Application of Artificial Intelligence Method for Estimation of Optimum Operating Conditions for Plate and Fin Type Heat Exchanger under Uncertain Process Conditions

By

Jihad Salah Khan

School of Chemical and Material Engineering

National University of Science and Technology

January 2021

Application of Artificial Intelligence Method for Estimation of Optimum Operating Conditions for Plate and Fin Type Heat Exchanger under Uncertain Process Conditions

Name: Jihad Salah Khan

Reg. No.: Fall-2018-MS-PSE-01-00000276833

This work is submitted as a partial fulfillment of the requirement for the degree of

MS in Process Systems Engineering

Supervisor Name: Dr. Iftikhar Ahmad

School of Chemical and Material Engineering (SCME)

National University of Sciences and Technology (NUST)

H-12, Islamabad, Pakistan

January 2021

Dedication

To my very Supportive, Loving, and Caring Family

Acknowledgments

First and foremost, praise is to Almighty Allah Who bestowed upon me with His blessings and guided me in completing this task. This thesis work was an uphill task for me due to the immense workload at my office and to manage my family business. It would not have been possible without the support of family. The foremost help and support of several individuals/colleagues who were available all the time and helped me with their suggestions to compile this work. I would like to extend my sincere gratitude towards my supervisor **Dr. Iftikhar Ahmad** for his timely guidance, valuable and practicable approach throughout this work. It would be worth mentioning here that it is only his constant pursuance that leads to complete my work. There were so many hurdles and difficulties during my research work, but he remained not always available but chaser me to complete the work more efficiently I am also thankful to my Guidance and Examination Committee (GEC) Members **Dr. Muhammad Ahsan**, and **Dr. Umair Sikander** for their valuable guidance. Besides, the contributions of several post graduate students are acknowledged, they have been a great source of support and motivation.

Abstract

Process industry has been one of the most energy consuming sector. In order to reduce energy consumption, efficient energy process is vital. Heat exchanger is one of the abundantly used equipment in process industry. Plate fin heat exchanger mostly used in process industries also got substantial share of research for realization it's optimum design and operation. The studies have been focused on maximizing the heat transfer rate and minimizing the pressure drop [Yidan Songa et al., 2015], minimize the total volume, CO_2 emissions and cost [Lixia Kanga., 2015], optimizing shape of fins of the plate and fins heat exchanger [Chunbao Liu et al., 2017]. In this study, a plate and fin heat exchanger model of a gas furnace of a tile factory was modeled in Aspen Exchanger Design & Rating (EDR) environment. The EDR was linked with an excel sheet and MATLAB to transform the model from a steady state to a dynamic mode. Several hundred scenarios were generated by inserting artificial uncertainty in the steady-state values of the process conditions such as inlet hot temperature, inlet cold temperature, and fouling resistance. Then Genetic Algorithm (GA) was applied to derive the optimum combination of the inlet flow rate of the hot and cold streams keeping minimization of the outlet temperature of the hot stream as the objective function. The datasets comprised of optimum operating conditions and their corresponding output were used to develop an Artificial Neural Networks (ANN), model. The ANN model was also used as a surrogate in SOBOL and Fourier amplitude sensitivity testing (FAST) based sensitivity analysis framework to find hierarchy in the input variables in terms of their impact on the model output.

Keywords: Plate Fin Heat Exchanger, Genetic Algorithm. Aspen EDR, Artificial Neural Network, Sensitivity Analysis

Nomenclature

Artificial Neural Network (ANN)

Heat Exchanger (HE)

Plate Fin Heat Exchanger (PFHE)

Exchanger Design & Rating (EDR)

Genetic Algorithm (GA)

Fast Order Sensitivity Test (FAST)

List of Figures

List of Tables

Contents

Chapter 1

Introduction

1.1 Overview

The consistent depletion of worldwide energy resources because of increased consumption by mankind has led to a decrease in natural energy resources, for example, flammable gas, oil and coal. It is anything but difficult to do a basic calculation and conjecture that worldwide non-renewable energy resources will be depleted within the following 50 years, if the current pace of consumption of these resources' proceeds. The question is 'by what means should the world react to take care of this significant issue of depletion of energy resources? The response to this question lies in the development of alternative energy resources, which are renewable and decrease of consumption of the as of now utilized energy resources. Process industry has been one of the most energy consuming sector. To decrease energy consumption, efficient energy process is vital. Heat exchanger is one of the most bountiful utilized gear in process industry. For energy efficient design of heat exchanger, the concept of exergy is getting attention of researchers because of its advantages on conventional energy analysis methods.

1.2 Plate fin heat exchanger

Plate fin heat exchangers are generally utilized in warming, heating, cooling applications, food, corrective, and synthetic cycles. The plate and fin type heat exchanger is broadly perceived today as the most practical and efficient type of heat exchanger available. Plate and fin heat Exchanger is a compact type of the heat exchanger (HE) that is usually used in most of chemical industries, power plants, and petroleum industries. In this type of HE thin extended surfaces are called as fins and they are used utilized to have higher surface area for heat exchange [1]. Most common types of fins include pin fins, curvy, louver, off-set strip and perforated fins [2]. Whereas the most reliable fins are off-set strip fins due to their high heat transfer productivity, high reliability and high compactness, this is why these are used in frameworks of airplanes, cars and HVACs [3]. In addition, there is an overall higher heat transfer performance of offset strip fins compared to plane fins. Moreover, the off-set strip fin offers good durability and are more reliable than louvre fins [4]. Plate fin heat exchanger mostly used in process industries also got substantial share of research for realization it's optimum design and operation. The studies have been focused on maximizing the heat transfer rate and minimizing the pressure drop [5] , minimize the total volume, CO_2 emissions and cost, optimizing shape of fins of the plate and fins heat exchanger [6]. Energy efficiency in particular got significant attention of the researcher.

