An Artificial Intelligence Method for Estimation of Optimum Operating Conditions of a Furnace under Uncertainty

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DEDICATION

To my very Supportive, Loving, and

Caring Family

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All acclaim and eminence be to "ALLAH", a definitive creator of this universe, who endowed us with the ability to comprehend and made us curious to investigate this entire universe. Infinite greetings upon the leader of this universe and hereafter "HOLY PROPHET HAZRAT MUHAMMAD (PBUH)": the wellspring of beneficial information and blessings for the whole humankind and Uma.

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ABSTRACT

Furnaces have been known as the central preliminary units employed for hydrocarbon processing in petrochemical industries. The most significant energy consumption part in refineries is associated with furnace units. Therefore, achieving higher thermal efficiencies is the primary concern in designing and during operation. Due to significant energy consumption in such systems, a minor improvement in thermal efficiency would lead to considerable savings. Much work has been done in the literature on the design and optimization of the furnace using different optimization methods. However, no one has focused on the optimization of the furnace under uncertain process conditions. The current work developed an Integrated Framework of Artificial Intelligence and Genetic Algorithm for the furnace of a petroleum refinery to predict the optimum amount of excess air and mass flow rates of crude oil and fuel stream in the presence of uncertainty in process conditions. Using optimized industrial data, a furnace model was regenerated in Aspen EDR. The COM server was used to build the interface between Aspen HYSYS and MATLAB. The data set was generated by inserting the variation of ±1, ±2, ±3, ±4, and ±5 in the crude oil composition as well as in the inlet temperature and pressure of cold crude oil, fuel, and air stream. The optimum amount of excess air and mass flow rates for each variation was determined using a single objective genetic algorithm. A total of 360 data points were generated. 70% were used for the Feedforward neural network (ANN) and the remaining data points were equally divided for the validation and testing of the model. The proposed artificial neural network (ANN) model achieved a correlation coefficient value of 0.99984. The high accuracy and robustness of the ANN model make it suitable for real-time industrial applications to reduce energy consumption.

KEYWORDS

Fired Heater, Artificial Intelligence, Genetic algorithm, Optimization, Uncertainty, Machine learning

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NOMENCLATURE

Straight Run (SR)

Computational Fluid Dynamics (CFD)

Artificial Intelligence (AI)

Support Vector Machine (SVM)

Feed-forward Neural Network (FFNN)

Genetic Algorithm (GA)

Exchanger Design and Rating (EDR)

Adaptive Heuristic Criticism (AHC)

Artificial Neural Network (ANN)

Graphical User Interface (GUI)

Barrels Per Day (BPD)

Machine Learning (ML)

CHAPTER 1: INTRODUCTION

1.1.Background

Energy, which once provided luxury to a valuable few, became a necessity without which the modern world could not survive. It forms the lifeline for industries that provide essentials like transport, electrical energy, and agriculture [1–3]. Even though the growing use of renewable energy resources has grabbed the interest of many scientists and investors, conventional fuels continue to be in high demand across the world. Fossil fuels are the most critical energy resource, and their consumption is increasing rapidly[4]. The statistics show that the global consumption of petroleum-based fuel is projected to increase from 85.6 million barrels per day (BPD) in 2008 to 112.2 million (BPD) by 2035 [5]. In order to bridge the energy supply-demand gap, energy production must be enhanced at the same pace as its consumption. The cost of manufacturing production is highly influenced by the amount of oil used and the fuel mixtures used. The increased demand for fossil fuels results in the hike in prices, environmental issues, and greenhouse gas emissions, which led to the number of concerns on advancement in the working process as well as lessening of fuel consumption of energy-intensive equipment in the industrial and manufacturing sector across the globe [6–9]. In several countries, various approaches have been used to analyze energy consumption efficiency and manufacturing efficiencies. Researchers are currently devising solutions to reduce total energy demand in this market. Furthermore, using excess energy increases industrial thermal productivity, thereby lowering emissions [10].

One of the most significant components of the petrochemical sector is refineries. In the petroleum refinery, heat-intensive processes are involved. Therefore, effective heat transfer equipment can perform a vital role. These effective heat transfer systems may play a significant role, from the preheating of the crude in the heated oven to the re-boiler and condensing portion in the distillation column. This will improve the heat transfer and thus reduce the related costs [11–13].

Several procedures must be carried out at refineries to convert crude oil into various products. These processes are more effective at high temperatures, and at low temperatures, they are impossible to sort out. As a result, a system that can increase the fluid process temperature is needed. Therefore, furnaces (fired heaters) are commonly used as hot utility systems in the oil refining and petrochemical industries [14,15].

1.2.Furnace (Fired heater)

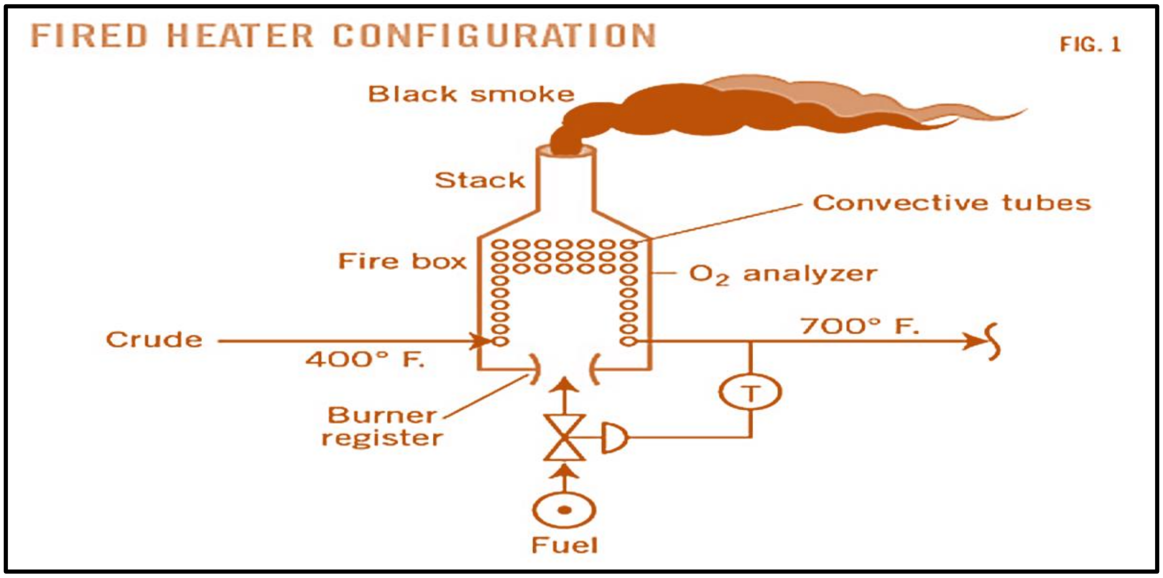
A furnace is a type of direct-fired heat exchanger that uses hot combustion gases to increase the temperature of a feed that flows through coils of tubes lined in the heater. These instruments usually raise the temperature of the crude oil (process fluid) from ambient (300 K) to the target (400 K) temperature before delivering it to the distillation unit [15–18]. Combustion, a complex phenomenon with several applications in various industries, provides the necessary heat for this operation. Furnaces have capacities ranging from 3 to 100 MW with several arrangements and configurations of coils and heaters. For significant heat duty purposes (20 MW and higher), the box heater is used, while in the case of small or medium-duty (below 20 MW).), the cylindrical heater type is usually preferred [14,19].

The heating coil, enclosure, and combustion equipment are the three main components of a furnace (fired heater) [20,21]. The front and cross-sectional views of the furnace are shown in Figure 1 and Figure 2, respectively.

- **Heating coil:** A bundle of tubes is mounted together containing the process fluid in the heating coil. The heat energy is supplied to the process fluid passing through the tubes.

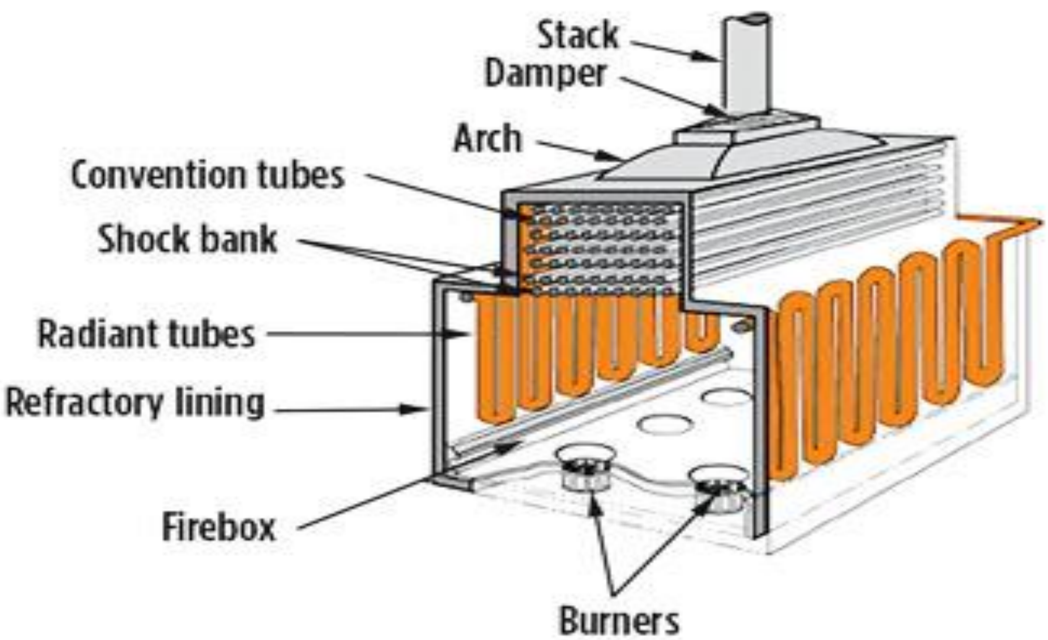
- **Enclosure:** The enclosure contains the firebox inside its structure. The whole enclosure is lined with the insulating material, mainly refractory bricks, which accumulate heat.

- **Combustion equipment:** A fuel stream is injected into a burner which generates heat energy. These burners are mounted on the floor or side wall. The coils absorb the heat generated by the burners in the radiant section through radiative and convective heat transfer from the flue gases ultimately discharged through the chimney or stack. The combustion air is taken from the atmosphere and used directly or preheated to enhance



thermal performance.

Figure 1: Front View of Fired Heater (Furnace)



CHAPTER 2: LITERATURE REVIEW

2.1. Literature Review

Several challenges and limitations are associated with the efficient designing of a furnace, such as ineffective heat transfer. Limitations from environmental agencies, heat losses from different sources including flues gases and walls of the furnace, usage of different fuels, and high ranged tools for data collection for various modeling tools. To address these challenges and limitations, many studies have been conducted based on mathematical modeling. These studies implemented and used various energy-saving approaches such as waste heat reclamation and the design of an air preheating system into the existing furnaces. Using such

Figure 2: : Cross-sectional View of Fired Heater (Furnace)

approaches can significantly enhance the efficiency of the furnaces, which can eventually reduce fuel consumption [22–25].

For instance, a mathematical model has been proposed by [16] for the estimation of the performance of the furnace based on variable operating parameters. This study was based on the actual industrial data of the refinery based in Iran. The given model evaluates variations in surrounding air conditions before presenting an optimal furnace design that includes surplus air minimization and combustion air preheating procedures. The model of the furnace is first design mathematically, followed by the simulation in the software. Then, various optimization techniques were employed, where the objective function was the excess air minimization and preheating combustion air, to get the optimized furnace operating conditions for achieving maximum efficiency. The findings demonstrate that preheating the air to 252 degrees Celsius and decreasing the surplus air by 15% lowers the exhaust temperature from 537.5 to 205 degrees Celsius and boosts furnace efficiency from 63 percent to 89 percent. In addition, by enhancing the heat transfer surface, the furnace throughput may be increased by up to 30% while maintaining the same efficiency.

In [26], two mathematical models (direct and indirect) have been proposed for estimating the efficiency of the refinery furnace using MATLAB software. In the direct method (input-output method), the net calorific value has been used and then the Sankey diagram is prepared for calculating the energy balances. After calculating the energy balances, the efficiency of the refinery furnace is determined. While in the indirect method (heat-loss method), the gross calorific value has been utilized. The MATLAB program is proposed for both the methods mentioned above for calculating the efficiency of the refinery furnace. In addition, the two case studies were proposed in this study. In the first case study, liquid fuel is considered while fuel gas is considered in the second case study. The proposed models achieved 73.81% (liquid fuel) and 75.78% (fuel gas) efficiencies of the refinery furnace. Therefore, the authors proposed that the direct comparison is more advantageous than the indirect method, as it is less time-consuming and requires less computing power. Figure 3 shows the schematic of the Sankey diagram for two case studies.

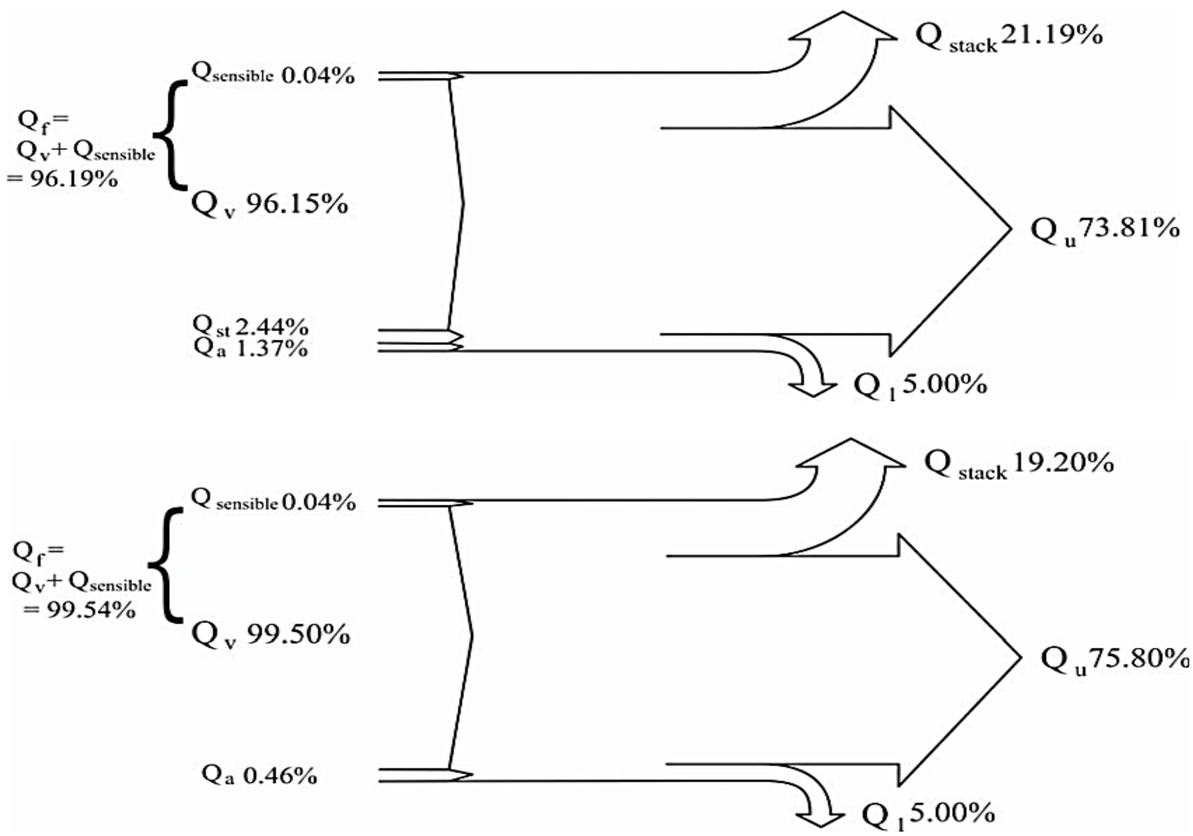


Figure 3: schematic of Sankey diagram for two case studies

In [27], mathematical models have been proposed to estimate the temperature in the radiant section of the refinery furnace. In this study, three MATLAB programs were developed, two programs using appropriate equations and one program using the Newton-Rapson method were written. The authors used computer programming to estimate the temperature of a gas in the radiant section and the temperature distribution profile and the rate of heat transfer in the convection section. Results showed that using these methods, the gas temperature and actual temperature of the flame in the refinery furnace (fired heater) were successfully calculated.

Furthermore, [28] developed a numerical model for estimating the influence of various input parameters on the process furnaces. The model was first developed manually by an iterative method using initial boundary conditions. The proposed model was then compiled in MATLAB software and the sensitivity analysis of the various operating parameters was carried out. The parameters examined during this study include inlet air temperature, excess air, fuel composition, tube pitch, and fuel flow rate. Among these parameters, excess air percentage was the most influential parameter that greatly influenced the furnace's performance. On the other hand, the fuel mass flow rate showed the slightest influence on the furnace performance.

In [29], developed a mathematical model for evaluating the thermal behavior of the refinery furnace and for the prediction of crude outlet temperature at variable operating parameters. All the sections of the refinery furnace, including the radiant section, combustion section, and convection system, were modeled using basic thermodynamic correlations, mass, and energy balances. The crude oil used in this study was comprised of twenty-one different fractions. MATLAB Simulink-based model was proposed for estimating the efficiency of the furnaces. Furthermore, different flow patterns were studies, including single and multi-phase flow. The results indicated that the proposed model could efficiently predict the outlet temperature of the hot crude based on variable operating parameters. Although such proven models are commonly used to assess the thermal behavior of furnaces in detail, they are not well suited to optimization design. The Block diagram of the model proposed in [29] is shown in Figure 4.

