Exergy Analysis and Estimation of Optimum Cut Point Temperature of a Crude Distillation Unit under Uncertainty

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Exergy Analysis and Estimation of Optimum Cut Point Temperature of a Crude Distillation Unit under Uncertainty

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Dedication

I dedicate this thesis to my parents, who have provided unwavering support, motivation, and love throughout my academic journey.

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I extend my most profound appreciation to the Almighty Allah for providing me with the strength, guidance, and knowledge to complete this thesis. Furthermore, I am eternally grateful for the boundless resources and wisdom bestowed upon me.

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Abstract

Energy-efficient design and operation have been the focus of research in process industries to mitigate global warming and realize a circular economy. The crude distillation unit (CDU) is a critical component in the refining process, but it also consumes a significant amount of energy. It is estimated that the CDU is responsible for 35-40% of the total energy consumption in a refinery. It highlights the need for efficient operation and process optimization to reduce energy consumption and costs. Improved operation and technology advancements can lead to significant energy savings in the CDU process. Optimum values of tray temperature, also known as the cut-point temperature, have been a challenge considering the uncertainty around crude composition and process conditions. Apart from cut-point temperature optimization, an analysis of energy and exergy is conducted to assess the energy efficiency of the CDU and identify potential areas for improvement. Compared to conventional energy analysis, exergy analysis is a more comprehensive method for evaluating the performance of the CDU, as it incorporates the second law of thermodynamics and traditional energy analysis techniques. In this study, we integrate the exergy analysis aspect in our previous study based on the hybrid framework of the Taguchi method and genetic algorithm (GA). A crude distillation unit (CDU) simulation was created using Aspen HYSYS to evaluate crude oil assays from Pakistan's Kunnar and Zamzama regions to improve performance. Multiple variations of the crude assay were created by introducing artificial uncertainty in the actual crude composition and operating conditions, resulting in hundreds of scenarios being examined to evaluate the effect of uncertainty. The hybrid model combining the Taguchi and genetic algorithms was created in MATLAB and integrated with Aspen HYSYS simulation to determine the optimal cut points. Minimizing exergy destruction in a column per kilo barrel of diesel production was set as an objective function. Three hundred and ten data samples comprised of a variant in process conditions and optimized cut points from the hybrid network were generated. Based on the results, an artificial neural network model was developed to predict optimal cut points for increased diesel production. The results produced by the artificial neural network (ANN) were then used directly in the Aspen HYSYS model, bypassing the hybrid structure. The results of the Hybrid optimization and ANN models were similar, indicating that the ANN model could accurately predict the optimal cut points for optimized diesel production. For the Kunnar crude, a 27%

increase in diesel production and a 26% decrease in exergy destruction within the column per kilo barrel of diesel were observed compared to straight-run results. For the Zamzama crude, there was a 12% increase in diesel production and a 13.22% decrease in exergy destruction within the column per kilo barrel of diesel.

Keywords: Hybrid Taguchi and Genetic Algorithm, ANN, industry 4.0, Exergy analysis, Cut-point temperature optimization, CDU

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Chapter 1

Introduction

1.1 Background

The ongoing depletion of fossil fuel resources and the increasing concerns over global warming have spotlighted the need for energy-efficient designs in industrial processes. With the future of energy resources uncertain, researchers focus on developing solutions that can deliver greater output while consuming less energy. The energy-efficient design optimizes various elements, such as heat exchangers, pumps, and compressors, to minimize energy consumption. It can be achieved using advanced materials, such as high thermal conductivity, and innovative technologies, such as microreactors. In addition, using renewable energy sources, such as solar and wind power, can also contribute to energy efficiency in industrial processes. Another critical aspect of the energy-efficient design is advanced control systems and automation. These systems can monitor and control parameters such as temperature, pressure, and flow rate to optimize the process and reduce energy consumption. Cohesive efforts by researchers, governments, and industrial stakeholders are required for the successful adoption and implementation of energy-efficient designs. The integration of energy-efficient technologies into current infrastructures can be considerably aided by policy frameworks and incentives that place a priority on environmentally responsible behaviors.

Furthermore, process integration and heat integration techniques can also be applied to optimize energy consumption and increase the overall efficiency of the process. Energy-efficient operation is another critical aspect of energy efficiency in industrial processes. It involves implementing best practices and procedures to minimize energy consumption during operation. For example, predictive maintenance can help reduce downtime and energy consumption by identifying and addressing potential issues before they occur. Additionally, real-time monitoring and control systems can help identify and address energy inefficiencies, thus reducing energy consumption. Energy-efficient design and operation are crucial to achieving a circular economy and mitigating global warming. By developing and implementing advanced technologies and best practices, researchers are working to minimize energy consumption and increase the efficiency of industrial processes, thus reducing the environmental impact of these processes. Advancements in technology and best practices are continually being developed by researchers and inventors. Automation, machine learning, and artificial intelligence are being used to better optimize processes and reduce energy waste. With the help of these technologies, businesses can function more precisely and quickly, which improves energy efficiency and lessens environmental impact. Furthermore, using renewable energy sources and advanced control systems can also contribute to achieving a sustainable future. A cleaner and more sustainable energy supply is ensured by switching from fossil fuels to renewable energy sources including solar, wind, and hydro power. Industries may reduce their carbon footprint and support the global effort to combat climate change by investing in renewable energy infrastructure. Incentives and policies from the government are also very important in improving energy efficiency in industrial processes. Government officials can support industries in adopting sustainable practices by offering funding, tax breaks, and legal frameworks. Such actions foster an environment where companies may give sustainability and energy efficiency top priority.

The crude distillation unit is a vital component in petroleum refineries, responsible for separating the various hydrocarbons found in crude oil into distinct fractions based on their boiling points. This process, known as fractionation, is a complex process that consumes a significant amount of energy, with estimates suggesting that crude distillation units account for 30-45% of the total energy consumption in refineries [1,2]. Due to this high energy consumption, researchers have optimized crude distillation to achieve production targets while minimizing energy consumption [3]. The crude distillation process starts with heating crude oil to a specific temperature, after which the oil is fed into the distillation unit. As the oil is heated and vaporized, it is directed through a series of trays or plates, separating the different hydrocarbons based on their boiling points. These fractions are then further broken down into components along a range of boiling points, resulting in a range of products, including naphtha, diesel, kerosene, ago, off-the-gas, wastewater, and residue. Therefore, we can minimize energy consumption by making our columns more efficient, mainly involving additional capital costs. There are plenty of ways to optimize the design of these units to improve energy efficiency. Process control methods like optimization and alternative designs have been utilized for this purpose. In addition to process control methods, technological advancements have played a crucial role in enhancing energy efficiency. Innovations in column internals, such as structured packing and trays with higher separation efficiencies, contribute to reducing energy consumption during distillation. Furthermore, the implementation of advanced heat exchangers and energy recovery systems can help harness waste heat and repurpose it for various heating requirements within the refinery. Moreover, research and development efforts continue to explore novel approaches to maximize energy efficiency in crude distillation. These efforts encompass the exploration of alternative energy sources, such as renewable energy integration and waste heat utilization. Additionally, advancements in materials science contribute to the development of more effective insulating materials, thereby reducing heat losses during the process.

Production of crude products depends on the tray's temperature of the crude distillation unit, also known as cut points. Tuning cut points can be used to increase the production of a specific product and minimize energy consumption in the column. However, the optimal cut points depend on the tray's temperature of the crude distillation unit, which can be affected by frequent changes in crude composition and any disturbance in process parameters. Therefore, estimating the optimal points for maximum efficiency makes it quite challenging. The crude oil composition can change due to the geographical origin of the crude, the season, and other factors. Any disturbance in process parameters, such as the feed rate, the reflux ratio, and the column pressure, can also affect the tray's temperature and the optimal cut points. Therefore, estimating the optimal points for maximum efficiency makes it quite challenging. The challenge of identifying the ideal cut points for maximum efficiency is made more difficult by the interaction between the composition of the crude oil and the process variables. To make informed decisions about adjusting the cut points in response to shifting conditions, refinery operators must continuously monitor and analyze data from numerous sensors and instruments. Refineries frequently use cutting-edge process management and optimization techniques to address these issues and improve energy efficiency. Operators can evaluate the operation of the distillation unit and promptly alter the cut points thanks to real-time data monitoring and analytics. Based on historical data and the current operating environment, artificial intelligence and machine learning algorithms can help forecast the behavior of the crude oil and optimize the cut spots. Researchers are exploring a systematic approach based on the second law of thermodynamics to improve the efficiency of crude distillation. The second law of thermodynamics states that the availability of thermal energy limits the efficiency of any thermodynamic process. By analyzing the energy consumption and production of the crude distillation unit, it is possible to identify opportunities for improvement and increase the efficiency of the process. Thermodynamic models are one of the most effective ways to analyze the energy consumption and production of the crude distillation unit. Thermodynamic models can simulate the performance of the crude distillation unit under different conditions and provide insights into the energy consumption and production of the process. Advanced simulation tools such as Aspen HYSYS can help optimize the crude distillation process by simulating different scenarios and identifying the optimal cut points that minimize energy consumption and maximize production. Using real-time monitoring and control systems can also aid in optimizing the crude distillation process. Real-time monitoring systems can provide insight into the unit's current performance and identify areas for improvement. By monitoring the process parameters, such as the feed rate, the reflux ratio, and the column pressure, it is possible to identify and correct any disturbances in the process and maintain optimal performance.

Multiple methods, such as cut-point temperature optimization, energy analysis, and exergy analysis, have been used to evaluate the energy efficiency of the CDU. Energy analysis provides an overview of the CDU's performance, but exergy analysis is more comprehensive as it considers the second law of thermodynamics. Exergy, representing the maximum amount of energy obtained from a system through a reversible process with its surroundings, offers a more accurate assessment of the CDU's work potential than energy analysis alone. In real processes, much irreversibility always occurs. Exergy is the usable energy that remains after accounting for losses. These losses, resulting from irreversible processes, are also known as exergy destruction or anergy. Exergy analysis is a powerful tool for evaluating the quality of energy and identifying inefficiencies within a process. Exergy analysis provides a broader understanding of a system's work potential by considering the second law of thermodynamics. Exergy analysis is a crucial tool for optimizing the performance of energy systems because it can help identify problem areas in processes, which can inform better design choices for the ones we manage. Exergy is based on the assumption that not all types of energy are equally useful for carrying out useful tasks. It understands that as energy passes through different changes, it can deteriorate and lose its capacity to perform work. Exergy, sometimes referred to as accessible or useful energy, is the amount of work that can be accomplished with a given energy stream once it has reached thermodynamic equilibrium with its surroundings. The capacity of exergy analysis to measure the magnitude of energy losses or inefficiencies in a process is critical. This quantification allows for a precise comparison of various processes and systems, allowing for more informed design decisions and resource allocation. Furthermore, exergy analysis can aid in the prioritization of improvement efforts by revealing which components or stages have the most impact on overall system inefficiencies. Exergy analysis is critical in the aim of optimizing energy systems. It provides a clear roadmap for improving overall system efficiency and reducing energy waste. Engineers can focus on designing novel solutions and implementing modern technology to reduce these inefficiencies by pinpointing the locations with the largest exergy destruction or losses. Finding inefficiencies and potential losses in energy systems is made easier with the help of exergy analysis. Engineers and researchers can better understand the reasons that obstruct a system's effectiveness by identifying these troublesome areas. With this information in hand, they can decide how to enhance system design and operational procedures. This study explores the potential for reducing energy consumption by retrofitting existing columns in industrial processes. The focus is on implementing the second law of thermodynamics, which states that energy cannot be converted from one form to another without some loss. This principle is particularly relevant in process industries, where energy consumption is a significant concern. One of the main challenges in optimizing energy usage in process industries is the impact of process uncertainty. Variations in feed and process conditions can lead to higher energy usage and product losses. It makes it crucial to consider the influence of process uncertainty when solving optimization problems. The study proposes using optimization algorithms that are more resilient to uncertainty. For example, stochastic and robust optimization approaches are designed to handle the unpredictable nature of process conditions. These algorithms can identify the optimal control variables that minimize energy usage while maintaining product quality. In addition to using robust optimization algorithms, the study also suggests implementing real-time monitoring and control systems. These systems can help minimize the impact of process uncertainty on energy usage and product losses. By providing real-time data on process conditions, these systems can allow rapid adjustments to control variables to maintain optimal performance. Overall, the study highlights the importance of considering the influence of process uncertainty in solving optimization problems in process industries. By using robust optimization algorithms and implementing real-time monitoring and control systems, achieving optimal performance while reducing energy consumption is possible. It not only results in cost savings for the industry but also helps in reducing the carbon footprint and achieving sustainability goals.

This research aims to maximize diesel production while minimizing exergy destruction in the column, considering uncertainty in crude composition and process parameters. It is an important goal, as exergy destruction can significantly impact the energy efficiency of a process and contribute to higher energy costs. By minimizing exergy destruction, it is possible to increase the overall efficiency of the process and potentially reduce energy consumption. To the authors' knowledge, the exergy analysis of CDU under uncertainty has never been reported in the literature.

1.2 Thesis Outline

The thesis structure is thoughtfully organized, demonstrating a clear and logical progression of ideas throughout its chapters. The second chapter delivers a comprehensive literature review, setting the groundwork by providing an overview of existing research and explaining the specific research objectives. In Chapter 3, a detailed explanation of the theoretical concepts surrounding Artificial Neural Networks (ANN), Genetic Algorithms (GA), and exergy analysis is presented, offering a solid theoretical foundation for the study. Chapter 4 further enriches the thesis by delving into the research methodology, offering a thorough description of the techniques employed to conduct the study. The pivotal point of the thesis lies in Chapter 5, where the results and discussions are presented, providing valuable insights into the findings and their implications. The final chapter, Chapter 6, offers a well-structured conclusion by summarizing the main points of the research and engaging in a thoughtful discussion of the broader implications of the study's outcomes.

Chapter 2

Literature Survey and Objectives

2.1 Literature Survey

With the unpredictability of energy resources, experts have focused on creating and managing effective industrial procedures. In recent years, energy research has grown interested in using exergy analysis to optimize industrial processes. One such process that has received significant attention is the crude distillation unit (CDU), also known as an air distillation unit, which separates the various components of crude oil based on differences in their volatility and boiling point It is a fundamental process in which crude oil is fractionated to separate its various components depending on their variable volatility and boiling points. The CDU is responsible for breaking down crude oil's complex blend of hydrocarbons into more manageable fractions such as naphtha, diesel, kerosene, and several other petrochemical feedstocks.

Using exergy analysis in the context of CDUs is a practical approach to identifying potential sources of inefficiency and waste. The exergy analysis provides a comprehensive assessment of the thermodynamic performance of the CDU process, including the quality of the input and output streams and the thermodynamic potential for improvement. Traditional energy analysis is primarily concerned with energy quantity, ignoring energy quality and the losses associated with energy transformations. Exergy analysis, on the other hand, takes into account the second rule of thermodynamics, which recognizes that not all energy is created equal and that energy can degrade as it undergoes transformations. Exergy analysis, as a result, provides a more accurate and insightful view of the system's performance. Furthermore, exergy analysis within the CDU can show potential for heat integration and energy recovery. Engineers can investigate strategies of utilizing this precious energy to meet additional heating or power demands within the refinery by finding streams with high exergy content. These approaches have the potential to dramatically reduce overall energy usage and, as a result, the environmental effect of the CDU and the entire refinery operation. Exergy analysis during the CDU process allows engineers to discover areas where exergy destruction occurs. During the fractional distillation of crude oil, important energy is irreversibly lost or destroyed. Researchers can develop and execute solutions to prevent such losses and improve the overall energy efficiency of the CDU by finding these inefficiencies.

One of the key challenges in applying exergy analysis to CDUs is estimating the optimal cut points for the different crude oil fractions. It is a complex problem that requires the consideration of multiple factors, including the properties of the crude oil, the design of the CDU, and the desired product specifications. Several research studies have proposed using hybrid optimization techniques, such as combining Taguchi methods with genetic algorithms or artificial neural networks (ANNs). These methods effectively identify the optimal cut points for CDUs by combining the advantages of the deterministic and stochastic optimization approaches. For instance, Taguchi methods provide a systematic way of evaluating the effects of different process parameters on the performance of the CDU. At the same time, genetic algorithms and ANNs offer the ability to handle complex, nonlinear relationships and to search for global optima. The studies conducted so far have shown promising results in terms of the accuracy and robustness of the estimated cut points, as well as the computational efficiency of the optimization algorithms. However, there is still a need for further research in this area, particularly regarding the scalability of the methods to larger-scale industrial systems and incorporating other vital factors, such as economic considerations and environmental impacts. Adjusting the points at which different fractions of crude oil are separated, known as cut-points, can be a valuable strategy to enhance the output of a particular product while also reducing energy consumption within the distillation column. It can be achieved by identifying and optimizing the cut points that result in the highest yield of the desired product while minimizing the energy required for the separation process. This approach can lead to more efficient operations and cost savings for the industry.

