	58.28444
Steam 3	599.15	210.17	367.4695
Off Gas	334.4193	121	6.97E-03
Naphtha	334.4193	121	2265.652
Waste water	334.4193	121	721.9591
Residue	666.4272	210	768.2184
Kerosene	518.8966	179.8404	722.6215
LDO	560.821	191.0426	957.7515
HDO	561.3861	199.6596	146.6618

Fig. 4. Simulation diagram of the CDU for New Port Harcourt refinery [19]
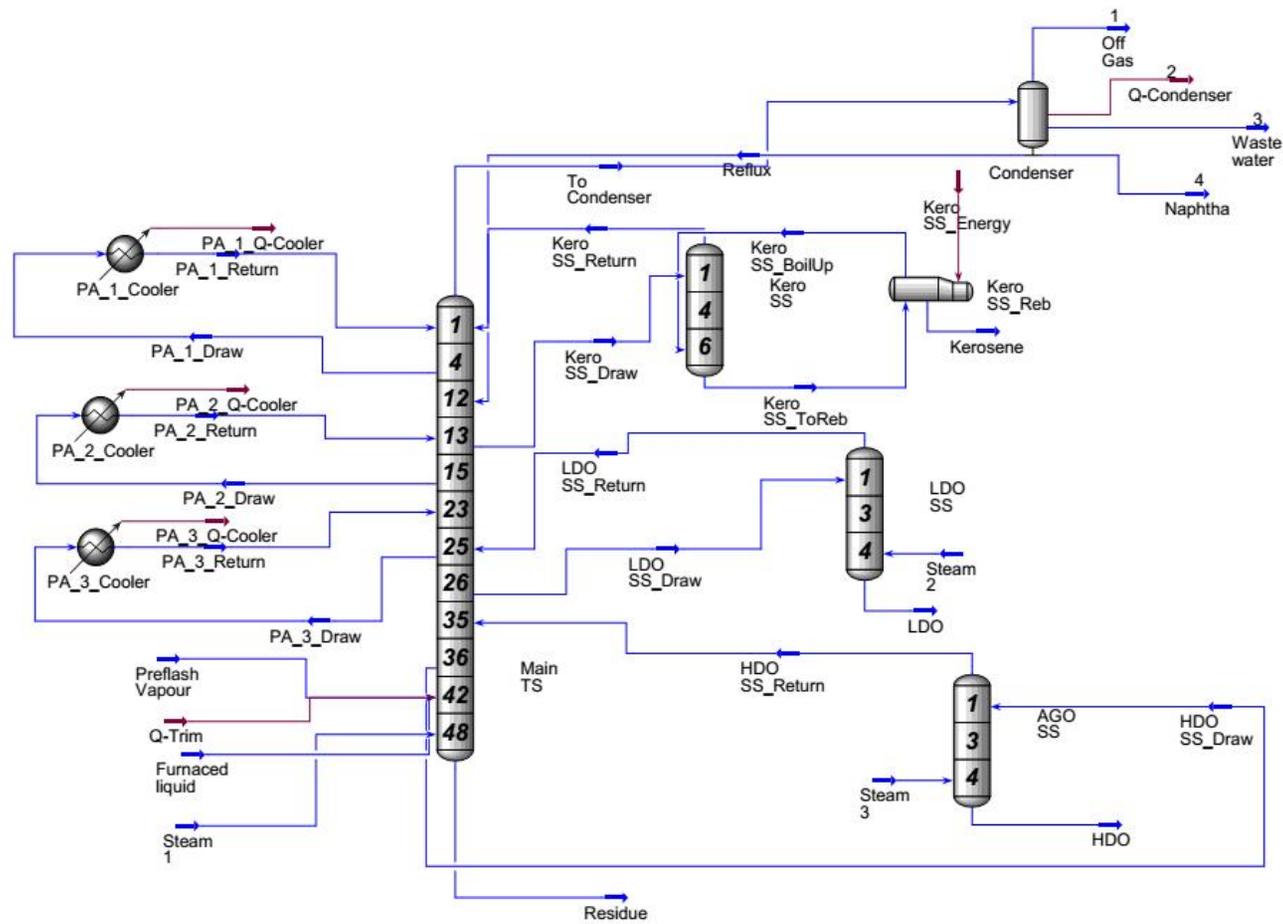
Fig. 5. Simulation diagram of the atmospheric distillation unit [19]

Table 4. State parameters from the simulation [19]