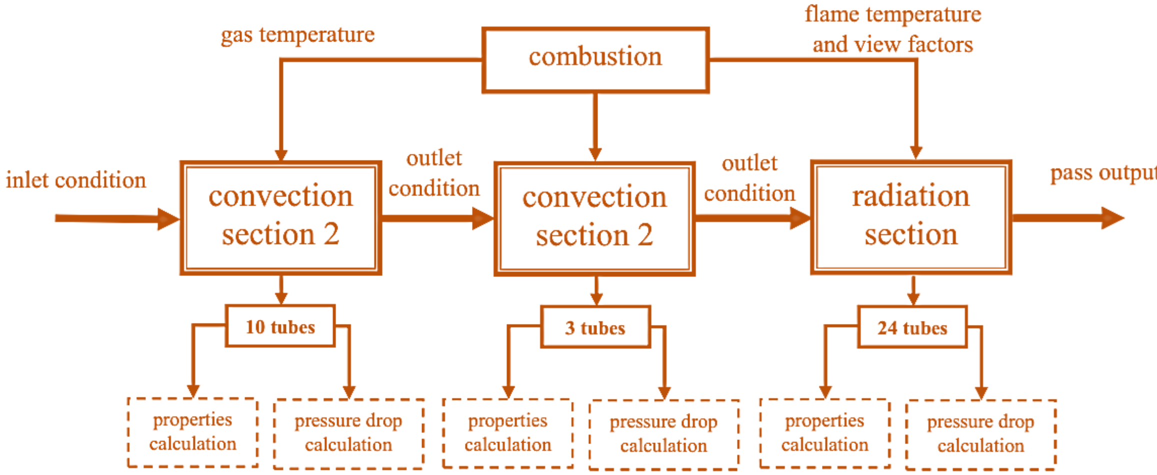


Figure 4: Block diagram of the model proposed in [15]

Recently, industries and researchers have used many simulation software to model and simulate furnaces, including Aspen software, CFD Fluent, IPSEpro, COILSIM1D, MATLAB, and FurnXpert. This software provides fast, accurate, and precise modeling and simulation of furnaces. Among these software packages, Aspen and CFD are widely used in chemical engineering applications. Aspen Plus is the leading process simulator in the world of chemical engineering. It permits a user to build and simulate new and existing processes using the graphical user interface (GUI), thermodynamic models, mathematical techniques, and complex calculations. Aspen plus hosts one of the largest databases or libraries of chemical species and their mathematically regressed parameters. Aspen plus is used for simulating radiant furnace section and cyanide elimination from blast furnace outlet in steel industry [30–32].

ANSYS Fluent is a computational fluid dynamics software used to model complex fluid problems using advanced physics models. Advanced solver techniques provide quick, precise simulation results, detailed meshes, and better parallel processing. ANSYS fluent gives the user the ability to implement new models and customize the existing ones. Post-processing of this simulator helps stop the simulation, examine results, make changes and then continue along. Integration of fluent with ANSYS workbench enables a user with connections to significant geometry modifications and complex meshing. Advance models help users model dynamic flow, turbulent, heat transfer, and reaction systems for a wide range of industrial systems like aircraft to combustion modeling inside furnaces, from retrofitting industrial steam cracking furnaces to furnace simulations in coupled run mode [33–36].

Motivated by the rapid, precise, and accurate results provided by the software mentioned above packages, many studies have been published considering the modeling and simulation of furnaces. For instance, CFD-based models are widely used by researchers for analyzing and estimating the heat flux, excess air effect, air preheating effect, and burner design. However, using these simulations, particularly for process designs optimization, entails many designs of various arrangements, which consumes a significant amount of computational time and is hence unsuitable for optimization applications [37].

In [38], developed a traditional and CFD-based model to examine the heat transfer in the refinery furnace (fired heater). The cylindrical furnace was used in this study. In the first design approach, the traditional design calculations were employed following the standards of the API. Its considerations are illustrated by focusing on the variation of heat flux arrangement on the tubes. The authors pointed out that the traditional classical approaches do not consider the variabilities in the furnace. These uncertainties may lead to the fouling and lack of safety of the heater. Therefore, the CFD-based approach has been employed in this study to overcome variabilities in the system. A 3D CFD-based model was implemented in the second design approach, analyzing the system's combustion, radiation, and turbulence. Moreover, the influence of the tube abnormalities on circular tube heat flux non-uniformity is investigated by using the 2D radiative heat transfer models. Figure 5 and Figure 6 show the flow visualization of two case studies based on

CFD.

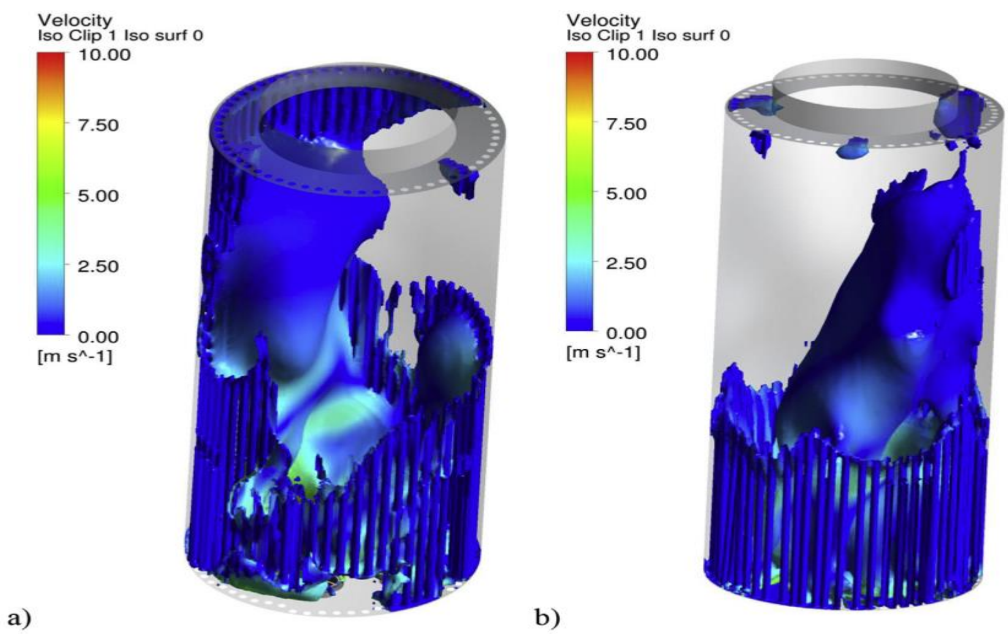


Figure 5: Flow visualization-surface of zero vertical velocity colored by velocity magnitude of two case studies

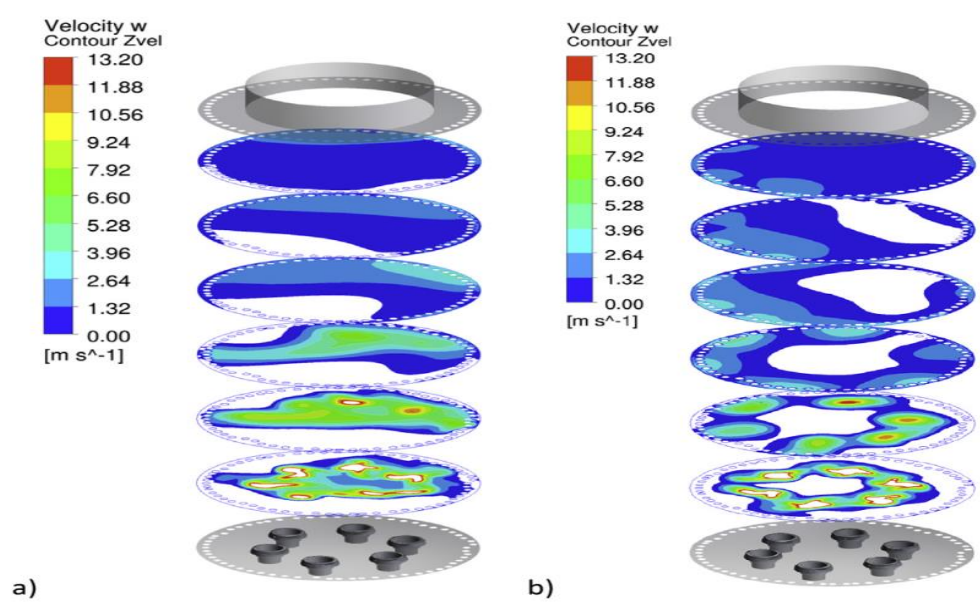


Figure 6: Flow visualization-contours of vertical velocity component on furnace cross-sections for two cases

With the beginning of the 4th industrial revolution and technological breakthroughs, advances in manufacturing sectors are unprecedented. Machine learning (ML), which may be defined as a branch of computer science and artificial intelligence (AI) concerned with creating models that can learn from and make data-based decisions and predictions. It is widely employed in industrial sectors such as process industries, manufacturing industries, petroleum industry, cement industry, pharmaceutical industry for process controls, process optimization, and fault diagnosis [39–41]. Some of the dominant ML methods include artificial neural networks (ANN), random forest (RF), decision tree (DT), and support vector machine (SVM). With the help of ML tools, the prediction, control, and optimization of nonlinear, mathematically complex, labor-intensive, and time-consuming processes has become very easy. It has multiple advantages over conventional techniques and empirical approaches. ML-based models do not need extensive knowledge and information about the process and require only an experimental data set [42].

In [43], developed SVM and ANN models to detect fouling in the refinery furnace. Fouling is considered one of the main issues of the refineries that results in the low efficiency of equipment. Here, the rate of the fouling and allowable limit of the fouling in the tube of the furnace is determined. This study was based on the actual industrial data. The fouling rate is determined using the furnace, tube temperature, pressure drop, and furnace output temperature. The maximum permissible fouling inside the tubes was measured at 3 %. The intensity of the fouling was estimated in the range of 1-100%. The proposed SVM and ANN model successfully detected the fouling by using artificial fouling to the furnace tubes. Therefore, the authors suggested that the proposed model can be used for designing the expert system for monitoring. The figures below show the estimated fouling rate predicted by SVR (accuracy=91.16%) and ANN (accuracy=96.24) based on Figures 7 and 8.

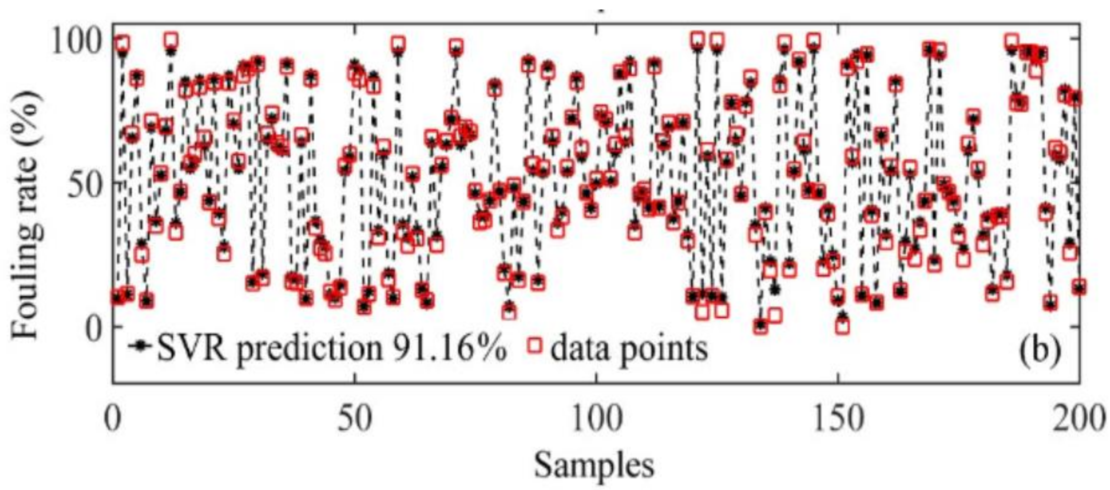


Figure 7: Estimated fouling rate by SVR: Prediction

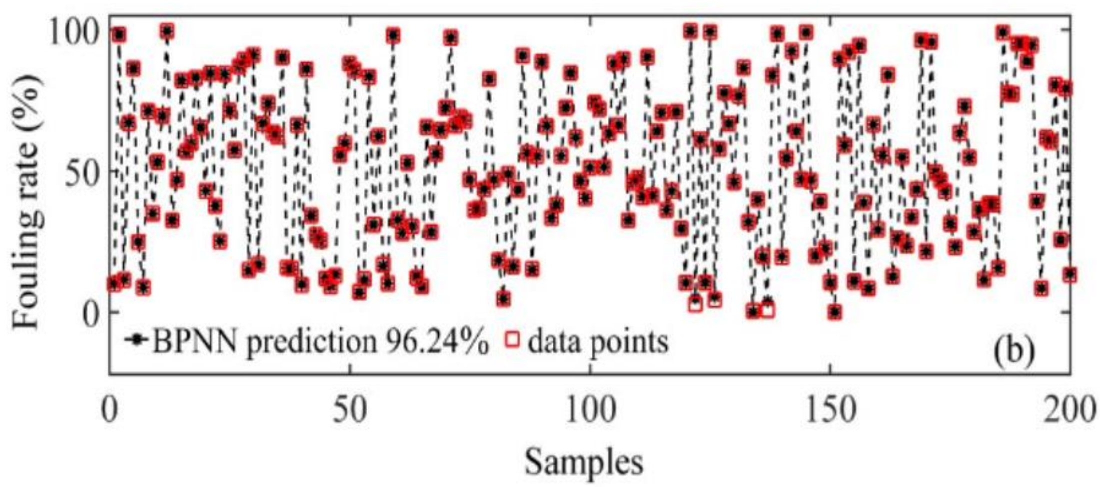


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Figure 8: Estimated fouling rate by BPNN: SVR

In [44], a novel adaptive heuristic criticism (AHC) based approach has been developed for controlling the various variables of the refinery furnace. In this study, a feedforward neural network (FFNN) based model has been proposed to produce the linear values of the control signals to reach the set point. The authors concluded that the proposed framework performed well and successfully predicted the outlet temperature under variabilities in the inlet temperature.

2.2. Problem Statement

Although many research works have been published on the topic of refinery furnaces. However, primarily, the literature focuses on designing and optimizing furnaces using different mathematical and optimization methods. In the literature, no article has been published on modeling and simulation of furnace in EDR environment. Similarly, no one has focused on the optimum operating condition's hybrid approach under uncertain process conditions. The process of a furnace under variable crude composition and process parameters roots low efficiency. Therefore, intelligent systems have been highly interested in coping with problems and realizing greater effectiveness in systems for energy management.

2.3. Objectives

The main contribution of this work will be as follows,

- Detailed modeling of furnace in Aspen HYSYS and EDR environment
- Development of an interface between Aspen EDR and MATLAB.
- Optimization of the model using a genetic algorithm-based approach.
- Development of Artificial Neural Network (ANN) model for prediction of optimum process conditions for the furnace.

2.4. Thesis Organization

This thesis is organized as follows. In section 1, the Introduction of this study is presented. Section 2 presents the literature survey of relevant published studies. Section 3 describes the overview of the modeling methods used. In section 4, the methodology adopted in this study is highlighted. In section 5, results and discussion is presented. Finally, the study is concluded in the conclusion and recommendation section at the end.

CHAPTER 3: OVERVIEW OF DEVELOPED MODELS

In this chapter, the general overview of all the modeling methods developed in this thesis is presented. These modeling methods include exchanger design and rating environment (EDR), genetic algorithm (GA), and artificial neural network (ANN).

3.1. Exchanger Design and Rating Environment:

Aspen Exchanger Design and Rating (EDR) is an extension and add-on of Aspen Plus and HYSYS used for detailed designing of the furnace. EDR uses standard sizing and design equations. The Aspen package uses the Aspen property database to calculate the heat transfer coefficient and thermodynamic properties. EDR provides run-time integration with Aspen HYSYS allowing changes to be made across the platforms. EDR allows the combined modeling of firebox and convection sections. EDR can handle and allow box, cylindrical, twin box, and twin cylindrical geometries of furnace design. Aspen EDR modeling of furnace allows ten process streams in a single heater. EDR supports plain or finned tubes in the firebox section of the fired heater. Combustion analysis and calculation of four fuels can be performed in Aspen exchanger design and rating environment. Tubes surface enhancements like a solid fin, serrated fin, chamfered can be included. Zonal analysis can be performed for radiation information in Aspen EDR [45–47].

Aspen EDR offers the following modes for fired heater designing:

i. Simulation Mode

In this mode, all process data and the geometry of the furnace are included. It calculates the outlet process stream conditions and duty based on the geometry we defined. This mode answers the question, " What duty will this furnace achieve?". In the case of a furnace, firebox and convection section geometries are defined by the user. Then simulation mode evaluates the outlet conditions that are achievable for the process streams at fixed flow rates.

ii. Rating / Checking Mode

As the name implies, this mode answers the question, "Can this fired heater perform this duty?" It must define the entire furnace geometry as well as the specifics of the process stream. The findings will be shown in the form of a ratio of actual heat transfer area to required heat transfer area. In a furnace, this mode is used to determine the amount of fuel required at the defined firebox and convection section geometry to achieve specified outlet temperatures.

iii. Design Mode

In this mode, the software can measure the furnace geometry based on the required thermal duty. We may also set design constraints based on convection tube shape, tube length, arrangement. The measured fired heater geometry contains all data, and the geometry is chosen based on either cost optimization or minimum area.

iv. Find Fouling Mode

This answers the question, "What is the maximum fouling that can be achieved for a given thermal duty?" It uses the same input as the Rating mode to measure the area ratio by considering the maximum fouling that can be deposited on convection tubes. Figure 9 shows the calculation modes in Aspen Exchanger Design and Rating tool.