Furthermore, it can also positively impact the environment by reducing the energy consumption and greenhouse gas emissions associated with crude oil processing. Therefore, various methods have been developed to optimize the cut points in crude oil distillation units in recent years. These methods aim to enhance the production of a specific product while minimizing energy consumption within the distillation column. Some of the methods that have been proposed in the literature include the following:

- The mode or categorization approach uses statistical analysis to identify the most likely cut points for a given crude oil sample [4].
- The swing cut modeling method uses a simulation-based approach to optimize the cut points by varying the feed conditions and process parameters [4].
- The fixed yield structure representations model uses a mathematical model to represent the relationship between the cut points and the product yields [5].
- The fractionation index model uses a thermodynamic approach to optimize the cut points based on the exergy of the input and output streams [6].
- The Taguchi method uses a statistical design of experiments to evaluate the effect of different process parameters on the performance of the distillation column [7].
- The weight transfer ratio (WTR) approach uses a mass balance to optimize the cut points based on the ratio of the mass of a product to the mass of the feed [8].
- Monotonic interpolation uses interpolation techniques to estimate the cut points based on the properties of the crude oil and the product specifications [9].
- The hybrid framework of genetic algorithm (GA) uses a combination of genetic algorithms and other optimization techniques to search for optimal cut points [10].
- The Taguchi-GA-ANN is a hybrid method that combines the Taguchi method, genetic algorithms, and artificial neural networks to optimize the cut points [11,12].

These methods effectively identify the optimal cut points for crude oil distillation units. However, each method has its strengths and limitations. The mode or categorization approach, for example, is simple and easy to implement, but it may not be able to handle complex nonlinear relationships. On the other hand, the swing cut modeling method is more complex and computationally intensive, but it can handle a wide range of feed conditions and process parameters. The fixed yield structure representations model, fractionation index model, Taguchi method, weight transfer ratio (WTR) approach, monotonic interpolation, and the hybrid framework of genetic algorithm (GA) have been used to optimize the cut points of crude oil distillation units and have shown promising results in terms of the accuracy and robustness of the estimated cut points. The Taguchi-GA is a hybrid method that combines the Taguchi method and genetic algorithms to optimize the cut points. It is a powerful optimization tool that can handle complex, nonlinear relationships and search for global optima. The literature suggests several methods have been developed for cut-point temperature optimization in crude oil distillation units. Each method has its strengths and limitations, and the choice of method will depend on the application's specific requirements. However, more research is needed to fully understand these methods' potential benefits and limitations and develop practical implementation strategies for industrial applications.

In the pursuit of energy efficiency and sustainability within the petroleum industry, exergy analysis and modeling techniques play a pivotal role in evaluating and optimizing crude oil distillation units. These studies provide valuable insights into the various aspects of energy utilization, process efficiency, and operational optimization Researcher conducted an important study that implemented energy and exergy analysis on single- and two-stage crude oil distillation units. By comparing the overall exergy efficiencies of these configurations, they demonstrated that the two-stage distillation unit outperformed the single-stage one by approximately 17.5%. This finding underscores the significance of multi-stage distillation systems in achieving higher energy efficiencies and more optimized processes [13]. Franzoi et al. (2020) contributed significantly to the field with their cut point temperature-modeling framework for distillation units. Their research focused on developing techniques to determine optimizable surrogate models, which establish correlations between key independent variables, such as crude oil compositions and temperatures, and various dependent variables, including stream yields and properties of distillates. The introduction of these surrogate models allows for more accurate and efficient modeling of the distillation process, aiding in better process control and optimization. [14]

Exergy analysis is a powerful method for evaluating energy systems' thermodynamic performance and identifying improvement opportunities. This technique is beneficial for crude distillation units (CDUs). In recent years, several studies have been published on the exergy analysis of CDUs. These studies have focused on a variety of topics, including the relationship between exergy efficiency and operating conditions [15], the number of trays in the distillation column [16], the use of flash preheating [17], and the integration of CDUs with other process equipment such as heaters, columns, and condensers [18,19]. In addition, several studies have also been reported on using optimization techniques for the exergy analysis of CDUs. For example, some researchers have used sequential quadratic programming to minimize exergy loss [20].

In contrast, others have used bootstrap aggregated neural networks (BANN) to estimate optimum process conditions for higher exergy efficiency [21]. The literature suggests that exergy analysis is a valuable tool for optimizing the performance of crude distillation units. By identifying problem areas in the process and informing better design choices, exergy analysis can help improve these systems' efficiency and profitability. Furthermore, the use of optimization techniques, such as sequential quadratic programming and BANN, can make it possible to minimize exergy loss and estimate the optimum process conditions for higher exergy efficiency. However, there is still a need for further research in this area, particularly regarding the scalability of these methods to larger-scale industrial systems and the incorporation of other essential factors, such as economic considerations and environmental impacts. The simulation-optimization approach presented by Ibrahim et al. (2017) represents a significant advancement in the field of crude oil distillation unit design. The integration of a rigorous tray-by-tray model with an optimization algorithm allows for a comprehensive and detailed examination of the system. This approach not only simplifies the modeling process but also enhances the accuracy of the optimization, leading to more efficient and well-designed distillation units [22]. On a broader scale, the study by Nguyen et al. (2014) emphasizes the importance of defining exergy efficiencies in petroleum systems, particularly within the context of crude distillation plants. The lack of uniformity across different formulations of exergy efficiency poses challenges in accurately evaluating the performance of such systems. Establishing a standardized approach to exergy analysis in the petroleum industry is essential to enable consistent comparisons and foster better understanding and improvements. The work of Ochoa-Estopier & Jobson (2015) introduces another vital aspect of optimization in crude oil distillation units: heat integration. By utilizing artificial neural networks, the study provides a dynamic representation of the distillation process, allowing for more precise control and adaptability. The proposed retrofit modifications for the heat exchanger networks offer practical solutions for enhancing the overall efficiency and performance of the distillation unit. [23]

In one research conducted, a retrofit-optimization framework was proposed for the design of crude oil distillation systems based on exergy analysis. Optimization of the entire process was undertaken by minimizing exergy loss as the objective function. The theoretical framework was used to analyze the influence of key factors on the exergy loss of different components in the crude oil distillation unit at Dalian Petrochemical Refinery. The process was retrofitted to reduce exergy loss by adding two pre-flashing drums, and the temperature of the pre-flashings and vapor feed stage of the main tower was optimized. Operational parameters were further optimized using the SQP methodology with exergy loss of each sub-unit as objective functions. The improved distillation process, considering optimized heat exchange networks, achieved higher exergy efficiency and a significant reduction in Total Annualized Cost (TAC). Compared to the basic process, the exergy efficiency increased from 28.9% to 41.4%, with a cost-saving of 28.8% for the entire distillation process. This retrofit-optimization framework has potential applications in enhancing energy and exergy efficiency in similar chemical separation processes, contributing to improved sustainability and economic viability in the petroleum industry. However, its applicability to reaction systems at this level needs further consideration. [24]

Considering these studies, it becomes evident that exergy analysis, coupled with advanced simulation and optimization techniques, can significantly contribute to the ongoing efforts to improve the energy efficiency and sustainability of crude distillation processes. By adopting these methodologies and implementing the findings, the petroleum industry can reduce energy consumption, lower greenhouse gas emissions, and enhance the overall performance of its refining operations.

In this research, we have incorporated exergy analysis into our previous work utilizing a hybrid approach that combines the Taguchi method and genetic algorithm [11]. Furthermore, we have also considered uncertainty in process variables such as temperature, pressure, and flow rate, in addition to the composition of the feed.

2.2 Research Objectives

This study aims to increase the production of diesel fuel while simultaneously reducing the exergy destruction in the distillation column, considering the unpredictability of crude oil composition and process parameters. This objective is crucial as exergy destruction can substantially affect a process's energy efficiency, ultimately leading to high energy expenses. The main contributions of the present study are given below:

- The development of an HYSYS-based fractionation model for Kunnar and Zamazama crudes, integrated with a MATLAB code, to analyze cut points and exergy in the CDU under artificially induced uncertainty in crude compositions and process conditions.

- Development of a hybrid framework combining Taguchi and Genetic Algorithm techniques to determine optimal cut points in the CDU column, resulting in higher production of diesel with minimal exergy losses.

- The development of an artificial neural network-based model to estimate optimal cut points without using GA and Taguchi methods.

Chapter 3

Process Description and Simulation Method

3.1 Process Flow Description

In this study, we conducted a simulation of a crude distillation unit using the Aspen HYSYS software to analyze the behavior of two distinct Pakistani crude oils: Kunnar and Zamzama. Prior to the simulation, we characterized the crude oils by examining various properties, including crude properties, API gravity, light end volume percent, TBP distillation, and ASTM distillation. These properties were utilized as input data in the Aspen HYSYS software, enabling us to generate compositions for pseudo components and identify known light-end components associated with each crude oil. Subsequently, we employed these compositions to simulate the crude distillation unit and assess the overall process performance. The main objective of our simulation was to evaluate how the crude distillation process behaves for Kunnar and Zamzama crude oils. Through the utilization of Aspen HYSYS, we gained insights into the separation of different components present in the crude oils, including their boiling points and other key characteristics. This allowed us to analyze the yields of various fractions, ranging from lighter components like gasoline and naphtha to heavier components such as diesel and atmospheric residue. By comparing the performance of the crude distillation unit for both crude oils, our simulation results offered valuable information for optimizing the distillation process for each specific type of crude oil. These findings contribute significantly to the knowledge and understanding of how different crude oils respond to the distillation process, which can have practical implications for refining strategies in the petroleum industry. The Aspen HYSYS model provides a valuable tool for understanding the behavior of the crude distillation unit and identifying opportunities for optimization. Both Kunnar and Zamzama crude oils are sweet and light. The crude oil is supplied to the flash column at a pressure of 517 Kpa and 232.2 C, then heated in a furnace to 343.3 C before entering the crude distillation unit. The pressure in the crude distillation tower is lower than the heater, so when the feed enters the 28th tray of the column, it begins to boil. Three pump-around systems are installed for internal reflux, and the column has 29 trays. The vapors produced by the boiling liquid, mainly containing the feed's lighter components, rise through the tower in a series of distillation stages. As the vapors rise, the temperature decreases, and the components condense. The liquid that remains after distillation, mainly composed of the heavier components of the feed, flows downward and accumulates at the bottom, where it is extracted as the bottom product. The yield of the distillation column refers to the percentage of each component, referred to as the product stream, that is separated during the process. The products of the distillation tower include residue, AGO, diesel, kerosene, naphtha, and off-gas. An ASPEN HYSYS spreadsheet was developed to include all essential parameters needed for optimization. Artificial uncertainty of +/-3% was incorporated into the composition of the crude feed and 12 additional operating parameters, including flow rate, pressure, and temperature. Exergy analysis was performed and stored in the spreadsheet. In the next step, the spreadsheet was linked to a MATLAB code to extract the required parameters for optimization. The primary aim of this research was to investigate and determine the optimal cut points within the crude distillation process, with a particular focus on maximizing the production of diesel while simultaneously minimizing exergy destruction occurring within the distillation column. To achieve this objective, a comprehensive and meticulous simulation using the powerful Aspen HYSYS software was conducted, enabling the exploration of various operating conditions and configurations. By repeatedly running the simulation under different scenarios, researchers could obtain comprehensive insights into how different parameters influenced the performance of the crude distillation unit and the subsequent yields of various product fractions. Through the rigorous analysis of the simulation results, valuable opportunities for process improvement were identified. The strategic optimization of cut points within the distillation process emerged as a key factor in fine-tuning the separation of components within the crude oil. By effectively adjusting the cut points, the distillation unit could achieve higher yields of diesel, a highly valuable and sought-after product in the petroleum industry, thereby potentially bolstering overall profitability and competitiveness for refineries. Furthermore, the study placed significant emphasis on reducing exergy destruction within the distillation process. Exergy destruction represents the irreversibility and inefficiency that occur during energy conversions in the refining process. By recognizing areas of significant exergy destruction and thoroughly understanding the underlying causes, researchers were equipped to propose targeted measures and strategies to minimize these losses. This aspect of the research is of paramount importance as it aligns with the growing focus on sustainability and environmental responsibility in the refining industry. By optimizing energy efficiency and minimizing exergy destruction, refineries can make strides toward reducing their ecological footprint and enhancing their overall environmental performance. It is essential to highlight that the findings and conclusions presented in this study were derived entirely from original research conducted through Aspen HYSYS simulations and rigorous experimentation.

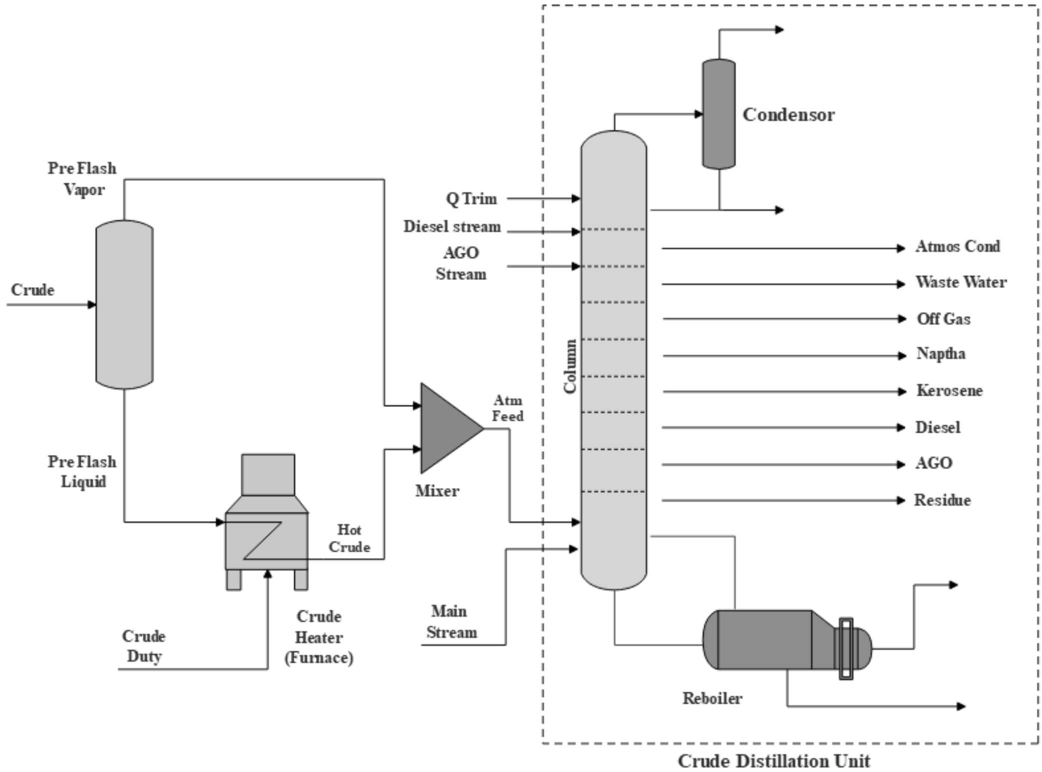

Figure 1 Process flow diagram of crude distillation unit

Table 1 Crude distillation unit parameters

Parameter	Value
Number of Total Stages	29
Column Temperature	70.99°C (top) 338.57°C (bottom)
Column Pressure	135.8 kPa (top) 225.5 kPa (bottom)
Number of pump-arounds	3
Number of side-strippers	3
Crude Inlet Rate	100.00 kBPD
Crude Inlet Location	Stage 28
Crude Inlet Temperature	328.60 °C
Crude Inlet Pressure	448.20 kPa
Condenser Category	Partial Condenser
Fluid Package	Peng-Robinson

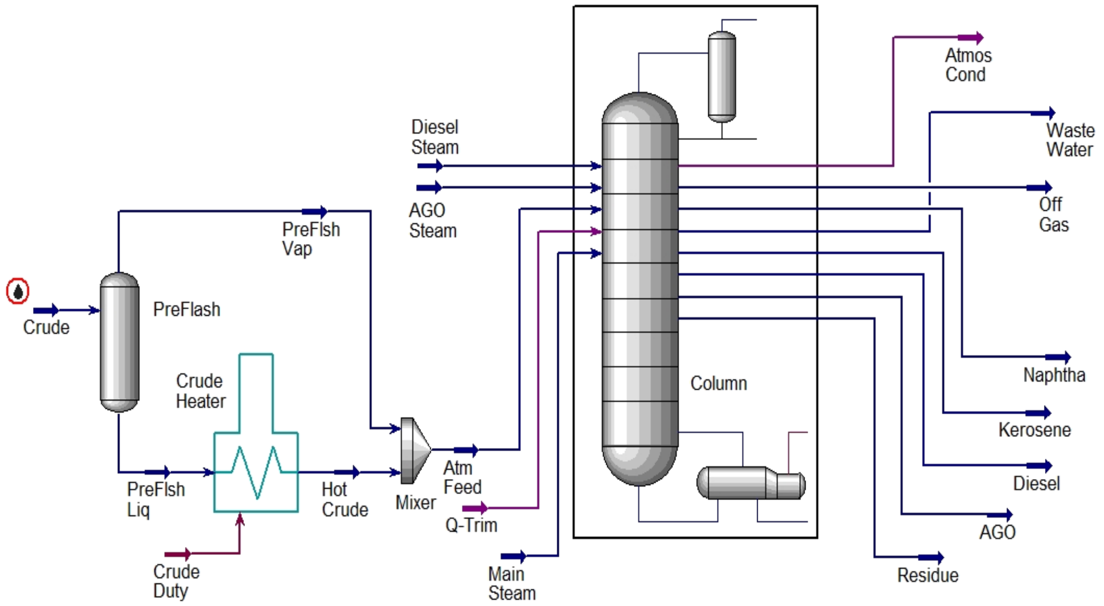

Figure 2 HYSYS Flow diagram of CDU

3.2 Taguchi Method:

The Taguchi method is a statistical technique often used to optimize the design of processes across various engineering fields. It is a powerful tool that can optimize various process parameters, including manufacturing, quality control, and product design. For example, the Taguchi method has been employed in chemical refineries to optimize chemical production, reduce energy costs, and improve safety. The basic principle behind the Taguchi method is to use experimental design to optimize a process or product by altering input parameters such as material properties and process conditions and observing the resulting output performance. The goal is to identify the combination of input parameters that yields the best output performance. In order to use the Taguchi method, one must first determine the goal function, quality attributes, and regulating elements and their levels.

