ANN Based Surrogate Model for Exergy Efficiency Optimization of Heat Exchanger Network of a Crude Distillation Unit Under Uncertainty

By

Kamran Zeb

School of Chemical and Materials Engineering

National University of Sciences and Technology

2023

ANN Based Surrogate Model for Exergy Efficiency Optimization of Heat Exchanger Network of a Crude Distillation Unit Under Uncertainty

Name: Kamran Zeb

Reg No: 00000327288

This work is submitted as an M.S. thesis in partial fulfillment of the requirement for the degree of

M.S. in Process Systems Engineering

Supervisor Name: Dr. Iftikhar Ahmad

School of Chemical and Materials Engineering (SCME)

National University of Sciences and Technology (NUST)

THESIS ACCEPTANCE CERTIFICATE

Certified that final copy of MS thesis written by Mr **Kamran Zeb** (Registration No 00000327288), of School of Chemical & Materials Engineering (SCME) has been vetted by undersigned, found complete in all respects as per NUST Statues/Regulations, is free of plagiarism, errors, and mistakes and is accepted as partial fulfillment for award of MS degree. It is further certified that necessary amendments as pointed out by GEC members of the scholar have also been incorporated in the said thesis.

Signature: ______________

Name of Supervisor: Dr Iftikhar Ahmad

Date: 06-12-2023

Signature (HOD): ______________

Date: 12/12/23

Signature (Dean/Principal): ______________

Date: 12-12-2023

Form TH-1

National University of Sciences & Technology (NUST)

MASTER'S THESIS WORK

Formulation of Guidance and Examination Committee (GEC)

Name: Kamran Zeb
NUST Reg No: 00000327288

Department: Department of Chemical Engineering
Specialization: Master of Science in Process System Engineering

Credit Hour Completed: 24.0
CGPA: 3.88

Course Work Completed

S/No:	Code:	Title:	Core/Elective:	CH:	Grade:
1.	PSE-801	Process Systems Theory	Compulsory	3.0	A
2.	RM-898	Research Methodology	Additional	2.0	Q
3.	TEE-820	Process Intensification	Compulsory	3.0	B+
4.	PSE-852	Process Modelling and Simulation	Compulsory	3.0	A
5.	PSE-802	Optimization and Decision Analysis	Compulsory	3.0	A
6.	PSE-823	Advanced Process Dynamics and Control	Compulsory	3.0	B+
7.	EME-902	Numerical Methods In Chemical Engineering	Elective	3.0	A
8.	CSE-801	Computational Fluid Dynamics	Elective	3.0	A
9.	ENE-809	Waste Water Treatment & Design	Elective	3.0	A

Date 14 - Oct - 2022
Student's Signature [redacted]

Thesis Committee

1. Name: Iftikhar Ahmad **(Supervisor)** — Signature
   Department: Department of Chemical Engineering
2. Name: Muhammad Ahsan **(Internal)** — Signature
   Department: Department of Chemical Engineering
3. Name: Dr. Nouman Ahmad **(Internal)** — Signature [redacted]
   Department: Department of Chemical Engineering

Date: 14 - Oct - 2022
Signature of Head of Department: 20/1/23

APPROVAL

Date: 14 - Oct - 2022
Signature of Dean/Principal: 27-1-2023

Form: TH-04

National University of Sciences &Technology (NUST)

MASTER'S THESIS WORK

We hereby recommend that the dissertation prepared under our supervision by

Regn No & Name: 00000327288 Kamran Zeb

Title: **ANN Based Surrogate Model for Exergy Efficiency Optimiaztion of Heat Exchangers Network of a Crude Distillation Unit Under Uncertainty.**

Presented on: **12 Oct 2023** at: **1500 hrs in SCME on MS Teams**

Be accepted in partial fulfillment of the requirements for the award of Master of Science degree in **Process Systems Engineering**.

Guidance & Examination Committee Members

Name: **Dr Nouman Ahmad** Signature:

Name: **Dr Muhammad Ahsan** Signature:

Supervisor's Name: **Dr Iftikhar Ahmad** Signature:

Dated: 02/11/2023

Head of Department
Date 2/11/23

Dean/Principal
Date 2/11/2023

School of Chemical &Materials Engineering (SCME)

Dedication

To my Loving, Caring and

Supportive Family

Acknowledgement

First and foremost, praise is to Almighty Allah Who bestowed upon me with His blessings and guided me in completing this task. It would not have been possible without the support of my family and the foremost help and support of several individuals/colleagues who were available all the time and helped me with their suggestions to compile this work.

I extend my heartfelt gratitude to my supervisor, **Dr. Iftikhar Ahmad**, for his timely advice and valuable, practical approach during this research work. It would be worth mentioning here that it is only his constant pursuance that leads to complete my work. There were so many hurdles and difficulties during my research work, but he remained not always available but chased me to complete the work more efficiently.

I also express my appreciation to **Dr. Muhammad Ahsan** and **Dr. Nouman Ahmad**, members of my Guidance and Examination Committee (GEC), for their invaluable assistance. Furthermore, the contributions of numerous postgraduate students are acknowledged, they have been an incredible source of encouragement and support.

Kamran Zeb

Abstract

In this work, a combined framework of the Artificial Neural Network and Genetic Algorithm was developed to realize higher exergy efficiency of Heat Exchanger Network of a Crude Distillation Unit, under uncertainty in process conditions. Initially, the steady-state exergy analysis was carried out using an Aspen HYSYS model to quantify the exergy destructions and exergy efficiencies of all the individual heat exchangers and the overall Heat Exchanger Network. Then the Aspen HYSYS model was changed to dynamic mode by introducing uncertainty of ±5% in various process parameters, i.e., temperatures, pressures, and mass flow rates of different process streams, to produce a dataset of 200 samples for HEN of CDU. Using the dataset, an ANN model was generated for the prediction of overall exergy efficiency of HEN. The trained ANN model was then used as a surrogate in the GA environment to attain improved overall exergy efficiency of the HEN in the presence of uncertainty. Using a GA-based approach, the optimized process conditions were found and then put into the Aspen HYSYS model for the purpose of cross-validation. The overall exergy destruction and exergy efficiency of the HEN were 17611.21 kW and 63.34%, respectively. The trained ANN model had a correlation coefficient (R) of 0.9996 and an RMSE of 0.0097 for overall exergy efficiency of HEN. The performance of the GA-based approach was good enough, and it significantly enhanced the overall exergy efficiency of HEN when compared to standalone Aspen HYSYS model of the process.

Keywords: Artificial Neural Network, Genetic Algorithm, Exergy efficiency, Exergy destruction, Heat Exchanger Network, Crude Distillation Unit, Uncertainty, Machine learning

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Nomenclature

CDU	Crude Distillation Unit
HEN	Heat Exchanger Network
ANN	Artificial Neural Network
GA	Genetic Algorithm
HS	Hot Streams
CS	Cold Streams
DCU	Delayed Cocking Unit
E	Exergy
E_{PH}	Physical exergy
E_{PT}	Potential exergy
E_{KN}	Kinetic exergy
E_{CH}	Chemical exergy
I	Irreversibility
I_{ex}	Irreversibility of heat exchanger
I_{HEN}	Irreversibility of heat exchanger network
E_d	Exergy destruction
$E_{H,in}$	Exergy of hot inlet stream
$E_{H,out}$	Exergy of hot outlet stream
$E_{C,in}$	Exergy of cold inlet stream
$E_{C,out}$	Exergy of cold outlet stream
T	Temperature
T_o	Reference temperature
S_{gen}	Entropy generated
η_{ex}	Exergy efficiency of heat exchanger
η_{HEN}	Exergy efficiency of heat exchanger network
E_p	Exergy produced
E_c	Exergy consumed
T_C	Temperature of cold stream
T_H	Temperature of hot stream

x_i	Inputs
w_i	Weights
RMSE	Root Mean Squared Error
R	Correlation coefficient
n	No. of test samples
Yi	Predicted value
Y_i^{exp}	Actual value
ROM	Reduced Order Model

Chapter 1

Introduction

1.1 Background

The significance of enhanced energy efficiency in industrial production is increasing due to its environmental, economic, and commercial implications. In addition to having immediate economic advantages such as better competitiveness and distinguished productivity, enhanced energy efficiency is a very promising approach for mitigating CO_2 emissions that are the consequence of fossil fuel utilization. The prioritization of energy efficiency is of particular significance for several industries operating in established and energy-intensive sectors. These industries often experience energy prices that exceed 30% of their overall production costs, necessitating a strategic focus on energy efficiency to maintain competitiveness in the future [1].

The petroleum refinery is widely recognized as being among the most energy-intensive industries. Therefore, it is imperative to achieve an energy-efficient approach to both the design and operation of processes. Crude oil processing in crude distillation unit (CDU) uses most of the energy because a large amount of heat is needed to fractionate the oil. The CDU accounts for about 15% to 25% of the whole energy used during the total refining process [2, 3]. **Figure 1** displays many possible opportunities for energy saving within the context of a petroleum refinery. As depicted from **Figure 1**, the crude distillation unit presents a significant opportunity for energy saving. Therefore, enhancing the energy efficiency of any process is always a priority to improve its viability and sustainability.

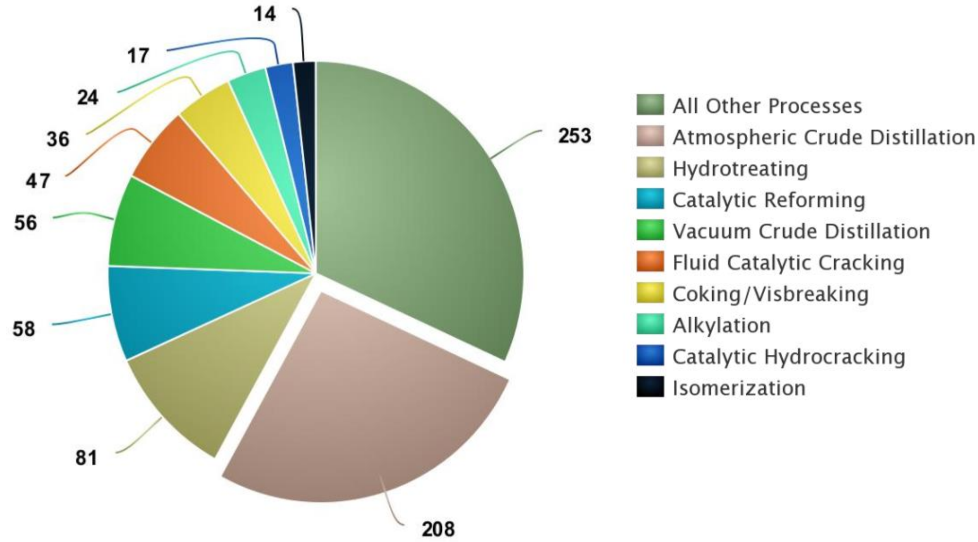

Figure 1: Potential of improvement for energy savings in petroleum refineries [4]

The processing of crude oil commonly involves the utilization of several units in order to obtain its end products, such as kerosene, petrol, and the other significant fuels. During the initial phase of treatment, the crude oil is fed into an atmospheric distillation column at a temperature that is quite high, almost 360 °C, which is subject to variation based on the specific conditions of the refinery and the origin of the crude oil. Initially heated up in a pre-heat train, crude oil then flows into the furnace, where the highest amount of energy is spent. Enhancing the energy efficiency of pre-heat train is necessary to raise the crude oil's temperature prior to the furnace to reduce the energy demand inside the furnace and, accordingly, the refinery's overall energy expenditure. The HEN of a Crude Distillation Unit includes crude pre-heat train along with some utilities heat exchangers. The pre-heat train is a distinctive HEN, which involves the interconnection of many heat exchangers with the goal of maximizing heat transfer among these various heat exchangers [5].