Owing to the ever-growing need of PFHE in industrial uses so every consumer is keen on its most optimum operation whereas this goal can be accomplished with various methodologies. The efficiency of heat exchanger is highly dependent on the temperature of cold and hot fluid at the inlet. Whereas the temperature at inlet depends upon the flowrate of associated fluid stream such as temperature can be controlled by controlling fluid flowrate. By reducing flowrate, the pressure drop increases thus requires higher pumping power, so a reasonable tradeoff is required.

In the present studies a structured neural network model is presented which is based on the simulated data of the genetic algorithm to locate the top-notch optimized process condition.

Current study highlights the importance of heat exchangers design parameters and operating variables under uncertain conditions. Thermal modeling and optimal operating variables of plate fin heat exchanger under uncertain process conditions are presented. Aspen EDR was used to simulate and model the heat exchanger. Inlet hot stream flow rate and inlet cold stream flowrate were considered as two operating variables. Genetic Algorithm was applied to obtain the optimum operating variables in order to achieve maximum effectiveness with the help of MATLAB *gaoptimset* function. By optimizing the objective function via the single-objective optimization approach, the optimum values of inlet hot stream flowrate and inlet cold stream flowrate were obtained under uncertain process conditions, representing the best solutions obtained from 20 iterations in GA. The random data was generated using MATLAB function Randi in order to create uncertainties in the process. Uncertainty in Inlet hot stream temperature, Inlet cold stream temperature and fouling resistance were considered. As these three variables are not in control of the process and uncertainty is caused from ambient air and from the flue gases. Now in order to overcome these uncertainties, inlet flowrates of both fluids are optimized to achieve higher effectiveness value. At different uncertain condition Genetic Algorithm was applied to get optimum inlet flowrates for a greater effectiveness. Around 200 cases were generated randomly with 5% uncertainty in all the three variables (Inlet Hot temperature, Inlet Cold temperature, Fouling resistance). The sensitivity analysis for optimum operating variables with change in specific variables during operation, for example, inlet hot stream temperature, inlet cold stream temperature and fouling resistance was also performed, and the outcomes are accounted for. As an easy route for picking the system optimal operating variables the relationships between two operating variables and other non-controllable operation variables with worthy exactness were presented using artificial neural network (ANN). There was observed to be significant improvements in heat exchanger performance as well as overall efficiency of the system. With the improved parameters and operating variables, the exergy of the system was also improved to the acceptable or desirable range. Data was generated by the interfacing of Aspen EDR, MATLAB and Excel were established for optimization of certain input variables. This study will provide a plate form for using optimization methods in real time operation.

1.3 Objectives

The objectives of the present study are given below:

- PFHE thermal modeling in Aspen Exchanger design and rating environment.
- Applying optimization technique for plate and fin type heat exchanger with maximization of outlet cold stream temperature as an objective and the input variables inlet hot stream temperature and cold stream inlet flowrate as an input to be optimized utilizing GA.
- Choosing the fin characteristics, for example, height, pitch, off-set length just as the heat exchanger geometry.
- Considering different operating variables and parameter i-e Inlet hot stream temperature, Inlet Cold stream temperature and fouling resistance with 200 random

cases to obtain optimum hot inlet flowrate and cold inlet flowrate for maximum cold stream out temperature so that maximum heat transfer takes place and effectiveness is increased.

1.4 Justification of the research

- To advance heat exchanger efficiency
- To Enable the optimized solution under uncertain conditions
- Genetic Algorithm is applied for optimization of operating variables to overcome uncertainty
- Artificial Neural Network helps improve in performance of heat exchangers and prediction of optimized input operating variables
- User defined input was provided for optimization using the Aspen-Excel- MATLAB.

1.5 Thesis Outline

The thesis work based on the simulation model of the Plate and Fin type Heat Exchanger for a gas furnace used in tile factory.

Initially, a plate and fin type heat exchanger were designed for a gas furnace in a tile factory in Exchanger Design & Rating in Aspen environment. The EDR was linked with excel sheet and MATLAB to transform the model from steady state to a dynamic mode. Two hundred scenarios were generated by inserting artificial uncertainty in the steady state values of the process conditions such as Inlet Hot temperature, Inlet Cold temperature, Fouling resistance. The GA was then applied to derive optimum combination of inlet flowrate of the cold and hot streams and achieve high effectiveness value of the HE. Then, ANN model was developed by using the inlets flowrates as its output variables and the other process conditions as its input variables. The ANN could predict optimum inlets flowrates of the streams for high energy efficient operation. The ANN was then used as a surrogate model in Sobol and FAST (Fast Order Sensitivity Test) based sensitivity analysis framework to find hierarchy in the input variables in terms of their impact on the effectiveness value. The use of ANN as predictive model and as a surrogate model

- A brief outline of current work is explained in Chapter-1
- Literature survey is documented in chapter -2.
- The fundamentals of model development and proposed methodology is discussed in Chapter -3.
- Optimized Results, ANN prediction, Sensitivity analysis and discussion are presented in chapter 4.

Chapter 2

Literature Review

The consistent consumption of worldwide energy resources because of expanded utilization by humankind has added to the extreme issue of depleting all accessible nonrenewable energy resources, for example, petroleum gas, oil and coal. It is easy to do a simple calculation and forecast that worldwide non-renewable energy resources will be depleted inside the following 50 years, if the current pace of utilization of these resources' proceeds. The question is 'in what manner should the world react to take care of this significant issue of consumption of energy resources? The answer to this question lies in the development of alternative energy resources, which are renewable, decrease of utilization of the presently utilized energy resources which can be acquired by making the processes more energy efficient. Process industry has been one of the most energy consumption sector. To lessen energy utilization, efficient energy process is essential. Heat exchanger is one of the most plentiful utilized hardware in process industry. For energy efficient design of heat exchanger, the idea of exergy is getting consideration of researchers because of its advantage on conventional energy analysis methods.