This study used the Taguchi method to estimate optimal cut points for a crude distillation column that would maximize diesel production and minimize exergy destruction. The Taguchi method is a well-recognized and effective statistical technique widely used to optimize process design problems across various engineering disciplines. It is a reliable tool for optimizing various process parameters and has been utilized in various settings, including chemical refineries, to optimize chemical production, reduce energy costs, and improve safety. Using experimental design to alter input parameters and observe the resulting output performance, the Taguchi method allows for identifying the combination of input parameters that yields the best output performance. This can be an invaluable tool for optimizing process design and improving efficiency.

Using the Taguchi method, the impact of various factors on the crude distillation unit (CDU) model can be systematically evaluated. The number of factors and levels considered determine the choice of an appropriate orthogonal array for the experiment. [25].

Table 2 Levels and Factors for Taguchi

Factors.		Level 1 .	Level 2 .	Level 3.
A .	Naphtha .Cutpoint .Temperature .	-5ºC .	Straight.Run.Temp.	+5ºC .
B .	Kerosene .Cutpoint .Temperature .	-5ºC .	Straight.Run.Temp...	+5ºC .
C .	Diesel .Cutpoint .Temperature .	-5ºC .	Straight.Run.Temp.	+5ºC .
D .	AGO .Cutpoint .Temperature .	-5ºC .	Straight.Run.Temp.	+5ºC .

Table 3 Orthogonal Array Selector

		Number of Factors								
		2	3	4	5	6	7	8	9	10
Number of Levels	2	L4	L4	L8	L8	L8	L8	L12	L12	L12
	3	L9	L9	L9	L18	L18	L18	L18	L27	L27
	4	L'16	L'16	L'16	L'16	L'32	L'32	L'32	L'32	L'32
	5	L25	L25	L25	L25	L25	L50	L50	L50	L50

Table 4 L9 (4-factors 3-levels) DOE standard orthogonal array

Trials	Factor A	Factor B	Factor C	Factor D
1	1	1	1	1
2	1	2	2	2
3	1	3	3	3
4	2	1	2	3
5	2	2	3	1
6	2	3	1	2
7	3	1	3	2
8	3	2	1	3
9	3	3	2	1

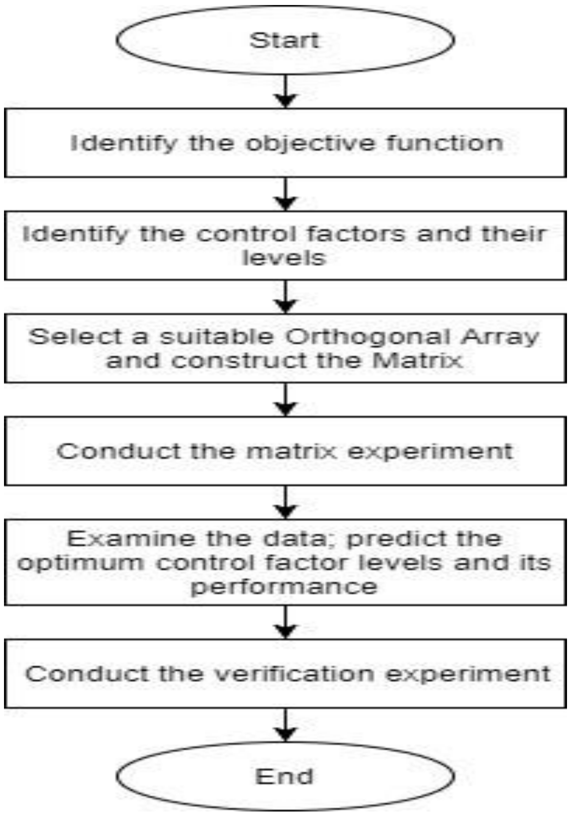

Figure 3 Taguchi Method Flow Diagram

3.3 Genetic Algorithm

A genetic algorithm (GA) is a computational method to optimize complex processes and solve difficult problems. It was developed by Japanese statistician Genichi Taguchi in the 1950s and is based on natural selection and heredity principles. A GA operates by simulating the process of evolution, in which individual solutions (often represented as chromosomes) are selected through mutation and crossover. This selection process is repeated until an optimal solution is achieved. This approach helps minimize the process's cost, time, and energy while maximizing efficiency. In addition, a GA can identify areas for improvement in large industrial processes, allowing companies to reduce costs and increase efficiency by finding the most optimal solution to a process. In crude distillation, GAs (Genetic Algorithms) can identify the optimal operating conditions for the distillation process, such as the best combination of temperature, pressure, and flow rates. The use of GAs in industrial processes has the potential to reduce costs and increase efficiency. By finding the most optimal solution to a process, GAs can help companies to produce more products with less waste. This can lead to significant savings in terms of raw materials, energy, and labor costs. In our study, a genetic algorithm was employed with the Taguchi Algorithm to predict the optimal cut points for a crude distillation unit, leading to minimal exergy destruction per kilo barrel of diesel.

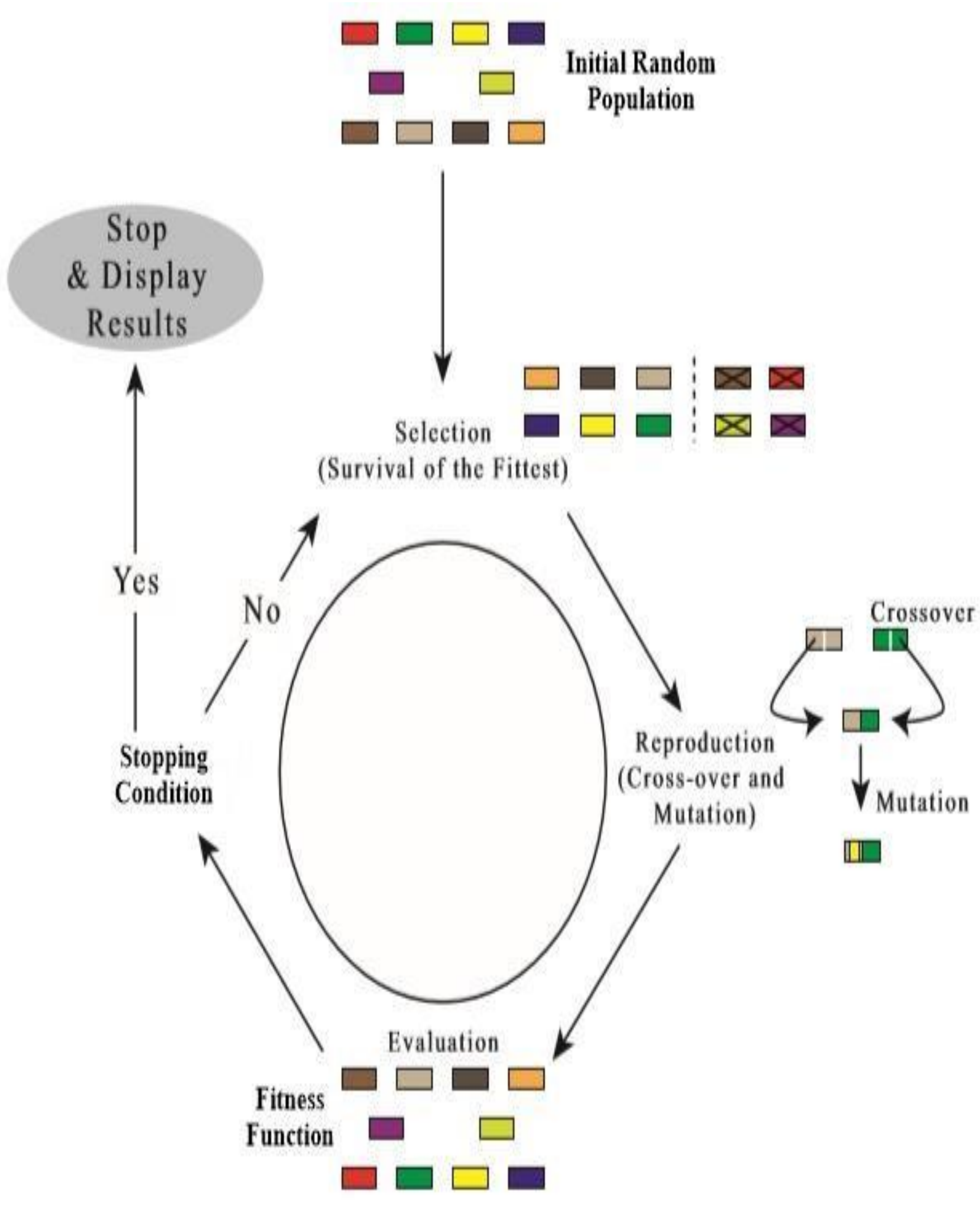

Figure 4 Schematic of Genetic Algorithm

The genetic algorithm comprises the following steps:

- Initialization: To begin, the algorithm creates an initial population of solutions, represented as chromosomes – strings of genes. The number of genes in each chromosome varies based on the specific problem.
- Evaluation: Each solution in the population undergoes evaluation to determine its fitness, measuring how effectively it solves the problem.
- Selection: A subset of solutions is chosen as parents, based on their fitness. Solutions with higher fitness have a higher chance of being selected.
- Crossover: The selected parents are used to produce offspring by combining their genes. The process of crossover involves randomly determining how the genes of the parents are combined.
- Mutation: Some offspring may undergo mutation, where a gene is randomly altered. The mutation process randomly selects genes to be changed and determines the nature of the change.
- Reevaluation: The fitness scores of the offspring are calculated through evaluation.
- Termination: The algorithm stops when a predefined condition is met. This condition could be reaching a maximum number of generations or finding a solution with a specified fitness score.

The genetic algorithm iterates through these steps until the termination condition is satisfied, usually when a solution with a fitness score above a certain threshold is found. Genetic algorithms are optimization techniques inspired by the process of natural selection. They work by iteratively applying the steps of initialization, evaluation, selection, crossover, mutation, and termination. By iteratively applying these steps, genetic algorithms efficiently explore the solution space and converge towards optimal or near-optimal solutions. Their ability to handle non-linear and multi-modal objective functions makes them particularly valuable in real-world scenarios where traditional optimization methods may fall short. As research and advancements in genetic algorithms continue, we can expect these algorithms to play an increasingly significant role in addressing complex optimization challenges across various industries and domains. [26,27,28]

3.4 Hybrid Taguchi and Genetic Algorithm

A hybrid algorithm combining Taguchi and genetic algorithms can be used to optimize crude distillation processes. The Taguchi algorithm is a statistical method commonly used to optimize process design across various engineering fields. It involves altering input parameters and observing the resulting output performance to identify the combination of input parameters that yields the best output performance. The genetic algorithm is a computational technique that simulates the process of natural selection and heredity to find optimal solutions to complex problems. Combining these two algorithms makes it possible to optimize crude distillation processes in terms of production yield, energy efficiency, and other relevant criteria. The hybrid Taguchi-genetic algorithm demonstrated in our research serves as a robust and effective tool for optimizing crude distillation processes, with the primary objective of enhancing their overall efficiency. Leveraging the capabilities of this hybrid approach, we successfully predicted the optimal cut points for a crude distillation unit by minimizing exergy destruction per kilo barrel of diesel. By integrating the Taguchi and genetic algorithm techniques, we harnessed their respective strengths to achieve more precise and reliable results in the optimization process. The developed hybrid model, implemented using MATLAB, played a pivotal role in streamlining the prediction and optimization procedures, making them more manageable and efficient. Through the application of this model, we observed significant improvements in production yield and exergy efficiency, indicating its potential for enhancing the performance of crude distillation processes in the oil industry. This research contributes valuable insights and practical implications, offering a promising direction for further advancements and implementations in the field of crude distillation optimization and process improvement.

3.5 Artificial Neural Network (ANN)

Artificial neural networks (ANNs) are computational models that take inspiration from the biological neural networks in the human brain. These models can recognize patterns and make decisions based on input data. ANNs are used in many fields, including computer vision, robotics, natural language processing, and speech recognition. They can also be utilized to optimize industrial processes by identifying the most efficient way to complete a task, thereby reducing time and energy costs. In addition, ANNs can optimize production processes and identify bottlenecks, allowing companies to reduce waste and increase efficiency. Artificial Neural Networks (ANNs) are a popular class of machine learning models that are often trained using supervised learning techniques. In the case of supervised learning, the ANN is presented with a labeled dataset, where each input data point is associated with a corresponding target or output value. During training, the network iteratively processes the input data, adjusts its internal weights and biases based on the differences between predicted outputs and actual targets, and gradually improves its performance.

In this research, a MATLAB-based ANN tool was opted to facilitate the optimization process. MATLAB, a powerful programming language and software development platform, is well-suited for creating ANNs due to its extensive capabilities and built-in functions tailored for designing and training neural networks. This choice ensured that the researchers had access to a wide range of tools and functionalities to fine-tune the ANN architecture and effectively handle complex datasets.

The advantages of using MATLAB for ANN development extend beyond its versatile capabilities. The platform's comprehensive visualization tools played a crucial role in facilitating the debugging and analysis of ANN performance. The ability to visualize the network's structure, weight distributions, and activation patterns during training allows researchers to gain valuable insights into the learning process and identify potential issues or areas of improvement.

Moreover, MATLAB's user-friendly interface and intuitive programming syntax enabled a more seamless integration of the ANN into the research workflow. This ease of use and clear syntax enabled the researchers to focus more on the optimization process and experimentation, rather than getting bogged down in complicated implementation details. By leveraging the power of MATLAB for ANN development and optimization, efficient and effective results were achieved. The combination of MATLAB's extensive functionalities, visualization tools, and user-friendly environment contributed to a streamlined and productive research process. As a result, the study yielded a well-optimized ANN model capable of making accurate predictions and extracting valuable insights from the complex dataset, further demonstrating the significance of employing MATLAB as a valuable tool in the field of artificial neural networks and machine learning research.

3.6 ANN MODEL Development

In this study, a novel hybrid Taguchi-genetic algorithm framework was developed and implemented in MATLAB to obtain results, which were then utilized to construct an artificial neural network (ANN) model. The dataset used in the experiment consisted of 307 data sets derived from Zamzama and Kunnar crudes.

To train the ANN model, 80% of the dataset (245 data sets) was used, while the remaining 20% (62 data sets) were reserved for testing and validation purposes. A feed-forward-backward propagation type network was chosen and trained with the backpropagation algorithm using the TRAINLM training method. The performance of the trained ANN was evaluated using the mean squared error (MSE) as the performance function, and the adaptive learning function LEARNGDM was employed to optimize the learning process. Additionally, the root mean squared error (RMSE) and the coefficient of determination (R2) were used as metrics to assess the accuracy and predictive capabilities of the trained ANN model.