The analysis of heat exchanger networks (HENs) is significant in the management of cost and energy consumption. In latest years, there has been a notable acceleration in the advancement of this field [6]. The assessment of energy losses and potential for improvement can be generally classified into two distinct categories. The first approach is based upon typical energy analysis, which relies solely on the first law of thermodynamics and simply measures the amount of energy wasted relative to the amount of energy put in without considering the energy's quality or its potential for driving a process [7]. While the other is based upon exergy analysis, which combines both the first and second laws of thermodynamics to determine the process's correct thermodynamic improvement potential [8, 9].

Numerous researchers have made substantial contributions through the utilization of these methodologies. The utilization of pinch analysis for the purpose of reducing thermal energy has been extensively used in the petrochemical and refining industries for a significant period of time. Various other industries, including the pulp and paper, chemicals, and food and beverage industries have also experienced advantageous outcomes as a result of implementing pinch analysis techniques [6]. The primary purpose of heat integration is to minimize the reliance on external energy sources, commonly referred to as utilities, by enhancing the recovery of energy between the hot streams (HS) and cold streams (CS) within the process. The pinch technique is employed for the determination of the optimal degree of heat recovery, which is dependent on the minimum temperature difference in the heat exchangers, denoted as DT_{min}. This method is applied to calculate the quantity of heat that can be exchanged between the hot and cold streams within the system, requirement of cold and hot utilities, as well as the minimum energy requirements (MER).

Exergy corresponds to the amount of energy that is available to be utilized. Exergy is a thermodynamic property that quantifies the maximum valuable work that may be acquired from a system when it comes into thermodynamic equilibrium with its surrounding [10]. The exergy analysis method has several benefits compared to traditional energy analysis due to its ability to identify the specific locations and types of irreversibilities occurring inside a particular system [11]. Whenever an irreversible process occurs, exergy is destroyed. It is the exergy dissipation that forces the process of heat transfer. Hence, it is more practical to evaluate exergy efficiency based upon the second law of thermodynamics than the conventional energy efficiency [12].

1.2 Objectives

The key objectives of the thesis are given below:

- Steady state exergy analysis of HEN of a crude distillation unit in Aspen HYSYS

- Development of an ANN model to investigate the effect of various process conditions on the overall exergy efficiency of HEN under uncertainty.
- Architecture optimization of ANN model
- Genetic algorithm-based optimization of overall exergy efficiency of HEN through ANN model

1.3 Thesis Outline

The thesis is ordered as follows. Chapter 1 describes the background and objectives, followed by chapter 2, which gives a detailed literature review. Chapter 3 discusses the research methodology to develop the framework to predict and optimize the overall exergy efficiency of HEN. Chapter 4 includes the results and discussion about steady-state exergy analysis and the optimization framework. In last section, conclusions of the research work are given.

Chapter 2

Literature Review

2.1 Literature Review

The crude distillation unit (CDU) is regarded as a primary processing unit of the refinery due to its substantial processing capability. The unit primarily comprises of a crude oil heater or furnace, a network of heat exchangers, and distillation columns. CDU fractionates the entire crude oil into fractions with the desired boiling ranges such as naphtha, kerosene oil and diesel etc. The stream of crude oil must be heated up to the required temperature in the furnace, for the purpose of its fractionation. Consequently, the traditional refining of crude oil in CDUs requires a substantial amount of heat energy and stripping steam. Petroleum refinery operators consistently seek to enhance the operational efficiency and energy utilization of their Crude Distillation Units (CDUs) in order to optimize gross margins and mitigate carbon emissions [13, 14].

To reduce the energy requirement inside the furnace, it is often required to increase the temperature of crude oil prior to its entry into the furnace by using a series of heat exchangers, collectively known as crude preheat train. Crude preheat train takes advantage of heat integration. Crude oil is preheated by taking advantage of heat from hot products and pump arounds of distillation column. Overall Heat exchanger network of a Crude Distillation Unit includes crude pre-heat train along with some utilities heat exchangers. Thus, the crude oil is preheated ahead of the furnace and the hot products of distillation are cooled down before they run down from the CDU.

Analysis of Heat exchanger networks (HENs) performs a fundamental role in the optimization of energy expenditure and cost. Several approaches have been implemented by researchers and designers to enhance the integration of heat exchanger network (HEN) and distillation, and as well as to enhance the design and retrofitting of HEN with the objective of reducing energy utilization. This can be accomplished through the reduction of process energy requirements or the maximization of process energy recovery [13]. The analysis of HENs, involving the identification of energy losses and potential areas for improvement, can generally be divided into two distinct categories. The first approach is based upon typical energy analysis, which relies solely on the first law of thermodynamics. However, the other is based upon exergy analysis, which combines both the laws of thermodynamics, the first and second laws of thermodynamics, to determine the process's actual thermodynamic improvement potential.

Several research studies based upon the first law of thermodynamics have been reported regarding the HENs of refineries. Most of the previous HENs analysis research methodologies are based on pinch analysis methods. For example, Mehdizadeh-Fard et al. [15] performed an assessment of a real-life case study involving a complicated natural gas refinery. The methodology of pinch analysis was employed to enhance the heat recovery and optimize the total cold and hot utilities for main processing units. The methodology employed in this study involved the utilization of a comprehensive approach known as super-targeting, which focused on the overall heat transfer area and cost. Two fundamental methodologies were devised: the "overall pinch method" for addressing both the cold and hot process streams collectively, and the "zonal targeting method" for targeting five distinct areas inside the refinery, each comprising some processing units. Subsequently, a comparative analysis was done to assess the outcomes, and the potential for improvement was determined for both cases. The results pointed a significant improvement in overall energy utilization and heat recoveries with the implementation of the “zonal targeting method” in the retrofitted HEN.

The use of pinch analysis approach has also been employed to decrease the energy expenditure of the crude distillation unit. Exercising pinch analysis, Ajao et al. [16] carried out the energy integration of crude pre-heat train of CDU I of the Kaduna Refinery and Petrochemicals industry. An entire cost index of 0.208 cost/s was required to achieve the optimal minimum approach temperature of 15 ℃. The temperature at the pinch point was found to be 220 ℃. It was found that the utilities targets for minimum approach temperature should be 1.112 x 108 kJ/hr for hot utilities and 1.018 x 108 kJ/hr for the cold utilities, correspondingly. To achieve the highest possible level of energy recovery, a total of 38 heat exchangers were necessary.

Similarly, Al-Mutairi et al. [17] carried out heat integration and retrofitting of HEN of a CDU. Pinch analysis of the existent design provided the scope for retrofitting project to be included in the design. The pinch methodology of network was used to identify the

HEN that maximized energy recovery inside the process. Multiple choices of design and subsequent revisions were conducted, ultimately resulting in the selection of the most optimal design. The economic assessment of the chosen design revealed a reduction in hot utilities and cold utilities consumption of 8.4% and 10.9%, correspondingly, compared to the present design. Furthermore, an annual savings in energy costs of $259860 was achieved. The payback time for the project of retrofitting the current HEN to cope up with the novel revised design was determined to be eleven months.

In another study, Bulasara et al. [18] performed the revamp study of HEN in the CDU of an actual refinery. This study investigated the effect of including the available unrestricted hot streams from the Delayed Coking Unit (DCU). The research investigated two sub-cases for revamping based on the pinch design method: (a) to install the new heat exchangers for whole network, and (b) to reutilize the current heat exchangers. The purpose of this research was to evaluate the possibility for heat integration of the accessible free hot streams of DCU section. Additionally, the profitability of these streams was analyzed when they were thermally coupled with the CDU, beside the revamp study. Mamdouh A. Gadalla [19] developed a novel graphical approach for describing an existing heat exchanger network or crude preheat train. The temperatures of cold streams were plotted against the temperatures of hot streams to represent the details of exchangers. The newly developed graphs facilitated the analysis and evaluation of performance of the present HENs in accordance with the rules of Pinch Analysis. The study detected energy inefficiencies in the present HEN and proceeded to the assessment of possible energy recovery by statistically assessing these inefficiencies. Alhajri et al. [20] applied the graphical representation method proposed by Gadalla to retrofit an existing HEN with the objective of optimizing the operations of a crude oil distillation process. The graphical method was implemented to investigate a case study involving a petroleum refinery situated in Kuwait. The primary aim of this investigation was to conduct an energy analysis and propose retrofitting measures for the present HEN. The study determined the minimum levels of utilities consumptions and proposed possible energy and cost reductions. The proposed method suggested that a potential energy savings of around 27% was attainable compared to the existing operational practices.

Exergy analysis, which is based upon the second law of thermodynamics, is getting the interest of researchers because it can measure the irreversibility of a process and assess its potential for improvement. Exergy analysis has been applied in combination with pinch analysis for analyzing the HENs. Zun-long et al. [21] performed exergo-economic analysis of HENs for two case studies, to determine optimum minimum approach temperature (ΔT_{min}). Exergy consumption was calculated from the balanced composite curves, based on the pinch analysis. Instead of utilities cost, exergy consumption expense was considered as operating cost, which trades off with capital cost in order to determine the optimal ΔT_{min} for HENs synthesis.

Several studies of exergy analysis have been reported on Heat Exchanger Networks of refineries. For example, Mehdizadeh-Fard et al. [12] performed exergy analysis of the HEN at a complicated natural gas refinery, located in the South Pars gas field. The approach of advanced exergy analysis was implemented to the serving HEN in order to assess the potential for enhancing energy efficiency within the system. This assessment considered the principles of the second law of thermodynamics, as well as techno-economical constraints, with the aim of minimizing exergy destruction and maximizing energy efficiency. Avoidable and unavoidable irreversibilities were computed for every heat exchanger in the plant's network. It was determined that the total exergy efficacy of the HEN in the facility was 62.8%, which could be improved up to 84.2%, indicating a great improvement potential.

Exergy analysis has also been applied to the crude distillation unit and its HEN. Benali et al. [22] outlined a specialized application of energy integration enhancement which was accomplished by altering the flowsheet of a CDU. Exergy analysis was applied for visual representation and better understanding of the distribution of energy degradations inside the distillation column, with the purpose of identifying an appropriate solution for their reduction. The observed distribution showed the avoidable presence of lighter species all over the whole distillation column. It was proposed that including a pre-flash in the pre-heating train of distillation process, along with the proper introduction of the rising vapors into the column, may possibly result in significant energy savings. These improvements were achievable by reduction of the duty of furnace, by accomplishing some preliminary fractionation, and thus minimizing the irreversibilities of column.

In another study, Izyan et al. [23] used exergy analysis as an approach to reduce the fuel expenditure of a CDU. It was noted that the major exergy destruction was occurring in the furnace, and as a result, two potential solutions were proposed for its mitigation: first, centered on minimizing the heat loss occurring in stack of the furnace, and second, based upon raising the inlet temperature of furnace. It was also suggested to establish the appropriate cleaning schedules for heat exchangers.

Similarly, Fajardo et al. [2] performed exergy analysis of crude preheat train of a CDU by investigating a case study. Both the typical and advanced exergy analyses were applied to determine the potential of improvement for the system as well as identify the critical spots. The outcomes indicated that the overall exergy destruction of the HEN exceeded 61.6 MW, with about 63% of this being classified as avoidable exergy destruction. Five heat exchangers were recognized as being critical since they were shown to contribute 39% of the overall exergy destruction within the network. Furthermore, to enhance the assessment of performance, the influence of unavoidable exergy destruction on the evaluation of exchanger's performance was investigated by analyzing exergy efficiency.