The compact heat exchangers optimization using genetic algorithm is carried out by G.N. Xie. This is another case of the literature review that has been directed in the ongoing past. In this research plate and fin compact heat exchanger (CHE) has been optimized. The structural size of CHE has been optimized by means of the genetic algorithm (GA). The minimum volume and cost of CHE has been taken as the objective function of GA. The three molded parameters are fluctuated for the optimization and geometries of the fin were steady or fixed. The results clarify that the pressure drop of optimized CHE gives practically 30% lower volume and practically 15% lower annual cost.[7]

Genetic algorithms have picked up significance throughout the years because of their high potential and capacity to fathom complex optimization issues and issues. A ton of researches directed in the past has taken assistance from GA. In Igor R. de S. Victorino's research GA was actualized for the optimization of activity parameters in the cyclic alcohol production industry. GA was utilized here to guarantee maximum production with operational improvements in the system, for example, lower operational temperature and diminished catalyst. This is another optimization application of the GA with results preferring the favored performance.[8]

A lot of researches that have been led in the past are legitimately corresponding with our research in any case, our research is more compact since we are using ANN and genetic algorithm for optimization and performance and then user defined input dependent on the sensitivity analysis has been given through excel-Aspen-MATLAB.

H Najafi (et al. 2010) did a multi objective optimization by means of the genetic algorithm. The objective was to decide the minimized pressure drop with the maximized heat transfer. A central angle was additionally featured regarding how the objective functions are superfluous and subsequently no single solution could legitimize the two objectives. In this manner, multi-objective research is led, and results are presented in the Pareto front style where the user can choose the ideal outcome dependent on the project limits and application. A sensitivity analysis has been led to dissect the impacts of multiple various parameters. MATLAB has been utilized for demonstrating the multi objective optimization of GA. [9]

The particle swarm optimization (PSO) methodology was utilized by RV Rao (et al. 2010) for the optimization of PFHE. The objective functions incorporate the minimization of volume and space alongside the minimized total cost. In any case, every one of these parameters are individually treated with any correlation with one another. For optimization heat exchanger length, fin recurrence, number of layers of fin, spear length, fin height and thickness have been remembered for this research. The results got from the PSO are contrasted and that of results acquired from the GA. Two optimization models are investigated for accuracy and effectiveness of the algorithm. The results show some genuine improvement in the system and the correlation between the PSO and GA clarifies the accuracy of these results [10]. Air heating unit is one of the main chunks in paddy drying to guarantee the efficacy of a drying process. Likewise, an optimized air heating unit doesn't just guarantee a decent paddy quality, yet additionally spare more for the operating cost. J Janaun's (et. al 2016) study decided the appropriate and fine specifications heating unit to heat air for paddy drying in the LAMB dryer. In this study, Aspen HYSYS was utilized to acquire the minimum flow rate of hot water required [11].

2.1 Research Gap

In the previous studies, A multi-objective optimization technique is utilized to take full advantage of the heat transfer rate and to lessen the pressure drop in shell and tube heat exchanger [12]. To minimize the total volume just as the total annual cost of a compact heat exchanger three shape parameters were considered as concluding variables [13]. Genetic algorithm is applied to improve essential energy saving, annual total cost saving, and carbon dioxide emission decrease [14]. To optimize the design parameters of a heat exchanger with rectangular fins Taguchi experimental-design method was utilized [15]. To minimize the total yearly cost of air-cooled heat exchangers global sensitivity analysis is utilized and to estimate the optimum geometric parameters of micro-channels in micro-heat exchangers is gotten by expanding the heat transfer rate and limiting the pressure drop as two objective functions [16], [17]. The optimum design parameters of plate fin heat exchanger proposed by Sepehr Sanaye *, Hassan Hajabdollahi for a particular case study were considered for modeling of PFHE [18].

In the recent past, serrated plate fin heat exchanger started utilizing particle swarm optimization technique, with then help of genetic algorithm, to improve the plate fin heat exchanger design [19]. Then again in 2011, another research on the CFD simulation with the help of Neural Network Model was conducted to amount the j and f factor of NNM [20]. The results explained that NNM is accurate between 1.3% and 1% which is higher compared to different models (having the accuracy between 3.8% and 8.2%) for dissecting a similar information of CFD simulation. Be that as it may, for an exact reaction neural network must be provided with very much defined factors. Similarly, in 2011, a research proposed that in offset strips fins blockage ratio of j and f factor was 20% more prominent with j being the Prandtl number [21]. This research recommended that optimized offset strip fin had improved j and f factor (by 24%) compared to non-optimized fins. In order to, comprehend the uniform distribution in PFHE, a research focused on the hydro dynamics of single-phase flow determining the modern correlations of f-factor [20]. These new correlation lotions were in alignment with the results obtained from the CFD simulations emphasizing on the uniform distribution in the compact heat exchangers. In another similar research from the same author in 2011, single-phase phase CFD simulations measured the pressure drop of offset strip fin heat exchangers, it helped great degree in understanding the experimental and mathematical differences and predictions of contact factors. In addition to that, the research demonstrated that two phase flow relies on the superficial velocities of gas and liquid based on the design. These multi objective problems are providing solutions to the industrial sector [22]–[25]. The creators too recommended the function of ambiguous logic applications in industrial domains [26].

Alternate optimization techniques were observed by Yosefi and Mohammadi in 2012 using the ICA algorithm with seven optimized variables helping reduce the cost and weight [19]. In 2013, a research emphasized on the optimization of heights, angles and intervals of heat exchangers in terms of design parameters to improve the efficiency.