This approach allowed for a comprehensive analysis of the ANN's performance, and the hybrid Taguchi-genetic algorithm framework contributed to enhancing the optimization process, ultimately leading to a more accurate and reliable artificial neural network model. The use of real-world crude oil data from Zamama and Kunnar crudes provided valuable insights into the effectiveness of the developed framework and the ANN's ability to handle complex datasets. The obtained results hold significant promise for various applications in the domain of crude oil analysis and prediction.

3.7 Exergy Analysis

Exergy analysis helps evaluate the efficiency of systems, processes, and components. It allows for assessing energy utilization and identifying potential areas for improvement. The analysis considers the energy content of available and valuable energy and their associated losses. Through this approach, the user can identify waste and optimize efficiency. Exergy analysis is a method that utilizes the principles of the first and second laws of thermodynamics. According to the first law, energy can be transformed but not created or destroyed. The second law states that energy degrades during conversion from one form to another. Exergy analysis then identifies the losses associated with energy conversion [29]. Exergy analysis is a common technique employed in various industries to enhance the efficiency of their processes. For instance, exergy analysis has been utilized in the refining industry to evaluate the energy efficiency of systems such as fuel, cooling, and steam networks. It has also been used to compare the efficiency of different refinery processes, including alkylation, cracking, distillation, and reforming. As a result, refineries can implement improvements to minimize energy consumption and improve efficiency by understanding the exergy losses in each process. Exergy analysis can optimize the separation of crude oil into various products, such as naphtha, kerosene, and diesel, within the crude distillation unit (CDU). By utilizing this technique, it is possible to identify the most energy-efficient operating conditions for the CDU and the optimal cut points for the various products. It can be achieved using process simulation software, such as Aspen HYSYS, which can model the CDU and forecast the exergy losses under different operating conditions.

Exergy can be classified into several types based on its origin and form. Farzad et al. proposed a straightforward method to calculate the exergies of a material stream within an HYSYS simulation [30]. The two parameters used to analyze the exergy content by Farzad were exergy destruction and exergy efficiency. The exergy destruction or irreversibilities represented by the symbol I are calculated using equation 10.

$$I = \sum_{i=1}^{N_{\mathrm{t}}} E_{in,i} + \sum_{i=1}^{N_{\mathrm{im}-at}} \mathrm{Q}_i \left(1 - \frac{T_0}{T_i}\right) - \dot{W} - \sum_{i=1}^{N_{\mathrm{cot}}} E_{\mathrm{out}\,,i} \ \dots \qquad \dots\dots(1)$$

The exergy efficiency was calculated as the ratio of the sum of the incoming exergies to the outgoing exergies represented by the symbol ϵ.

$$\epsilon = \frac{\sum_{i=1}^{N_{\mathrm{out}}} E_{\mathrm{out}\,,i} + \dot{W}_{\mathrm{out}} + \sum_{i=1}^{N_{\mathrm{ot}}} \left|\dot{Q}_i\right| \left(1 - \frac{T_0}{T_i}\right)}{\sum_{i=1}^{N_{\mathrm{in}}} E_{\mathrm{in},} + \left|\dot{W}_{\mathrm{in}}\right| + \sum_{i=1}^{N_{\mathrm{w}}} \dot{Q}_i \left(1 - \frac{T_0}{T_i}\right)} \ \dots\dots \qquad \dots.(2)$$

By definition of the above equation, the exergy input to a control volume is the total amount of exergy that enters the system and it is equal to the sum of exergy destroyed within the control volume and the exergy that is desired to be outputted from the control volume

$$\epsilon = \frac{|\Delta E_{desired}|}{|\Delta E_{desired}| + 1} \dots\dots \qquad \dots.(3)$$

3.8 Methodology

STEP 1: The crude distillation process involves separating the crude oil into various fractions or components based on their boiling points. The ASPEN HYSYS software is widely used in the petroleum industry for simulating and optimizing the crude distillation process. This study's crude oil assay data for Zamzama and Kunnar Blend was input into the ASPEN HYSYS environment. The software then used this data to characterize the crude oil and generate multiple hypothetical pseudo components based on their boiling points. These pseudo components were then used to simulate the crude distillation process, allowing the US to optimize the process and improve production yields.

STEP 2: The ASPEN HYSYS model was essential in our study of the crude distillation unit (CDU) and its pretreatment processes. In the next step, the crude distillation system was simulated. We used the built-in features of HYSYS to evaluate the exergy of the CDU and recorded the results in a spreadsheet. To make our simulations more realistic, we introduced artificial uncertainty to some crude parameters by varying them by +/-1%, +/-2%, and +/-3%. This helped us account for the variability encountered in actual field conditions. Combining the ASPEN HYSYS model and the spreadsheet provided a comprehensive and accurate analysis of the CDU's performance.

STEP 3: Integrating the HYSYS model with MATLAB code was crucial in our optimization process. It allowed us to access and use relevant information from ASPEN HYSYS to guide our optimization efforts. We generated optimized results by modifying specific parameters within HYSYS using this code. We employed a hybrid optimization framework comprising Taguchi and Genetic Algorithm techniques to achieve this. This optimization process aimed to identify optimal cut points for the crude distillation column that would maximize diesel production while minimizing exergy destruction. It was accomplished by developing and customizing the hybrid optimization framework to fit the specific needs of our system.

STEP 4: In the concluding stage of our project, we utilized the data generated by the Hybrid Taguchi and Genetic Algorithm to develop an Artificial Neural Network (ANN) model in MATLAB. A portion of the data, precisely 80%, was designated for training the ANN model, while the remaining 20% was reserved for testing and validation. Upon implementing the ANN model, we discovered that it successfully determined optimal cut points aligned with our objective. Furthermore, it eliminated the need to utilize the Taguchi and Genetic Algorithm techniques further. Overall, the integration of the ANN model proved to be an asset in optimizing the performance of our system.

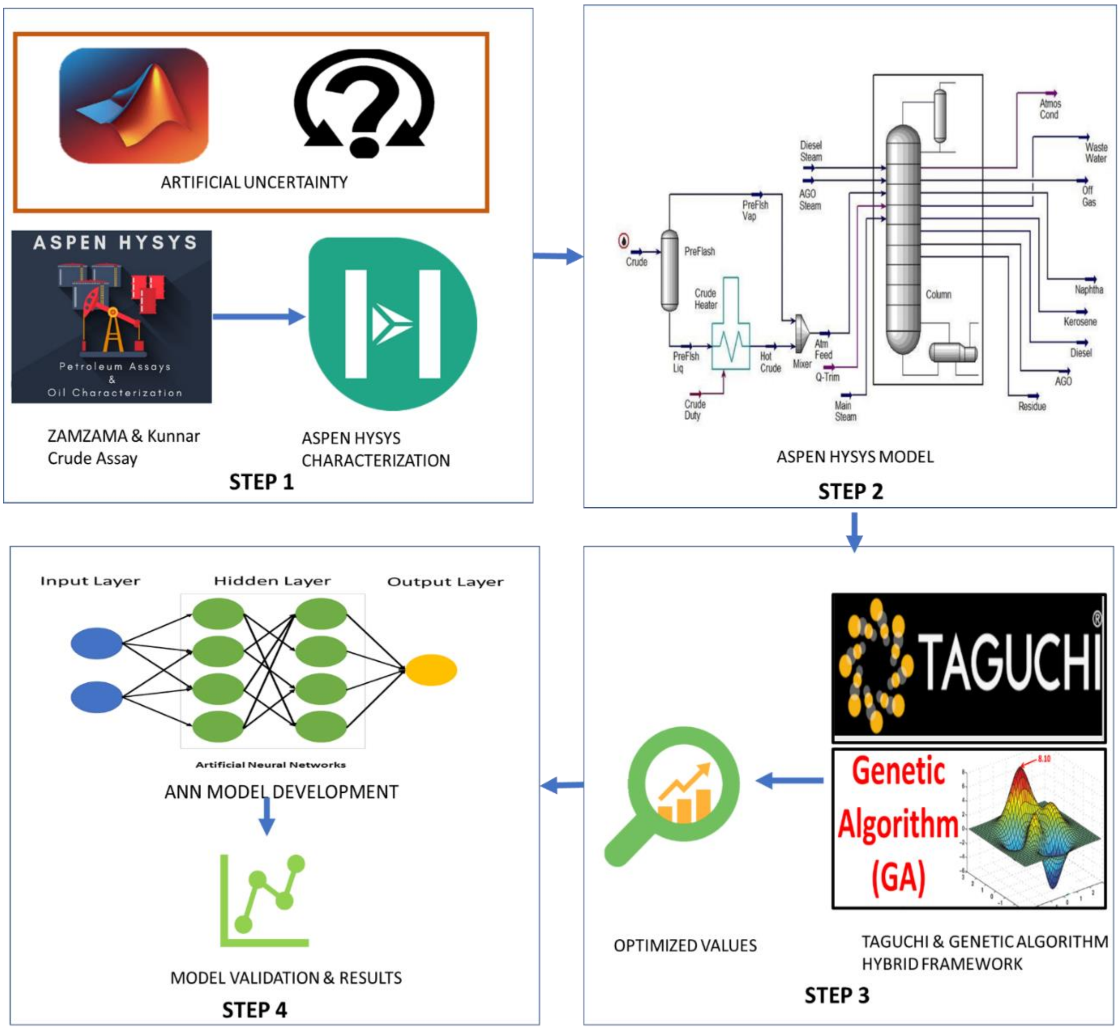

Figure 5 Description of steps involved in research methodology.

Results and Discussion

In this section, the results of comprehensive study on Pakistani crude oils - Zamzama and Kunnar is presented. Through careful analysis and experimentation, I divided the findings into two distinct cases to facilitate a specific examination of each crude oil type. Case 1 focuses on Zamzama crude oil, providing insights into its key properties and behavior, while Case 2 delves into Kunnar crude oil, highlighting its unique characteristics. This systematic approach allowed for a clear understanding of the individual features of each crude oil type, contributing valuable knowledge to the oil industry and scientific community. By presenting the data in a well-structured manner, transparency and accuracy in analysis is ensured, furthering the understanding of Pakistan's crude oil reserves and their potential applications.

Method	Test Description	Zamzama	Kunnar
D-1298	Specific Gravity 60/60 F	0.7934	0.7588
D-1551	Total Sulphur Content (Wt.%)	0.0376	0.0083
D-96	Basic Sediment (Vol %)	< 0.05	< 0.05
D-95	Water Content (Vol %)	< 0.05	< 0.05
D-3230	Salt Content Lb/1000 bbl	4.5	Nil
D-445	Kinematic Viscosity 40 °C (cSt)	1.27	0.78

Figure 6 Properties of Crude Oils

Case 1: Kunnar Crude

In Case 1, we selected Kunnar crude oil and fed the crude data into the HYSYS model designed for the crude distillation process. This oil is characterized by its sweet, light properties with a specific gravity that falls within the range of 0.75 to 0.76. In order to incorporate artificial uncertainty, we modified the crude oil composition and 10 process parameters. Six data sets were generated by introducing uncertainty of -3%, -2%, -1%, +1%, +2%, and +3% in the original process conditions. In order to make the model adapt to changes in the composition of any single component, we introduced uncertainty within the range above in each component of the crude oil individually. The data set for process conditions are illustrated in Figure 7.

Process Conditions	Data set 1	Data set 2	Data set 3	Data set 4	Data set 5	Data set 6
Kunnar Mass Flow (kBPD)	97.0	95.1	94.1	95.1	97.0	99.9
Kunnar Temperature (°C)	501.6	491.6	486.6	491.5	501.3	516.4
Kunnar Pressure (kPa)	225.3	220.8	218.5	220.7	225.1	231.9
Condenser Pressure (kPa)	131.8	129.1	127.8	129.1	131.7	135.6
Main Steam Mass Flow (kg/h)	3299.9	3233.9	3201.6	3233.6	3298.3	3397.2
Main Steam Temperature (°C)	184.8	181.1	179.3	181.1	184.7	190.3
Main Steam pressure (kPa)	1003.2	983.1	973.3	983.0	1002.7	1032.8
AGO Steam Mass Flow (kg/h)	1100.0	1078.0	1067.2	1077.9	1099.4	1132.4
AGO steam Temperature (°C)	144.4	141.5	140.1	141.5	144.4	148.7
AGO steam Pressure (kPa)	334.4	327.7	324.4	327.7	334.2	344.3

Figure 7 Data sets of various parameters with artificial uncertainty

Exergy analysis was performed using the built-in feature of ASPEN HYSYS. The exergy efficiency and destruction in the crude distillation column were calculated and recorded in an HYSYS sheet. This sheet was integrated with a MATLAB code that used hybrid Taguchi and Genetic algorithms to optimize diesel production while minimizing exergy destruction in the column. The optimal cut points were determined by minimizing the target function of "Exergy destruction in the column per unit diesel production (EX/V). 147 data sets were generated using a hybrid structure, including optimized crude distillation unit cut points. These data sets were fed into an Artificial Neural Network (ANN) model in MATLAB, using 118 data sets for training and 29 data sets for testing and validating the ANN model.

The ANN model contained two hidden layers, with 20 neurons in the first layer and 4 neurons in the second layer per output in the output layer. 49 neurons were selected as input for the ANN model. Data randomization was first performed in an EXCEL sheet. Then the "dividerand" function was used to divide the data. Both hidden layers utilized the TANSIG (tangent sigmoid) transfer function. The TRAINLM function, utilizing the Levenberg-Marquardt algorithm, was employed to train the neural network. The training was completed with a gradient of 0.22329 at epoch 26. The mean squared error

(MSE) was used as a performance metric to evaluate the model's accuracy. Figure 9 demonstrates that the ANN model was trained to a superior level of accuracy and precision, as indicated by the R2 value of 0.99996.

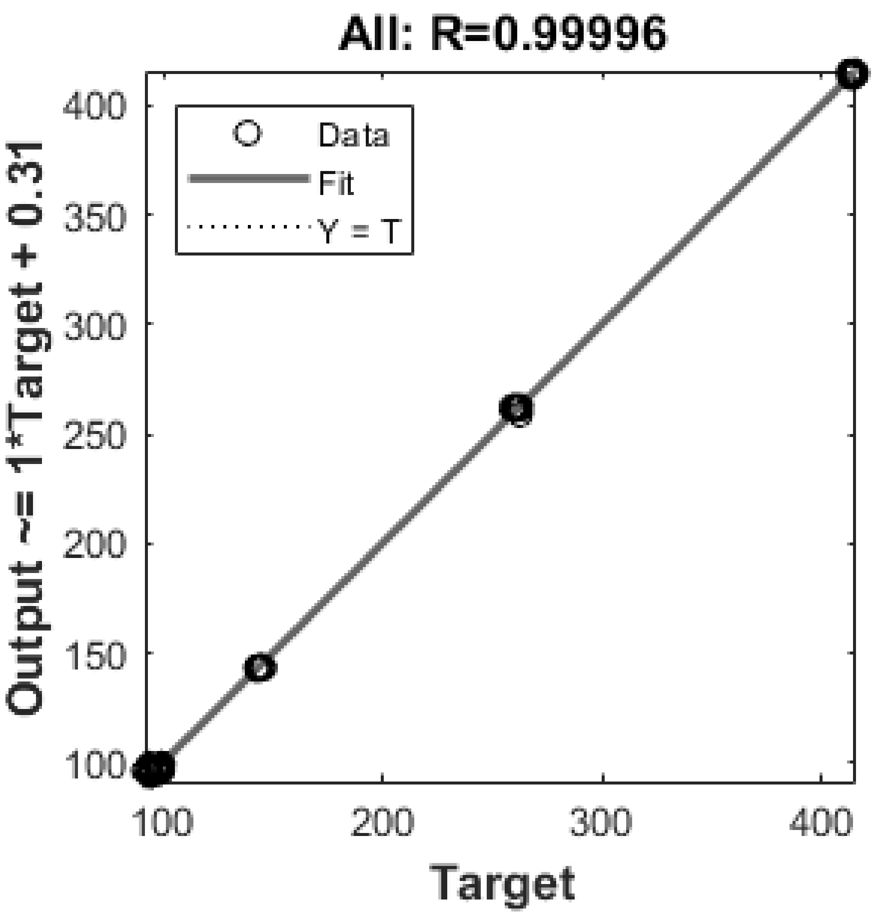

Figure 8 ANN MSE value for combined Training, Validation, and Testing

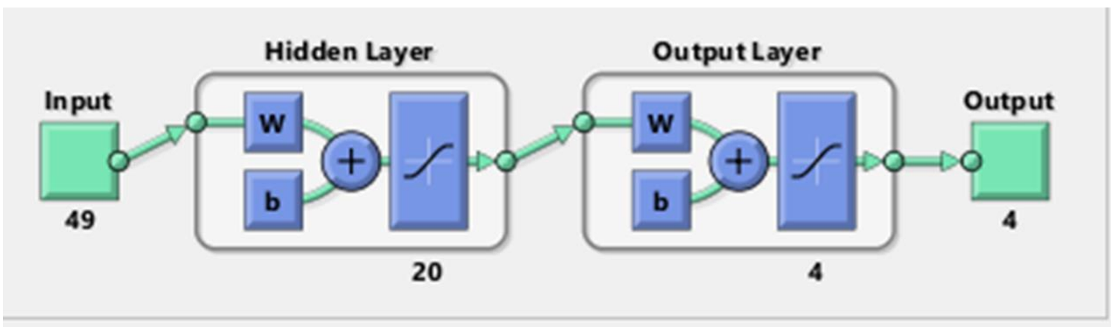

Figure 9 ANN model for Case 2: Kunnar Crude

Model was also robust, requiring minimal computational resources and producing reliable estimations. Figure 10 presents a graphical comparison of the cut points predicted by the ANN model and those optimized using a combination of Taguchi and Genetic algorithms, revealing a high degree of similarity.