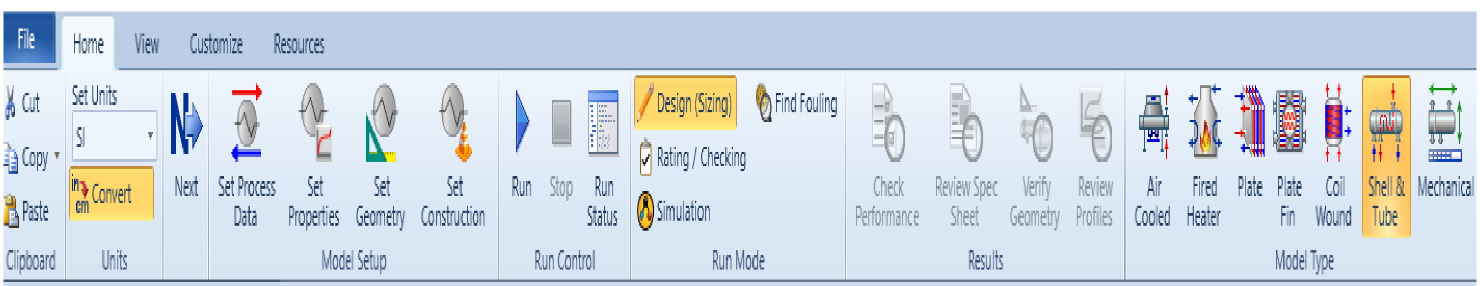


Figure 9: Calculation Modes in Aspen Exchanger Design and Rating Tool

In this study, the rating mode is used as the complete information of fired heater geometry is known. First of all, the given process stream data is specified by clicking on the tab "set process data." Then, the crude oil and fuel properties and excess air steams are specified by clicking on the tab "set properties." Furthermore, the information related to the geometry of the fired heater, shown in table 2, is defined in the tab "set geometry." In the end, some construction details are defined before running the model.

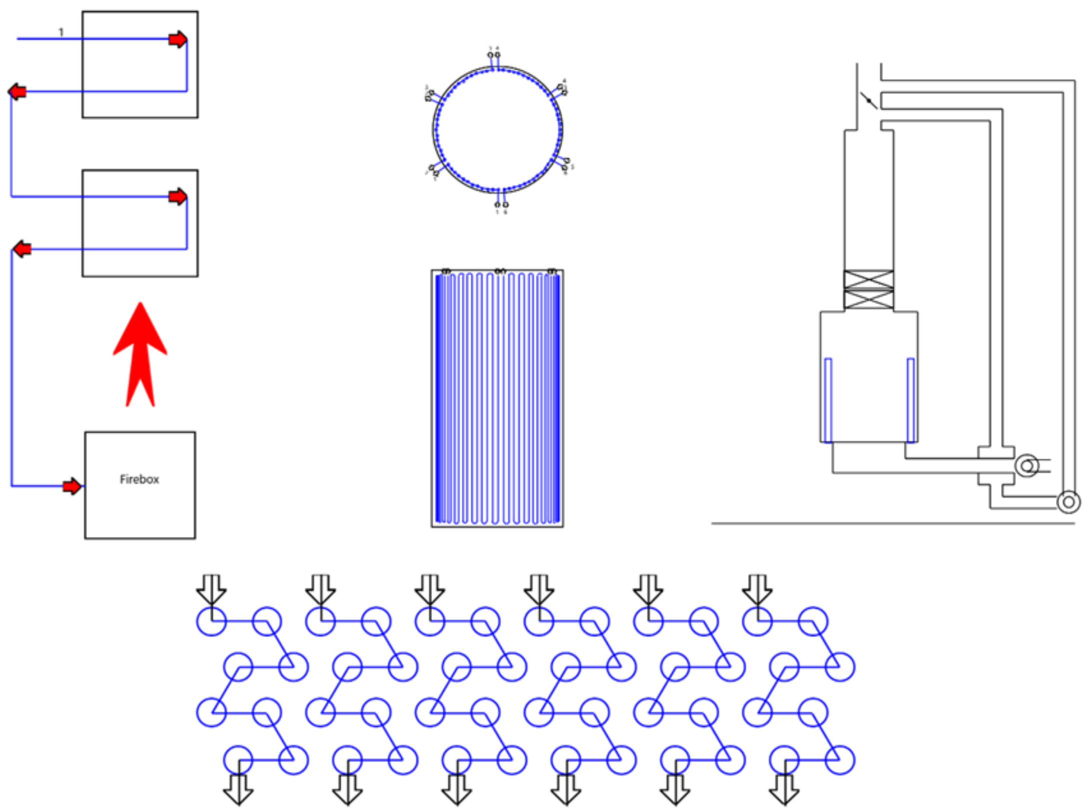


Figure 10: EDR Geometries of Fired Heater

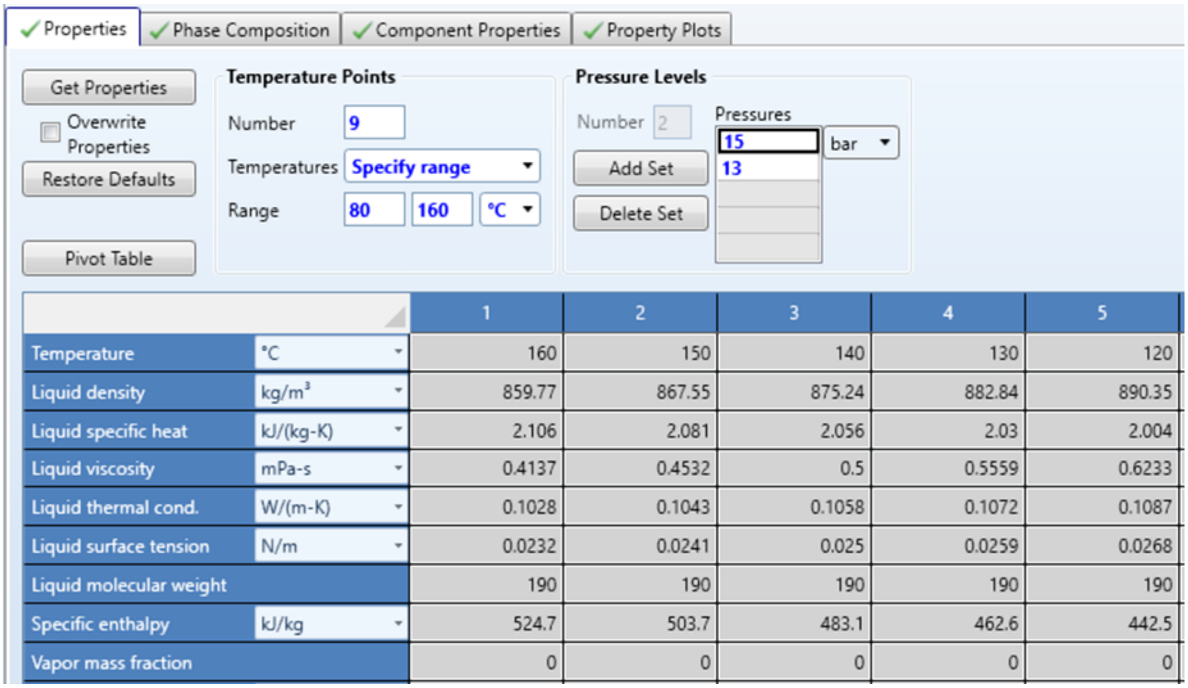


Figure 11: Physical Properties required in EDR.

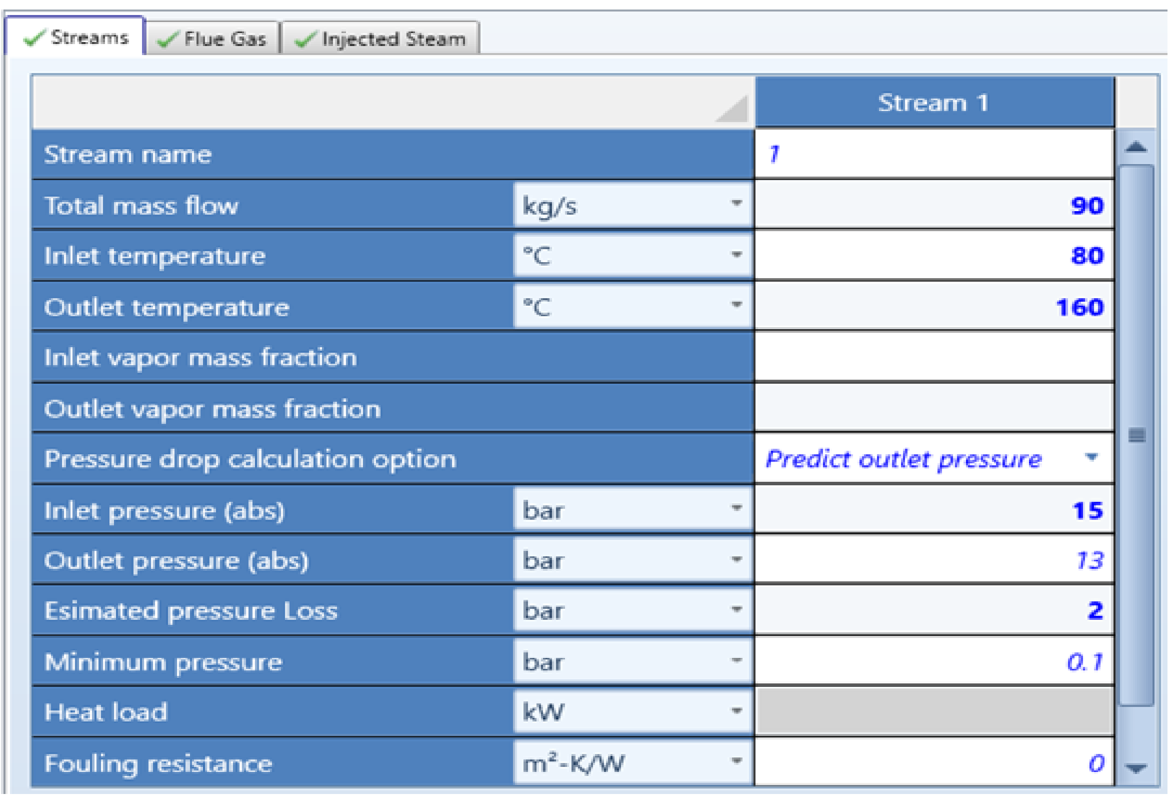


Figure 12: Input Variables for furnace design in EDR

Table 1: Geometric details required for EDR furnace design

Firebox	▪ Layout	▪ Height ▪ Diameter ▪ Fired heater type ▪ Tube row layout
	▪ Main tube rows	▪ Tube passes ▪ Tube straight length ▪ Tube to wall clearance
	▪ Tube details	▪ Tube outside diameter ▪ Tube wall thickness ▪ Tube spacing
Convection Banks	▪ Layout	▪ Tube surface enhancement type ▪ Tube length ▪ Flow direction
	▪ Tubes	▪ Outside diameter ▪ Tube wall thickness
	▪ Fins and Studs	▪ Fin height, thickness and frequency ▪ Stud height, thickness and frequency
	▪ Bundle details	▪ Tube pitch ▪ Number of rows of tubes ▪ Number of parallel paths ▪ Row arrangement

3.2. Genetic Algorithm

3.2.1. Inspiration

Genetic Algorithms (GA) is a kind of evolutionary algorithm that mimics the biological evolution process. Holland presented a concept for genetic algorithms in 1975. GA was influenced by Darwin's evolutionary theory, which mimicked the survival of fitter creatures and their genes. Many researchers have used GA's to evaluate the solution of difficult problems whose objective functions lack the properties of continuity, differentiability [48,49]. It is a population-based algorithm and is based on the concepts of natural selection and genetic inheritance. Each parameter indicates a gene, and each solution represents a chromosome. GA uses a fitness (objective) function to assess the fitness of each member in the population. The finest alternatives are picked arbitrarily using a selection strategy to improve wrong solutions. Because the probability is related to the fitness, this operator is somewhat more certain to select the best solutions (objective value). The possibility of selecting wrong solutions also increases the probability of avoiding local optima. It indicates that if perfect alternatives become stuck in a local solution, they can be extracted with the help of other solutions. This procedure is repeated unless an optimal solution(s) is (are) establish, or a extreme integer of iterations or population is grasped, or a relative difference between solutions is less than a specific limit [50,51].

Because the GA method is stochastic, one could wonder how trustworthy it is. The practice of keeping the best answers in each generation and utilizing them to enhance subsequent alternatives is what makes this technique trustworthy and capable of estimating the global optimum for a particular problem. As a result, the entire population improves with each passing generation. Mutation helps this method as well. This operator alters the genes in the chromosomes at random, keeping the population's variety and increasing GA's inquisitive activity [52]. The flow diagram of the Genetic Algorithm is shown in Figure 17.

3.2.2. Genetic Algorithm Vocabulary:

The terms used in the genetic algorithm are shown in the table below.

Table 2: Voacbulary used in genetic algorithm

S.No.	Genetic Algorithms	Explanation
1	Chromosome (string, individual)	Solution (coding)
2	Genes (bits)	Part of solution
3	Locus	Position of gene
4	Alleles	Values of gene
5	Phenotype	Decoded solution
6	Genotype	Encoded solution

3.2.3. Genetic Algorithm Methodology

a. Gene Representation

Every chromosome, as previously described, refers to a possible solution to the particular problem of optimization. Multiple genes structure a chromosome showing the changing parameters in the optimization problem. The initial stage in employing the GA technique is to state the problem, followed by establishing the vectors. The GA consists of two variants: one is binary and the other is continuous. Two values could be specified to a binary version (e.g., 0 or 1). The incessant values having upper and lower bounds are utilized in continuous form. When multiple values are to be selected, this is referred to as binary GA. Other bits must be allocated to the variables here. For example, problem including two parameters, every parameter may be given eight distinct values, every parameter will require three genes [53,54]. Thus, log2n is employed to compute the number of genes for selecting n discrete values. It has been shown that chromosomes encoded using real value numbers result in more efficient GAs and produce better solutions. It is worth noting that genes may also be characters or parts of a program. The GA algorithm can employ genes as long as they are put into a fitness function and result in a fitness value. Genetic Programming refers to distinct sections of a computer program for each gene [55].

b. Initialization

Initially, a large number of individual solutions are produced at random to establish an initial population. The size of the population varies depending on the situation, but it usually comprises several hundred or thousands of potential solutions. Generally, the population is created at random, encompassing all potential outcomes. Sometimes, solutions are "seeded" in places where the best solutions are most likely to occur [56]. The following code is used while using binary GA:

where Xi is the ith gene and ri is a unique random number produced for each gene in the range [0,1].

$$\mathbf{Xi} = \int_{\mathbf{2}}^{\mathbf{1}} \quad \begin{matrix} \boldsymbol{ri < 0.5} \\ \boldsymbol{Otherwise} \end{matrix} \;\ldots\ldots\ldots\ldots\ldots\ldots\ldots. \;(1)$$

The following equation is used to initialize the genes in the continuous GA randomly:

$$\boldsymbol{Xi = (ubi - lbi\,) * ri + lbi} \ldots\ldots\ldots\ldots\ldots\ldots\ldots. \;(2)$$

In the above equation, Xi represents i-th gene, ri represents the random number in the range [0,1] produced independently for each gene, ubi represents i-th gene's upper bound, and lbi represents i-th gene's lower bound.

The major goal of the initialization stage is to distribute the solutions as evenly as possible over the search area to enhance population diversity and improve the chances of identifying exciting regions. The stages to enhance the chromosomes in the first population are discussed in the following sections.

c. Selection

The primary source of motivation for this element of the GA algorithm is natural selection. The fittest individuals have a better chance of finding food and pairing in nature. As a result, their genes play a more significant role in developing the following generation of similar species [57]. The GA method, based on this simple concept, uses a roulette wheel to allocate probability to people and choose them for the subsequent generation. An illustration of a roulette wheel for six people is shown in Figure 4.1. Table 4.1 lists the facts for each of these people. The finest individual (#5) has a significant proportion, the poorest one (#4) has the smallest. Because a roulette wheel is a stochastic operator, poor ones have a low chance of contributing to the next generation's creation. When bad answer is fortunate, the genes are passed on following cohort. Dismissing these resolutions will limit population variety and should be prevented. Assignment of the probability of selection to individuals is a common step in all of these schemes. There are various methods for this assignment like a roulette wheel, linear ranking and geometric ranking. The roulette wheel is one of the numerous selection operators described in the literature [58,59].