In 2014, a research was conducted where heat transfer and flow rate characteristics of offset strip fin, experimental and numerical value of Reynolds Number ranging from 500-5000. The outcome highlighted that the fin length and pitch were reliable factors for compact heat exchangers. In the same year, a research focused on the seven channel types of PFHE and it was observed the individual heat transfer from curly, off-set strip, pin, perforated, louvered, plain channel and vortex generator. A similar request followed for the most extreme capacity to diminish the surface zone of the PFHE in contrast with the plain one. Alongside the accumulated data above we accentuation on other literature with respect to ANFIS. PFHE model helps predict the heat transfer and pressure drop based on neuro-fizzy inference system. Average Nusselt number and dimensionless pressure indicated great concurrence with the work accessible by Tahseen Ahmad 2013 another in ANFIS identified with thermal work. In another research two logics were such as (Adaptive Neuro-Fuzzy Inference System-based control) and ANN based towards the customization of temperature control system [22].

The research work by Sepehr Sanaye mostly correlates with the research that I am directing. A great deal of researches have been directed in the past with respect to the thermal demonstrating and design of compact heat exchangers. His work underlines on the six parameters of the heat exchangers, for example, fin height, fin offset length, fin pitch, cold stream flow length, hot stream flow length and no flow length. e-NTU method was utilized to decide the pressure drop and effectiveness of heat exchanger. Using the ANN, a correlation was shaped between the six parameters and the two objectives. Fast and elitist non-dominated sorting genetic algorithm was executed to alter the cost and effectiveness. The results are presented as Pareto optimal solutions where a user defined input is accommodated the optimization [18].

Chapter 3

Model Development

3.1 Modeling methods

3.1.1 Aspen EDR Model

The Aspen Exchanger Design & Rating (EDR) software includes a number of programs for the designs like mechanical, thermal, drawings and price assessment for heat exchangers and pressure vessels.

3.1.2 Plate Fin Heat Exchanger

Aspen Plate Fin is part of Aspen Exchanger Design and Rating (EDR).

Plate-fin heat exchangers are most viable for multiple processing plans in the industry and other gas separation processes. High thermal effectiveness can lead to multiple savings and even the capital cost with the help of this technology. In Plate-fin exchangers single exchanger can handle multiple streams hence leading to high thermal integration. This helps with the minimization the energy usage, plant layout and construction of modular. Theta material used for heat exchanger construction is to be light weight, efficient heat transfer capacity and low temperature operating conditions. Aspen Plate Fin Exchanger draws on AspenTech's deep heritage and leading technology in order to assist with the efficient and precise modelling.

In a plate and fin type exchanger, the process streams pass between metal plates which are held together by corrugations (fins) which provide extended surfaces and also enhance the heat transfer coefficient. The edges of the plates are sealed by side bars. The material of construction is typically aluminum but stainless steel and nickel alloy units are well established in the aircraft industry are now entering the process industry.

Features

• Aspen HYSYS Run-time integration

• Geometry specification is layer-based

• Calculation modes comprises of, stream-by-stream simulation, design and layer-by-layer simulation

• Range of 20 process streams

• Co-current and counter-current flow with any complexity of exchanger inlet and outlet geometry

• Both pass cross flow (simple and multi)

• kettle type core shell

• Single-phase and two-phase calculations

• Flow maldistribution check

• Vertical or horizontal alignment

• Plain, wavy, serrated, perforated and hard way fins

• Exchanger, distributor, header, and nozzle pressure drop calculations

Thermal Outputs

- Exchanger performance summary

• Diagram and graphs of exchanger temperature

• All process streams having temperature as well as vapor quality contour

• Very precise and compact information on pressure drop

• Program recorded data of performance of fin

• Metal temperature calculations

• Thermal conduction

• Analytical based graphical results for all temperatures

3.1.3 Genetic Algorithm (GA)

Genetic Algorithms (GA) is a type of evolutionary algorithms that imitates the process of biological evolution. First developed by John Holland in early 1970s [27], GA is based on the concepts of natural selection and genetic inheritance. Genetic algorithms are domain independent and can be applied to several problems in many fields. Many researchers have used GA's to evaluate the solution of difficult problems whose objective functions lack the properties of continuity, differentiability, etc. [7] [13] [14].

GA encodes potential solutions into data structures that are similar to chromosomes and maintains a population of such chromosomes during searches [28]. It requires an objective function that assign a scalar payoff (or reward) to any particular solution. GA looks forward to authentic solutions once they develop proper scheme and evaluation function. It proceeds with creating an initial population of certain number of strings or chromosomes, called the population size. Next step is to evaluate each solution in the initial population by payoff function. Better solutions are awarded high payoffs while rest of the solutions are awarded a lower payoff. Next generation is then generated by employing genetic operators like mutation, crossover etc. on these evaluations. This procedure is repeated unless an optimal solution(s) is (are) found or maximum number of iterations or population is reached or relative difference between solutions is less than a certain limit. Schematics of GA are shown in Figure 3-1. Brief description of components of GA are given below:

1. Representation: Genetic algorithm needs the solutions or individual in a population to be represented in the form of chromosomes. Structure of a problem and the type of genetic operators that will be used depends upon the representation scheme used. Specific alphabets are used to develop a sequence of gene that make up the chromosome. Binary digits (0 and 1) and real value numbers can constitute these specific alphabets. It has been shown that chromosomes encoded using real value numbers results in more efficient GAs and produce better solutions [29].
2. Selection Function: Successive generations in GA are generated by selection of individuals from a previous generation. Selection is based on the concept that every individual has a chance or probability of being selected once or more than once, based

on their fitness value, for reproduction in the next generation. Roulette wheel selection, scaling techniques, tournament, elitist models and ranking methods are some of the selection schemes. Assignment of probability of selection to individuals is a common step in all of these schemes. There are various methods for this assignment like roulette wheel, linear ranking and geometric ranking [30].