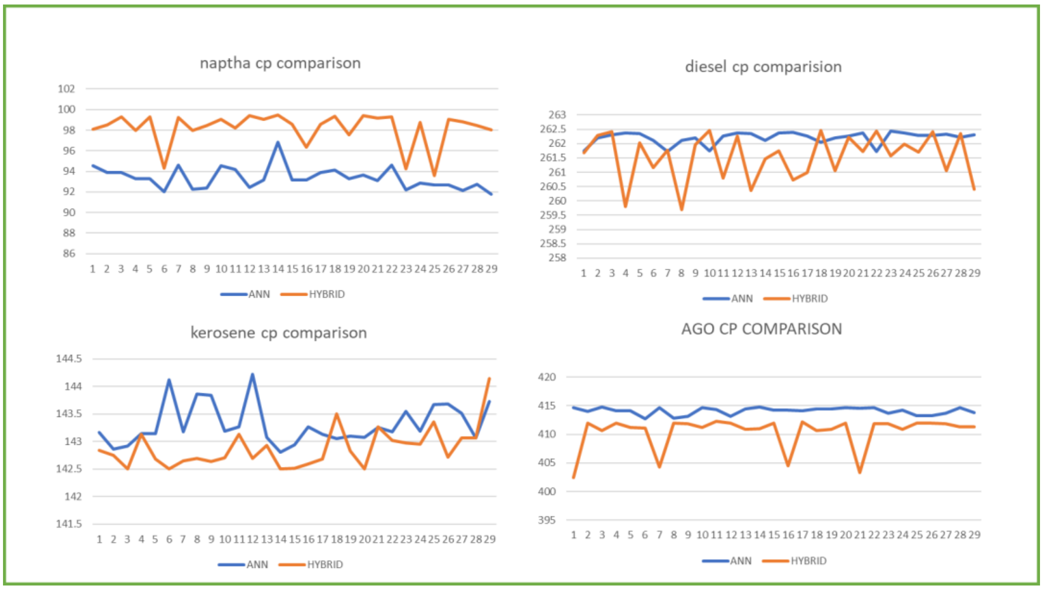

Figure 10 Comparison of cutpoints derived from Hybrid and ANN model

Table 5 Straight Run Model exergy analysis parameters and production data

STRAIGHT RUN								
DIESEL Ex/V	EXERGY EFFICIENCY	EXERGY DESTRUCTION	NAPTHA(KBPD)	KEROSENE (KBPD)	DIESEL (KBPD)	AGO(KBPD)	Residue (KBPD)	Total
5689.61	47.41	126375.34	20.83	19.16	22.21	29.54	8.15	99.89
5645.60	47.32	119493.55	19.65	18.32	21.17	28.20	7.76	95.09
5661.87	47.35	122175.51	20.11	18.65	21.58	28.73	7.91	96.98
5661.12	47.35	122162.90	20.14	18.63	21.58	28.72	7.91	96.98
5661.24	47.36	122229.44	20.15	18.64	21.59	28.74	7.91	97.03
5625.41	47.31	118105.61	19.72	17.86	20.98	27.91	7.67	94.14
5690.34	47.40	126375.28	20.83	19.16	22.21	29.54	8.15	99.89
5633.62	47.26	118380.06	19.77	17.86	20.96	27.89	7.66	94.14
5631.37	47.33	119438.60	19.90	18.04	21.21	28.18	7.75	95.08
5690.34	47.40	126375.28	20.83	19.16	22.21	29.54	8.15	99.89
5691.08	47.54	121520.93	20.27	18.63	21.46	28.72	7.91	96.98
5685.30	47.24	118324.21	19.72	18.10	20.76	27.89	7.67	94.14
5684.94	47.36	122107.83	20.27	18.62	21.48	28.70	7.91	96.98
5668.82	47.34	119385.23	19.90	18.28	21.06	28.10	7.75	95.09
5634.72	47.33	119372.61	19.90	18.27	21.18	27.98	7.75	95.08
5655.59	47.38	122186.90	20.28	18.64	21.61	28.60	7.91	97.03
5664.50	47.11	123119.63	20.27	18.62	21.57	28.66	7.91	97.03

5664.61	47.37	122201.16	20.27	18.62	21.57	28.66	7.91	97.03
5704.32	47.14	123139.36	20.27	18.63	21.59	28.65	7.90	97.03
5666.38	47.41	122194.95	20.27	18.62	21.57	28.71	7.88	97.03
5652.51	47.40	119414.46	19.88	18.25	21.13	28.14	7.69	95.09
5689.37	47.41	126375.16	20.83	19.16	22.21	29.54	8.14	99.89
5670.56	47.25	119798.64	19.88	18.25	21.13	28.15	7.69	95.09
5666.64	47.39	122201.48	20.27	18.62	21.57	28.71	7.87	97.03
5671.45	47.25	119791.15	19.88	18.25	21.12	28.14	7.70	95.09
5654.80	47.34	119411.06	19.88	18.25	21.12	28.13	7.70	95.08
5657.14	47.34	119410.64	19.88	18.25	21.11	28.13	7.71	95.08
5666.97	47.38	122201.43	20.27	18.62	21.56	28.71	7.88	97.03
5647.50	47.34	118081.47	19.69	18.07	20.91	27.86	7.61	94.14

Table 5 presents data for the straight run of a crude distillation unit without any optimization techniques. The data set comprised 29 distinct sets and was also utilized to test and validate an artificial neural network model. The first column of the table displays the exergy destruction within the column, quantified in kilowatts per diesel production, which serves as the objective function for the optimization problem. The second and third columns contain information regarding exergy destruction and efficiency. In contrast, the remaining columns present data on producing various crude distillation unit products under uncertainty in process conditions and feed composition. It is manifest from these results that a reduction in the production of the other products accompanies an augmentation in the production of one product.

Table 6 Hybrid model exergy analysis data, cut points and production data

HYBRID												
DIESEL Ex/V	EXERGY EFFICIENCY	EXERGY DESTRUCTION	NAPTHA CUTPOINT	NAPTHA (KBPD)	KEROSENE CUTPOINT	KEROSENE (KBPD)	DIESEL CUTPOINT	DIESEL (KBPD)	AGO CUTPOINT	AGO (KBPD)	Residue (KBPD)	Total
4170.87	46.73	126719.65	98.07	20.08	142.84	16.89	261.67	30.49	402.42	23.93	8.49	99.89
4105.62	47.84	119592.61	98.53	19.39	142.75	15.74	262.29	29.23	412.01	23.48	7.25	95.09
4086.19	47.79	122310.08	99.30	20.04	142.50	15.53	262.42	30.04	410.69	23.91	7.46	96.98
4201.19	47.87	122225.67	97.99	20.03	143.14	16.34	259.79	29.20	411.98	24.04	7.37	96.98
4129.53	47.80	122359.88	99.29	20.17	142.68	15.46	262.03	29.74	411.17	24.21	7.46	97.03
4195.88	47.53	118190.48	94.32	16.96	142.50	18.36	261.17	28.27	411.06	23.27	7.28	94.14
4120.79	47.00	126701.45	99.22	20.78	142.65	15.89	261.77	30.86	404.32	24.05	8.31	99.89
4103.61	47.83	118182.47	97.94	18.80	142.69	15.95	259.69	28.90	412.00	23.32	7.16	94.14
4070.99	47.98	119524.87	98.47	20.01	142.64	14.86	261.96	29.47	411.87	23.56	7.19	95.08
4096.29	47.77	126530.29	99.03	20.76	142.71	16.00	262.46	31.00	411.17	24.41	7.73	99.89

4164.73	47.92	122192.00	98.24	19.93	143.14	16.22	260.79	29.44	412.23	24.03	7.35	96.98
4139.35	48.66	117966.75	99.43	19.47	142.69	15.74	262.27	28.60	412.00	23.67	6.66	94.14
4117.33	47.70	122256.94	99.04	20.20	142.93	15.62	260.37	29.80	410.90	23.85	7.53	96.98
4102.87	47.87	119495.68	99.48	19.97	142.50	15.30	261.47	29.23	411.00	23.34	7.25	95.09
4094.68	47.87	119480.81	98.54	19.67	142.52	15.43	261.75	29.28	411.93	23.45	7.24	95.08
4148.45	46.81	122489.40	96.35	19.17	142.59	16.79	260.72	29.63	404.52	23.30	8.14	97.03
4108.43	48.05	122274.87	98.57	20.04	142.68	15.83	260.98	29.87	412.20	24.00	7.29	97.03
4109.55	47.71	122346.00	99.37	20.13	143.51	15.83	262.47	29.88	410.63	23.67	7.52	97.03
4122.45	47.75	122328.80	97.52	19.58	142.83	16.35	261.06	29.78	410.84	23.85	7.48	97.03
4079.64	48.01	122308.11	99.44	20.34	142.50	15.36	262.21	30.09	412.00	23.92	7.33	97.03
4090.31	46.84	119757.16	99.19	19.80	143.27	15.14	261.73	29.38	403.29	22.82	7.96	95.09
4228.48	47.73	126454.06	99.29	19.63	143.03	18.02	262.44	30.01	411.87	24.53	7.69	99.89
4224.60	47.71	119477.79	94.24	16.86	142.97	19.09	261.58	28.38	411.84	23.56	7.19	95.09
4130.39	47.72	122342.78	98.75	20.08	142.96	15.87	261.97	29.73	410.91	23.87	7.48	97.03
4233.34	47.74	119465.00	93.58	16.96	143.36	19.04	261.70	28.32	412.00	23.58	7.19	95.09
4123.97	47.92	119507.70	99.07	19.81	142.72	15.49	262.42	29.08	411.92	23.52	7.17	95.08
4139.75	47.83	119510.50	98.81	19.72	143.07	15.68	261.05	28.97	411.79	23.49	7.23	95.08
4117.91	48.34	122214.33	98.44	20.00	143.07	16.05	262.35	29.78	411.36	24.13	7.07	97.03
4141.23	47.72	118193.09	98.02	19.26	144.14	15.83	260.42	28.64	411.33	23.21	7.19	94.14

Table 6 displays data on exergy destruction within the column, quantified in kilowatts per production of diesel, as well as exergy efficiency, exergy destruction in the column, and optimal cut points estimated through the application of a hybrid Taguchi and Genetic algorithm on a crude distillation model under uncertain feed composition and process conditions. The data set consisted of 29 distinct sets and was also utilized to test and validate an artificial neural network model. These results show that an increase in the production of one product is accompanied by a decrease in the other products' production. In this case, diesel production is increased at the expense of a decrease in the remaining products' production.

Table 7 ANN model exergy analysis parameters, cut points and production data

DIESEL EX/V	EXERGY EFFICIENCY	EXERGY DESTRUCTION	NAPTHA CUTPOINT	NAPTHA (KBPD)	KEROSENE CUTPOINT	KEROSENE (KBPD)	DIESEL CUTPOINT	DIESEL (KBPD)	AGO CUTPOINT	AGO (KBPD)	Residue (KBPD)	Total
4215.60	48.42	126292.04	94.57	17.81	143.16	19.75	261.75	30.07	414.65	25.08	7.18	99.89
4168.75	48.16	119462.81	93.86	16.75	142.87	18.82	262.20	28.76	413.98	23.79	6.97	95.09
4173.05	48.40	122097.58	93.89	17.17	142.91	19.17	262.31	29.36	414.74	24.30	6.97	96.98
4184.44	48.21	122119.13	93.30	17.11	143.15	19.30	262.36	29.29	414.14	24.20	7.09	96.98
4184.69	47.94	123131.52	93.31	17.12	143.15	19.31	262.36	29.30	414.16	24.21	7.09	97.03
4211.01	47.87	118112.61	92.03	16.65	144.12	18.83	262.12	28.15	412.74	23.46	7.06	94.14
4215.77	48.42	126293.67	94.60	17.82	143.18	19.74	261.72	30.06	414.64	25.08	7.19	99.89
4208.83	47.89	118097.40	92.26	16.62	143.87	18.84	262.12	28.16	412.86	23.48	7.04	94.14
4130.50	48.48	119339.73	92.37	16.79	143.85	19.04	262.20	28.46	413.17	23.73	7.07	95.08
4130.50	48.48	119339.73	94.53	17.82	143.19	19.74	261.74	30.06	414.62	25.08	7.19	99.89
4205.89	48.27	122063.97	94.16	17.33	143.26	19.22	262.27	29.13	414.29	24.26	7.05	96.98
4233.42	47.95	118028.50	92.43	16.61	144.23	19.14	262.38	27.98	413.13	23.40	7.01	94.14
4198.53	48.33	122044.51	93.19	17.22	143.08	19.31	262.35	29.17	414.47	24.26	7.01	96.98
4130.50	48.48	119339.73	96.83	18.88	142.81	16.53	262.12	29.00	414.73	23.86	6.83	95.09
4180.77	48.22	119326.99	93.17	16.90	142.95	18.92	262.36	28.64	414.21	23.68	6.93	95.08
4189.75	48.24	122133.77	93.14	17.22	143.27	19.37	262.39	29.25	414.21	24.11	7.08	97.03
4219.48	47.99	123096.02	93.86	17.32	143.13	19.20	262.27	29.28	414.12	24.15	7.09	97.03
4193.81	48.33	122139.19	94.15	17.34	143.05	19.17	262.06	29.23	414.47	24.27	7.03	97.03
4192.89	48.32	122139.84	93.30	17.24	143.09	19.30	262.20	29.23	414.48	24.24	7.03	97.03
4187.96	48.44	122120.76	93.66	17.29	143.08	19.22	262.26	29.26	414.67	24.30	6.95	97.03
4177.36	48.44	119343.21	93.10	16.97	143.25	18.84	262.38	28.67	414.50	23.82	6.79	95.09
4216.20	48.42	126288.80	94.58	17.82	143.18	19.75	261.72	30.06	414.64	25.08	7.18	99.89
4194.03	48.11	119403.04	92.18	16.72	143.55	19.21	262.44	28.57	413.71	23.64	6.95	95.09
4191.88	48.27	122153.78	92.86	17.16	143.19	19.39	262.37	29.24	414.27	24.21	7.03	97.03
4227.10	47.82	120016.73	92.66	16.79	143.68	19.14	262.28	28.50	413.25	23.64	7.02	95.09
4206.06	48.00	119409.84	92.65	16.79	143.68	19.14	262.28	28.49	413.25	23.64	7.02	95.08
4200.19	48.10	119389.09	92.16	16.71	143.51	19.20	262.32	28.53	413.70	23.68	6.97	95.08
4190.89	48.38	122129.52	92.75	17.15	143.07	19.39	262.23	29.25	414.62	24.29	6.96	97.03
4213.41	48.04	118326.43	91.78	16.50	143.73	19.13	262.31	28.18	413.83	23.47	6.86	94.14

Table 7 displays data on exergy destruction within the column, quantified in kilowatts per diesel production, and exergy efficiency, exergy destruction in the column, and optimal cut points estimated by applying the ANN Model on a crude distillation model under uncertain feed composition and process conditions. The data set consists of 29 distinct sets obtained from ANN. Cut points of naphtha, kerosene, diesel and AGO obtained from the ANN model are quite similar to the results of the Hybrid optimization model, while cut points for the straight run model remain the same. The objective was set to minimize EX/V of diesel, which results in a significant increase in diesel production with minimum exergy destruction inside the column. The reported diesel production for these 29 data sets is illustrated in Figure 10.