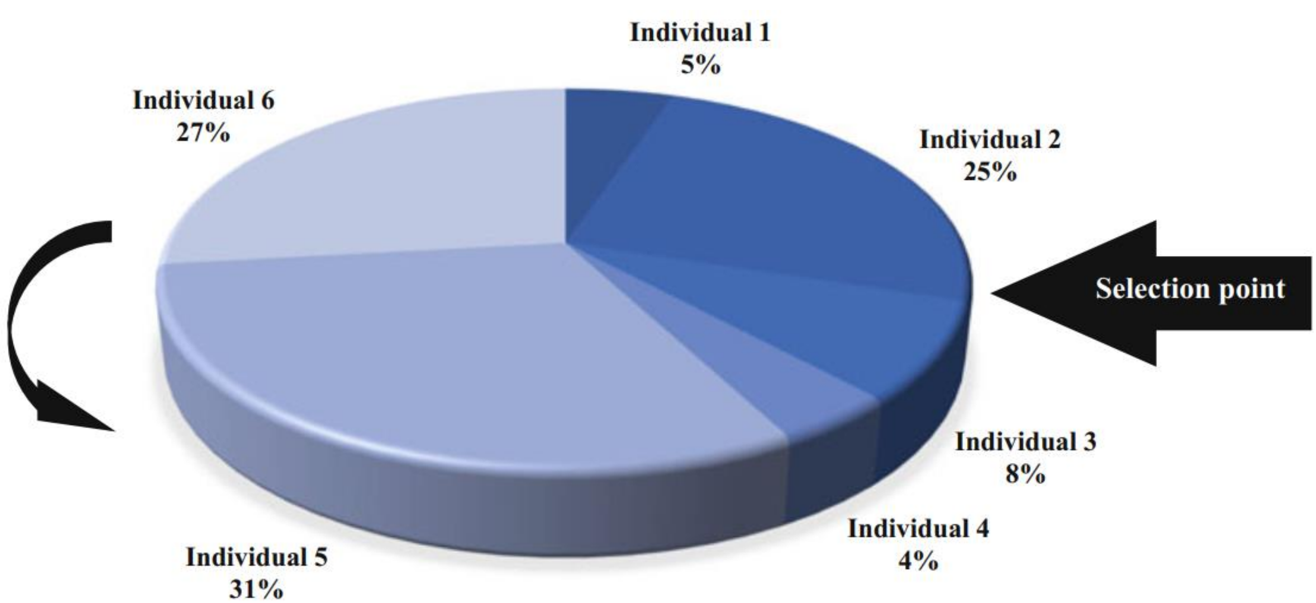


Figure 13: Mechanism of the roulette wheel in genetic algorithm

Table 2: Details of individuals in Figure 14

Individual no.	Fitness value	% of Total
1	12.0	5.0
2	55.0	24.0
3	20..0	8.0
4	10.0	4.0
5	70.0	30.0
6	60.0	26.0
Total	**227.0**	**100.0**

d. Crossover

Individuals must be used to generate the new generation after being selected using a selection operator. Naturally, the chromosomes of parents genes are joined to form a new chromosome [60]. It is emulated by merging answers chosen by the rou. wheel to create two new solutions in the GA algorithm. Several crossover operator approaches in the literature are reported, two of which are depicted in Figure 15. The genes of two-parent solutions are exchanged before and after a single point in a single-point crossover. However, two crossing points are present in a double-point crossover, and only the chromosomes between them are exchanged [61]. Other crossover approaches that are mentioned in the literature contain:

- Uniform crossover
- Three parents crossover
- Masked crossover
- Multi-point crossover
- Half uniform crossover
- Cycle crossover
- Heuristic cross over

Crossover's central aim is to guarantee that genes are transferred and the offspring inherit the DNA from their parents. In the GA, the fundamental technique of exploitation is crossover. If the crossover is done using a random crossover point for two given parents, the algorithm will try to verify and search for alternative combinations of genes from the parents. As a result, those viable solutions are exploited without the introduction of a single additional gene. It is worth noting that the Probability of the Crossover (Pc) variable in GA shows the possibility of admitting a new child. For every child, a random variable from the same range is produced. The child is conceded on to the next generation if this random number is smaller than Pc. The parent will be transmitted if this is not the situation. This also occurs in nature when not all of the offspring survive [62,63].

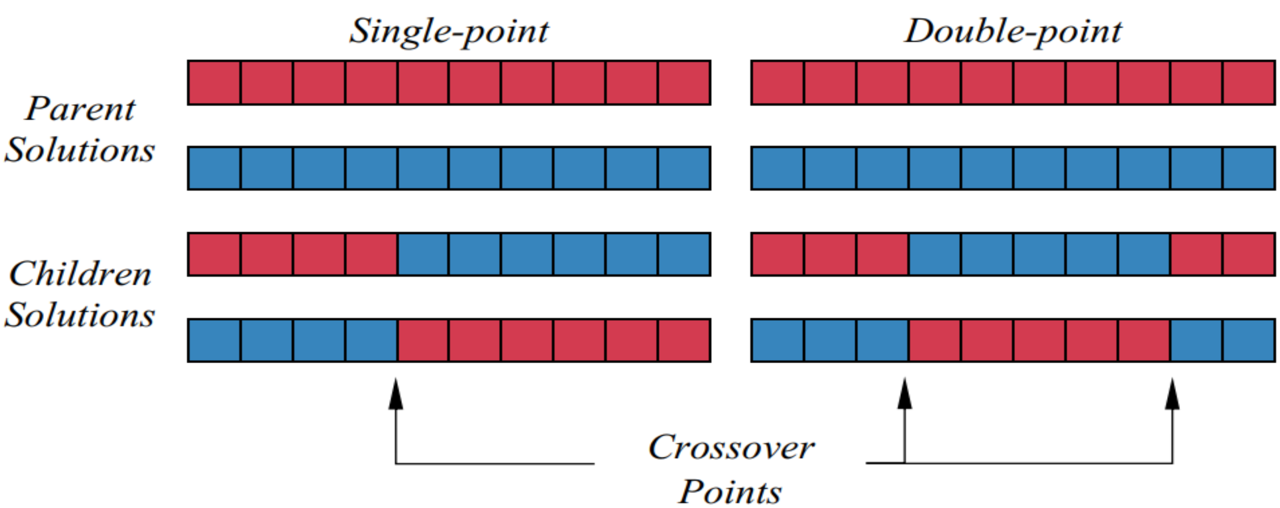


Figure 14: Single-point and double-point crossover are two prominent crossover strategies in GA. The chromosomes of two-parent solutions are exchanged before and after a single point in a single-point crossover. There are two crossing points in a double-point crossover

e. Mutation

The final evolutionary operator, where genes are changed once children's solutions are created. GA has a low mutation rate because significant mutation rates turn GA into a rudimentary random search. By adding another degree of unpredictability to the population, the mutation operator keeps the population diverse [64]. In reality, this operator prevents solutions from becoming identical in the GA algorithm and increases the chances of avoiding local solutions. Figure 16 depicts a conceptual illustration of this operator. After the crossover (replication) phase, minor alterations in some randomly chosen genes may be detected in this diagram [65].

The following are some of the most often used mutation strategies:
• Varying probability of mutation
• Uniqueness mutation

The majority of EAs use 3 operators of selection, crossover, and mutation. Each generation is subjected to these operators to enhance the superiority of the genes in following cohort. Elitism is standard operator where excellent solutions are kept and passed down to the following cohort unchanged. When using the crossover or mutation operators, the key goal is to avoid degrading such solutions (elites). The GA algorithm begins with a arbitrary population of entities. Using the three operators stated above, this method enhances the population until the end of the end. For a given issue, the finest solution in the previous population is resumed as the best estimate of global optimum. During the optimization, the selection rate, crossover, and mutation can be adjusted or set to fix quantities. Following sections look into the influence of altering on GA presentation [66,67].

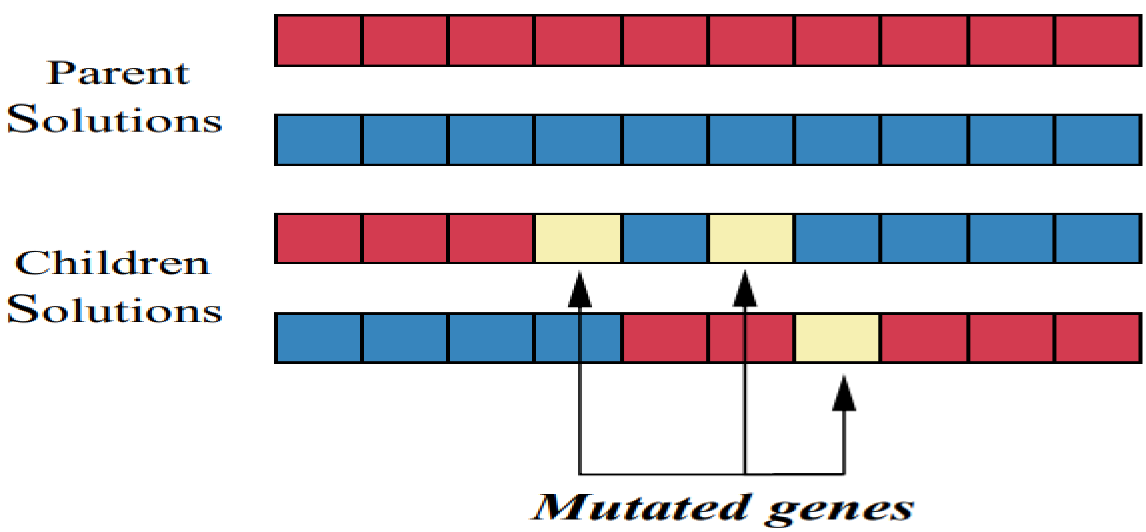


Figure 15: After the crossover phase, the mutation operator changes one or more genes in the children's solutions.

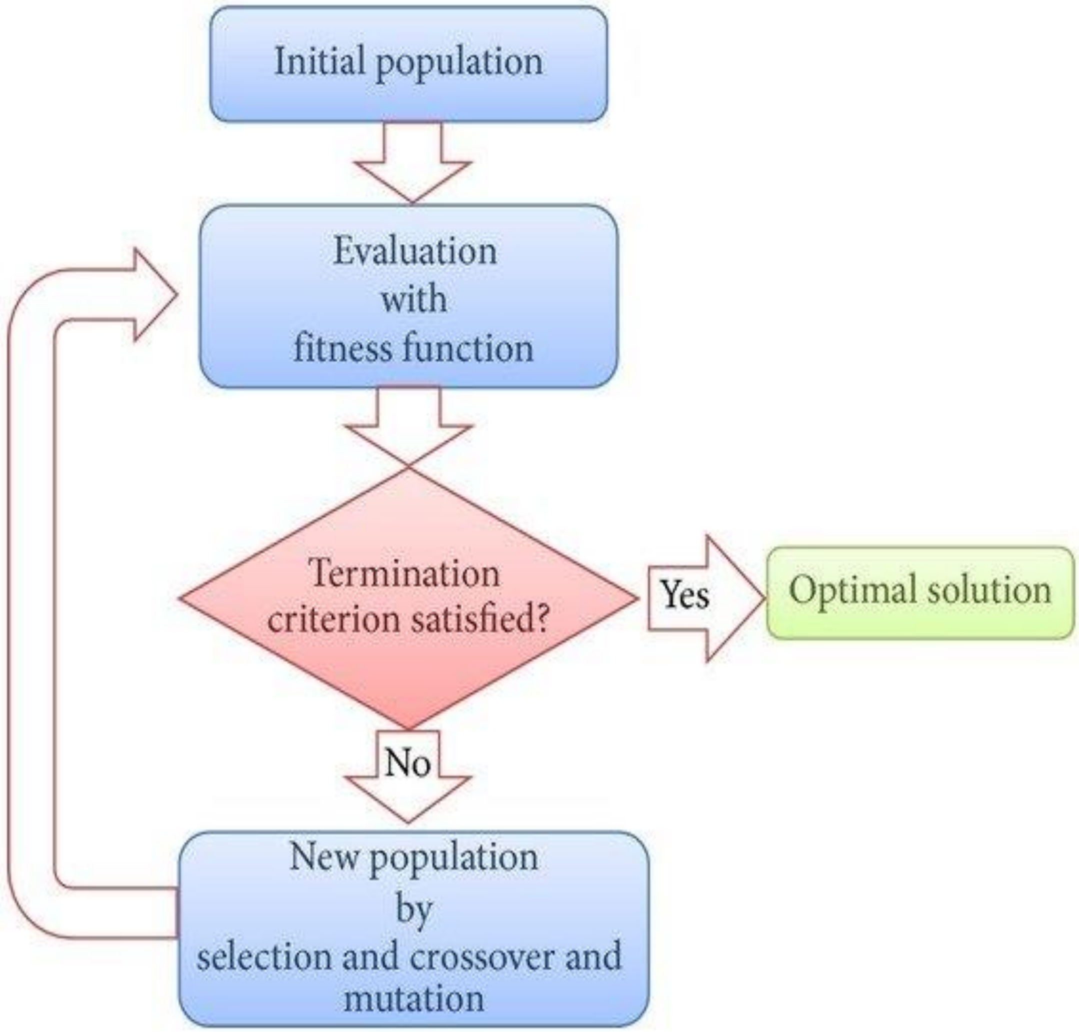


Figure 16: Flow diagram of Genetic Algorithm

3.3. Artificial Neural Network (ANN)

3.3.1. Fundamental Theory

The theory of an artificial neural network (ANN) was first presented in biology, where neural networks play a crucial role in the human body. Hebb's rule, which was established on hypotheses and findings of neurophysiologic environment, was introduced in 1949 as the first approach for training ANN. ANN are computer models based on the nervous system of live organisms. They may acquire and store knowledge (information-based). They can be described as a collection of units depicted by neurons, interconnected by many interconnections, and executed by synaptic weights vectors and matrices [68,69].

3.3.2. Artificial Neuron

The ANNs architectures were created using existing biological nervous system concepts as well as the human brain itself. Artificial neurons are modified replicas of real neurons that serve as computational components or processing units. The study of how a neuron's cell membrane creates and promotes electrical signals motivated these concepts. Artificial neurons in ANNs are nonlinear, with continuous outputs and fundamental functions, including collecting information from their inputs, combining them according to their operating units, and creating

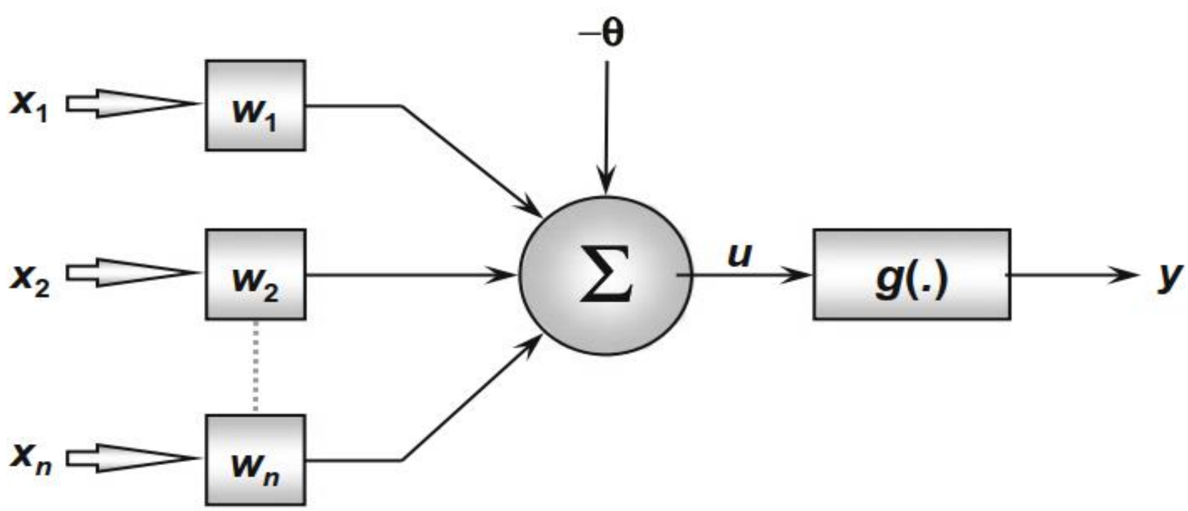


Figure 17: The Artificial Neuron

a response based on their intrinsic activation functions. Figure 18 shows the schematic of the artificial neuron [70,71].

3.3.3. ANN Architecture and Training Process

Generally, ANN comprises input, hidden, and output layers, which are described as follows,

(a) Input layer

The input layer is in charge of getting data, signals, characteristics, or assessments from the outside world. These inputs are often normalized within the bounds of activation functions. This normalization improves the numerical consistency of the network's numerical computations.

(b) Hidden layers

The hidden layers are made up of neurons in charge of extracting information related to the system under investigation. These layers handle the majority of a network's internal operations.

(c) Output layer

Like the preceding levels, this layer is made up of neurons and is in charge of creating and displaying the final network outputs, which are the consequence of the processing done by the neurons in the preceding layer. The significant designs of ANNs may be classified into the following categories, given that the neuron disposition, interconnected, and how their layers are unruffled: There are four types of feedforward networks: recurrent networks, mesh networks. Single-layer and multilayer feedforward networks [72–74].

3.3.4. Single-Layer Feedforward Architecture

There is only one input layer and a single neural layer (output layer) in this ANN architecture. A simple-layer feedforward network with n inputs and m outputs is shown in Figure 19. Information always travels in one direction, from the input layer to the output layer (hence, unidirectional). The number of network outputs in networks adhering to this design would always match the number of neurons, as shown in Figure 19. Pattern categorization and linear filtering issues are typical applications for these networks [75].

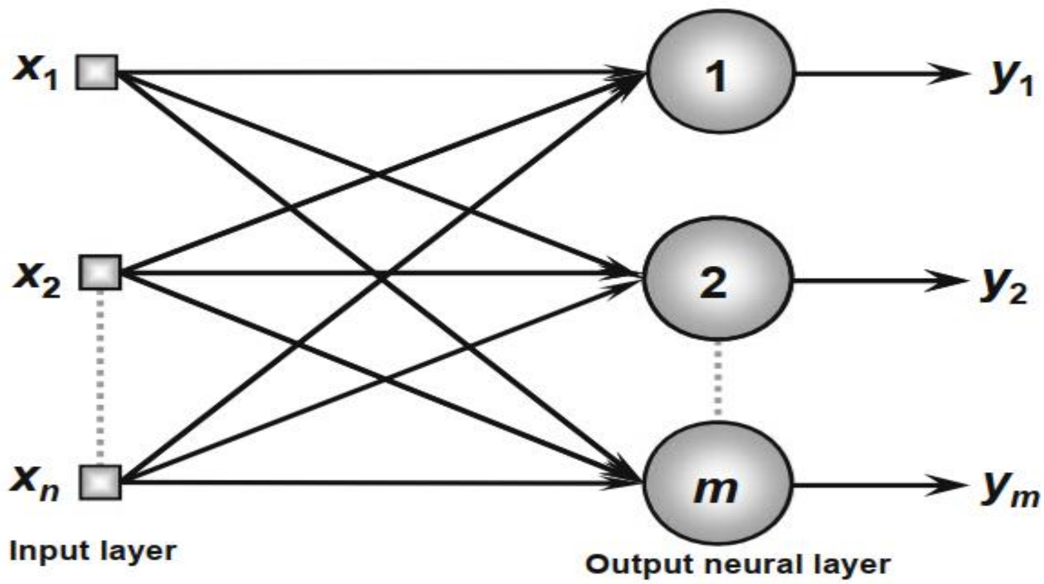


Figure 18: Schematic of Simple-layer feedforward network

3.3.5. Multiple-Layer Feedforward Architectures

Unlike networks of the initial design, feedforward networks with many layers are hidden neural layers. They are used to solve various problems, including function approximation, pattern classification, system identification, process control, optimization . For example, figure 20 depicts a feedforward network with several layers, including an input layer with n sample signals, two hidden neural layers with n1 and n2 neurons, and one output neural layer with m neurons reflecting the problem's output values. The MLP and RBF are two of the most common networks that employ multiple-layer feedforward topologies [76]. The number of neurons that make up the first hidden layer is usually dissimilar from the number of signals that make up the network's input layer, as seen in Figure 20.