3. Genetic Operators: Search mechanism opted by GA are provided by genetic operators. Genetic operators create new solutions in the population by applying operations on existing solutions. Crossover and mutation are two basic genetic operators which are widely used. Both are analogues to their counter parts in actual genetic processes. Crossing overtake two individual chromosomes and transfer portion of these chromosomes between the both to produce two new chromosomes. While in mutation a single chromosome is altered at a single location to produce a new chromosome. Usage of both operators depends upon the type of the representation scheme used for chromosomes. Types of these operators for both binary and real value chromosomes are given in Table 3.2.
4. Initialization or Initial population: GA needs an initial population to start the procedure for finding the best solution. Initial population can be produced by generating random solutions inside the upper and lower bound of the variables. Another method is to seed the initial population with already established best solutions to improve the existing solutions. The remainder of the population can be randomly generated solutions.
5. Termination GA operations are terminated once a termination criterion is met. The termination criterion can be anyone or combination of the followings; (a) Number of generations reaches a specified maximum value. (b) Population converges to a single solution. (c) Difference among solutions becomes smaller than a specified threshold. (d) Best solution doesn't improve over a specified number of generations. (e) Evaluation values reaches some acceptable threshold.
6. Evaluation or Objective Functions Many different forms of evaluation functions can be used to determine the fitness of each solution produced during the search. These functions are independent of GA and should meet the requirement that they could easily figure out the growth in a set. In this research, GA was used to optimize 2 operation variables i-e hot stream inlet flow rate and cold stream flow rate. As in online

applications the changes made into the operational parameters should not be large so the lower and upper bounds of parameter search space was selected to be 5% above and below of the non-optimized parameters. Optimization was terminated when relative difference among solutions become smaller than $1 \times 10{-}4$. Objective function was developed using artificial neural networks discussed in the next section.

Table 3.1 Chromosomes

Chromosome 1	1101100100110110
Chromosome 2	1101111000011110

Table 3.2 Crossover

Chromosome 1	11011 | 00100110110
Chromosome 2	11011 | 11000011110
Offspring 1	11011 | 11000011110
Offspring 2	11011 | 00100110110

Table 3.3 Mutation

Original offspring 1	1101111000011110
Original offspring 2	1101100100110110
Mutated offspring 1	1100111000011110
Mutated offspring 2	1101101100110100

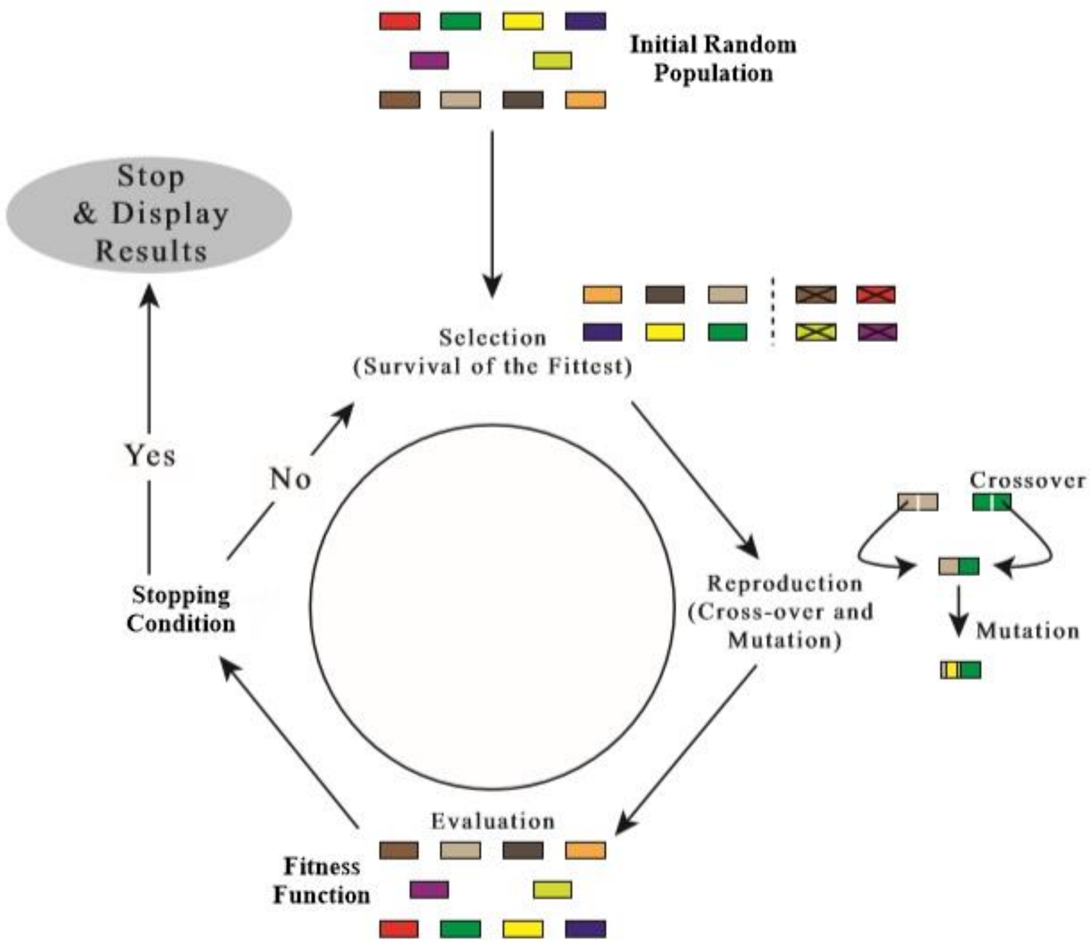


Figure 3-1 Schematic diagram of GA

3.1.4 Artificial Neural Network

3.1.4.1 Employment of Neural Network Model

The primary reason of the development of the model is to formulate an efficiently working neural network. Based on the Levenberg–Marquardt propagation training algorithm the network simply acts as a feed structure applied introduced by (Eq. (3.1)). Neural network technology is primarily associated with the MATLAB models. Unsubscribe sigmoid transfer function is actuated, all neurons:

$$\log\sin\ (x) = \frac{x}{1-e^{-x}} \qquad (3.1)$$

Where x is the input signal. The learning set comprised of 200 instances of the plate-fin heat exchanger.