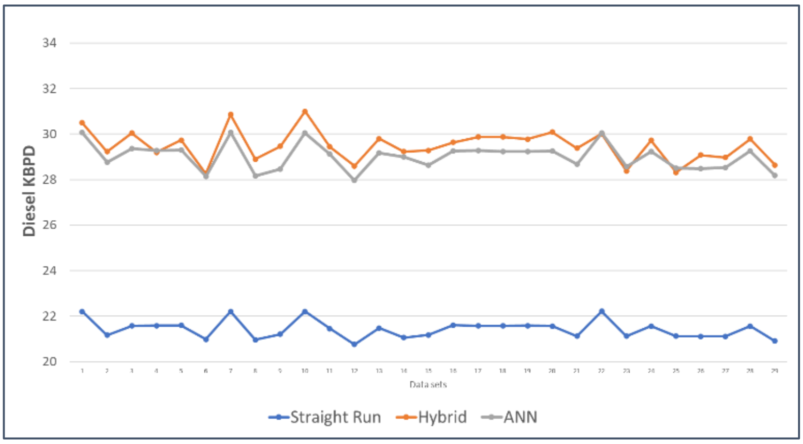

Figure 11 Diesel production data from Straight run, hybrid and ANN model

Figure 11 illustrates that diesel production in kilo barrels per day has significantly increased when using Hybrid Taguchi and Genetic Algorithm, as well as Artificial Neural Network models, compared to the straight run model. Additionally, the graph demonstrates that the production trends for diesel are similar for both the Hybrid optimization and ANN models, indicating the effectiveness of the ANN model.

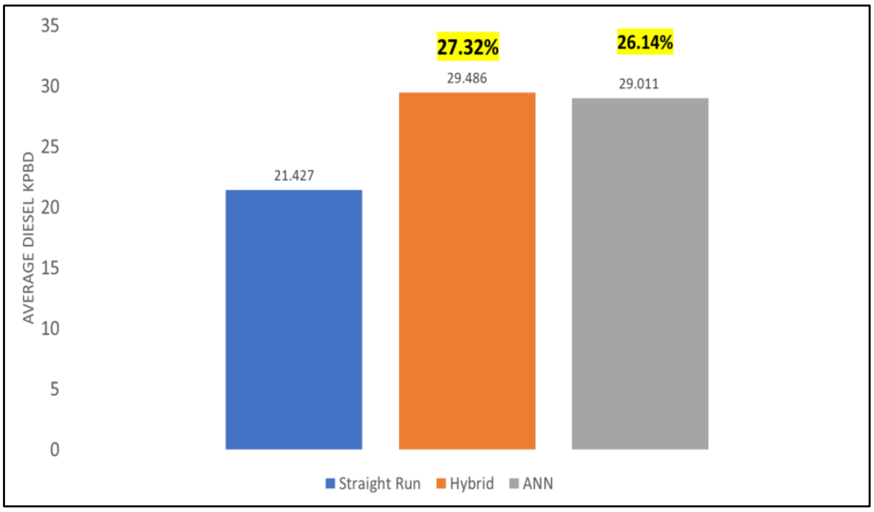

Figure 12 Comparison of average diesel production of straight run, hybrid and ANN models

Figure 12 presents the average diesel production for 29 data sets using the straight run, hybrid, and ANN models. By applying a hybrid Taguchi and genetic algorithm, we observed a 27.32% increase in diesel production in kilo barrels per day compared to the straight-run model. Similarly, using an ANN model resulted in a 26.14% increase in diesel production. Both the ANN and hybrid models outperformed the straight-run model, which had lower average production values of diesel. These results demonstrate the effectiveness of optimization techniques in improving diesel production.

In contrast, the straight-run model, which did not utilize any optimization techniques, had lower average production values than the hybrid and ANN models. The hybrid model, which combines the strengths of the Taguchi and genetic algorithm methods, achieved a greater increase in diesel production. Additionally, the similarity in production trends for diesel between the hybrid optimization and ANN models suggests that ANNs can accurately model and predict production outcomes, as demonstrated in the case of diesel production, where they significantly improved production levels.

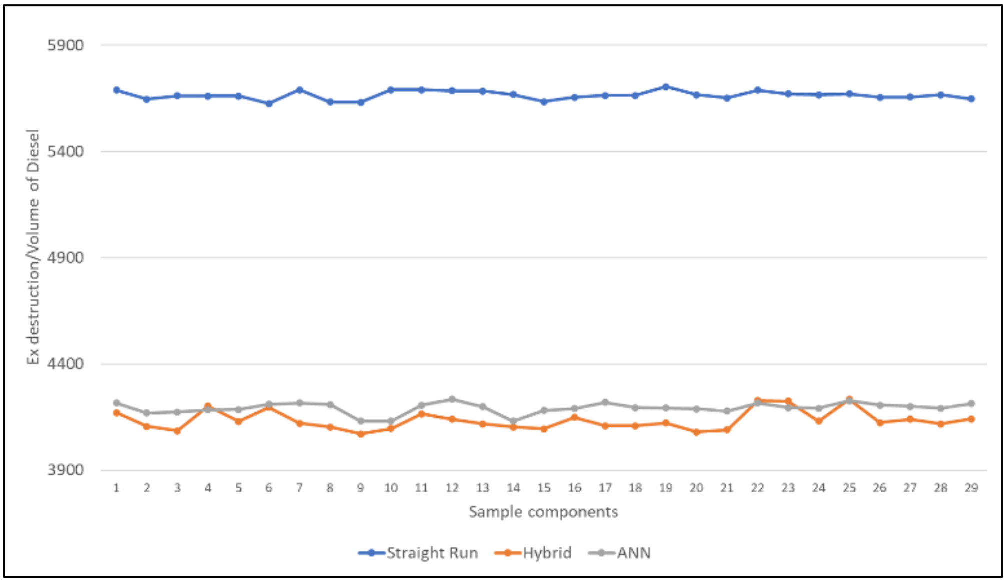

Figure 13 Exergy destruction per kilo barrel of diesel data from straight run, hybrid and ANN models

Figure 13 illustrates that the exergy destruction in the column per diesel production has significantly decreased when using Hybrid Taguchi and Genetic Algorithm, as well as Artificial Neural Network models, compared to the straight run model. The desired objective in the optimization problem was to minimize exergy destruction per diesel flow. It was a critical goal, as reducing exergy destruction can lead to significant energy savings, increasing diesel production. Additionally, the graph demonstrates that the output results for EX/V values are similar for both the Hybrid optimization and ANN models, indicating the effectiveness of the ANN model.

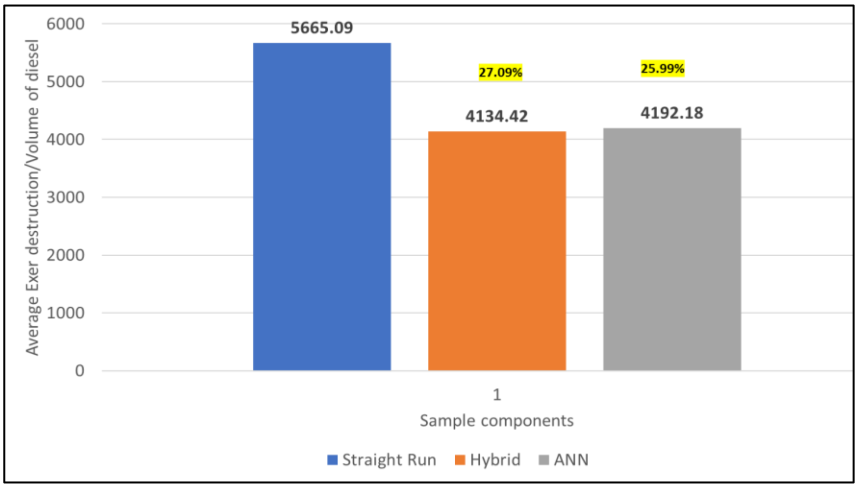

Figure 14 Comparison of average exergy destruction per kilo barrel of diesel from straight run, Hybrid and ANN models

Figure 14 presents the average exergy destruction per diesel flow for 29 data sets using the straight run, hybrid, and ANN models. By applying a hybrid Taguchi and genetic algorithm, we observed a 27.09% decrease in exergy destruction per follow of diesel compared to the straight run model. Similarly, using an ANN model resulted in a 25.99% decrease in exergy destruction per follow of diesel. Both the ANN and hybrid models outperformed the straight-run model, which had higher exergy destruction per follow of diesel values. The hybrid optimization and ANN models showed a similar decrease in exergy destruction per diesel flow, indicating that ANNs can accurately model and predict production outcomes.

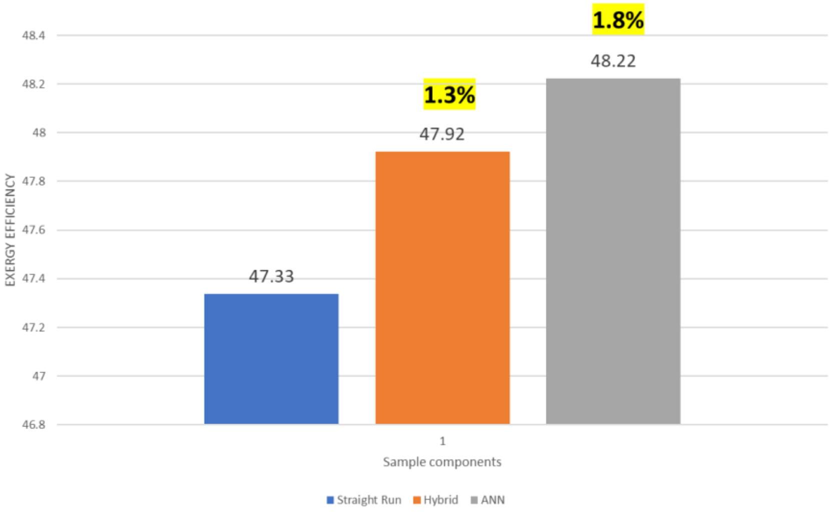

Figure 15 Comparison of average exergy efficiency of straight run, hybrid and ANN models

In Figure 15, the exergy efficiency data of the crude distillation system is compared for all three models. The data set consists of 29 distinct sets, thoroughly analyzing the system's performance. It is vital to consider exergy efficiency when evaluating the effectiveness of a crude distillation system, as it measures the amount of energy that is available to do work. Despite a significant increase in diesel production, the exergy efficiency for the hybrid Taguchi and genetic algorithm model and the ANN model increased. Nevertheless, it is a positive outcome, indicating that the system can produce more diesel while maintaining high energy efficiency.

Hybrid Taguchi and Genetic Algorithm model showed a 1.3% increase in exergy efficiency compared to the straight-run model. It demonstrates this model's effectiveness in improving the system's energy efficiency. Similarly, using an ANN model resulted in a 1.8% increase in exergy efficiency compared to the straight-run model.

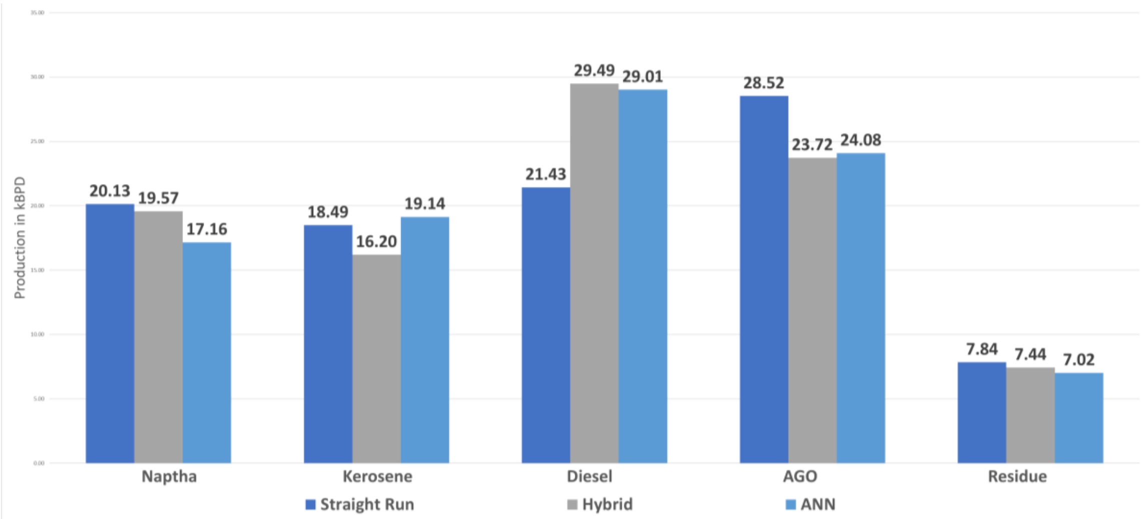

Figure 16 Comparison of average production of crude components of Kunnar Field

Figure 16 summarizes the Kunnar crude production, comparing the production of Naphtha, Kerosene, Diesel, and AGO, as well as residue, for the straight runs, hybrid, and ANN models. The hybrid and ANN models resulted in an increase of around 27% in diesel production compared to the straight runs model. A decrease in the production of the remaining components accompanied this increase in diesel production. An increase in diesel production was achieved while exergy efficiency was improved in a crude distillation unit. This is a significant accomplishment, as it demonstrates the ability of the unit to produce more fuel while also using energy more efficiently.

Case 2: Zamzama Crude

For Case 2, we selected Zamzama crude oil as an input for an HYSYS model that simulates the crude distillation process. This oil is known for its sweet, light properties and a specific gravity between 0.75 and 0.76. We modified the crude oil composition and 10 process parameters to introduce artificial uncertainty. We generated six data sets by making slight changes (-3%, -2%, -1%, +1%, +2%, and +3%) to the original process conditions. We also introduced uncertainty within the specified range for each component of the crude oil. The data set for the modified process conditions are shown in Table 8.

Table 8 Data set of process conditions with uncertainty

Process Condition	Data set 1	Data set 2	Data set 3	Data set 4	Data set 5	Data set 6
Zamzama Mass Flow (kBPD)	97	95.1	94.1	95.05	96.9	99.7
Zamzama Temperature (°C)	225.2	220.7	218.5	220.7	225.1	231.9
Zamzama Pressure (kPa)	554.1	542.9	537.6	542.9	553.8	570.4
Condenser Pressure (kPa)	131.8	129.1	127.8	129.1	131.7	135.7
Steam Mass Flow (kg/h)	3299.9	3233.9	3201.6	3233.6	3298.3	3397.2
Steam Temperature (°C)	184.9	181.2	179.4	181.2	184.8	190.4
Steam pressure (kPa)	1003	982.9	973.1	982.8	1002.5	1032.6
AGO Steam Mass Flow (kg/h)	1099.9	1077.9	1067.2	1077.9	1099.4	1132.4
AGO steam Temperature (°C)	144.4	141.5	140.1	141.6	144.4	148.7
AGO steam Pressure (kPa)	334.4	327.7	324.4	327.6	334.2	344.2

Exergy analysis was performed using ASPEN HYSYS, resulting in the calculation and recording of exergy efficiency and exergy destruction in the crude distillation column in an HYSYS sheet, as we did with case 1. This sheet was integrated with a MATLAB code that utilized a combination of Taguchi and Genetic algorithms to estimate optimal cut points resulting in our desired objective, "Exergy destruction in the column per unit production of diesel (EX/V)" to optimize diesel production while minimizing exergy destruction in the column. 169 data sets were generated using a hybrid structure, including optimized crude distillation unit cut points. These data sets were fed into an Artificial Neural Network (ANN) model in MATLAB, using 135 data sets for training and 34 data sets for testing and validating the ANN model.

The ANN model contained two hidden layers, with 10 neurons in the first layer and 4 neurons in the second layer per output in the output layer. 43 neurons were selected as input for the ANN model.

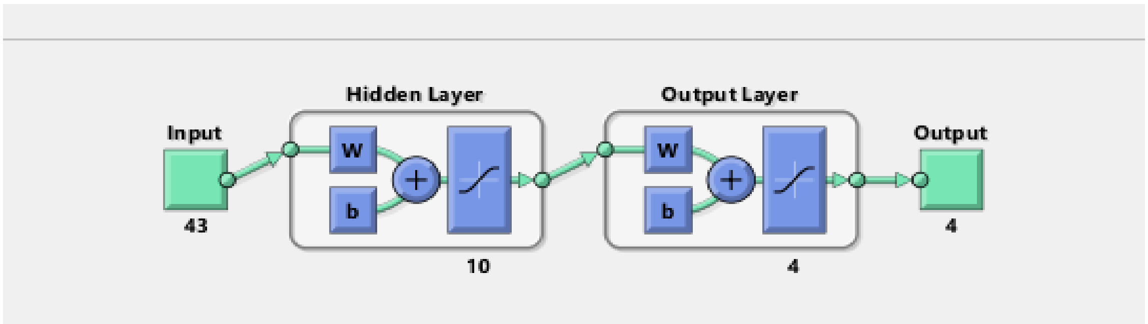

Figure 17 ANN model of Case 2: Zamzama

Both hidden layers utilized the TANSIG (tangent sigmoid) transfer function. The TRAINLM function, utilizing the Levenberg-Marquardt algorithm, was employed to train the neural network. The training was completed with a gradient of 0.252 at epoch 200. The mean squared error (MSE) was used as a performance metric to evaluate the model's accuracy. Figure 18 demonstrates that the ANN model was trained to superior accuracy and precision, as indicated by the R2 value of 0.99995. This is because the model has learned to identify the relationships between the input features and the target variable with a high degree of precision.