Although several research investigations have been issued regarding the steady state exergy analysis of crude distillation units or their HENs. Similarly, the identification of improvement potentials has also been done but no work has been stated about the optimization of exergy efficiency of HEN of a crude distillation unit by applications of ANN and GA based models to the best of the author's knowledge. Furthermore, no work has been done to optimize the exergy efficiency of HEN of a crude distillation unit under uncertainty.

Chapter 3

Process Description and Methodology

3.1 Process Description

Figure 2 depicts a petroleum refinery's crude distillation section schematically. The flowsheet is based on Aspen HYSYS model of a simplified crude distillation column with a Heat Exchanger Network containing crude pre-heat train and few utilities heat exchangers. In the first section of crude pre-heat train, cold crude oil is heated to 232°C ahead of being sent to the pre-flash drum so that the light naphtha and gases are extracted from the heavy components. The second section of the preheat train heats the bottom of pre-flash drum to 279°C before transferring it to the crude furnace. The high temperature crude from the furnace is then pumped to the crude distillation column at 343°C, where it is separated into different straight-run fractions which include naphtha, kerosene, diesel, and gas oil etc. A sub-flowsheet titled "Preheat Train" has been used to model the whole Heat Exchanger Network. Two dummy heaters named "HEN-1" and "HEN-2" are included in the simulation to represent the first and second sections of the preheat train, respectively, due to tight thermal coupling between the HEN model and the crude distillation column. **Figure 3** shows the exchanger matches between the cold and hot process streams as well as the overall structure of the entire Heat Exchanger Network. As shown, the network includes twenty-one shell and tube heat exchangers that are connected together so that the heat input required in furnace can be reduced.

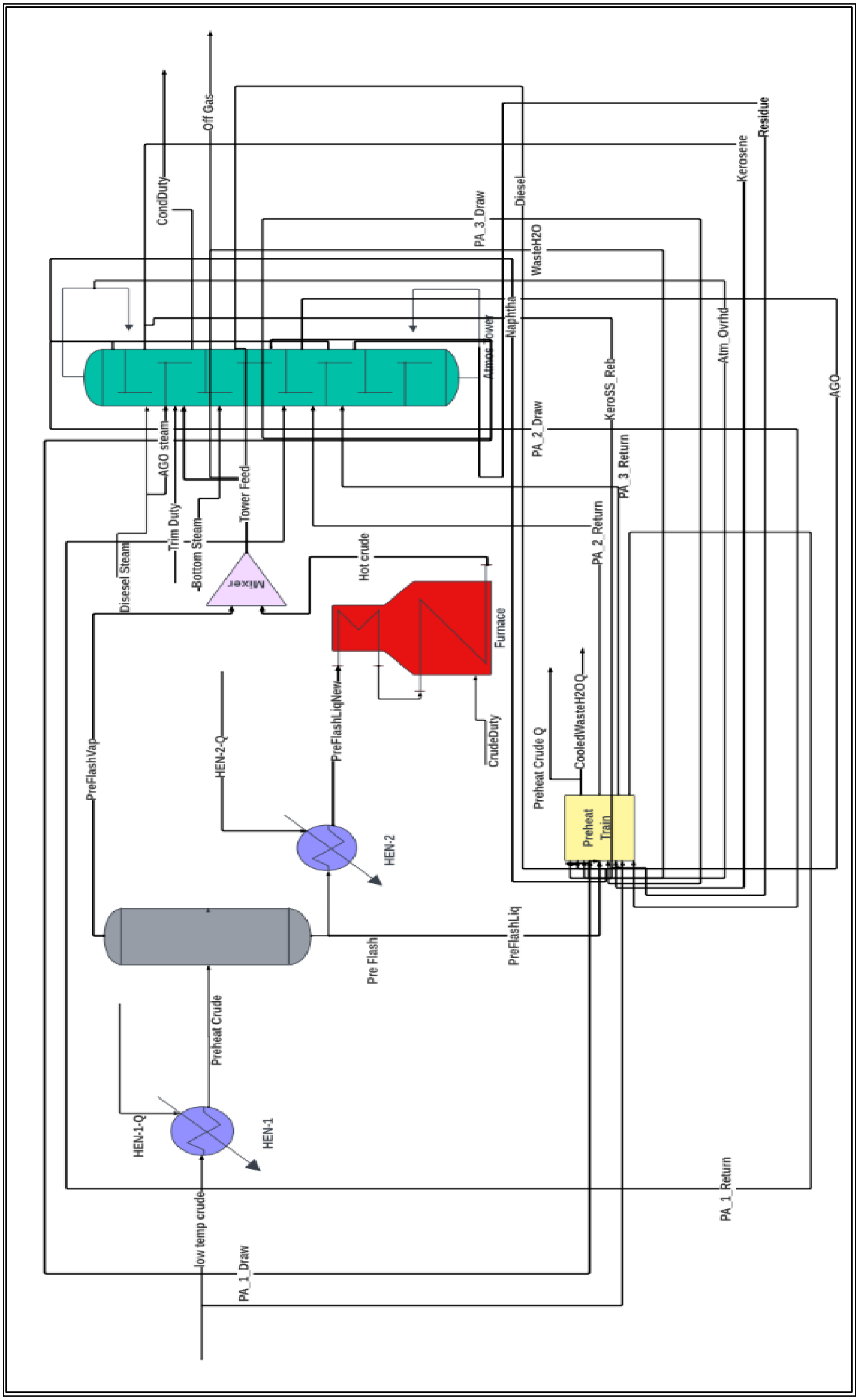

Figure 2: Flowsheet of a crude distillation unit

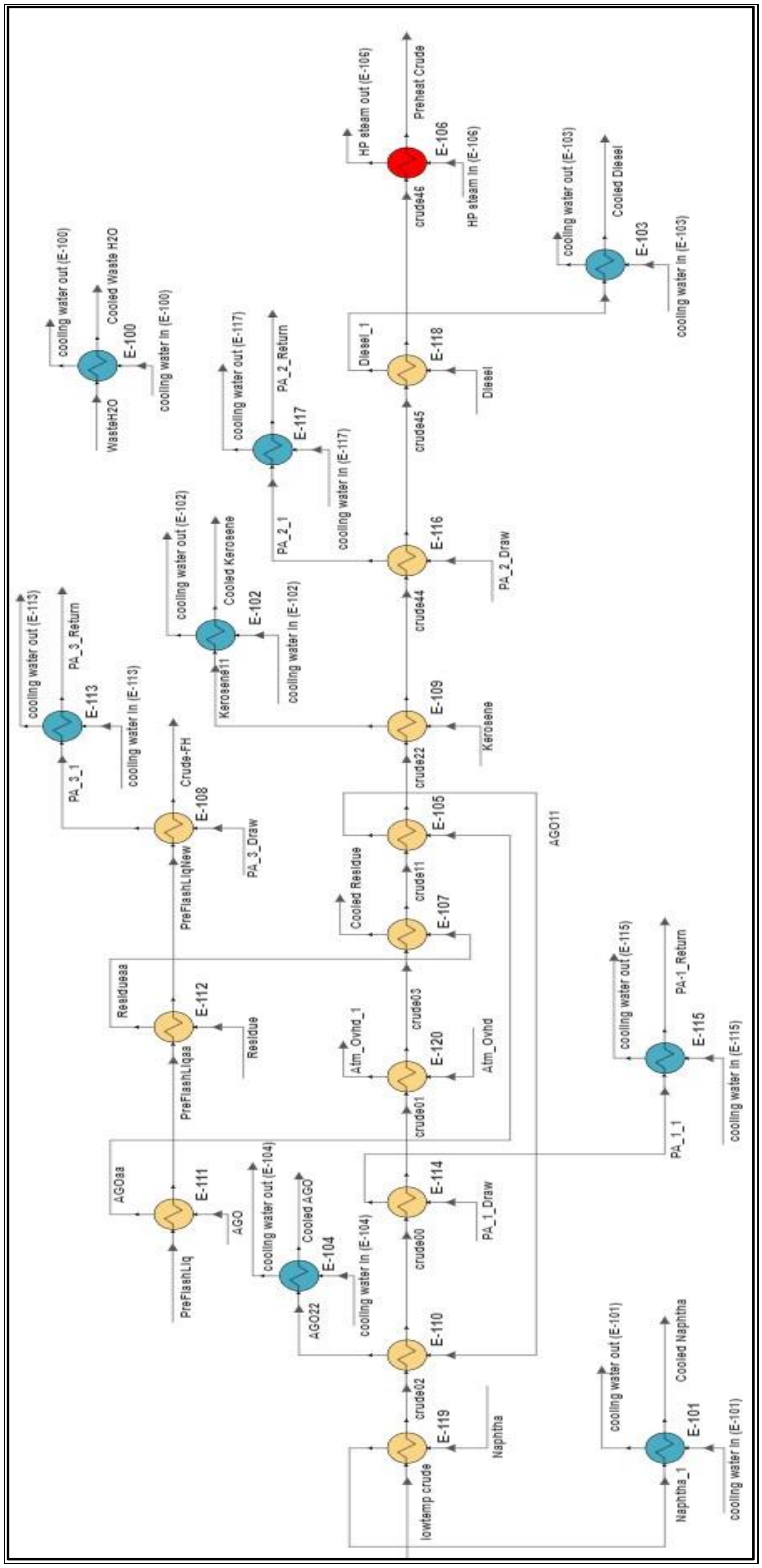

Figure 3: HEN of crude distillation unit

3.2 Exergy Analysis Formulations

Exergy can be well-defined as “the system's useful energy”. It is the summation of physical, chemical, kinetic, and potential exergies [3].

$$E = E_{PH} + E_{CH} + E_{KN} + E_{PT} \tag{1}$$

As there are no chemical reactions involved, any change in exergy of the HEN is due to physical changes. Furthermore, the changes in potential exergy and kinetic exergy can also be ignored.

3.2.1 Exergy Analysis of Heat Exchangers

The analysis of thermodynamics second law can be used to examine the distribution of exergy load inside a heat exchanger or heat exchanger network containing cold and hot process streams, to study the process of heat exchange. The values of exergy for all the input and output streams must be computed to perform an exergy balance on a heat exchanger. The following steady-state equations can be employed to perform the exergy balance of any heat exchanger.

$$I_{ex} = E_d = \left(E_{H,in} - E_{H,out}\right) + \left(E_{C,in} - E_{C,out}\right) = T_o S_{gen} \tag{2}$$

Exergy efficiency is a quantitative parameter employed to assess how effectively the exchange of exergy is occurring between cold and hot process streams of a heat-transfer process. The exergy efficacy of heat exchanger can be stated as "the ratio of exergy produced to the exergy consumed”. The exergy content of one process fluid rises while the exergy content of the other decreases in case of heat exchangers. Thus, the hot process stream or cold process stream will release or consume the exergy, accordingly.

$$\eta_{ex} = \frac{E_p}{E_c} = \frac{(E_{C,out} - E_{C,in})}{(E_{H,in} - E_{H,out})} \quad For\ T_H \& T_C > T_o \tag{3}$$

$$\eta_{ex} = \frac{E_p}{E_c} = \frac{(E_{H,out} - E_{H,in})}{(E_{C,in} - E_{C,out})} \quad For\ T_H \& T_C < T_o \tag{4}$$

The exergy content of cold process stream reduces rather than improves in case of heat transfer occurring across the ambient temperature. Because the stream creates no exergy or very minimum exergy, the efficiency will also be zero or extremely low.