The Network has an input layer, a hidden layer with 5 neurons and output layer produces results. The structure of the simplified network given in Figure 3-2.

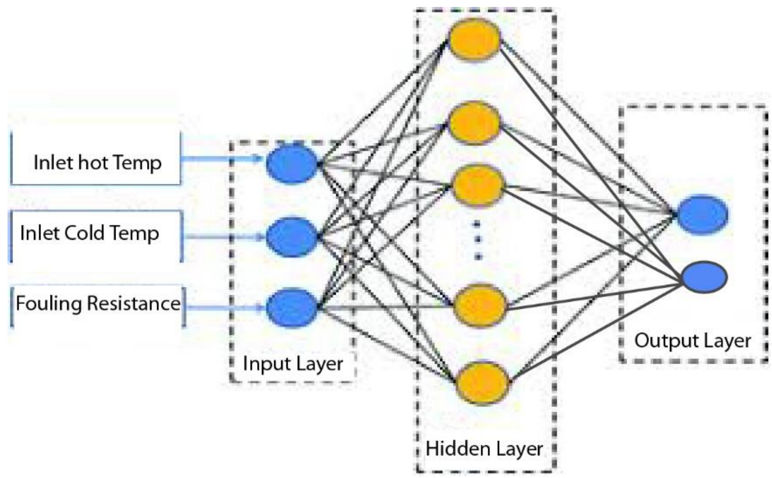


Figure 3-2 Structure of Simplified network.

The data set has been customized based on the network weights and validation and testing data sets which helps adds up to the performance of the network. The regression analysis provides the data on network performance introduced in Results segment *Figure 4-6*. Network performance appears to be acceptable accuracy. Improving the parameters is a major issue based on the systematic changes to process the data is prepared to outline. The network builds up its least difficult structure.

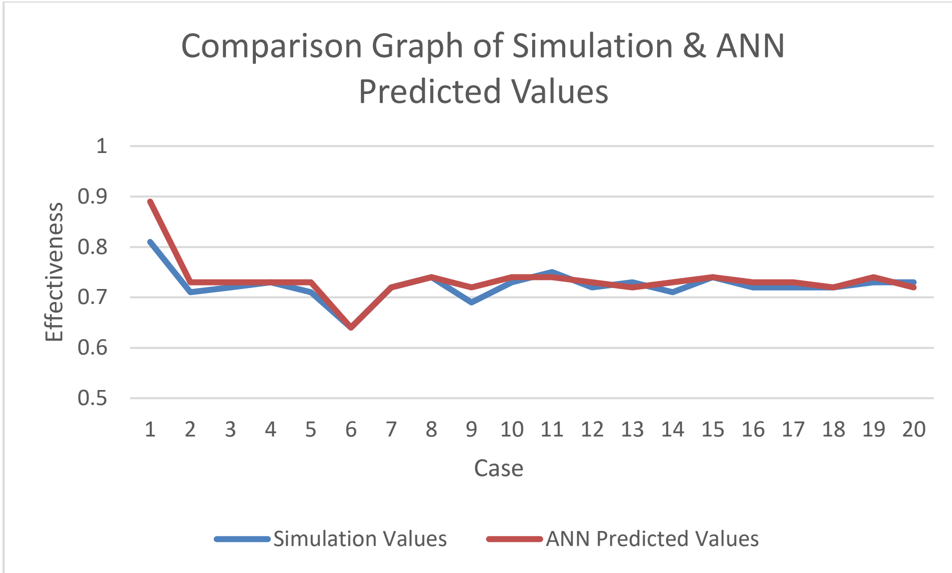


Figure 3-3 ANN Accuracy.

This Plate and Fin Type Heat Exchanger (PFHE) based on the ANN network enactment could be gotten from the input data. At the end of the day, the outlet and intlet temperature and the temperature contrast and both cold and hot sides of the ribs geometries could be determined based on the efficient mass flow rate. Experimental data is restricted by the designers in order to figure out the efficiency of Plate and fin heat exchanger ANN approach which is highly advantageous. This heat transfer and flow qualities can communicate through the mathematical assessment that are extremely perplexing wonder, which doesn't need a comprehension of ANN approach.

3.1.5 Sensitivity Analysis

The necessity of quantitative and qualitatively understanding of intricate process systems intensifies the use of models to predict sensitivity for certain inputs and outputs. The peculiar mechanism of these models allows for a thorough representation of the underlying network of process outputs and also their response to certain inputs. Sensitivity analysis (SA) predicts the influence on output by any input or set of inputs. It provides much information about the input variable which triggers much of variation into the model output [45]. SA application can be summarized as

a) Input and output relationship understanding.

b) Recognizing the imperative and significant model parameters that drive model outputs and

c) Managing prospect experimentation.

The results of sensitivity analysis help researchers to more focused on the most sensitive and acute parameter that govern model output. Figure 3-4 depicts the steps to follow for data gathering, setting up model, sensitivity analysis and qualification.

Generally, there are two main types of sensitivity analysis which are (i) Local sensitivity analysis and (ii) Global sensitivity analysis.

Local SA determines any variations in the output of a model only with respect to single model input. The input variable only changes one at a time with very low increment like 0.1% and the effect of this individual variable on output is calculated by local sensitivity indices. In this analysis, only one variable is responsible for the output also any interaction or relation between input parameters cannot be taken into consideration. So, to overcome this problem global sensitivity analysis is used.

Global SA In the global sensitivity analysis all of the input variables are varied at a time over whole parameter space, which allows estimating the involvement of each variable and any interaction/relation between them to the model outputs. Input variables have normally wide varieties of variables like temperature, pressure, flow rate, concentration or density. So, this is kind of an advanced approach to determine which process stream having certain behavior constitutes the maximum impact on outputs.