In general, the number of hidden layers and the number of neurons in each layer are determined by the type and difficulty of the problem being addressed by the network and the amount and type of accessible data. However, as with simple-layer feedforward networks, the number of output signals would always be equivalent to the number of neurons in that layer [77].

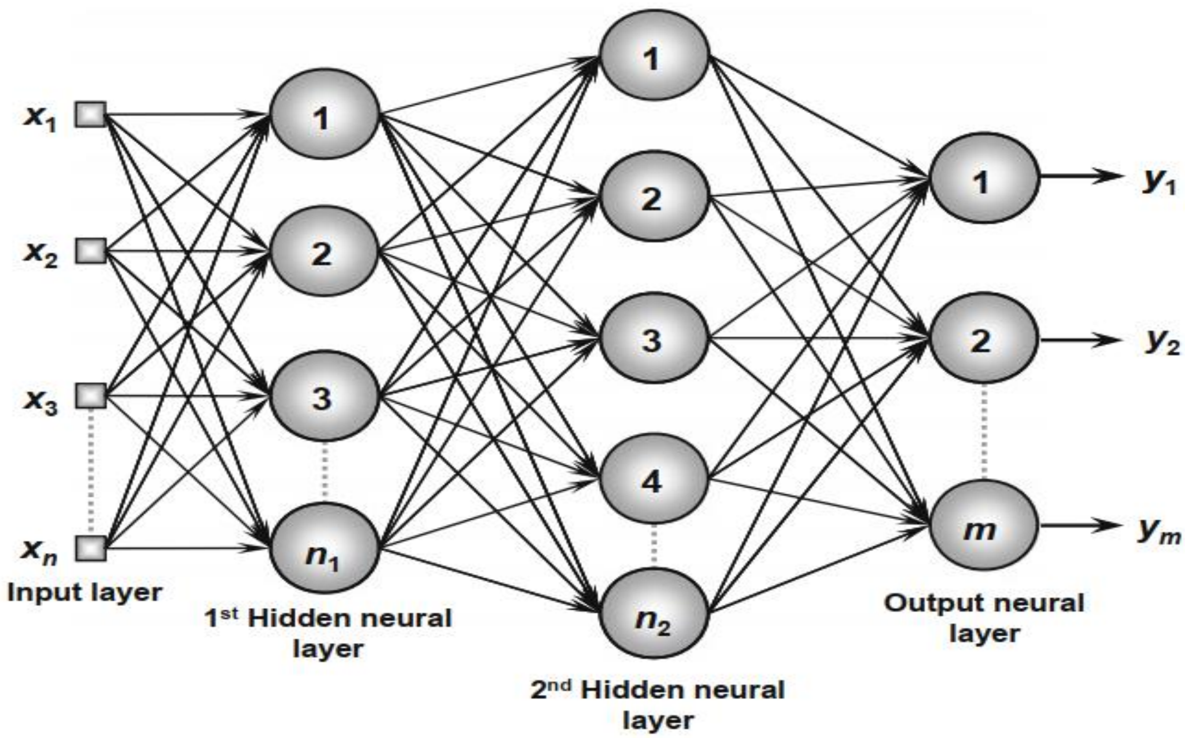


Figure 19: Schematic of Multi-layer feedforward network

3.4. Exergy Analysis

The second law of thermodynamics gives designers and engineers a powerful and efficient tool known as Exergy analysis, which can be used to analyze heat exchanger performance. Exergy is a measure of how far a system's state deviates from that of its surroundings. It can be defined as the maximum amount of work obtained from the system to equilibrium with the environment. Exergy, unlike energy, is not conserved; instead, it is destroyed by irreversibilities. Because of these irreversibilities, Exergy loss during a process is proportionally associated with entropy generation [78,79]. The following formulas were used to calculate exergy.

CHAPTER 4: METHODOLOGY

4.1. Overview of Methodology

An industrial process furnace's actual design and operational data were obtained in this study, and a furnace model was regenerated in Aspen EDR. Mass flow rate, temperature, and pressure of process fluid (crude oil), fuel (field gas), and flue gas are among the operational parameters. The number of tubes (convection side), tube length, tube pitch, number of passes, number of burners, and firebox dimensions is among the design or mechanical parameters.

Aspen HYSYS was then used to import the improved furnace model. To build the data collection, the MATLAB and Aspen HYSYS interfaces were created. While altering the crude composition and other process parameters, a single objective genetic algorithm is utilized to identify the optimal crude flow rate, fuel flow rate, and excess air. Finally, the data set was used to train an artificial intelligence system to forecast the optimal crude flow rate, fuel flow rate, and excess air under unknown process circumstances.

In this work, an ANN model was developed to forecast the optimal crude oil mass flow rate, fuel mass flow rate, and excess air under variations in crude composition and other process factors such as crude oil inlet temperature and pressure, air stream, and fuel stream.

Figure 21 depicts the workflow of the current research.

Step 1: Using improved industrial data, the detailed design of the furnace was recreated in Aspen EDR. The Aspen EDR furnace type was later converted to Aspen HYSYS.

Step 2: The link between Aspen HYSYS and MATLAB was built using the COM server. Furthermore, the data set is created by entering the 1, 2, 3, 4, and 5 variations in crude oil composition, crude oil, fuel, and air inlet temperature and pressure. For each modification, the optimal mass flow rate and excess air were calculated using a single objective genetic algorithm. The function aimed to increase furnace efficiency while lowering energy usage.

Step 3: Finally, 360 data points were created, with 70% of the data set used for training and the remaining data set split equally for ANN model validation and testing.

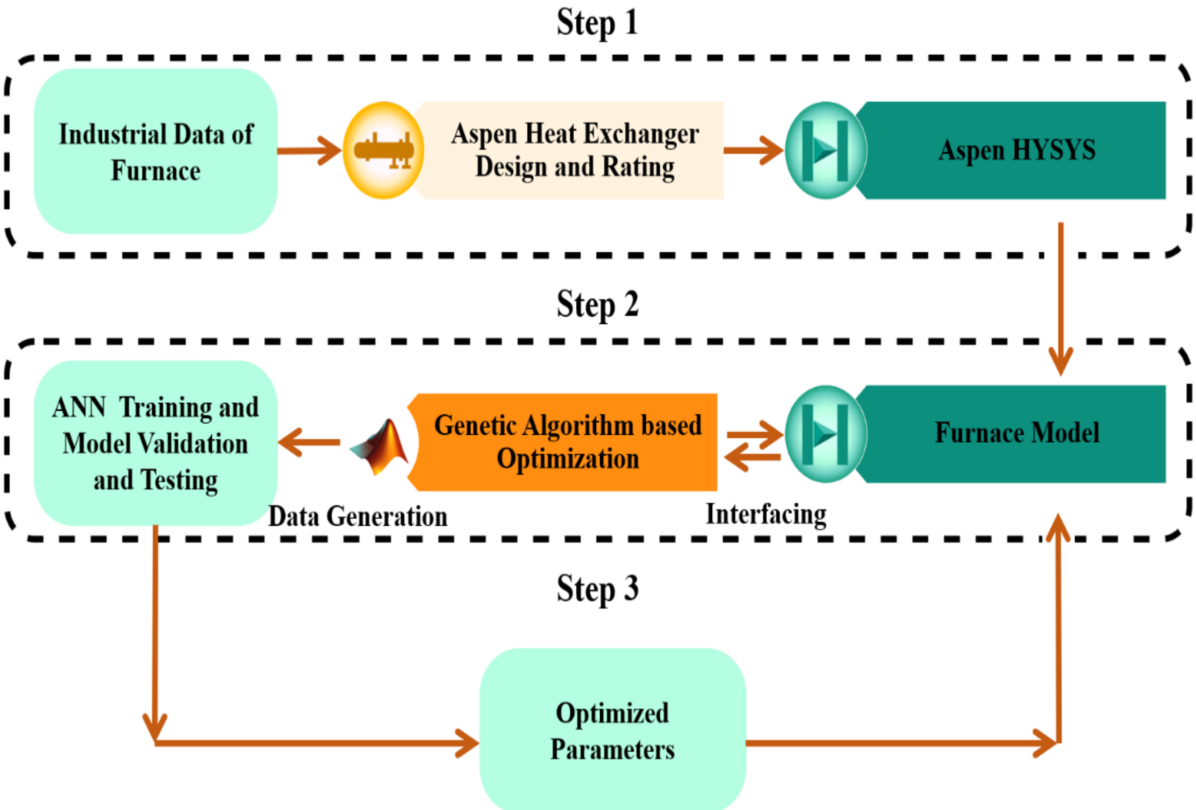


Figure 20: Schematic of workflow of the current research.

4.2. Furnace Process Description

In this study, a cabin-type furnace was employed for modeling and simulation. Figure 22 depicts a furnace diagram with two distinct convection and radiation sections. The process fluid (crude oil) enters the furnace from the top and travels through convection sections 2 and 1 before exiting the furnace. In this section, the fluid is usually a one-phase liquid. High heat fluxes are applied to tubes in the radiation section, forcing crude oil to boil and evaporate, raising the temperature to around 366 oC. Heat is transferred from the fuel-burning with air to the process flow in this stage by direct radiation and convection from gases. The considered furnace's nominal flow rate is 132224 kg/hr. The inlet process pressure is 6.2

kg/cm2g. Table 3 lists some of the furnace's nominal parameters. Hot exhaust gases first heat the process flow before being sent to the central firebox portion to improve thermal performance. As seen in Figure 22, the process fluid is separated into four-stream flows in this segment, with four streams heading to the furnace's center.

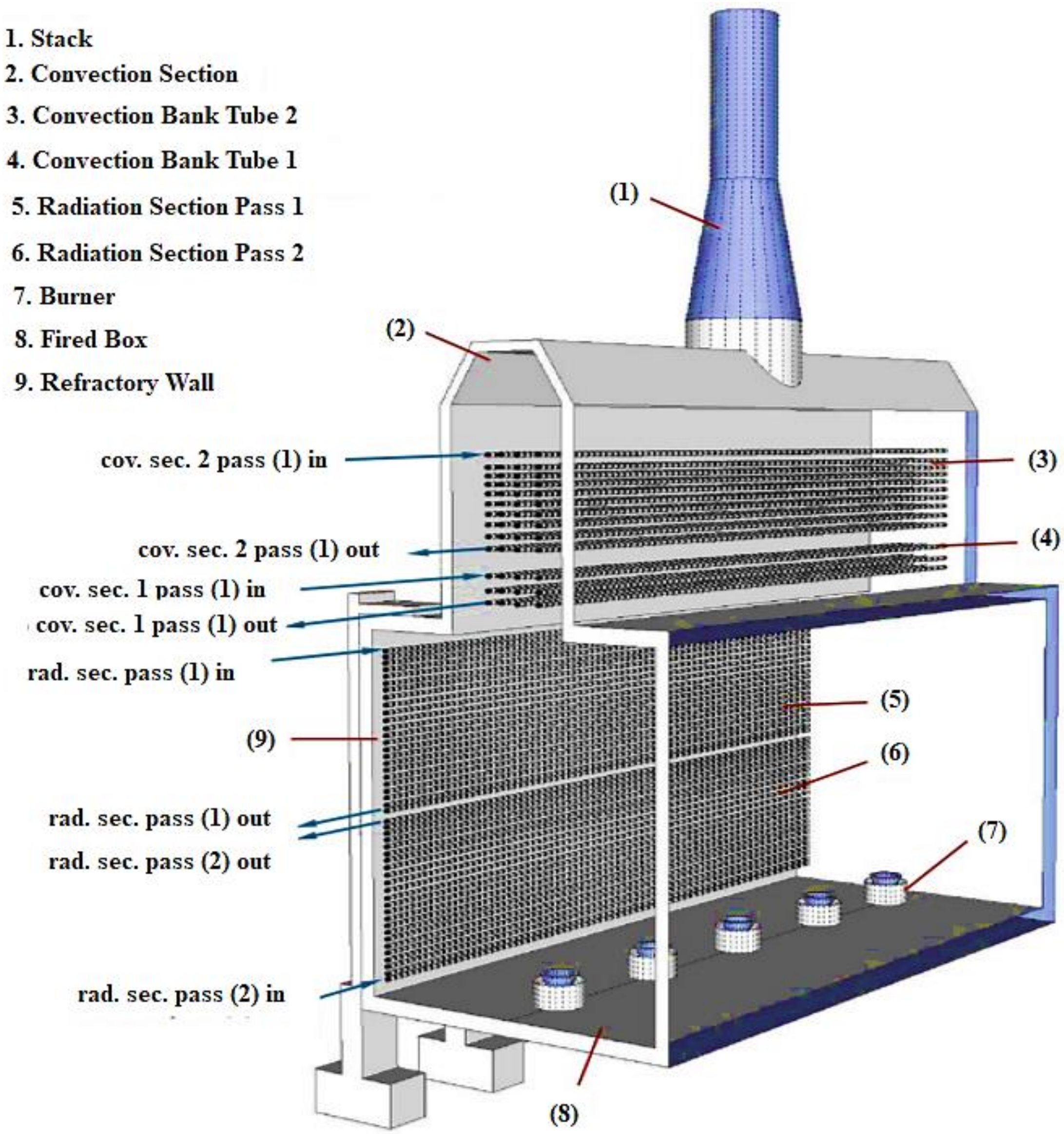


Figure 21: Schematic of Industrial Process Furnace

Table 3: The nominal parameters of the furnace.

Parameters	**Symbol**	**Values**
Process fluid flow rate (kg/hr.)	m_{in}	132224
Process fluid inlet temperature (^oC)	T_{in}	294
Process fluid outlet temperature (^oC)	T_{out}	366
Process fluid inlet pressure (kg/cm^{2}g)	P_{in}	6.2
Process fluid outlet pressure (kg/cm^{2}g)	P_{out}	3.4
Fuel flow rate (kg/hr.)	m_{fuel}	971
Fuel gas lower heating value (kcal/kg)	LHV	10120
Fouling factor (m^{2}h^{o}C/kcal)	f	0.0014
Allowable pressure drop	P_{drop}	2.8
Tube out diameter (mm)	d_{out}	141.3
Tube wall thickness (mm)	$d_{thickness}$	6.55
Tube length (m)	L_{tube}	7.814
Firebox height (mm)	$h_{firebox}$	9960
Firebox inner diameter (mm)	$d_{firebox}$	5120

Table 4: Process conditions

Parameter	Crude Oil	Fuel (Field Gas)	Air
Inlet Temperature (^oC)	294.9	47	47
Outlet Temperature (^oC)	366	--	--
Inlet Pressure (kg/cm2-g)	6.2	0.0171	0.0171
Outlet Pressure (kg/cm2-g)	3.4	--	--
Inlet Mass Flow rate (kg/hr)	132224	1036	1036

Table 5: Design parameters

Parameters	Values
Tube out diameter (mm)	141.3
Tube wall thickness (mm)	6.55
Tube length (m)	7.81
Number of tubes/rows	120/10
Number of tubes (conv. section)	12
Firebox height (mm)	9960
Firebox inner diameter (mm)	5120
Fouling factor ($m^2h^oC/kcal$)	0.0014

4.3. Aspen EDR Model Development

4.3.1. Simple Furnace (Fired Heater)

In this study, the model of the furnace was first simulated in Aspen HYSY using the following steps.

- Specify the crude assay and suitable fluid package in Aspen HYSYS.
- Shift to the Simulation Mode
- Select the Fired Heater model from the model palette; if the model palette is not visible, go to the View menu bar and select Model Palette. The currently used icon may be changed; the available icons will be shown in Figure 23.
- By double-clicking on the furnace icon, you may access the fire heater connection and specification page. The page seen in Figure 24 displays.
- The Simple fire heater model must be selected on the Design Parameters page.
- Navigate to the Worksheet and enter the stream settings indicated in Figure 25. The user-defined parameters are presented in blue, while the HYSYS-calculated parameters are used in black.
- Navigate to the Worksheet's Composition page and determine the composition of both input streams. HYSYS calculates the output stream composition.