Streams	Temperature [K]	Pressure [kPa]	Molar flow [kgmole/h]	Molar enthalpy [kJ/kgmole]	Molar entropy [kJ/kgmole-K]	Physical Exergy (MW)	Total exergy (MW)	Enthalpy (MW)
Raw Crude	396.15	2210	4846.267	-346137	254.2901	7.352417	7.3875456	48.35482
Hot Raw Crude	475.15	493.4323	4846.267	-311267	335.2233	21.8103	21.845424	95.29649
Preflash Vapour	475.15	493.4323	270.0916	-130255	183.9727	1.063672	1.289169	4.400336
Preflash liquid	475.15	493.4323	4576.176	-321951	344.1503	20.58496	20.60887	90.90949
Pumped Liquid	475.7579	1915.55	4576.176	-321467	344.3255	21.13343	21.157339	91.52435
Heated liquid 2	510.15	1719.4	4576.176	-304836	378.1802	29.44346	29.467369	112.6652
Liquid IN	626.15	395.5	4576.176	-220477	529.3757	79.37454	79.398448	219.8988
Steam 1	530.15	210	310.8503	-233896	187.3189	1.078273	1.0809121	4.518121
Steam 2	581.15	202.33	58.28444	-232048	190.9534	0.214548	0.2171865	0.877063
Steam 3	599.15	210.17	367.4695	-231392	191.7497	1.395352	1.3979904	5.596587
Off Gas	334.4193	121	6.97E-03	-148192	158.3043	2.71E-06	0.4290047	3.43E-05
Naphtha	334.4193	121	2265.652	-207746	51.03373	0.261046	0.3362186	4.534764
Waste water	334.4193	121	721.9591	-283398	62.635	0.031969	0.0346081	0.565984
Residue	666.4272	210	768.2184	-438986	1117.176	25.89994	25.899937	69.63923
Kerosene	518.8966	179.8404	722.6215	-269029	309.5246	4.49242	4.4924584	16.88083
LDO	560.821	191.0426	957.7515	-328185	496.6708	10.62238	10.622379	35.42203
HDO	561.3861	199.6596	146.6618	-418314	672.9251	2.044832	2.0448267	6.82418

3.1 Artificial Neural Network (ANN) Results

The ANN was used to determine the optimum operating parameters that were obtained from the simulation results in other to get highest exergy efficiency without compromising the products qualities.

3.2 Artificial Neural Network Model

The ANN was trained to represent the knowledge data base of the ADU operating system using the ADU simulated runs from HYSYS. 2840 data set as used in training the ADU. 15% of the data set was used to test the trained model. The relative error of the trained model and tested data was below $1x10^{-4}$ which shows that the ANN model was quite reliable in describing the input-output

relationship of the ADU. The ANN model was able to adequately represent the complex process of the ADU due to non-linear characteristics of the ANN structure. Fig. 6 illustrate the best linear regression fit of the training, testing, and validation and their combination for output and the target data of the ADU which is equals to 1. Fig. 7 presents the validation performance of the ADU which is 0.37143.

All of this showed that the trained model for the refinery predict accurately and it determines the outcome of changes in any of the input parameters. It also correlates the relationship between the input and output variables of the refinery. It also predicts and point out the effects of the operating variables on the products as well as the efficiency.
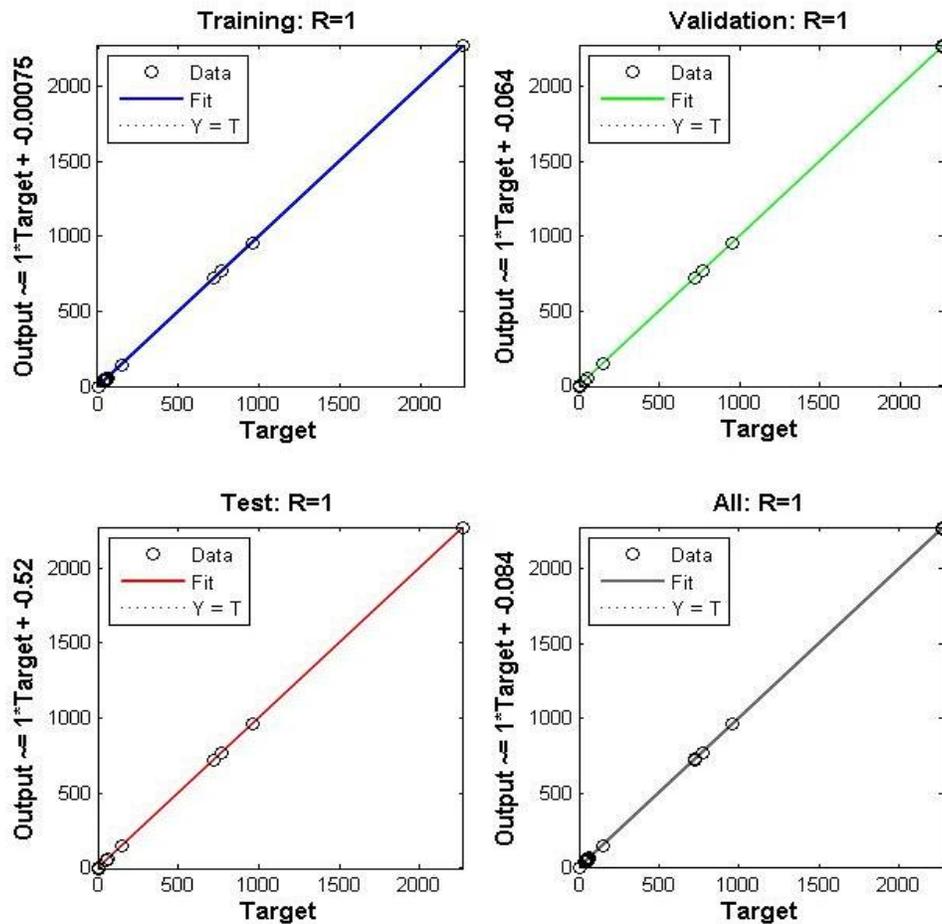