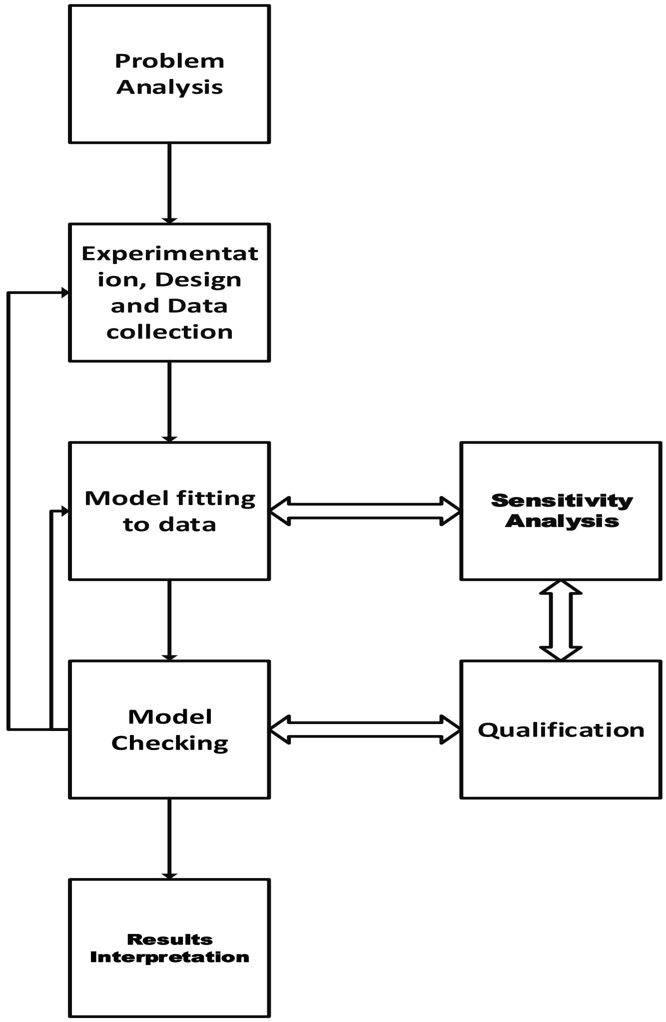


Figure 3-4 Steps for sensitivity analysis and model development

It involves the three-dimensional study of complexity on design, position and process model level. There are other approaches to evaluate multiple model simulation models, reverse parameter modelling methods and sampling-based methods by can uncertainty methods. The main accuracy of study is focused on the SOBOL test methodology and the Fourier Amplitude Accuracy Scale (FAST). Both SOBOL and FAST methods are based on variance decomposition techniques to provide a quantitative contribution of input variables to the output variables. The main difference between SOBOL and FAST is the algorithm based on the integration of indices a Monte Carlo integration is used in the SOBOL while the sinusoidal function is used in the FAST method [46].

3.1.5.1 SOBOL Sensitivity Analysis

SOBOL check is a variance-based analysis that is named by Ilya M.Sobol, as a SOBOL tool or SOBOL map. SOBOL in a probabilistic context used to determine the effect of the individual input or series of data on the overall model output variance in computational modelling[33]. The input variables are evaluated for sensitivity analysis, so they will collectively measure their impact on output. SOBOL doesn't identify what causes the input variability it just identifies the impact on the model output. SOBOL SA has some features listed as follows.

- No supposition(s) between model input and output parameters.
- Evaluation of input parametric variation and interactions between them over the entire space.
- High computation intensity is the main shortcoming.

So, to understand how input variables interact each other to have final output the SOBOL indices can be calculated. For a model $y = f(\boldsymbol{x})$, where y is output linked by a function f to a set of p input factor $\boldsymbol{x}= (x1, x2, \cdots , xp)$. D is the variance, f(x) is the random variable and fo is the mean.

$$f\mathrm{o} = \int f(x)dx \qquad (3.2)$$

$$\mathrm{D}{=}\int f(x)^2\, dx - fo^2 \qquad (3.3)$$

SOBOL method depends on the disintegration of D into commitments from effects of single boundaries, consolidated effect of boundaries and this is done by decaying f(x).

$$f(x) = fo + \sum_{i=1}^{p} f(xi) + \sum_{1\leq i<j\leq p} fi,j(xi,xj) + \cdots + f1,\ldots p(xi \ldots xp) \qquad (3.4)$$

The decomposition terms are then created as below.

$$fi(xi) = \int f(x) \prod_{k \neq i} dxk - fo \quad (3.5)$$

The illustration of *f*(x) variance analysis is based on fulfilment of condition.

$$\int fi1, \dots \dots, ip(xi1, \dots \dots, xip) dxk = 0 \; for \; k = i1, \dots, ip. \quad (3.6)$$

Now by squares on both sides of equation *f*(x) and integration, we get.

$$D = \sum_{i=1}^{k} Di + \sum_{i<j} Dij + \sum_{i<j<l} Dijl + \cdots + D1,2, \dots, k \quad (3.7)$$

Where $D_{i1,\dots,ip} = \int f^2_{i1,\dots,ip} (x_{i1,\dots,ip}) dxi_1,\dots,xi_p$ is a variance of , termed as partial variance matching to that subgroup of parameters. SOBOL indices can then be deduced as,

$$D = \sum_{i=1}^{k} Di + \sum_{i<j} Dij + \sum_{i<j<l} Dijl + \cdots + D1,2, \dots, k \quad (3.8)$$

Sensitive indices can be then obtained from the above-mentioned equation by dividing it with D. So, Si shows the partial variance with the total variance and indices should sum up to 1.

$$1 = \sum_{i=1}^{k} Si + \sum_{i<j} Sij + \sum_{i<j<l} Sijl + \cdots + S1,2, \dots, k \quad (3.9)$$

3.1.5.2 Fourier Amplitude Sensitivity Analysis (FAST)

Fourier Amplitude Sensitivity Analysis (FAST) has been applied successfully in many modelling and non-linear problems, here it is an additional technique used in the present study for sensitivity analysis [34]. The main idea of employing FAST is to convert n-dimensional integral of *f*(x) into one-dimensional integral.