3.2.2 Exergy Analysis of Heat Exchanger Network

In case of heat exchanger network, the sum of exergy destructions for all those specific heat exchangers operating in the network, can be used to compute the overall irreversibility caused due to the total heat transferred:

$$I_{HEN} = \Sigma E_d = \Sigma E_{in} - \Sigma E_{out} = \Sigma\left(E_{H,in} - E_{H,out}\right) + \Sigma\left(E_{C,in} - E_{C,out}\right) \tag{5}$$

Also, the overall exergy efficiency of entire heat exchanger network can be calculated as:

$$\eta_{HEN} = \frac{\Sigma E_p}{\Sigma E_c} \tag{6}$$

3.3 Artificial Neural Networks

In the emerging field of artificial intelligence, Artificial Neural Networks (ANNs) fulfil a crucial role. The human nervous system has served as the basis for the development of artificial neural networks, which are computational models. They can learn and remember information and can be conceptualized as a network of the processing units, which are denoted by artificial neurons, that mimic real neurons but are linked together by so many artificial synapses that are accomplished using matrices and vectors of the synaptic weights**.** The neuron processing unit in an artificial neural network can be used to represent a various objects including letters, ideas, features, or some meaningful abstraction pattern [24]. The ANN involves a complex network of artificial neurons. Neurons get inputs in the form of variables and utilize their intrinsic activation function to compute the values of the output. Every input is associated with a respective weight. As shown in **Figure 4**, the computation of the output of neuron involves a nonlinear integration of its inputs (x_1, x_2, $x_{3\ldots,}$ x_n) and corresponding weights (w_1, w_2, w_3...., w_n). The synaptic weight is determined because of the learning process. The aim of learning is to optimize the network by using a data set in which the output and input values are already specified [25].

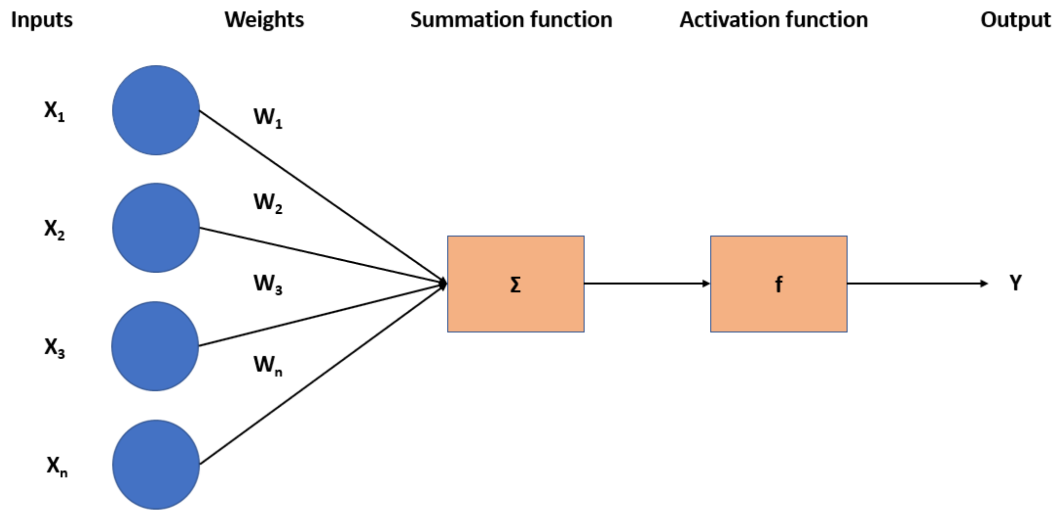

Figure 4: Neuron

A conventional ANN's algorithmic structure has at least three distinct layers, including the input layer, the hidden layer, and the output layer as shown in **Figure 5**. There are a certain number of neurons in each of these layers. Each neuron is interconnected with all neurons in the subsequent layer [26]. The input layer is tasked with receiving features, data, or information from exterior environments. The neurons located in hidden layers are responsible for obtaining information related to the system being analyzed. The output layer of neurons is tasked with generating and presenting the ultimate network outputs, which arise from the computational operations conducted by the neurons in the previous layers [27].

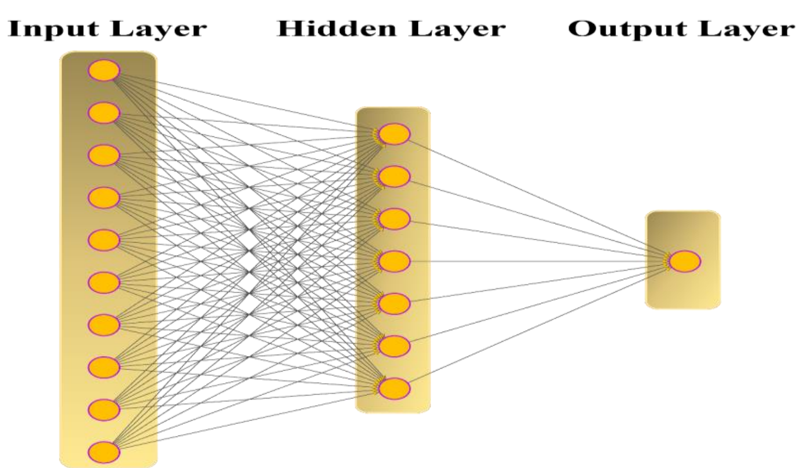

Figure 5: General ANN architecture

3.3.1 The Levenberg-Marquardt Method

This method solves the nonlinear programing problem by decreasing the sum of the squared errors between the data points and model function through a sequence of well-selected parameters updated through the Gauss-Newton update and gradient descent update, as shown in equation (7).

$$[J^{\top}WJ + \lambda(J^{\top}WJ)\,]h_{|m} = J^{\top}W(y - \hat{y}) \tag{7}$$

By varying the parameters in the steepest-descent way, the sum-up of the squared errors is reduced in the gradient descent way. Assuming that the smallest square's function is locally quadratic in the parameters and determining the least of this quadratic, the Gauss-Newton approach lowers the total of the squared errors. If the damping parameter λ is small it results in Gauss-Newton update, and if the λ is large it results in a gradient descent update. The value of λ is set to be big at the start so that the first updates are short steps in the steepest-descent path. The λ got minimized as the solution improved and the algorithm approached the Gauss-Newton method the solution moved toward a local minimum [28].

3.3.2 ANN Performance

Using the criteria of correlation coefficient (R) and root mean squared error (RMSE), the performance of ANN model was evaluated. Equation (8) has been used to calculate the RMSE values [29].

$$RMSE = \sqrt{\frac{1}{n}\sum_{i}^{n}(Y_i^{exp} - Y_i)^2} \tag{8}$$

where *n* denotes the no. of test samples, Y_i^{exp} represents the actual value and Y_i is the predicted value.

3.4 Genetic Algorithm

Genetic algorithm (GA) is an optimization technique inspired by natural selection. It operates on the basis of the survival of the fittest concept, hence making it a population-founded search algorithm. The fundamental elements of GA are the chromosomal representation, selection process, crossover and mutation operations, and also the fitness function evaluation [30, 31]. The algorithm consistently updates the population of unique solutions. At each step, the GA produces off springs to form the subsequent generation. The process involves the random nomination of individuals from the existing population, who are then used as parents in order to establish the optimal solution based on the fitness function. The algorithm terminates when the criteria of the objective function are met. Otherwise, the iterative assessment process is repeated till the population progressively converges towards the optimal solution, facilitated by the mechanisms of crossover, mutation, and selection probabilities [30]. **Figure 6** depicts a general flowchart of a genetic algorithm, outlining the steps and processes within the algorithm.

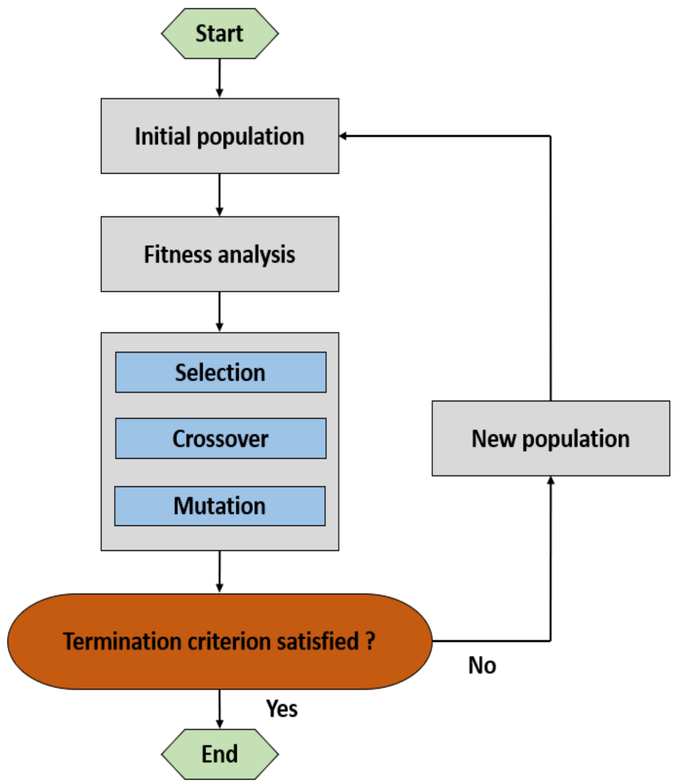

Figure 6: Schematic representation of Genetic Algorithm

3.4.1 Genetic Algorithm Operators

The functions of all the genetic algorithm operators are as follow:

3.4.1.1 Population

An initial group of the population was generated randomly. Each possible solution is called a chromosome as shown in **Table 1**.

$$P = \{p_1, p_2, \dots, p_{pop\_size}\} \tag{9}$$

$$p_i = \left[p_{i_1}\, p_{i_2}\, \cdots\, p_{i_j}\, \cdots\, p_{i_{no-vars}}\right] \tag{10}$$

$$para\,{}^{j}_{min} \le p_{i_j} \le\, para\,{}^{j}_{max} \tag{11}$$

Table 1: Chromosomes

Chromosome No. 1	1011000101110010
Chromosome No. 2	1001010110111001

In equation (9) pop_size indicate the total size of population, and no_vars in equation (10) indicate the number of variables to be tuned, $para^{j}_{min}$ and $para^{j}_{max}$ are the smallest and highest values of parameter p_{i_j}.

3.4.1.2 Selection

During the process of selection, both the chromosomes which are selected for reproduction and mating and the number of off springs that each selected chromosome generates are determined. The primary objective of the process of selection is “the better an individual is; the higher is its probability of being selected as a parent” [32]. Some well-known selection methods are as follow:

Tournament Selection. This is widely considered to be the most prevalent in the field of genetic algorithms due to its notable efficiency and simple implementation [33]. The process of tournament selection involves the random pick-up of individuals from an extended population. Subsequently, there is a competition among the individuals who have been selected. The competition serves the purpose of identifying the individual having greatest fitness value, which will subsequently be utilized in the production of a new population. The individuals involved in the competition are often organized into pairs, commonly referred to as binary tournaments or tournament size. The tournament selection process guarantees diverseness by providing a same opportunity for all individuals to be selected, despite the potential drawback of reduced convergence speed. One of the advantages of tournament selection is its ability to effectively use time, particularly when implemented in parallel. This approach also exhibits minimal vulnerability to being dominated by certain individuals, hence enhancing its robustness. Additionally, tournament selection eliminates the need for fitness scaling or sorting procedures [34].

Proportional Roulette Wheel Selection. In roulette wheel selection probable strings are plotted onto a wheel, and fractions of the wheel are allocated depending on their respective fitness values. The wheel is then randomly revolved to choose the particular solutions that will take part in the creation of the upcoming generation, as shown in **Figure 7**. Rank selection is upgraded from of roulette wheel. Individuals are evaluated based on their ranks rather than fitness value, giving every individual a chance to get selected [35].