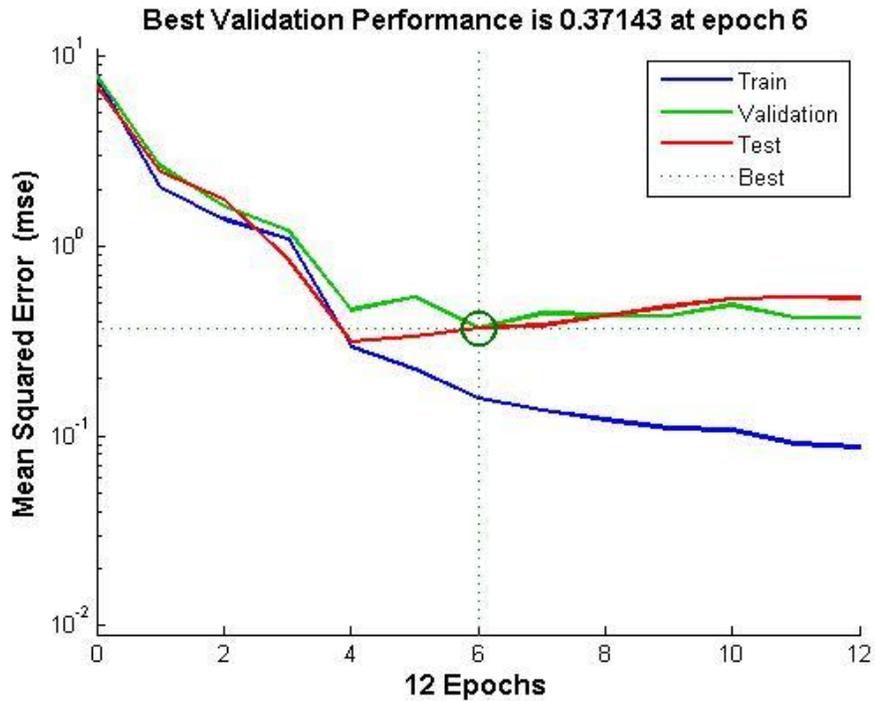**Fig. 6. Correlation between the predicted values and simulated values [19]**

Fig. 7. Validation performance [19]

Table 5. Operating variables with minimum and maximum values before optimization

	Minimum operating value	Maximum operating value
Liquid inlet temperature	586.1 ºK	706.1 ºK
Liquid inlet pressure	345.5 kPa	595.5 kPa
Condenser temperature	304.4 ºK	394.4 ºK
Condenser pressure	115 kPa	133 kPa
Pump-around flow rate 1	520.6 m^3/h	920.6 m^3/h
Pump-around flow rate 2	607.9 m^3/h	1007.9 m^3/h
Pump-around flow rate 3	278.8 m^3/h	678.8 m^3/h

3.3 Optimum Operating Conditions

The optimization problem which consists of an objective function (exergy efficiency of 51.9% which was calculated with Equation 3) was maximized with constraints from design and operating conditions. The operating variables liquid inlet temperature, liquid inlet pressure, condenser temperature, condenser pressure, pump-around flow rate 1, 2 and 3 with maximum and minimum values within which the simulation of the refinery will converge on the HYSYS software were as shown in Table 5.

The knowledge database of the neural network model was used in the optimization procedures. About 96 generations were made and the output with the least error was returned as optimum.

The optimum operating variables derived after ANN optimization were liquid inlet temperature, liquid inlet pressure, condenser temperature, condenser pressure, pump-around flow rate 1, 2 and 3 were as shown in Table 6.

Table 6. Operating variables values after optimization with ANN

	Operating value
Liquid inlet temperature	586.1 ºK
Liquid inlet pressure	410.0 kPa
Condenser temperature	332.6 ºK
Condenser pressure	127.5 kPa
Pump-around flow rate 1	696.3 m^3/h
Pump-around flow rate 2	799.0 m^3/h
Pump-around flow rate 3	585.8 m^3/h

The corresponding exergy efficiency for these combinations was 70.6%. This was a great improvement because the exergy efficiency increased as compared to the base case of 51.9%. The ANN predicted the optimum operating conditions at which the ADU can operate with the least irreversibility and without changing the design and compromising the products quality. This can assist the operators in the decision making of running the column efficiently and thus reduce the environmental implications of unutilized energy.

4. CONCLUSION

The corresponding exergy efficiency for the combinations using ANN as optimization tool was 70.6% as compared to the base case of 51.9%. Optimization using ANN, improved the efficiency of the ADU with the least irreversibility and without changing the design and compromising the products quality.

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COMPETING INTERESTS

Author has declared that no competing interests exist.

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