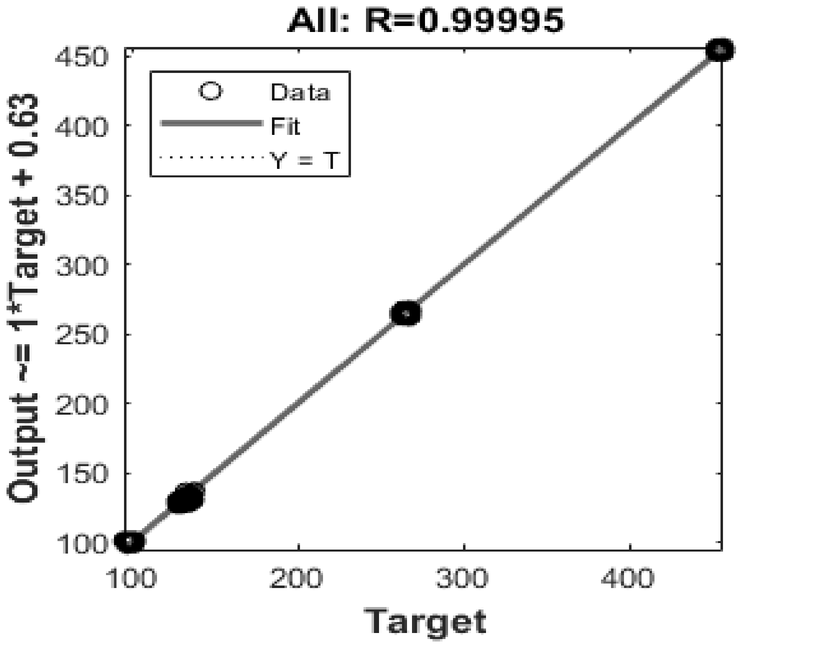

Figure 10 ANN MSE value for combined training, validation, and testing

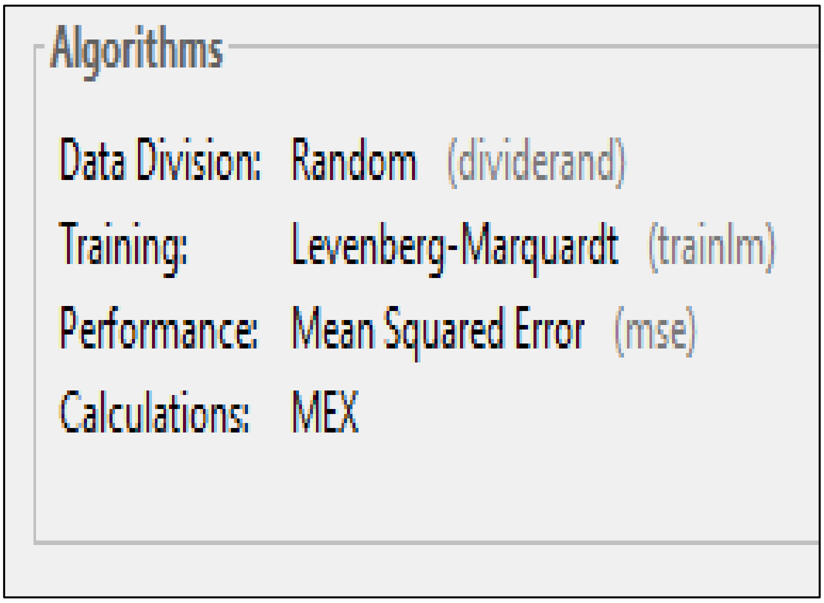

Figure 19 Training and performance monitoring parameters of ANN

Figure 20 compares the cut points predicted by the Artificial Neural Network (ANN) model with those optimized through a hybrid of Taguchi and Genetic algorithms, demonstrating a high level of similarity. This finding suggests that the ANN model accurately predicted the optimal cut points for the crude distillation process.

Figure 20 Comparison of cut point temperatures obtained from Hybrid and ANN models

Table 9 Straight run model exergy analysis parameters and production data

Straight Run								
Exergy destruction / Diesel flow	EX EFF	EX DEST	NAPTHA KBPD	KEROSENE KBPD	DIESEL KBPD	AGO KBPD	Residue KBPD	Total FLOW KBPD
833.95	26.86	31210.51	12.06	22.87	37.42	26.74	0.79	99.89
860.78	26.15	30699.24	11.34	21.83	35.66	25.49	0.76	95.08
860.87	26.14	30705.27	11.34	21.83	35.67	25.49	0.76	95.09
833.82	26.86	31212.51	12.05	22.87	37.43	26.74	0.79	99.89
849.37	26.48	30849.99	11.76	22.17	36.32	26.01	0.77	97.03
833.83	26.86	31209.70	12.06	22.87	37.43	26.74	0.79	99.89
866.77	26.17	30636.08	11.55	21.92	35.36	25.51	0.76	95.09
866.65	26.17	30635.55	11.55	21.92	35.34	25.52	0.76	95.08
863.83	26.15	30629.48	11.55	21.82	35.46	25.50	0.76	95.08
833.79	26.87	31206.45	12.06	22.87	37.43	26.74	0.79	99.89
851.14	26.45	30840.24	11.75	22.23	36.25	25.98	0.77	96.98
833.79	26.87	31206.45	12.06	22.87	37.43	26.74	0.79	99.89
862.89	26.15	30618.23	11.54	21.81	35.48	25.49	0.75	95.08
869.36	26.00	30518.69	11.44	21.60	35.10	25.25	0.75	94.14

833.89	26.86	31209.52	12.06	22.87	37.43	26.74	0.79	99.89
850.25	26.45	30838.49	11.75	22.24	36.27	26.00	0.77	97.03
867.56	26.00	30512.05	11.44	21.59	35.18	25.18	0.75	94.14
864.61	25.97	30524.83	11.44	21.60	35.30	25.04	0.76	94.14
857.98	26.10	30639.42	11.54	21.80	35.71	25.27	0.77	95.09
847.64	26.41	30846.59	11.75	22.22	36.39	25.85	0.78	96.98
833.77	26.86	31209.77	12.06	22.87	37.43	26.74	0.79	99.89
859.37	26.09	30647.29	11.54	21.79	35.66	25.33	0.76	95.08
866.79	25.93	30553.72	11.44	21.58	35.31	25.06	0.75	94.14
833.82	26.86	31211.21	12.06	22.87	37.43	26.74	0.79	99.89
848.85	26.41	30856.50	11.74	22.22	36.35	25.90	0.77	96.98
866.01	25.92	30564.18	11.43	21.58	35.29	25.08	0.75	94.14
866.27	25.92	30566.33	11.43	21.58	35.28	25.09	0.75	94.14
866.27	25.92	30566.33	11.53	21.79	35.63	25.37	0.76	95.08
833.80	26.86	31210.20	11.75	22.23	36.36	25.92	0.78	97.03
860.93	26.10	30664.57	11.53	21.78	35.62	25.40	0.75	95.08
860.93	26.09	30667.69	11.53	21.78	35.62	25.41	0.75	95.09
849.32	26.42	30859.49	11.74	22.21	36.33	25.93	0.77	96.98
849.03	26.44	30862.58	11.74	22.22	36.35	25.97	0.75	97.03
866.85	25.95	30572.67	11.43	21.57	35.26	25.19	0.70	94.14

Table 9 presents data for the straight run of a crude distillation unit without any optimization techniques. The data set comprises 34 distinct sets. The first column of the table displays the exergy destruction within the column, quantified in kilowatts per diesel production, which serves as the objective function for the optimization problem. The second and third columns contain information regarding exergy destruction and efficiency. In contrast, the remaining columns present data on the production of various crude distillation unit products under uncertainty in process conditions and feed composition. These results show that an increase in the production of one product is accompanied by a reduction in the other products' production.

Table 10 Hybrid model exergy analysis parameters, cut points and production data

Hybrid												
Exergy dest /Diesel flow	EX EFF	EX DES	NAPTHA CUTPOINT	NAPTHA KBPD	KEROSENE CUTPOINT	KEROSENE KBPD	DIESEL CUTPOINT	DIESEL KBPD	AGO CUTPOINT	AGO KBPD	Residue KBPD	Total FLOW KBPD
752.57	28.79	30924.93	101.45	17.19	127.50	15.32	266.66	41.08	456.57	25.74	0.57	99.89
788.20	28.10	29858.53	101.42	13.83	137.09	18.09	267.15	37.87	456.58	24.76	0.54	95.08
751.45	27.74	30008.06	101.34	15.74	129.22	14.47	265.98	39.92	456.71	24.44	0.52	95.09
720.10	28.40	30555.54	96.70	18.70	128.00	13.13	263.02	42.42	456.71	25.07	0.57	99.89
752.44	28.30	30087.25	101.44	14.22	133.00	17.61	267.22	39.97	456.76	24.67	0.56	97.03
747.22	28.79	30387.06	101.29	14.62	128.71	18.02	266.82	40.65	456.79	26.06	0.54	99.89
724.96	27.40	30128.10	100.20	18.04	127.50	11.11	267.15	41.54	456.79	23.84	0.56	95.09
752.05	27.64	30025.35	101.03	17.87	127.50	12.59	262.98	39.91	456.80	24.06	0.65	95.08
754.80	27.63	30013.16	99.80	17.30	132.84	12.43	266.79	39.75	456.81	24.93	0.67	95.08
771.07	28.96	30314.87	101.39	14.60	128.39	18.99	267.23	39.30	456.83	26.47	0.53	99.89
744.57	28.17	30116.38	99.78	14.22	127.74	17.29	265.39	40.43	456.83	24.32	0.73	96.98
738.68	27.60	30022.91	99.55	16.41	127.80	13.67	267.36	40.63	456.84	23.84	0.55	95.09
755.92	27.68	29995.41	98.07	17.88	135.87	12.57	267.25	39.67	456.87	24.43	0.53	95.08
734.30	27.29	30002.83	101.47	17.31	127.65	11.69	267.34	40.84	456.87	23.76	0.54	94.14
720.77	28.39	30559.23	99.91	18.82	127.66	12.86	267.47	42.38	456.90	25.25	0.57	99.89
730.36	27.99	30193.64	98.07	16.51	128.19	14.31	267.07	41.33	456.92	24.32	0.57	97.03
728.55	27.20	30019.36	96.87	18.11	130.58	10.53	265.75	41.19	456.94	23.77	0.54	94.14
754.82	27.46	29907.40	101.48	17.48	127.50	12.27	266.90	39.61	456.97	24.25	0.53	94.14
762.84	27.90	29891.80	101.15	13.94	127.57	17.75	267.26	39.17	456.99	23.53	0.71	95.09
726.32	27.77	30276.30	101.23	18.56	127.50	10.89	267.34	41.67	457.03	25.34	0.52	96.98
711.05	28.28	30603.91	101.38	18.91	127.50	12.30	263.00	43.02	457.07	25.10	0.56	99.89
796.09	28.07	29827.87	100.48	14.49	127.61	17.55	267.46	37.45	457.09	25.08	0.51	95.08
749.16	27.36	29965.06	96.50	17.86	135.77	12.16	267.16	39.98	457.09	23.58	0.55	94.14
745.12	28.76	30399.47	101.26	14.63	134.27	18.18	266.79	40.78	457.11	25.74	0.56	99.89
747.67	28.03	30175.38	100.78	17.03	127.87	13.60	267.24	40.34	457.14	25.48	0.52	96.98
754.13	27.57	29883.57	101.06	13.85	134.02	16.73	266.96	39.61	457.15	23.30	0.65	94.14
729.05	27.18	30047.49	97.08	17.31	127.69	11.70	265.98	41.20	457.25	23.37	0.56	94.14
785.83	27.91	29902.56	100.04	17.70	128.16	14.93	266.76	38.04	457.26	23.86	0.55	95.08
779.72	28.49	29994.69	100.47	14.14	127.58	19.41	266.66	38.45	457.28	24.46	0.57	97.03
801.09	28.10	29833.63	101.25	14.93	127.60	17.91	267.17	37.23	457.28	24.32	0.69	95.08
792.10	28.14	29817.17	100.35	13.87	127.74	19.20	267.30	37.63	457.41	23.84	0.56	95.09
787.79	28.53	29973.10	99.75	14.11	127.52	19.72	267.24	38.03	457.42	24.55	0.57	96.98
808.98	28.63	29942.28	99.51	14.11	127.63	19.64	267.49	37.00	457.44	25.79	0.49	97.03
751.60	27.48	29941.58	101.40	15.49	127.73	14.82	267.07	39.82	457.48	23.34	0.67	94.14

Table 10 displays data on exergy destruction within the column, quantified in kilowatts per production of diesel, as well as exergy efficiency, exergy destruction in the column, and optimal cut points estimated through the application of a hybrid Taguchi and

Genetic algorithm on a crude distillation model under uncertain feed composition and process conditions. The data set consists of 29 distinct sets. In this case, diesel production is increased at the expense of a decrease in the remaining products' production.

Table 11 ANN model exergy analysis parameters, cut points and production data

ANN												
Exergy destruction/Diesel	EX EFF	EX DES	NAPTHA CUTPOINT	NAPTHA KBPD	KEROSENE CUTPOINT	KEROSENE KBPD	DIESEL CUTPOINT	DIESEL KBPD	AGO CUTPOINT	AGO KBPD	Residue KBPD	Total FLOW KBPD
745.7	28.7	30414.7	101.5	14.3	127.5	17.9	267.2	40.8	456.2	26.2	0.7	99.9
743.1	27.6	30108.6	101.5	17.8	133.8	12.2	267.5	40.5	452.9	24.0	0.6	95.1
743.5	27.6	30103.5	99.6	17.8	129.6	12.2	265.7	40.5	454.2	24.0	0.6	95.1
750.1	28.7	30407.7	99.2	16.5	129.5	16.6	265.7	40.5	454.1	25.6	0.6	99.9
732.0	27.9	30252.8	95.7	18.4	127.5	12.2	262.5	41.3	452.6	24.5	0.6	97.0
744.2	28.7	30445.3	101.5	17.2	127.8	15.6	266.5	40.9	455.1	25.6	0.6	99.9
754.1	27.6	30027.2	101.5	18.0	128.0	12.5	266.7	39.8	455.1	24.1	0.7	95.1
753.7	27.6	30028.4	101.5	18.0	127.5	12.5	267.1	39.8	454.8	24.1	0.7	95.1
721.8	27.3	30137.3	101.5	18.3	128.2	10.6	267.4	41.7	454.5	23.8	0.6	95.1
744.9	28.7	30434.3	99.2	16.7	130.1	16.1	265.6	40.8	454.2	25.7	0.6	99.9
712.0	27.7	30325.3	101.5	18.6	127.6	10.8	265.6	42.6	455.6	24.3	0.7	97.0
719.8	27.3	30152.7	101.5	18.3	127.5	10.6	263.1	41.9	454.6	23.6	0.7	95.1
732.3	27.2	30010.7	101.5	18.1	137.0	10.5	263.5	41.0	455.2	24.0	0.6	95.1
730.8	27.4	30088.3	101.5	18.2	129.8	11.0	265.2	41.2	456.1	24.1	0.5	94.1
753.2	28.0	30171.9	101.5	18.4	127.5	12.5	267.0	40.0	452.9	25.6	0.6	99.9
750.1	28.7	30415.3	99.6	16.6	129.8	16.4	265.8	40.5	454.2	25.7	0.6	97.0
725.1	27.2	30029.9	101.5	18.1	127.6	10.5	267.3	41.4	453.4	23.6	0.5	94.1
743.0	27.4	29780.1	101.5	18.1	127.6	10.5	266.6	40.3	454.4	24.6	0.6	94.1
766.1	27.7	29958.6	101.5	17.9	128.7	13.0	266.4	39.1	452.9	24.5	0.5	95.1
719.9	27.7	30287.4	101.5	18.5	128.6	11.4	266.4	42.1	452.9	24.4	0.6	97.0
749.6	28.7	30416.2	101.5	16.5	128.0	16.3	266.7	40.6	455.7	25.8	0.6	99.9
719.6	27.2	30168.7	101.5	18.3	127.7	10.7	267.4	41.9	455.3	23.5	0.7	95.1
728.5	27.1	30059.1	101.5	18.1	128.3	10.6	267.4	41.2	454.6	23.6	0.6	94.1
744.1	28.7	30440.3	101.5	17.2	132.7	15.5	266.4	40.9	455.9	25.7	0.6	99.9
720.2	27.7	30310.6	101.5	18.6	127.5	10.9	264.1	42.1	456.2	24.8	0.5	97.0
741.6	27.2	30027.8	101.5	18.1	132.2	10.5	267.4	40.5	454.3	24.5	0.5	94.1
727.2	27.1	30072.7	101.5	18.1	128.3	10.8	266.9	41.3	455.1	23.4	0.6	94.1
775.2	27.8	29950.7	101.5	17.8	128.3	14.4	266.9	38.6	455.1	23.6	0.7	95.1
756.8	28.1	30151.6	101.5	18.2	127.5	14.2	266.3	39.8	455.9	24.2	0.6	97.0
739.8	27.5	30087.4	99.1	18.0	130.4	12.1	265.9	40.7	454.2	23.7	0.6	95.1
739.7	27.5	30087.7	101.5	18.0	128.5	12.1	264.1	40.7	454.7	23.7	0.6	95.1
767.3	28.2	30116.2	101.5	18.1	127.5	14.4	267.4	39.2	452.6	24.7	0.6	97.0
799.9	28.4	30033.9	101.5	18.1	127.8	15.2	267.2	37.5	454.1	25.7	0.5	97.0
741.1	27.3	30030.3	99.1	17.9	129.8	11.6	265.3	40.5	454.2	23.5	0.6	94.1

Table 11 displays data on exergy destruction within the column, quantified in kilowatts per production of diesel, as well as exergy efficiency, exergy destruction in the column, and optimal cut points estimated through the application of an Artificial Neural Model on a crude distillation model under uncertain feed composition and process conditions. The data set consists of 34 distinct sets obtained from ANN. Cut points of naphtha, kerosene, diesel and AGO obtained from the ANN model are quite like the results of the Hybrid optimization model, while cut points for the straight run model remain the same. The objective was set to minimize the EX/V of diesel, which results in a significant increase in diesel production with minimum exergy destruction inside the column. The reported diesel production for these 34 data sets is illustrated in the figure 21.