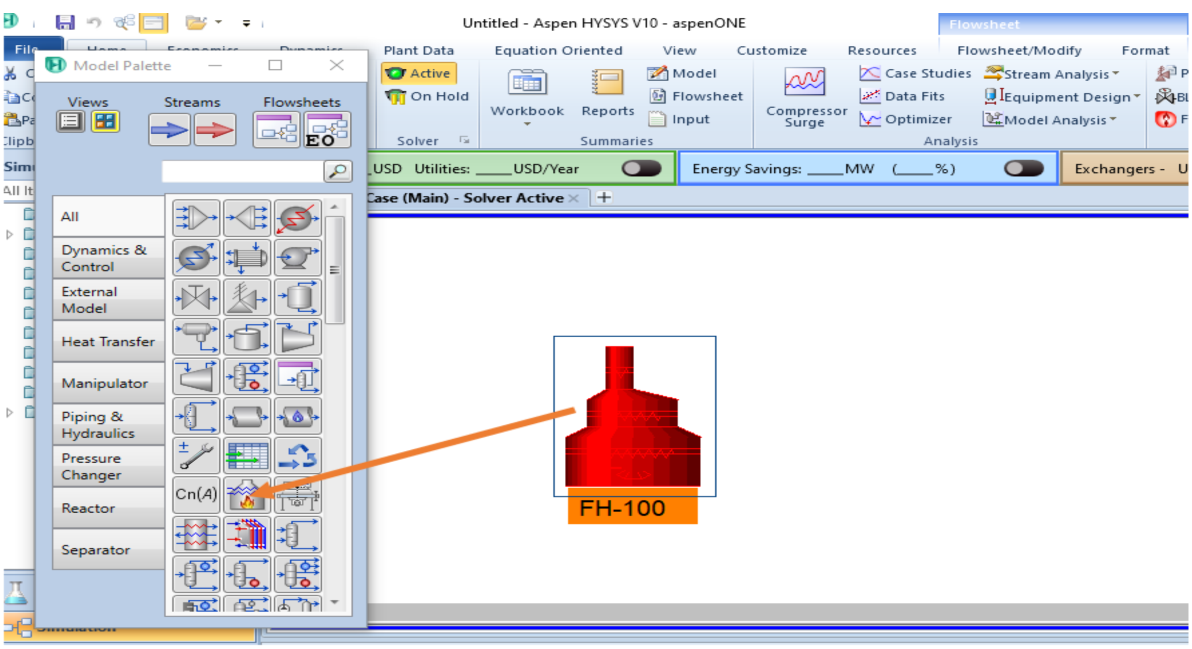


Figure 22: Selection of Fire heater Model in Aspen HYSYS

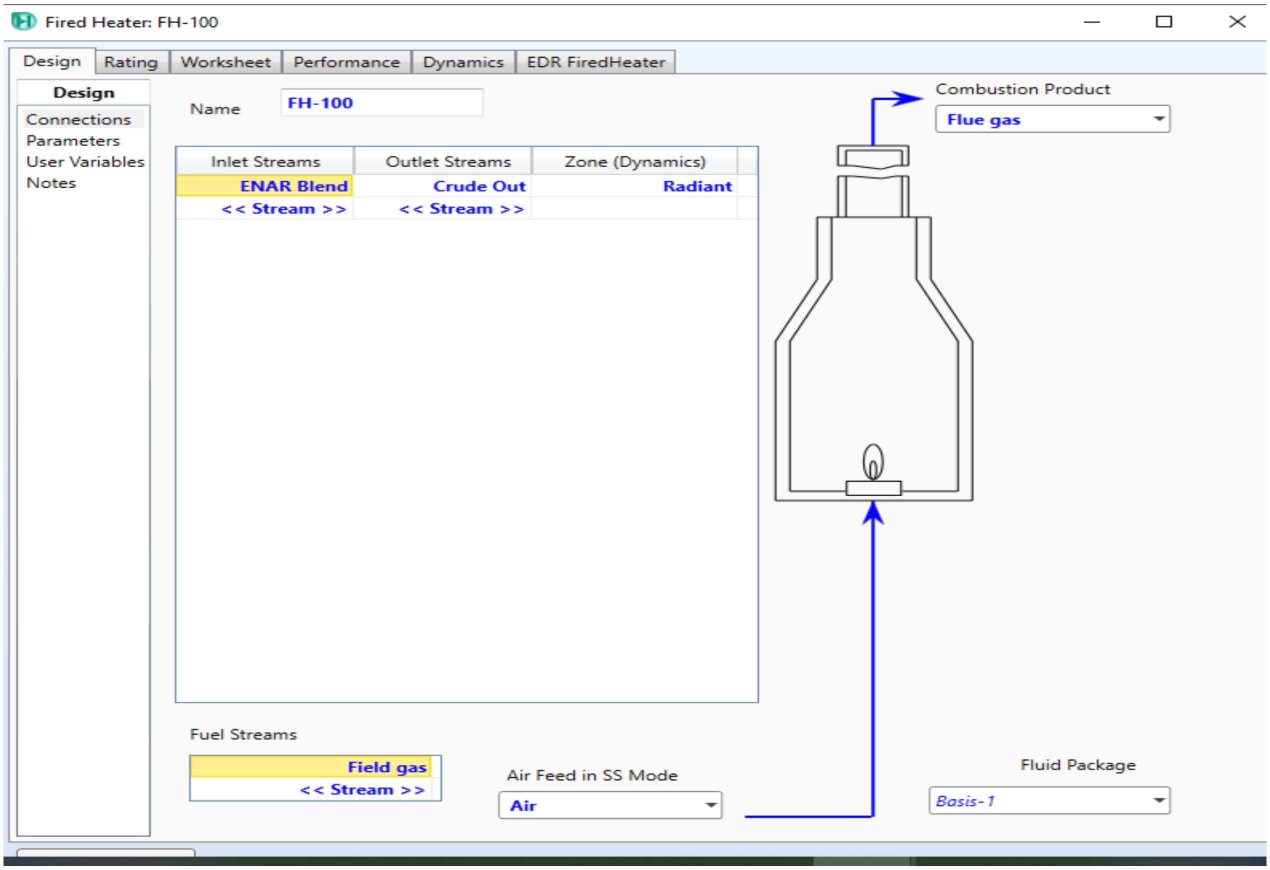
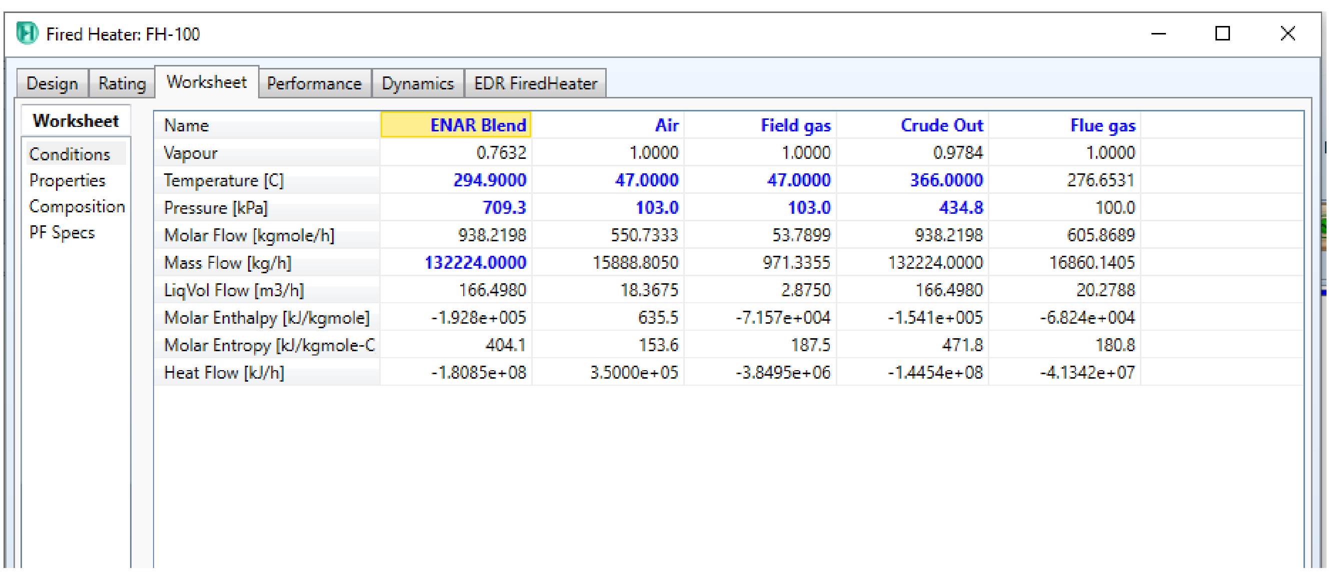


Figure 23: Connections of streams in Fired heater model



Name	ENAR Blend	Air	Field gas	Crude Out	Flue gas
Vapour	0.7632	1.0000	1.0000	0.9784	1.0000
Temperature [C]	294.9000	47.0000	47.0000	366.0000	276.6531
Pressure [kPa]	709.3	103.0	103.0	434.8	100.0
Molar Flow [kgmole/h]	938.2198	550.7333	53.7899	938.2198	605.8689
Mass Flow [kg/h]	132224.0000	15888.8050	971.3355	132224.0000	16860.1405
LiqVol Flow [m3/h]	166.4980	18.3675	2.8750	166.4980	20.2788
Molar Enthalpy [kJ/kgmole]	-1.928e+005	635.5	-7.157e+004	-1.541e+005	-6.824e+004
Molar Entropy [kJ/kgmole-C	404.1	153.6	187.5	471.8	180.8
Heat Flow [kJ/h]	-1.8085e+08	3.5000e+05	-3.8495e+06	-1.4454e+08	-4.1342e+07

Figure 24: worksheet for inserting Input parameters

4.3.2. Detailed Model Development

The rigorous rating model of the furnace was developed in Aspen EDR using the following step

- To transfer the previous Aspen HYSY model to Aspen EDR, open Aspen EDR and select Import from the File menu.
- From the home menu, select the Rating mode.
- The main menu chooses Set process data to provide the input variables for the furnace model, as illustrated in Figure 26.
- Set the geometrical information for the furnace model as shown in Table 5 by clicking on the Set Combustion item in the main menu. Figure 28 depicts the geometrical information.
- Finally, specify the geometry and start the simulation.

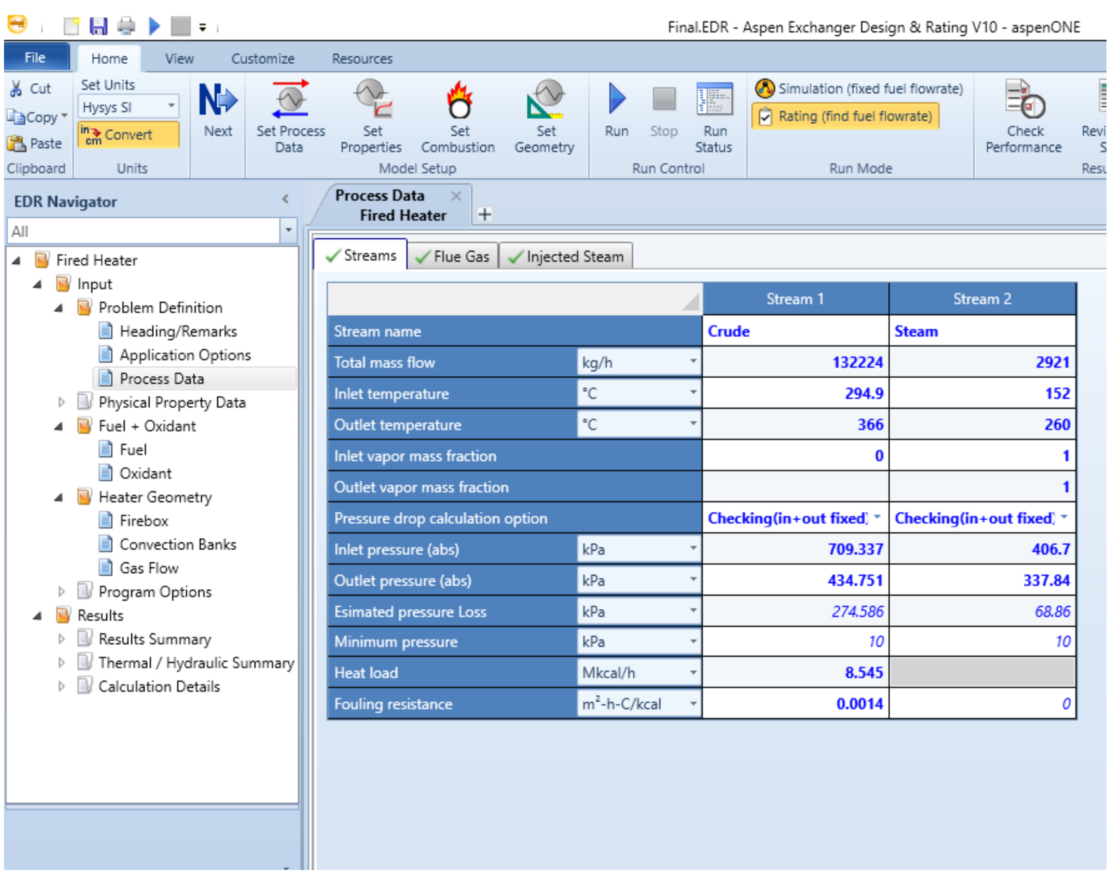


Figure 25: Entering inputs for the Fired heater model

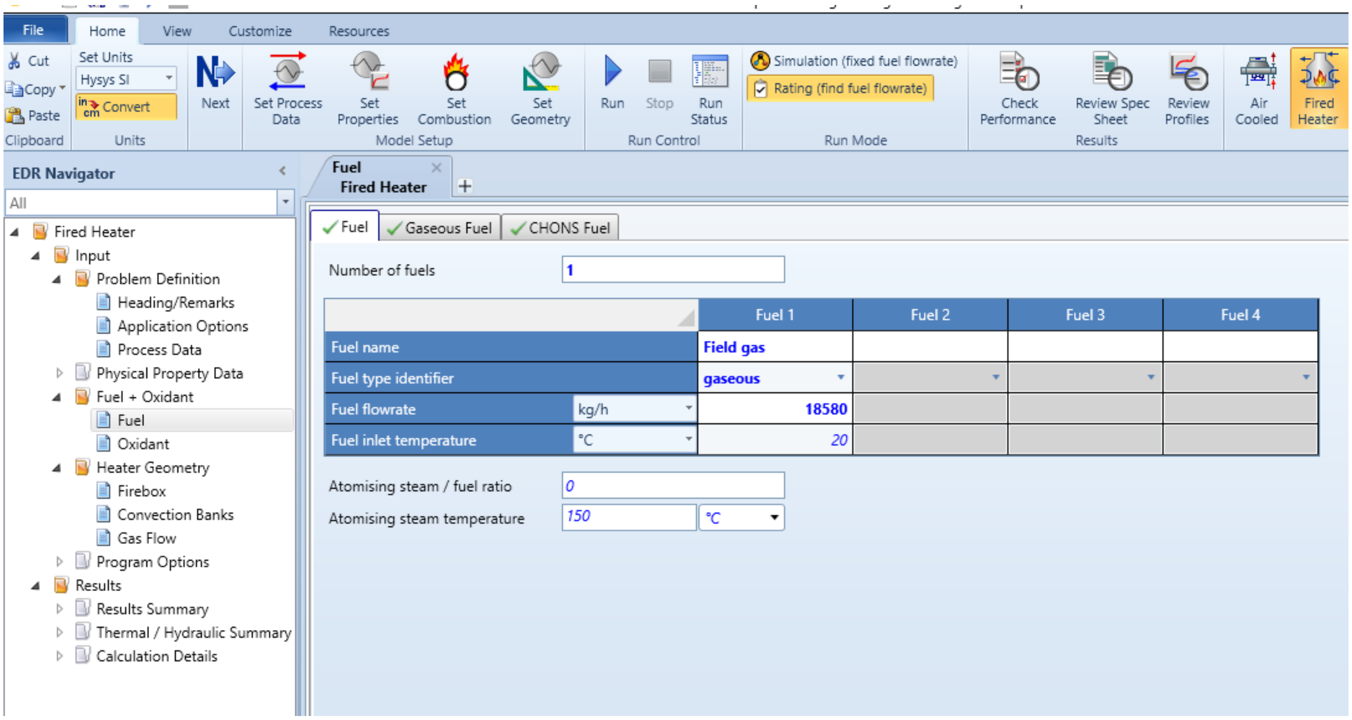


Figure 27: Inserting combustion information for the Fired heater model in Aspen EDR

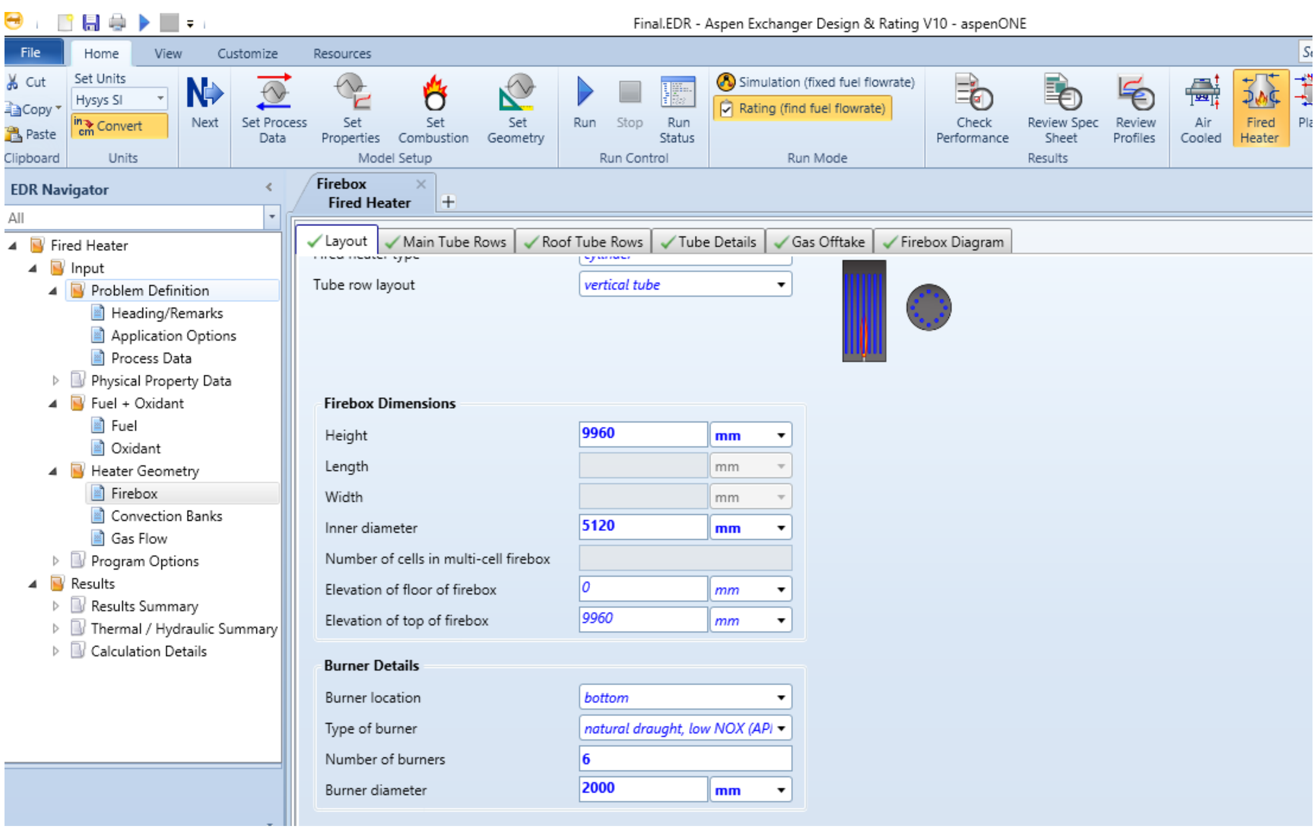


Figure 26: Inserting geometrical information for the Fired heater model in Aspen EDR

4.4. Aspen HYSYS and MATLAB Interfacing

The detailed Aspen EDR model of the furnace was first imported to Aspen HYSYS. Then, the seven process variables, i.e., crude composition, inlet crude stream temperature, inlet crude stream pressure, temperature and pressure of field gas and temperature and pressure of air stream, were selected as uncertain variables. Next, the seven uncertain process variables and objective variables (crude and field gas mass flow rate and excess air) were imported to the spreadsheet inside Aspen HYSYS. Then, the interface between the spreadsheet of Aspen HYSYS and MATLAB software was developed using a COM server, as shown in Figure29.