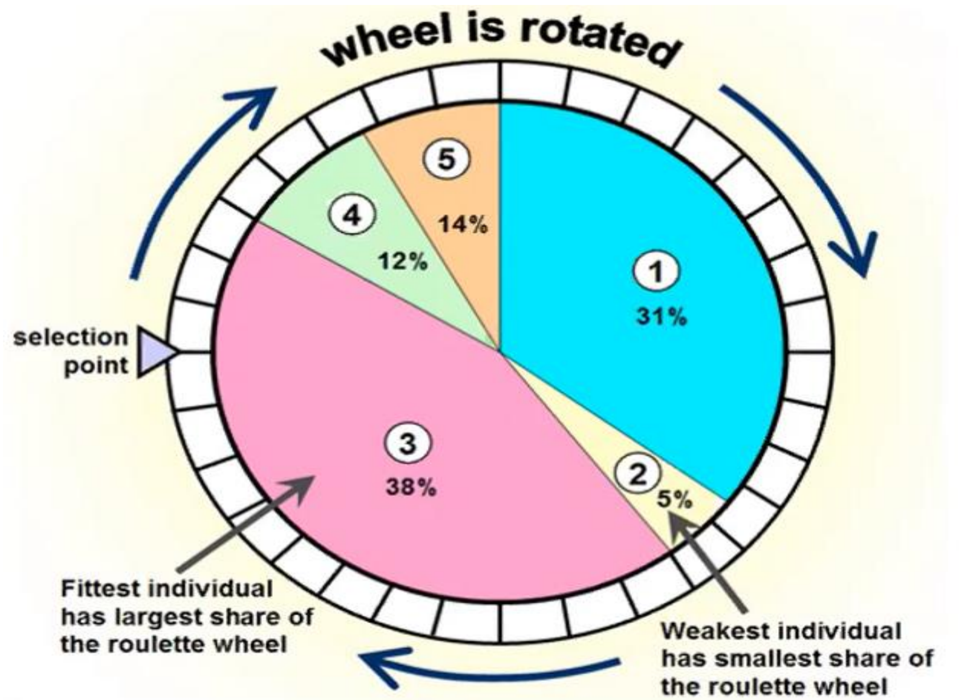

Figure 7: Roulette wheel selection

Rank Selection. The process of parent selection involves the use of a ranking mechanism. In this context, fitness value is used to assign a ranking to individuals within the population, with the highest-ranked individual receiving a rank of (n) and the lowest-ranked individual receiving a rank of (1). Each chromosome is assigned a ranking based on its expected value [36].

3.4.1.3 Crossover

The process of crossover combines the genetic data of two or more parents to generate the offspring. The commonly used crossover operators in genetic algorithms are single point, double points, and uniform.

Single Point Crossover. Single point crossover implies the random appointment of a crossover point. Then the genetic data of two parents will be exchanged with each other, beyond that certain point, as shown in **Figure 8** [30].

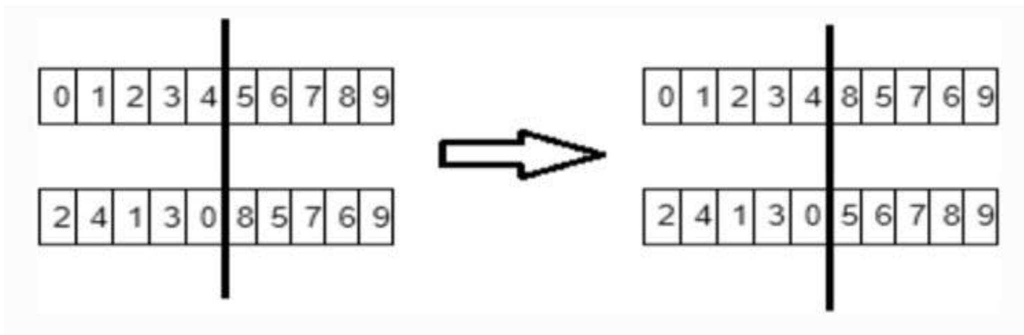

Figure 8: Single point crossover

Double Points Crossover. Double points crossover involves the random selection of two or more crossover points. Subsequently, the genetic data of the parents are exchanged based on the segments that have been generated, as shown in **Figure 9** [30].

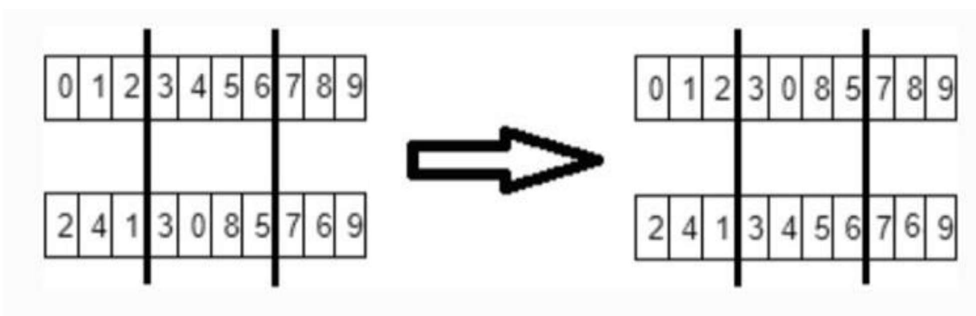

Figure 9: Double points crossover

Uniform Crossover. In the case of a uniform crossover, the parental individual can't be split into distinct parts. The parent may be thought of as representing every gene independently. The decision of whether to exchange a gene with its counterpart at the same position of a different chromosome is made by a random process, as shown in **Figure 10** [30].

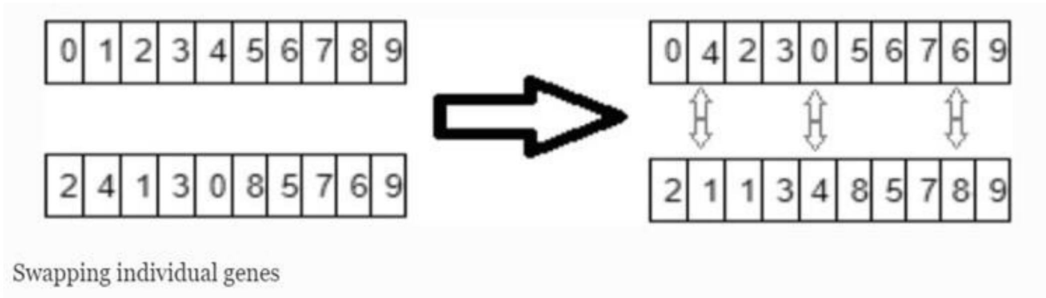

Figure 10: Uniform crossover

3.4.1.4 Mutation

Mutation maintains the variety of genes from one population to the next. The chromosomes' genes are changed during the mutation procedure. As a result, the characteristics of chromosomes acquired from their parents may be altered. The mutation procedure will produce three additional progeny [37]. In the GA algorithm, this operator avoids solutions from becoming identical and increases the chances of avoiding local solutions. **Figure 11** depicts a conceptual illustration of this operator. After the crossover (replication) phase, minor alterations in some of the randomly chosen genes may be detected in this diagram [38].

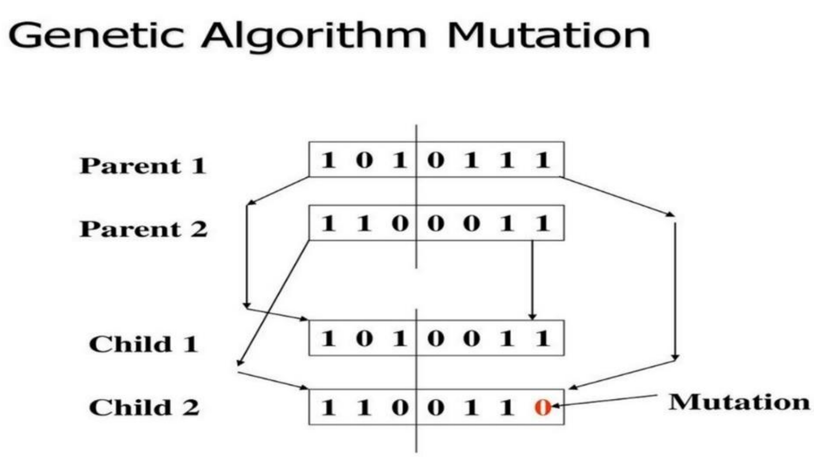

Figure 11: After the crossover phase, the mutation operator changes one or more genes in the children's solutions.

3.5 Surrogate Model

The surrogate model is an analytical method to statistically relate the input and output behavior of complex systems. Surrogate models can be divided into two classes based on estimation approach (i) model-driven and (ii) black box or data-driven. Model-driven, also known as Reduce Order Model (ROM), reduces the computational cost by using order equations to approximate the original equations. However, the simulator source code is needed to apply this method which is mostly impossible when using commercial software. In a data-driven surrogate model is generated using input data and output response.

Following steps are used to develop a surrogate model:

1) The design space is conveniently sampled to identify the input parameters of data sets.
2) The simulator is run, or experiments are performed to calculate the outputs corresponding to the input parameters.
3) A surrogate model is selected and trained on training data (based on inputs and outputs).
4) Determined the model performance based on test data. If the model accuracy is unsatisfactory, the whole process repeats from step 1 [39].

3.6 Methodology

Figure 12 shows a summary of methodology used for this study. The methodology consists of three main steps, which are briefly explained below:

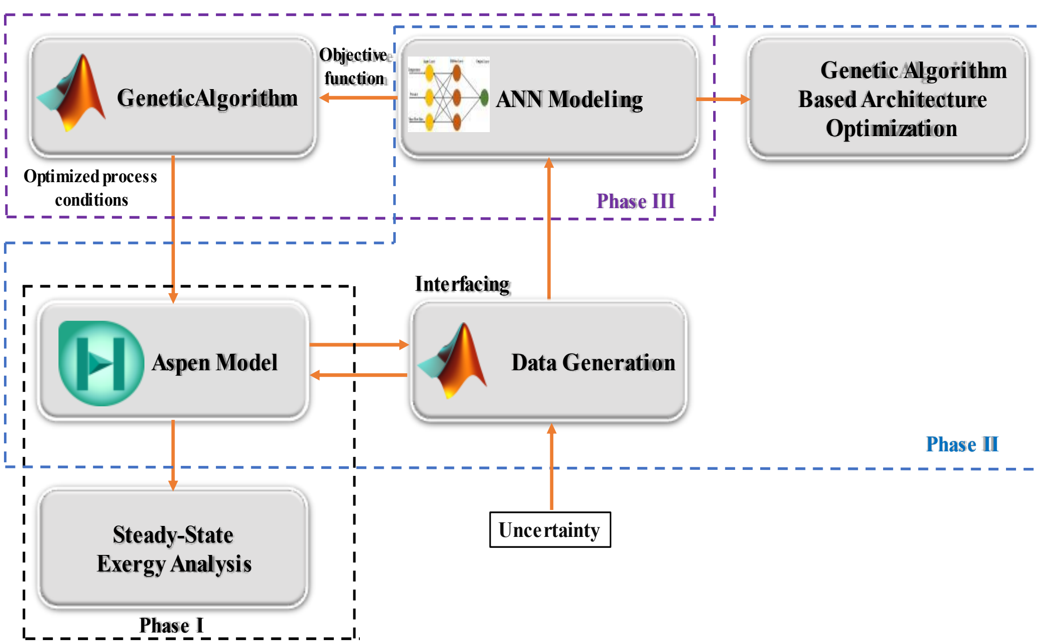

Figure 12: Methodology

3.6.1 Phase I – Steady state Exergy Analysis

The following suppositions were made during the process of performing exergy analysis.

1) Heat exchanger units were modelled and evaluated as a steady state flow system.
2) The values of potential and kinetic exergies were neglected.
3) The reference conditions for exergy calculations were established at a temperature of 25℃ and a pressure of 101.325 kPa.

The values of physical exergies of the process streams were computed using the property set of Aspen HYSYS V.10. Then using the values of physical exergy, irreversibilities and exergy efficiencies of individual heat exchangers were determined by using equations (2) and (3). Furthermore, equations (5) and (6) were used for calculation of the irreversibilities and exergy efficiency of whole Heat Exchanger Network.