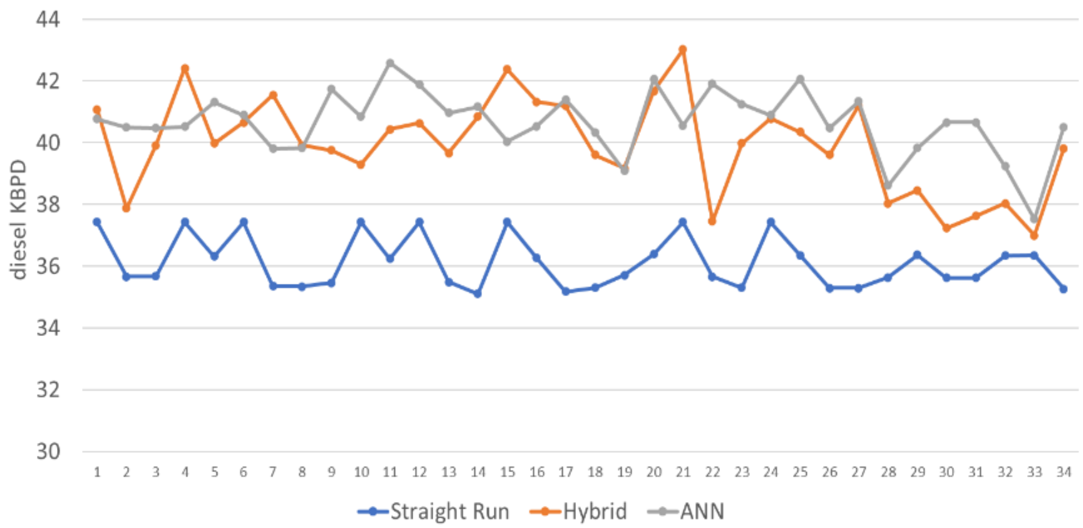

Figure 21 Diesel production data derived from straight run, hybrid and ANN models

Figure 21 illustrates that diesel production in kilo barrels per day has significantly increased when using Hybrid Taguchi and Genetic Algorithm, as well as Artificial Neural Network models, compared to the straight run model. Additionally, the graph demonstrates that the production trends for diesel are similar for both the Hybrid optimization and ANN models, indicating the effectiveness of the ANN model.

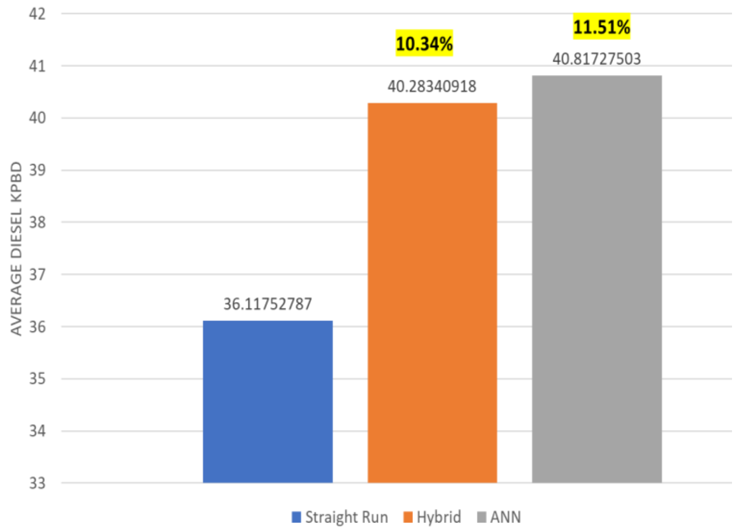

Figure 112 Comparison of average diesel production derived from straight run, hybrid and ANN models

Figure 22 presents the average diesel production for 34 data sets using the straight run, hybrid, and ANN models. By applying a hybrid Taguchi and genetic algorithm, we observed a 10.34% increase in diesel production in kilo barrels per day compared to the straight-run model. Similarly, using an ANN model resulted in an 11.51% increase in diesel production. Both the ANN and hybrid models outperformed the straight-run model, which had lower average production values of diesel.

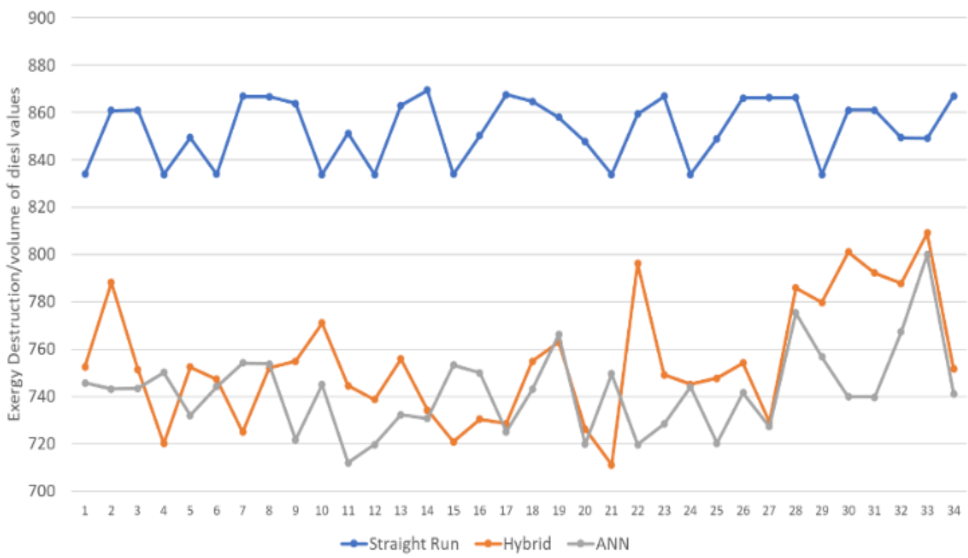

Figure 23 Exergy destruction per kilobarrel diesel production data from straight run, hybrid and ANN models

Figure 23 illustrates that the exergy destruction in the column per diesel production has significantly decreased when using Hybrid Taguchi and Genetic Algorithm, as well as Artificial Neural Network models, compared to the straight run model. The desired objective in the optimization problem was to minimize exergy destruction per diesel flow. The graph demonstrates that the output results for EX/V values are similar for both the Hybrid optimization and ANN models, indicating the effectiveness of the ANN model.

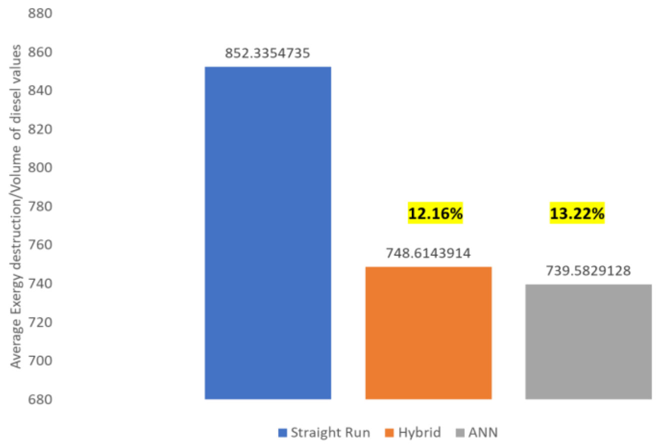

Figure 24 Comparison of average exergy destruction per kilo barrel production of diesel from straight run, hybrid and ANN models

Figure 24 presents the average exergy destruction per diesel flow for 29 data sets using the straight run, hybrid, and ANN models. By applying a hybrid Taguchi and genetic algorithm, we observed a 12.16% decrease in exergy destruction per diesel compared to the straight run model. Similarly, using an ANN model resulted in a 13.22% decrease in exergy destruction per follow of diesel. Both the ANN and hybrid models outperformed the straight-run model, which had higher exergy destruction per follow of diesel values.

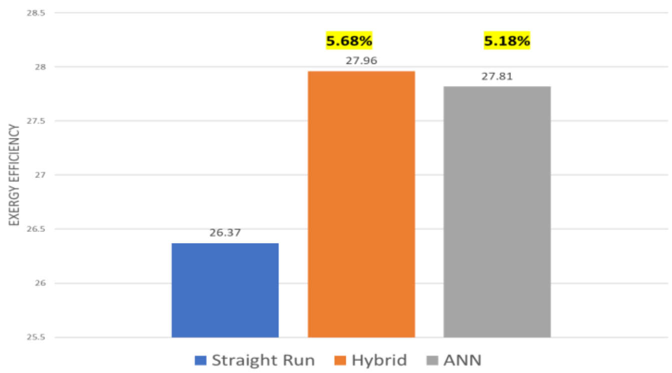

Figure 25 Comparison of average exergy efficiency of straight run, hybrid and ANN models

Figure 25 compares the exergy efficiency data of the crude distillation system for three different models using a data set of 34 distinct sets. Despite increased diesel production, the hybrid Taguchi and Genetic Algorithm model and the ANN model showed increased exergy efficiency. It is a positive result, indicating that the system can produce more diesel while maintaining an elevated level of energy efficiency. The Hybrid Taguchi and Genetic Algorithm model showed a 5.68% increase in exergy efficiency compared .to the straight-run model, and the ANN model resulted in a 5.18% increase compared to the straight-run model.

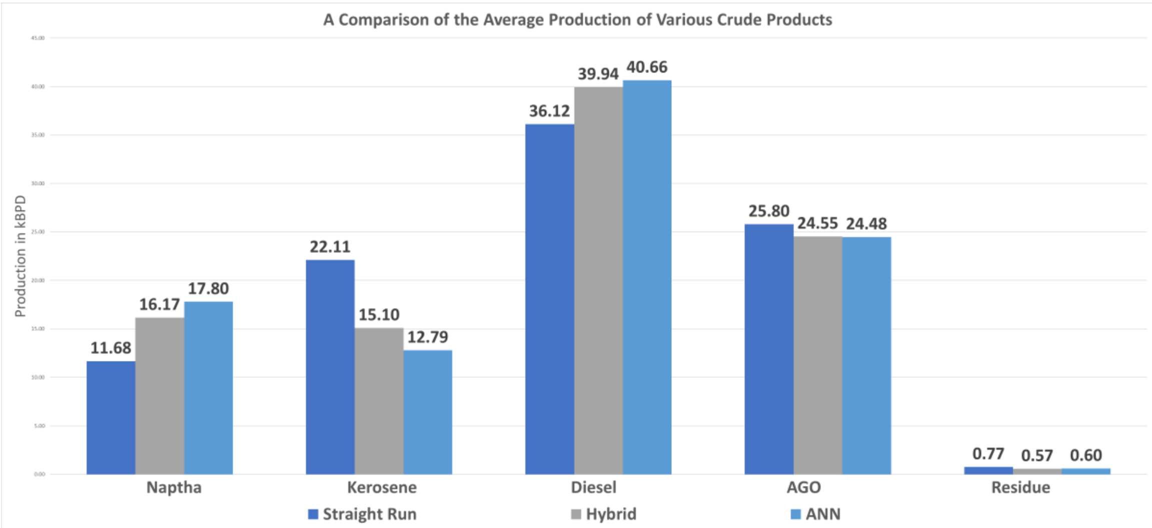

Figure 146 Comparison of average production of various crude products obtained from Zamzama crude

Figure 26 summarizes the Zamzama crude production, comparing the production of various products, including Naphtha, Kerosene, Diesel, AGO, and residue for the straight runs, hybrid, and ANN models. The results show that both the hybrid and ANN models increased around 11% in diesel production compared to the straight runs model. This increase in diesel production was achieved while exergy efficiency was also improved in the crude distillation unit. It is a notable achievement, as it demonstrates the ability of the unit to produce more fuel while using energy more efficiently. The results suggest that the use of advanced machine learning and optimization techniques such as the hybrid Taguchi and Genetic Algorithm model and ANN models can effectively optimize crude distillation processes, leading to improvements in both fuel production and energy efficiency.

Conclusions & Recommendations

Conclusions

In conclusion, the results of this study demonstrate the effectiveness of using Hybrid Taguchi and Genetic Algorithm and Artificial Neural Network models in optimizing the crude distillation system for producing diesel under uncertain process conditions. The output results for both the Hybrid optimization and ANN models were similar, indicating the effectiveness of the ANN model in accurately predicting optimal cut points for optimized diesel production. These models outperformed the straight-run model in terms of increasing diesel production. The Hybrid and ANN models resulted in around 27% and 11.5% increases in diesel production for Kunnar and Zamzama crudes, respectively. In addition to increasing diesel production, the Hybrid and ANN models demonstrated significant reductions in exergy destruction per kilo barrel of diesel. It leads to energy savings, increased production, and potential cost and resource savings for the crude distillation system. The Hybrid and ANN models resulted in around 27% and 13% decreases in exergy destruction per kilo barrel of diesel and 1.3% and 5.7% increases in exergy efficiency for Kunnar and Zamzama crudes, respectively. Overall, using these optimization models can significantly improve the performance of the crude distillation system. It is crucial in today's global energy market, where demand for diesel continues to grow and efficiency is critical to staying competitive. The successful implementation of the Hybrid Taguchi and Genetic Algorithm and Artificial Neural Network (ANN) models in this study showcases the immense potential of these optimization techniques in revolutionizing not only crude distillation systems but also various other industries and systems. By utilizing these advanced optimization models, crude distillation processes can significantly enhance its production while simultaneously achieving notable reductions in energy consumption and operational costs. The demonstrated efficacy of these models opens up new avenues for the application of optimization techniques in diverse domains, empowering industries to improve their efficiency, sustainability, and overall performance. From manufacturing and logistics to energy management and healthcare, the integration of these optimization methods can lead to remarkable advancements, making processes more streamlined, resource-efficient, and cost-effective. As such, this research contributes to the broader field of optimization, offering valuable insights and paving the way for future innovation and advancements across various sectors.

Recommendations

The successful implementation of the optimization models in the crude distillation system demonstrates their potential to revolutionize the energy industry. Energy companies should consider integrating these advanced optimization techniques into their processes to improve efficiency, reduce energy consumption, and lower operational costs. The positive results obtained from this study suggest that there is a need for further research and development in optimization techniques. Investing in more studies and experiments can lead to the refinement and customization of these models to suit specific crude types and distillation systems, potentially unlocking even greater performance improvements. The conclusion highlights that the potential of these optimization techniques is not limited to the energy sector. Industries spanning manufacturing, logistics, healthcare, and more could benefit from incorporating Hybrid Taguchi and Genetic Algorithm and Artificial Neural Network models to enhance their processes, improve resource efficiency, and reduce costs.

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