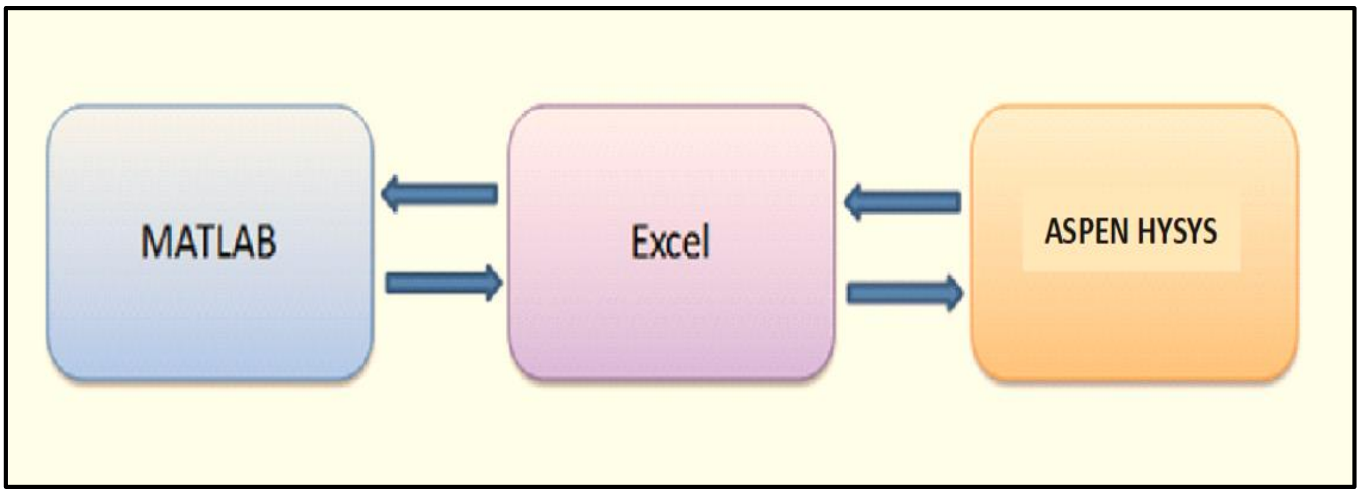


Figure 28: MATLAB and Aspen HYSY interfacing

4.5. Single objective Genetic algorithm for optimization

In this study, a single objective genetic algorithm was used to optimize the mass flow rate of crude oil and fuel oil and the excess air under uncertainty in the selected seven process variables. The objective function of the genetic algorithm was to maximize the fired heater or furnace efficiency. The mass flow rate of inlet crude oil and inlet fuel oil and excess air was selected as manipulating variables for GA. The inbuilt function, i.e., the "ga" command of MATLAB software, was used to implement` GA. The population size and number of generations were 20 and 5, respectively. The following lines describe the workflow for the genetic algorithm.

- First of all, the uncertainty in the selected process variables was inserted.
- Then, the genetic algorithm generates the initial populations of size 20
- Each chromosome in the population was put in the Aspen HYSY software to evaluate the objective function, i.e., fired heater efficiency
- When one generation has completed, the population for the next generation was selected using GA operator, i.e., selection, crossover and mutations.
- This process was continued up to 5 generations
- After the completion of the number of generations, the mass flow rate of crude oil, the mass flow rate of fuel oil and the amount of excess air that gives the maximum efficiency of the fired heater were selected as the best solution.

4.6. Data generation

Using Aspen HYSYS and MATLAB interfacing, the data was generated to train a feedforward neural network (FFNN). A total of 360 data points was generated. The data was generated using the 5 % uncertainty in the seven selected process variables. Table 6 shows ten data samples of generated data for six process variables. The first row of data points was generated with -5 percent variation, the second row with -4 percent variation, the third row with -3 percent variation, and the last row with +1 percent variation.

Table 6: Ten Data sample of generated data

Inlet Crude stream temperature (C)	Inlet crude stream pressure (kPa)	Inlet fuel temperature (C)	Inlet fuel pressure (kPa)	Inlet air pressure (kPa)	Inlet air temperature (C)
280.15	673.87	44.65	97.85	97.85	44.65
268.94	646.91	42.84	93.93	93.94	42.86
260.88	627.50	41.57	91.11	91.11	41.57
255.66	614.95	40.74	89.29	89.29	40.74
253.10	608.80	40.33	88.40	88.40	40.33
255.63	614.89	40.74	89.28	89.28	40.74
260.74	627.19	41.55	91.07	91.07	41.55
268.57	646.01	42.80	93.80	93.80	42.80
279.31	671.85	44.51	97.55	97.55	44.51
293.28	705.44	46.74	102.43	102.43	46.74

4.7. Artificial neural network (ANN) model training and validation

ANN model was trained using the data generated from Aspen HYSYS and MATLAB interfacing. Three hundred sixty data points were generated, with 70% used for training, 15% for validation, and 15% for testing the ANN model. A multi-output feedforward multilayer neural network was trained with the Levenberg-Marquardt (trainlm) training algorithm. The crude stream composition, inlet crude temperature, inlet crude stream pressure, fuel stream temperature and pressure, and air stream temperature and pressure were considered as an input to the ANN model. The mass flow rates of crude oil, a mass flow rate of fuel, and excess air were considered an output of the ANN model. The hidden layers and the number of neurons in the hidden layer were selected using a multi-objective genetic algorithm approach. The objective function for GA was the root mean square error (RMSE) for the three outputs of the ANN model. Both the generation and population of 50 were selected. The optimum architecture of ANN consists of 3 hidden layers. The number of neurons in layers 1, 2 and 3 were 15, 15 and 27, respectively, as shown in Figure 30. The tansig and purlin activation functions were used in the hidden layer and output layer, respectively. Figure 31 shows the ANN model-based predicted values of excess air, the mass flow of crude oil, and the mass flow rate of fuel vs. the target values. The trained ANN model has a high correlation coefficient of 0.99984, making it suitable for industrial applications.

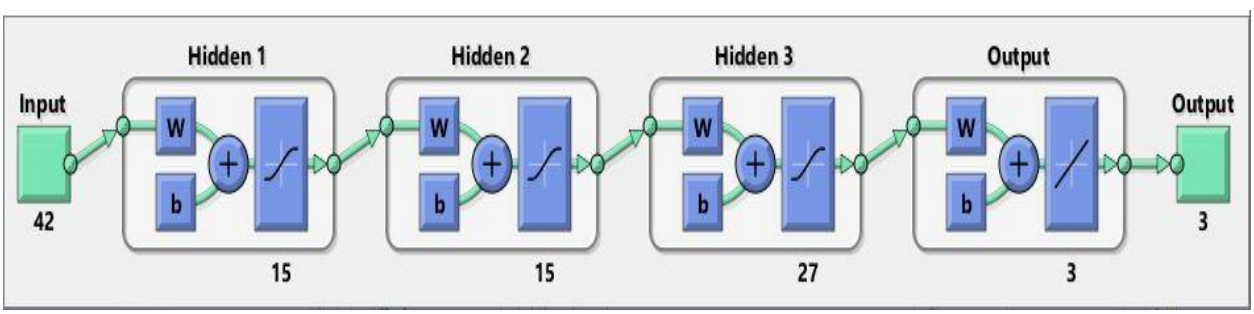


Figure 29: Proposed ANN model Architecture

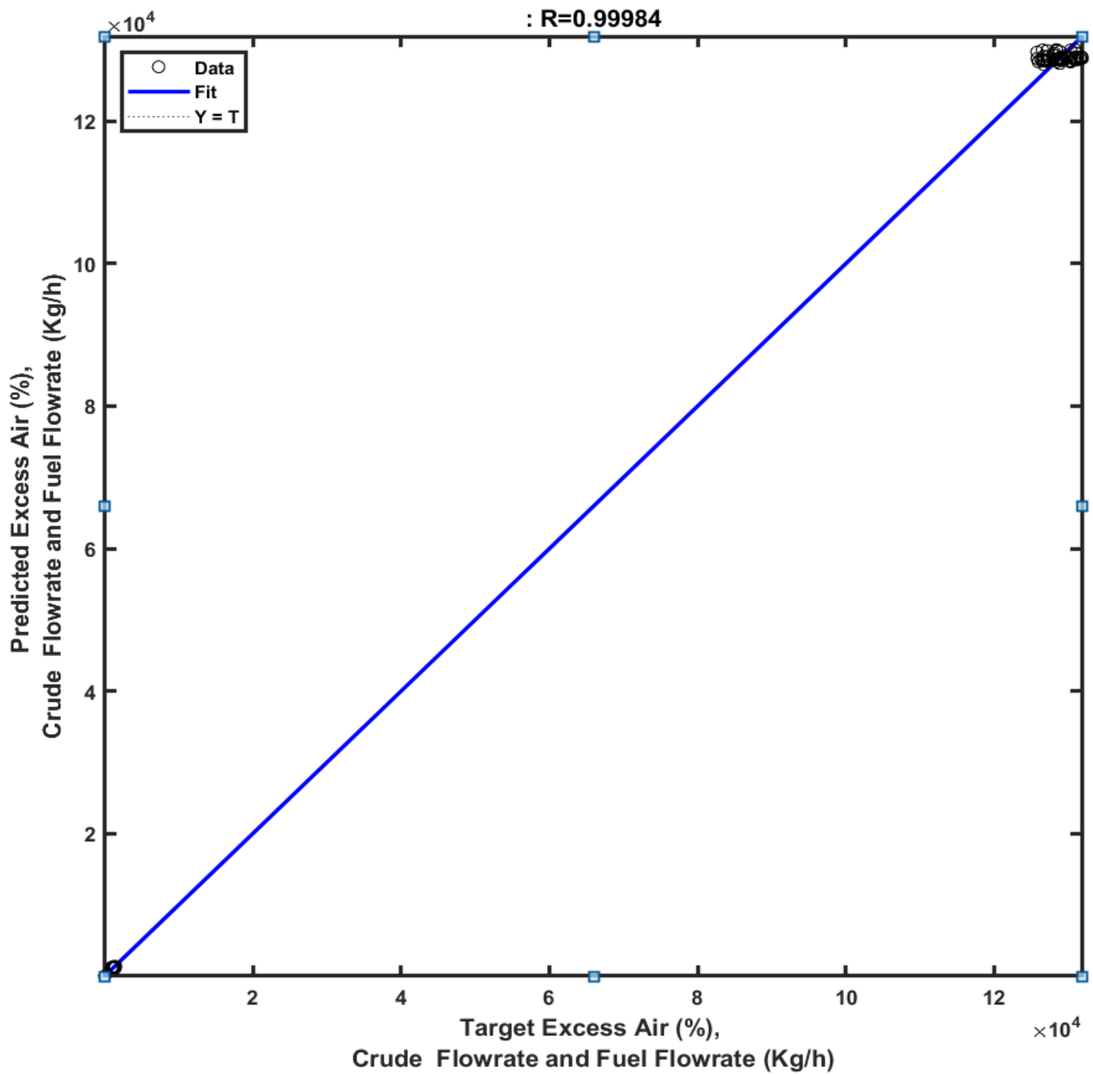


Figure 30:Actual vs. predicted value based on ANN model

4.8. Exergy Loss and Exergy Efficiency

Exergy analysis, which is based on the second law of thermodynamics, gives designers and engineers a quick and accurate way to assess equipment efficiency. Exergy is a statistic for determining how different a system's condition is from its surroundings. It is the maximum amount of work a system can generate once it has achieved equilibrium with its environment. Exergy, unlike energy, is not conserved; rather, it is destroyed by irreversibilities. Because of these irreversibilities, exergy loss during a process is proportionally associated with entropy generation [24].

The total exergy rate of the furnace can be expressed as equation (3),

$$\dot{E}x = (Ex)^{\cdot ch} + E\dot{x}^{ph} \text{........ (3)}$$

Ex is the exergy rate, KW

Ch and Ph means the chemical and physical exergy, KW

In thermal systems, physical exergy is derived from enthalpy and entropy change.

$$\text{Exph} = (\text{H} - \text{Ho}) - \text{To}\,(S - \text{So}) \text{ ------------ (4)}$$

Exph represents the physical exergy of the stream, To represents the environmental temperature (25 oC), H and S are the enthalpy and entropy of the stream, respectively. Whereas, Ho and So denotes the enthalpy and entropy of the stream at dead state (25 oC, 1 bar).

The equation for the exergy of destruction is as follows;

$$\text{Exergy destruction} = \sum \text{Ex}_{in} - \sum \text{Ex}_{\text{out}} \text{ ----------- (5)}$$

The chemical exergy of the stream can be represented as the equation (6),

$$(Ex)^{\cdot ch} = \dot{m}e\dot{x}^{ch} \text{........ (6)}$$

The exergy efficiency of the system is defined as “the ratio of the gained exergy and to the spent exergy “as equation (7) (Dogbe et al., 2018; Mert & Reis, 2016),

$$\text{Exergy efficiency} = \frac{E\dot{x}_{gain}}{E\dot{x}_{pay}} \times 100\% .... (7)$$

CHAPTER 5: RESULTS AND DISCUSSION

5.1. Optimization through Genetic Algorithm

The dataset for this study was generated by selecting the first component of crude oil, as well as the inlet temperatures and pressures of crude oil, fuel, and air stream and inserting an artificial variation of -5 % to +5%. Then, a single-objective genetic algorithm was used to optimize the amount of excess air and mass flow rates of crude and fuel streams. Similarly, the second component was chosen along with the same process variables and went through the same variations as the first, ranging from -5 % to +5 % and so on. In the same way, after inserting the uncertainty in the 36 components of the crude oil, a total of 360 data points were generated

The inlet crude composition, crude stream inlet temperature, crude stream inlet pressure, fuel temperature, fuel pressure, air temperature and air pressure were all subjected to 5% variations. The goal of using a single objective genetic algorithm was to find the optimum mass flow rates of crude oil, the mass flow rate of fuel stream and the amount of excess air entering the fired heater under each variation while maximizing the furnace efficiency. The upper and lower bounds for the GA were determined by inserting a 5% variation in the initial values of the manipulating variables. The number of generations and population size of 20 and 5 was chosen for the genetic algorithm, respectively. Table 7 compares the results of the straight run and the genetic algorithm for 20 data samples. In this study, straight run (SR) refers to the simulation of the fired heater model under uncertainty in the process variables without optimization. Table 7 shows that the genetic algorithm outperforms the straight run. In addition, the results of the genetic algorithm showed higher furnace efficiency than the straight run results.

Table 7: Comparison between SR and GA based efficiency of Furnace model

Number of Samples	**Straight Run Efficiency**	**GA based Efficiency**
Case1	83.62	85.40
Case2	83.62	85.55
Case3	81.92	85.29
Case4	83.62	85.41
Case5	83.73	85.55
Case6	83.62	85.41
Case7	83.39	85.50
Case8	83.73	85.55
Case9	82.52	85.41
Case10	81.92	85.10

5.2. Prediction through ANN

Artificial Neural Network (ANN) model was trained using the data generated from Aspen HYSYS and MATLAB interfacing. A total of 360 data points were generated, with 70% used for training, 15% for validation, and 15% for testing the ANN model. A multi-output feed-forward multilayer artificial neural network was trained with the Levenberg-Marquardt (trainlm) training algorithm. The crude stream composition, inlet crude temperature, inlet crude stream pressure, fuel stream temperature and pressure, and air stream temperature and pressure were used as input parameters of the ANN model. The mass flow rates of crude oil, mass flow rate of fuel, and amount of excess air were considered as an output of the ANN model.

Table 8 shows the comparison between the straight run (SR), genetic algorithm (GA) and ANN-based prediction of furnace efficiency. The number of hidden layers and the number of neurons in the hidden layer were selected using a multi-objective genetic algorithm approach. The optimum architecture of ANN consists of 3 hidden layers. The number of neurons in layers 1, 2 and 3 was 15, 15 and 27. The tansig and purlin activation functions were used in the hidden layer and output layer, respectively. The trained ANN model achieved a high correlation coefficient of 0.999, which makes it suitable for industrial applications.

Figure 32 compares the Straight (SR), ANN, and Genetic algorithms for the average value of furnace efficiency. The prediction based on the ANN model and the genetic algorithm is nearly identical. The variation of furnace efficiency over 10 data samples was shown in Figure 33, respectively. It was observed that the ANN model exhibits almost the same trend as the GA. As a result of the high correlation coefficient and robustness of the ANN model, it is suitable for real-time industrial applications, reducing energy consumption and increasing the equipment life by enhancing the effectiveness of the heat exchanger.