3.6.2 Phase II - ANN Modelling

MATLAB R2022a was used to construct and validate the ANN model of HEN of a CDU. The ANN modelling phase included data generation, model selection, training, and validation.

3.6.2.1 Data Generation

The COM server established a connection or interface amongst MATLAB and Aspen HYSYS model to generate data sets from the selected degree of freedom. The data sets were created randomly under -5 percent and +5 percent uncertainty in different process parameters. Overall, 200 data sets were generated. The overall exergy efficiency of Heat Exchanger Network was calculated using equation (6) for each data set. 80% of the 200 data sets were applied for training and 20% for the validation of ANN model. **Table 2** shows data samples of Heat Exchanger Network.

Table 2: Data samples of Heat Exchanger Network

Streams	**Process Conditions**	**Data Sample 1**	**Data Sample 2**	**Data Sample 3**	**Data Sample 4**	**Data Sample 5**
lowtemp crude	Temperature (℃)	30.6666289	28.7051127	30.5134919	31.215475	29.1396443

	Pressure (kPa)	528.5904607	494.7804591	525.950889	538.0507377	502.2703362
	Mass Flow (ton/hr)	147.370189	137.944014	146.634281	150.007699	140.03218
Cooling water in (E-100)	Temperature (°C)	34.43649703	33.54739761	35.53347292	36.31722851	33.92637318
	Mass Flow (ton/hr)	10.7373229	10.3763326	10.8781152	11.3864417	11.2052979
Cooling water in (E-101)	Temperature (°C)	35.09442913	34.68435775	35.75287461	36.2748914	35.79322985
	Mass Flow (ton/hr)	48.7085435	45.0962344	46.8836542	44.6908677	47.0005027
Cooling water in (E-102)	Temperature (°C)	35.9742623	34.80055807	34.95799775	35.15638855	36.15178258
	Mass Flow (ton/hr)	375.863494	408.447244	392.692871	412.323036	393.244179
Cooling water in (E-103)	Temperature (°C)	34.2257459	34.4877365	36.5259144	35.0385285	35.1818665
	Mass Flow (ton/hr)	505.219996	491.96522	505.726877	530.489887	496.726597
Cooling water in (E-104)	Temperature (°C)	36.27635391	35.24188859	33.66000808	33.49577515	35.30737219
	Mass Flow (ton/hr)	42.4904969	44.4397235	41.7214809	44.9216243	41.3031691
Cooling water in (E-113)	Temperature (°C)	34.08957116	34.47001242	35.64717973	36.479497	33.43278235
	Mass Flow (ton/hr)	291.99051	275.920549	298.97675	291.024878	294.467321
Cooling water in (E-115)	Temperature (°C)	34.92791541	33.74818902	36.64550622	34.76011719	35.37995817
	Mass Flow (ton/hr)	255.5443	235.34477	238.75029	241.76503	238.86054

Cooling water in (E-117)	Temperature (°C)	36.52148233	35.84184306	35.91120171	35.772532	34.6719798
	Mass Flow (ton/hr)	117.881857	113.7533	115.210875	108.693515	115.734198
HP steam in (E-106)	Temperature (°C)	510.4454489	508.4124658	495.1475789	493.7030096	502.7653812
	Pressure (kPa)	3072.96617	3059.77382	3003.0121	3126.80557	2888.27372
	Mass Flow (ton/hr)	8.2071043	7.9479794	7.88822923	7.92834686	7.63060902
Naphtha	Pressure (kPa)	129.895957	137.547656	137.855582	135.445384	129.023572
AGO	Pressure (kPa)	215.013018	226.857919	223.927416	218.524306	216.811032
Residue	Pressure (kPa)	214.322756	229.161032	221.034051	221.192298	225.240352
Atm_Ovhd	Pressure (kPa)	204.393012	205.329435	189.77842	206.822075	191.168804
Diesel	Pressure (kPa)	213.75882	212.906164	220.562623	223.895376	217.163672
Kerosene	Pressure (kPa)	203.045623	198.418695	203.527701	206.079129	195.878801
PA_1_Draw	Pressure (kPa)	193.462864	190.3101944	204.3758135	208.6976115	191.3353428
PA_2_Draw	Pressure (kPa)	214.3440053	218.1762178	206.7513239	212.6568215	223.2573966
PA_3_Draw	Pressure (kPa)	213.9981392	214.4025746	210.060636	216.9832537	229.0021678
Overall exergy efficiency of HEN		63.4633809	62.66869599	63.75498626	63.83252213	63.0790105

3.6.2.2 Selection, Training and Validation of ANN Model

The Levenberg-Marquardt (trainlm) training method was applied in order to train a feed-forward multilayer artificial neural network. The inputs of ANN model included the temperature, pressure, and mass flow rate of a low temperature crude stream, as well as the corresponding parameters for several other process streams. As presented in **Figure 13,** the overall exergy efficiency of Heat exchanger Network was regarded as an output of the ANN model. The process of selecting the architecture of ANN model included: (a) to determine the optimal number of hidden layers and (b) to estimate the suitable number of neurons in these hidden layers. This selection process was carried out with the help of a multi-objective Genetic Algorithm (GA) approach. The objective function used in this GA based architecture optimization was the root mean square error (RMSE) for the output of ANN model.

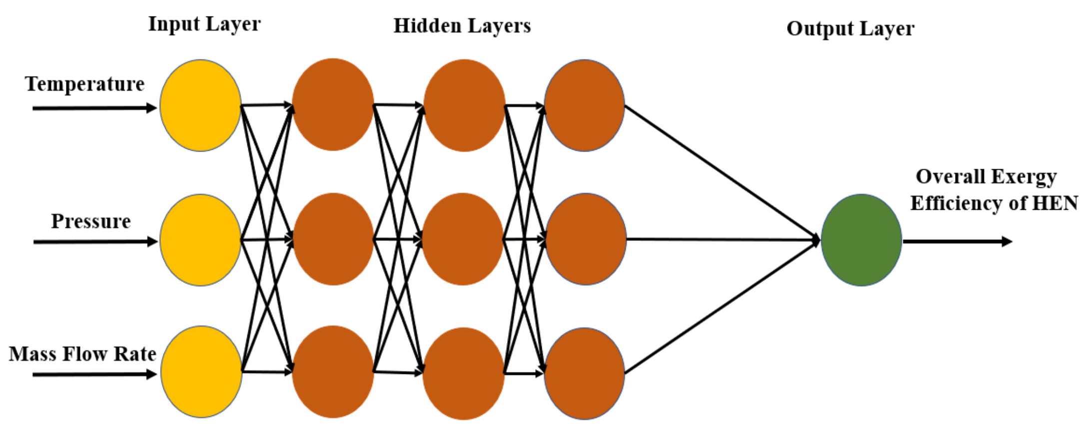

Figure 13: ANN model used in methodology.

3.6.3 Phase III - Optimization

The trained ANN model is applied as a surrogate in the GA environment where the overall exergy efficiency of Heat Exchanger Network serves as objective function for optimization under uncertainty. The GA determined the optimal values of parameters with maximum overall exergy efficiency as shown in **Figure 14**. The successful performance of the suggested optimization was confirmed by putting the optimized results values in the Aspen HYSYS model. The algorithm steps for GA are as follow:

1) The algorithm starts by generating a set of random populations of individual solution.

2) Performed fitness evaluation of each individual of the population using surrogate model and rank them according to their fitness value.
3) Based on their fitness value, parents are chosen to generate offspring using crossover operator.
4) Mutation operators are utilized to enhance the quality and maintain the genetic diversity of the proceeding generation.
5) The algorithm terminates when the criteria of objective function are met, otherwise, steps 2-4 are repeated until optimal solution is reached.

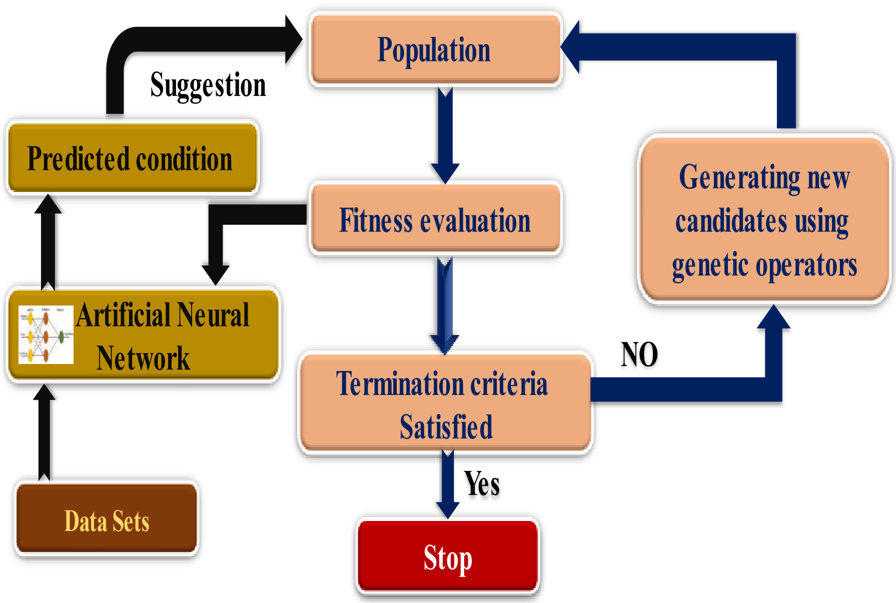

Figure 14: Working mechanism of GA optimization.

Chapter 4

Results and Discussion

Section 4.1 describes exergy analysis results of the entire Heat Exchanger Network. In section 4.2, the data-based modelling and optimization of overall exergy efficiency through hybrid framework of ANN and GA is presented.

4.1 Exergy Analysis

Table 3 presents the exergy calculations and other operating conditions of the process streams. Physical exergy values of the process streams were computed using the Aspen HYSYS environments. The estimation of the chemical exergies of the process streams was not performed. Heat exchanger network of crude distillation unit included twenty-one shell & tube heat exchangers. From the data of process streams, the exergy destructions and exergy efficiencies were determined for all the individual heat exchangers of Heat Exchanger Network as shown in **Table 4 and Table 5**. Furthermore, the complete exergy destruction and the overall exergy efficiency for whole HEN of crude distillation unit were calculated.

Table 3: Operating conditions and exergy data of streams

Streams	Mass flow rate (ton/hr)	Temperature (C)	Pressure (kPa)	Physical Exergy (kW)
AGO	26.04	298.7	218.6	1641.144467
AGO 11	26.04	211	218.6	787.3345787
AGO 22	26.04	120	218.6	209.6166746
AGOaa	26.04	262.1779479	218.6	1252.521404
Atm_Ovhd	128.8	147.3	197.9	2928.327572
Atm_Ovhd_1	128.8	110	197.9	854.042127
Cooled AGO	26.04	70	218.6	48.44919235
Cooled Diesel	86.2	50	213.6	50.95301445
Cooled Kerosene	64.01	40	205.8	15.78079073
Cooled Naphtha	91.84	38	135.8	14.00215082
Cooled Residue	251.1	156.5030884	225.5	3821.999381
Cooled Waste H2O	5.694	40	135.8	1.491510471
cooling water in (E-100)	39.04	35	101.3	3.062926337

cooling water in (E-101)	168.7	35	101.3	13.2355449
cooling water in (E-102)	1414	35	101.3	110.9369324
cooling water in (E-103)	1841	35	101.3	144.4376892
cooling water in (E-104)	154.2	35	101.3	12.09793138
cooling water in (E-113)	1041	35	101.3	81.67280525
cooling water in (E-115)	884.7	35	101.3	69.41011605
cooling water in (E-117)	411.3	35	101.3	32.26899597
cooling water out (E-100)	39.04	40.00065806	101.3	9.853806137
cooling water out (E-101)	168.7	38.0346747	101.3	29.22807099
cooling water out (E-102)	1414	39.89416795	101.3	350.3280291
cooling water out (E-103)	1841	39.91276101	101.3	457.6081158
cooling water out (E-104)	154.2	39.90102361	101.3	38.25002028
cooling water out (E-113)	1041	39.99968879	101.3	262.7071214
cooling water out (E-115)	884.7	40.00381776	101.3	223.423293
cooling water out (E-117)	411.3	40.01171383	101.3	104.0126432
crude00	519	40.90152006	517.1	189.0726997
crude01	519	75	517.1	1279.818519
crude02	519	35	517.1	113.8101684
crude03	519	98.24012751	517.1	2644.159154
crude11	519	163	517.1	8928.659124
crude22	519	165.8574912	517.1	9285.906291
crude44	519	167.7212294	517.1	9522.416521
crude45	519	187.3923329	517.1	12185.22629
crude46	519	192.5214424	517.1	12928.86403
Crude-FH	496.9	278.5742355	517.1	28173.13999
Diesel	86.2	249.3	213.6	3685.402031
Diesel_1	86.2	220	213.6	2823.585138

HP steam in (E-106)	28.41	500	3000	10247.32722
HP steam out (E-106)	28.41	234.5766931	3000	2406.603146
Kerosene	64.01	233.2	205.8	2360.905188
Kerosene 11	64.01	219	205.8	2065.321843
lowtemp crude	519	30	517.1	76.76901899
Naphtha	91.84	74.26	135.8	196.9954839
Naphtha_1	91.84	48.50190726	135.8	45.43424984
PA_1_1	239.2	103.1787586	198.9	1334.475146
PA_1_Draw	239.2	167.8	198.9	4297.055699
PA_1_Return	239.2	70.41	198.9	453.2267438
PA_2_1	151.3	201	213.6	4098.863925
PA_2_Draw	151.3	264.2	213.6	7326.227411
PA_2_Return	151.3	180.7	213.6	3243.555708
PA_3_1	155.1	290	218.6	9209.687194
PA_3_Draw	155.1	319.9	218.6	11246.04365
PA_3_Return	155.1	245.2	218.6	6499.498518
PreFlashLiq	496.9	232.2	517.1	18518.67018
PreFlashLiqaa	496.9	234	517.1	18865.85863
PreFlashLiqNew	496.9	270	517.1	26252.0342
Preheat Crude	519	232.2	517.1	19844.85384
Residue	251.1	347.4	225.5	21500.22511
Residueaa	251.1	273.5921206	225.5	13170.20841
WasteH2O	5.694	74.24	135.8	21.99774107

4.1.1 Exergy Destruction

Process irreversibility determines the measure of exergy destroyed in a unit operation or process. Irreversibility in any unit operation or process is caused due to:

1) Spontaneous chemical reaction
2) Depletion of work into heat by the solid or fluid friction.
3) Heat transfer at finite temperature differences
4) Unconstrained expansion or thermal equilibrium in a mixing [8, 40]

Table 4 represents the exergy destruction of individual heat exchangers and the overall exergy destruction of entire Heat Exchanger Network. The value for overall exergy destruction of HEN was 17611.21 kW. **Figure 15** represents the exergy destruction contributions of all heat exchangers to the overall exergy destruction of HEN. Heat exchangers predominantly contributing to the overall exergy destruction include E-107, E-113, E-103 and E-102 with the exergy destruction values of 3063.709063 kW, 2529.154359 kW, 2459.461697 kW and 1810.149955 kW respectively. Only these four out of twenty-one heat exchangers contribute 56 % to the overall exergy destruction of HEN. So, to enhance the exergy efficacy of HEN and achieve more significant energy savings, priority must be given to the optimization of these four heat exchangers. Using energy optimization strategies, the primary purpose is to minimize the exergy destructions of these heat exchangers.

Table 4: Exergy destruction of all the individual heat exchangers

Exchanger No.	Inlet and outlet streams				Exergy Destruction (kW)
	Hot in	**Hot out**	**Cold in**	**Cold out**	
E-100	WasteH2O	Cooled Waste H2O	cooling water in (E-100)	cooling water out (E-100)	13.71535
E-101	Naphtha_1	Cooled Naphtha	cooling water in (E-101)	cooling water out (E-101)	15.43957
E-102	Kerosene 11	Cooled Kerosene	cooling water in (E-102)	cooling water out (E-102)	1810.15
E-103	Diesel_1	Cooled Diesel	cooling water in (E-103)	cooling water out (E-103)	2459.462
E-104	AGO 22	Cooled AGO	cooling water in (E-104)	cooling water out (E-104)	135.0154
E-105	AGOaa	AGO 11	crude11	crude22	107.9397
E-106	HP steam in (E-106)	HP steam out (E-106)	crude46	Preheat Crude	924.7343
E-107	residueaa	Cooled Residue	crude03	crude11	3063.709
E-108	PA_3_Draw	PA_3_1	PreFlashLiq New	Crude-FH	115.2507
E-109	Kerosene	Kerosene 11	crude22	crude44	59.07312
E-110	AGO 11	AGO 22	crude02	crude00	502.4554
E-111	AGO	AGOaa	PreFlashLiq	PreFlashLiqa	41.43461
E-112	Residue	Residueaa	PreFlashLiqa	PreFlashLiqNew	943.8411
E-113	PA_3_1	PA_3_Return	cooling water in (E-113)	cooling water out (E-113)	2529.154
E-114	PA_1_Draw	PA_1_1	crude00	crude01	1871.835

E-115	PA_1_1	PA_1_Return	cooling water in (E-115)	cooling water out (E-115)	727.2352
E-116	PA_2_Draw	PA_2_1	crude44	crude45	564.5537
E-117	PA_2_1	PA_2_Return	cooling water in (E-117)	cooling water out (E-117)	783.5646
E-118	Diesel	Diesel_1	crude45	crude46	118.1792
E-119	Naphtha	Naphtha_1	lowtemp crude	crude02	114.5201
E-120	Atm_Ovhd	Atm_Ovhd_1	crude01	crude03	709.9448

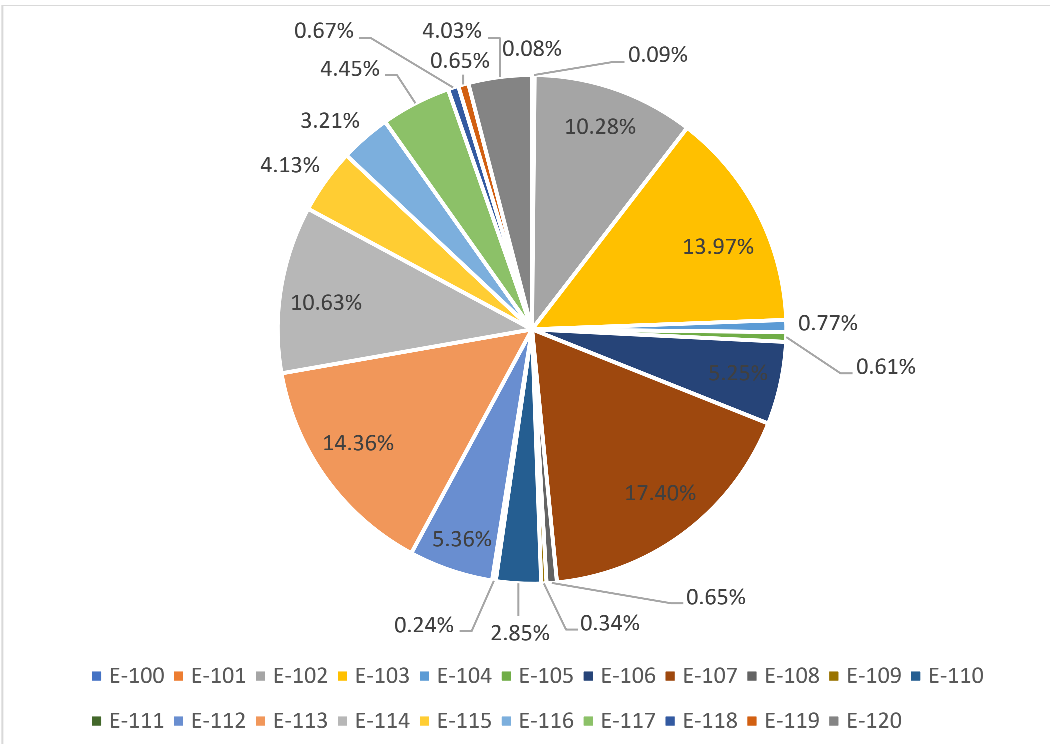

Figure 15: Contribution of heat exchangers to the overall exergy destruction of entire HEN.

4.1.2 Exergy Efficiency

The exergy efficiency quantifies the effectiveness of a system in relation to its performance. The overall exergy efficiency of Heat Exchanger Network was 63.34%. **Table 5** presents the exergy efficiencies of individual heat exchangers, calculated from equation (3). Among the heat exchangers, E-113 was least efficient followed by E-117, E-103, E-102 and E-110 with exergy efficiency of 6.679768%, 8.388046%, 11.29506%, 11.68023% and 13.02756% respectively. While E-108 has the highest exergy efficiency of 94.34035%. **Figure 16** shows the visual presentation of exergy efficiencies of individual heat exchangers belonging to the HEN. Effective heat exchangers designing can limit the losses of heat and pressure [41, 42]. The exergy efficiency of heat exchangers can be improved by enhancing the thermal designs of heat exchangers, keeping in mind the techno-economic aspects.

Table 5: Exergy efficiencies of individual heat exchangers

Exchanger No.	**Inlet and outlet streams**				**Exergy Efficiency (%)**
	Hot in	**Hot out**	**Cold in**	**Cold out**	
E-100	WasteH2O	Cooled Waste H2O	cooling water in (E-100)	cooling water out (E-100)	33.11618
E-101	Naphtha_1	Cooled Naphtha	cooling water in (E-101)	cooling water out (E-101)	50.8796
E-102	Kerosene 11	Cooled Kerosene	cooling water in (E-102)	cooling water out (E-102)	11.68023
E-103	Diesel_1	Cooled Diesel	cooling water in (E-103)	cooling water out (E-103)	11.29506
E-104	AGO 22	Cooled AGO	cooling water in (E-104)	cooling water out (E-104)	16.22665
E-105	AGOaa	AGO 11	crude11	crude22	76.79649
E-106	HP steam in (E-106)	HP steam out (E-106)	crude46	Preheat Crude	88.20601
E-107	Residueaa	Cooled Residue	crude03	crude11	67.22678
E-108	PA_3_Draw	PA_3_1	PreFlashLiqNew	Crude-FH	94.34035
E-109	Kerosene	Kerosene 11	crude22	crude44	80.01473
E-110	AGO 11	AGO 22	crude02	crude00	13.02756
E-111	AGO	AGOaa	PreFlashLiq	PreFlashLiqaa	89.3381
E-112	Residue	Residueaa	PreFlashLiqaa	PreFlashLiqNew	88.6694
E-113	PA_3_1	PA_3_Return	cooling water in (E-113)	cooling water out (E-113)	6.679768
E-114	PA_1_Draw	PA_1_1	crude00	crude01	36.81742
E-115	PA_1_1	PA_1_Return	cooling water in (E-115)	cooling water out (E-115)	17.4767
E-116	PA_2_Draw	PA_2_1	crude44	crude45	82.50728
E-117	PA_2_1	PA_2_Return	cooling water in (E-117)	cooling water out (E-117)	8.388046
E-118	Diesel	Diesel_1	crude45	crude46	86.28721