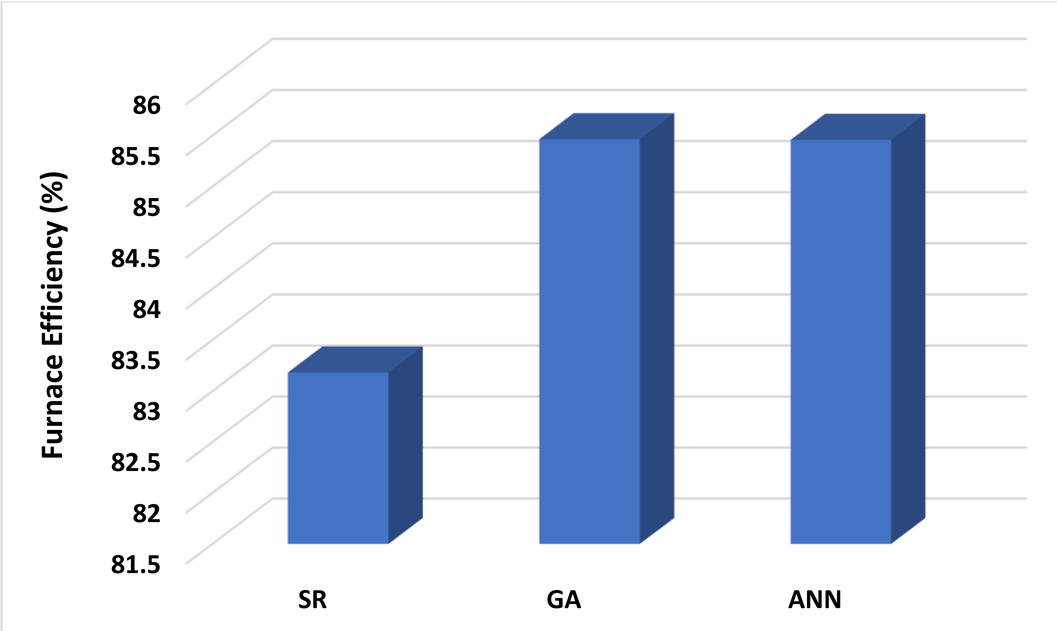


Figure 31: Average efficiency predicted by SR, GA and ANN model

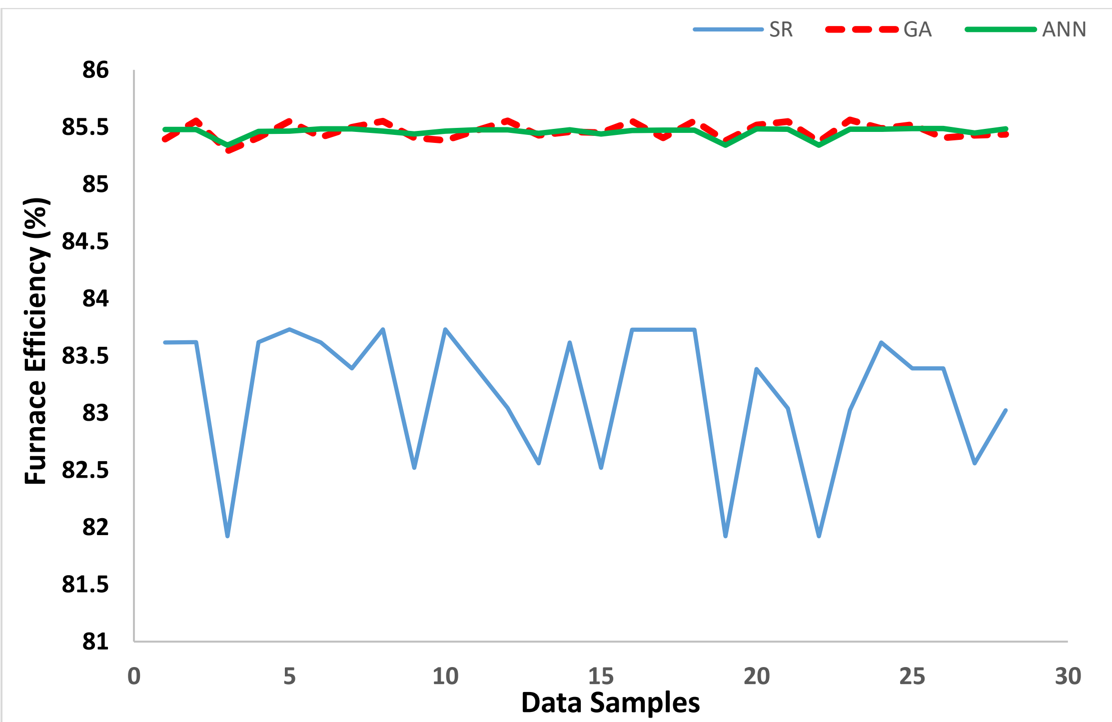


Figure 32:Average trend for the efficiency predicted by SR, GA and ANN model

Table 8: Comparison of efficiency predicted by SR, GA and ANN model

Number of Samples	Straight Run Efficiency	GA based Efficiency	ANN based Efficiency
Case1	83.62	85.40	85.48
Case2	83.62	85.55	85.48
Case3	81.92	85.29	85.34
Case4	83.62	85.41	85.46
Case5	83.73	85.55	85.46
Case6	83.62	85.41	85.48
Case7	83.39	85.50	85.49
Case8	83.73	85.55	85.46
Case9	82.52	85.41	85.44
Case10	83.73	85.38	85.46
Case11	83.39	85.47	85.48
Case12	83.04	85.55	85.48
Case13	82.56	85.43	85.44
Case14	83.62	85.46	85.48
Case15	82.52	85.45	85.44
Case16	83.73	85.55	85.47
Case17	83.73	85.41	85.47
Case18	83.73	85.55	85.47
Case19	81.92	85.38	85.34
Case20	83.39	85.52	85.49

5.3. Exergy Analysis

The analysis of the furnace is performed using SR, GA, ANN models. In the case of SR, exergy loss and efficiency were calculated by incorporating the artificial uncertainty in crude composition and process parameters while keeping the amount of excess air and mass flowrates of crude oil and fuel constant. A similar strategy was adopted for the exergy analysis based on GA but in this case, the amount of excess air and mass flowrates of crude oil and fuel were optimized using single-objective GA. Likewise, in the case of ANN, the exergy loss and efficiency were estimated by inserting the mass flowrates and excess air predicted by ANN into the Aspen HYSYS model of the furnace.

Figures 34 and 35 depicted the contrast of Exergy loss and Exergy efficiency for both the straight run (SR) and ANN models for the current fired heater model. It was discovered that the Exergy loss and Exergy efficiency predicted by the ANN model and the straight run has a significant difference (SR). In comparison to the straight run, the ANN model-based prediction shows a high Exergy efficiency. The high Exergy efficiency means that there is little irreversibility in the process, which means that less energy is wasted and extended equipment life.

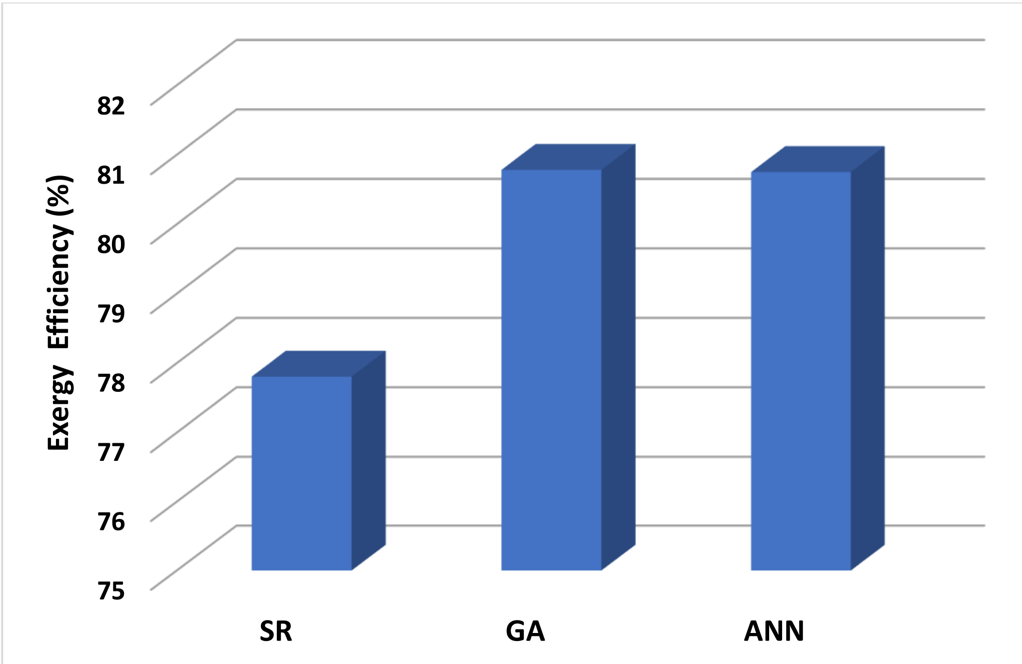


Figure 33: Average exergy efficiency for SR and ANN model

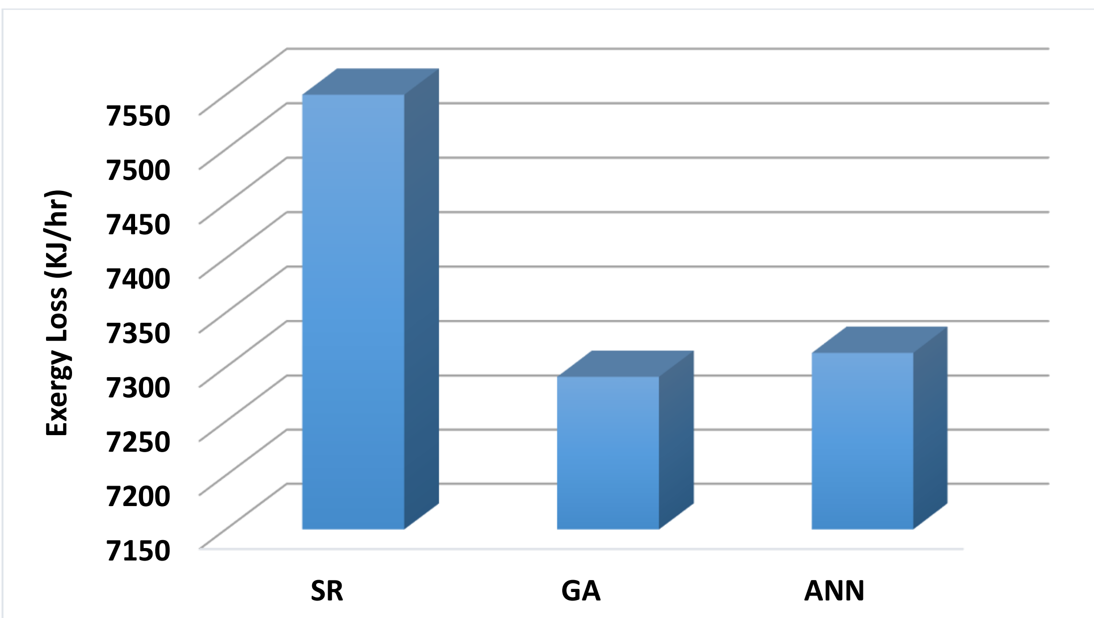


Figure 34:Exergy Loss comparison for the SR and ANN model

5.4. Graphical User Interface (GUI)

Figure 36 depicts an easy-to-use graphical user interface created in MATLAB. When the inlet process stream conditions are uncertain, the GUI is used to predict the mass flow rate of the inlet streams using the proposed ANN model. The GUI interface was created to provide an easy-to-use interface to the end-user. When the inlet process stream conditions are uncertain, the GUI is used to predict the mass flow rate of the inlet streams using the proposed ANN model. The GUI consists of input and output panels. In the input panel, the process condition including crude inlet temperature, crude inlet pressure, fuel temperature, fuel pressure, air temperature, and air pressure are to be inserted while the composition of the crude oil is inserted by clicking on the “Loadxlx.”. After that, by clicking the RUN tab the results are shown in the output panel. The results include the amount of excess air, the mass flow rate of crude oil, and mass flowrate of fuel.

The following are instructions about how to get results from a GUI.

- Put the input data for the six process variables in the ***Input data*** panel
- Load the composition of the crude oil from the excel file using the 'Load.xls.'
- Press the 'Run' button to see the results in the ***Result*** panel
- Use the ***Reset button*** to clear all the data

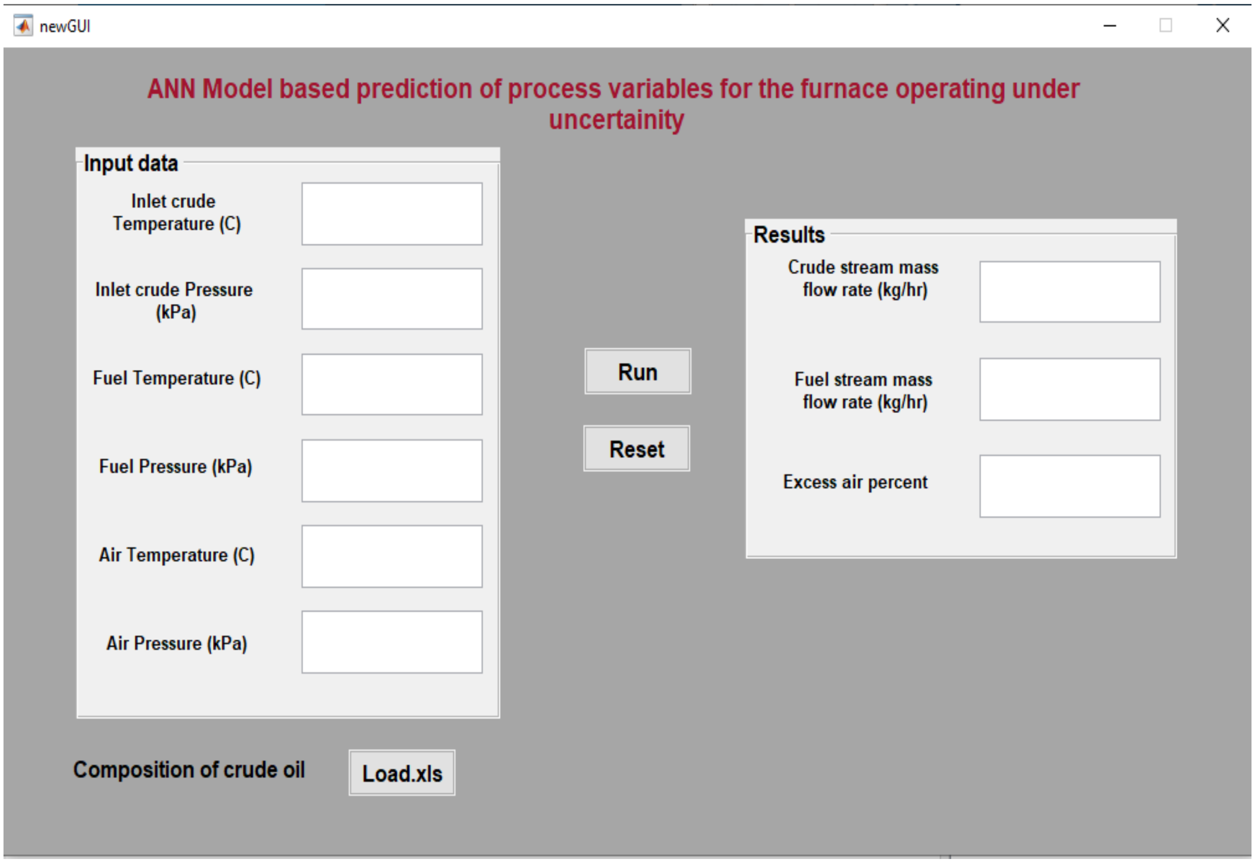


Figure 35: Graphical user interface (GUI) for the furnace

CHAPTER 6: CONCLUSION AND RECOMMENDATIONS

6.1. CONCLUSION

Furnaces have long been recognized as the primary preliminary equipment used in the petrochemical industry for hydrocarbon processing. Furnace units account for the majority of energy usage in refineries. As a result, obtaining better thermal efficiency is the major focus in both design and operation. Since such systems consume a substantial amount of energy, even a modest gain in thermal efficiency might result in significant savings. Therefore, in this study, an ANN model was developed to predict the optimum mass flow rates of crude oil, mass flow rates of fuel, and excess air for the furnace in the presence of uncertainty in the inlet crude composition and six process conditions. The six process variables were the inlet temperature and pressure of the crude oil, fuel, and air stream. A total of 360 data points were generated with the help of Aspen HYSYS and MATLAB interfacing with the variation of ±1, ±2, ±3, ±4, and ±5 in the inlet crude composition and process conditions. The optimum mass flow rate for the crude and fuel stream and excess air for each variation was determined using a single objective genetic algorithm.

The objective function for the single objective genetic algorithm was to maximize the overall efficiency of the furnace. The architecture of a multi-output feedforward neural network (MFFNN) was selected using a multi-objective genetic algorithm approach. The optimized ANN framework consists of three hidden layers. The number of neurons in layers 1, 2, and 3 was 15, 15, and 27. The genetic algorithm approach was incorporated using the optimization toolbox of the MATLAB-2019b version. The proposed ANN model achieved a high correlation coefficient of 0.99984. It was discovered that the ANN model experiences almost the same pattern as the GA for the efficiency of the furnace. The proposed ANN model's reliable prediction and robustness will aid in lowering energy consumption and increasing equipment life by improving furnace effectiveness. The high accuracy and robustness of the ANN model make it suitable for real-time industrial applications to reduce energy consumption.

6.2. RECOMMENDATIONS

1. The suggested approach could be broadened to the furnaces (fired heaters) used in industries other than oil refineries. Such as chemicals and synthetics, olefins, ammonia, and fertilizer plants for the estimation of optimum operating conditions under uncertainty.
2. Uncertainty in process conditions can also be added to more variables such as furnace fuel composition and steam process conditions etc.
3. To achieve more accurate results, a deep learning-based approach can also be incorporated into the proposed framework by generating a large database.
4. The proposed framework can be extended to other unit operations in the oil refineries for efficient operation under uncertain process variables.

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