E-119	Naphtha	Naphtha_1	lowtemp crude	crude02	24.43973
E-120	Atm_Ovhd	Atm_Ovhd _1	crude01	crude03	65.77401

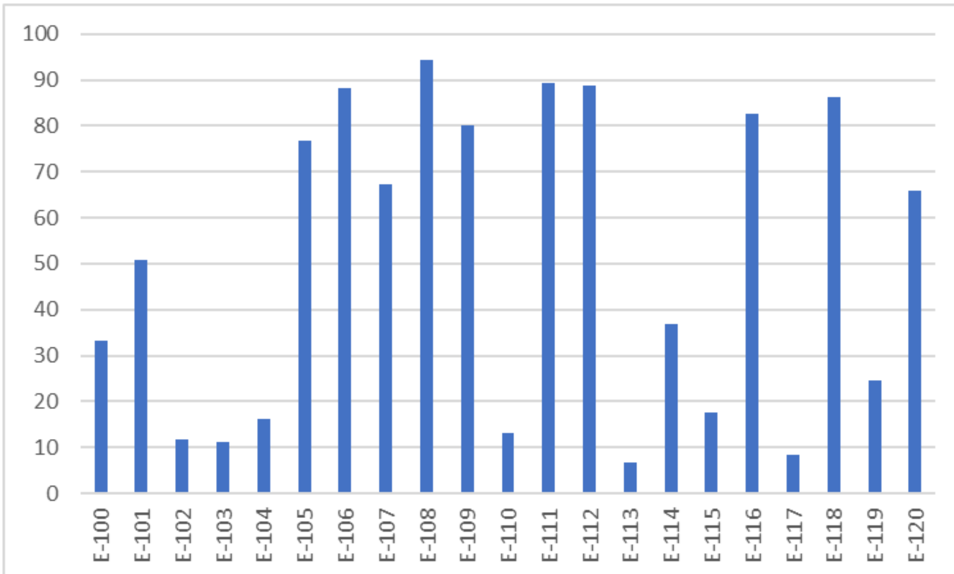

Figure 16: Exergy efficiencies of all the heat exchangers of HEN

4.2 Data Based Modelling and Optimization

In the previous section, a steady-state exergy analysis of Heat Exchanger Network of a crude distillation unit was performed. While in this section, we incorporate uncertainty in different process parameters and generate different data samples where input was uncertainty in process parameters and output was overall exergy efficiency of HEN. Then we developed ANN model on generated data samples and used it as a surrogate in GA environment to optimize the uncertain process condition. Optimization algorithms aimed to overcome the artificially inserted uncertainty to achieve maximum overall exergy efficiency of HEN.

4.2.1 ANN Model Training, Validation and Prediction

The ANN model was established using MATLAB R2022a. The 31 uncertain process conditions provided in **Table 2** were assigned random uncertainties of +5% and -5%. Then a dataset consisting of 200 samples was produced, with 160 samples allocated for training the model and 40 samples reserved for validation of model. The training of ANN model was carried out using the Levenberg-Marquardt backpropagation or trainlm training method, and the network's behavior was regulated by Tansig activation function. The architecture optimization process of an ANN model included the selection of suitable number of hidden layers and the number of neurons in these hidden layers. This selection was carried out with the help of a multi-objective genetic algorithm (GA) technique. The initial or starting population size and maximum number of generations were both set at 50. The optimal design of ANN model contained three hidden layers and the optimum number of neurons in these hidden layers were 1, 3 and 1, respectively as shown in **Figure 17**. The use of the Root Mean Square Error, or RMSE, was devoted for assessing the performance of the architecture of the model. **Figure 18** displays the ANN model-based predicted values of overall exergy efficiency of HEN vs. the respective target values. The trained ANN model exhibited a great correlation coefficient denoted as "R" with a value of 0.9996. Furthermore, the root mean square error (RMSE) for the total exergy efficiency of the heat exchanger network (HEN) was determined to be 0.0097.

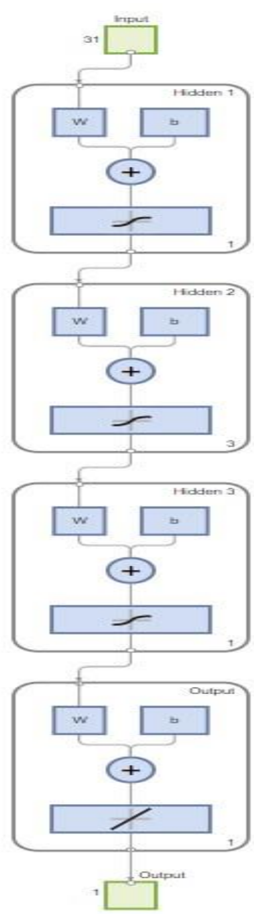

Figure 17: Proposed ANN model architecture

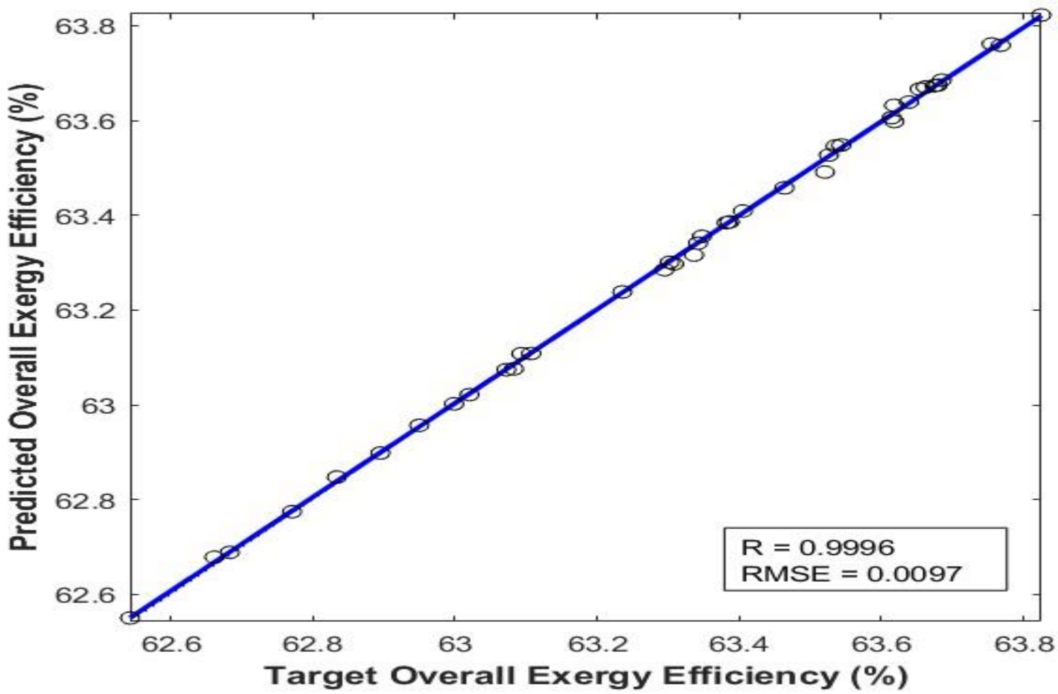

Figure 18: Predicted vs actual overall exergy efficiency of HEN

4.2.2 Genetic Algorithm Based Optimization

Genetic Algorithm used the trained ANN model as a surrogate in order to optimize the overall exergy efficiency of Heat Exchanger Network. This optimization was done under uncertainty in different process parameters. **Table 6** presents the parameters of GA which were used to improve the overall exergy efficiency.

Table 6: GA parameters used to optimize the overall exergy efficiency of HEN.

GA Parameters	Specifications
Size of initial population	50
Crossover	Over scattered
Crossover probability	0.8
Elite members	15
Selection	Tournament
Mutation	Adapt feasible

4.2.2.1 Optimization of Overall Exergy Efficiency of HEN

Table 7 presents a comparative analysis of the overall exergy efficiency of HEN for standalone (SA) model and the GA-based framework. The SA model corresponds to the first-principle model of Aspen HYSYS, which does not use any optimization techniques in the presence of uncertainty. The framework based on genetic algorithms demonstrated superior performance compared to the SA model for all test data samples. For instance, in case of first data sample, the SA model presents an exergy efficiency of 62.94%, but the GA optimizes it to 64.40%. Similarly for the second data sample, the SA model shows an exergy efficiency of 63.72%, and the GA optimizes it to 64.41%.

Table 7: Comparative analysis of SA model and GA optimized overall exergy efficiency of HEN.

S. No	**SA model exergy efficiency (%)**	**GA based optimized exergy efficiency (%)**
Data sample 1	62.94150343	64.40068586
Data sample 2	63.71680111	64.4090027
Data sample 3	63.01594203	64.40083869
Data sample 4	62.94150343	64.40016911
Data sample 5	63.71680111	64.40848794

The performance of GA based framework was cross-validated by putting the optimized values of process conditions obtained from GA-based approach, into the Aspen HYSYS model and then determining the values of absolute error. The performance comparison of GA based optimization approach is shown in **Table 8**. From **Table 8**, it can be confirmed that the accuracy of GA model is good enough. For example, in case of data sample 1, GA model exhibits an absolute error of 0.40% and in case of data sample 2, the value of absolute error is -0.26%.

Table 8: GA performance validation for overall exergy efficiency optimization of HEN

S. No	**GA optimized exergy efficiency (%)**	**Aspen model validated exergy efficiency (%)**	**Absolute error (%)**
Data sample 1	64.40068586	64.65863776	0.40
Data sample 2	64.4090027	64.23754415	-0.26
Data sample 3	64.40083869	63.97301938	-0.67
Data sample 4	64.40016911	64.08397866	-0.50
Data sample 5	64.40848794	64.13926284	-0.42

Conclusions

The Heat Exchanger Network of a crude distillation unit had an exergy efficiency and overall exergy destruction of 63.34% and 17611.21 kW respectively. The exergy destructions and exergy efficiencies for all the individual heat exchangers of network were also calculated. Heat exchangers predominantly contributing to the overall exergy destruction included E-107, E-113, E-103 and E-102 with the exergy destruction values of 3063.71 kW, 2529.15 kW, 2459.46 kW and 1810.15 kW respectively. Only these four out of twenty-one heat exchangers contributed 56 % to the overall exergy destruction of HEN. So as an immediate step to improve energy savings is that these four heat exchangers must be prioritized for energy optimization targets, that is to decrease their exergy destruction as much as feasible. Regarding the exergy efficiency, the heat exchanger E-113 was least efficient followed by E-117, E-103, E-102 and E-110 with exergy efficiency of 6.68%, 8.39%, 11.30%, 11.68% and 13.03% respectively. In general, utility heat exchangers exhibited higher exergy destruction and lower efficiencies. The primary factor contributing to exergy destruction in these heat exchangers is the temperature difference between the hot and cold process streams. In the case of utility heat exchangers, the mass flow rates of cold streams or cooling water streams were excessively high, leading to elevated temperature differences. Consequently, this resulted in increased exergy destruction and decreased efficiencies.

Following the completion of the exergy analysis, the development of ANN model was carried out. The trained ANN model then served as a surrogate model in the GA environment for optimization under conditions of uncertainty. The primary objective function of this optimization process was to maximize the overall exergy efficiency of the HEN. The ANN and GA based framework outperformed Standalone model of Aspen HYSYS in achieving the greatest overall exergy efficiency of HEN. The performance of the developed framework was cross validated by adding the optimized values of process conditions to the Aspen HYSYS model and calculating the absolute error. Overall, the functioning of the developed framework was good enough. The proposed integrated method enhances the feasible energy usage in crude distillation units of petroleum refineries. The present study will provide a fundamental basis for the simulation of Refinery 4.0.

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