In Fourier series, the function is expressed like.

$$f(x) = \sum_{k1=-\infty}^{\infty} \sum_{k2=-\infty}^{\infty} \dots \sum_{kn=-\infty}^{\infty} C_{k1.k2.....kn} e^{j2\pi(k1x1+k2x2+\cdots+knxn)} \tag{3.10}$$

With

$$C_{k,k_2......kn} = \int_{I^n} f(x) e^{-j2\pi(k1x1+k2x2+\cdots+knxn)} \tag{3.11}$$

By considering the ANOVA disintegration [35], the component can be stated as Fourier series by taking into the account the elements in above equation *f*(x) with the only non-null indices (i.e $ki_1 \dots Ki_p$).

In that approach the resulted in invariance in the sums of modules of Fourier Coefficients.

$$var\left[f_{i1.....ip}\right] = \sum_{ki1=-\infty}^{\infty} \dots . \sum_{kip=-\infty}^{\infty} |C_{ki1.....kip}| \tag{3.12}$$

As recommended by *Satelli et al. (1999)* a new independent variable "s" is introduced to quantify multi-dimensional integration into single-dimensional integral [36].

$$x_i(s) = \frac{1}{2}\arcsin(\sin(\omega_i s)) \tag{3.13}$$

Where set is linear independent frequencies.

The output variance of first-order function the ones depending only on input factor *x*i.

$$E[y|xi] = \sum_{i} C_{ki} \tag{3.14}$$

And coefficient can be calculated as

$$C_{ki} = \frac{1}{2\pi} \int_{-\pi}^{\pi} f(s) e^{-j2\pi ki\omega is} ds \tag{3.15}$$

3.2 Proposed Methodology

The current study is based on realizing energy efficient operation of a plate and fin type heat exchanger through Genetic Algorithm (GA) assisted by an Artificial Neural Networks (ANN) model. Initially, a plate and fin type HE was designed for a gas furnace in a tile factory in Exchanger Design & Rating in Aspen environment. The EDR was linked with excel sheet and MATLAB to transform the model from steady state to a dynamic mode. Two hundred scenarios were generated by inserting artificial uncertainty in the steady state values of the process conditions such as Inlet Hot temperature, Inlet Cold temperature, Fouling resistance. The GA was then applied to derive optimum combination of inlet flowrate of the hot and cold streams and achieve high exergy efficiency of the heat exchanger. Then, ANN model was developed by using the inlets flowrates as its output variables and the other process conditions as its input variables. The ANN was capable of predicting optimum inlets flowrates of the streams for high energy efficient operation. The ANN was then used as a surrogate model in SOBOL and Fast Order Sensitivity Test (FAST) sensitivity analysis to find hierarchy in the input variables in terms of their impact on the effectiveness of the heat exchanger.

3.2.1 Process Data

3.2.1.1 Case Study

The Plate and Fin type HE optimum operating parameters were acquired for a gas furnace in a tile factory. Furnace temperature is around 106.85 C in starting stages and around 926.85 C in the end stages. The gas (hot stream) leaves from center phases of furnace with mass flowrate of 1.45 kg/s and goes through the HE at 346.85 C. The outside air (cold stream) with mass flow rate of 1.35 kg/s goes through the exchanger at 41.85 C. Schematic diagram of the furnace including the examined HE are shown in Figure 3.5 and Figure 3.6. The PF HE metal was from stainless steel with thermal conductivity kw = 18 W/m K. Operating conditions and the cost function steady qualities are recorded in Table 3-4. The thermo-physical properties of air, for example, viscosity, specific heat and Prandtl number were considered as temperature dependent.

Table 3.4 The operating conditions of the PFHE (input data for the model)

Hot stream inlet flowrate (kg/s)	1.450
Cold stream inlet flowrate (kg/s)	1.350
Hot Inlet temperature (C)	346.85
Cold Inlet temperature (C)	41.85
Pressure (Inlet hot side) (kPa)	180.0
Pressure (Inlet cold side) (kPa)	120.0

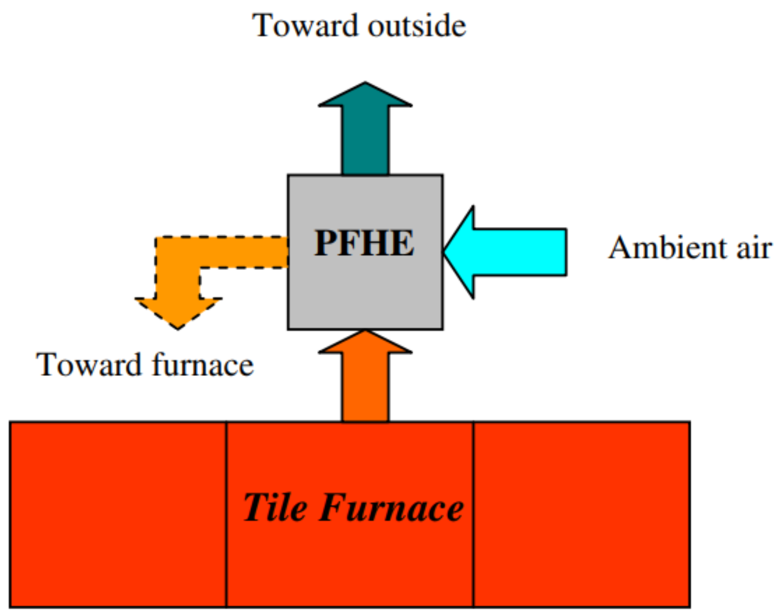


Figure 3-5 Plate and fin type heat exchanger with a tile furnace

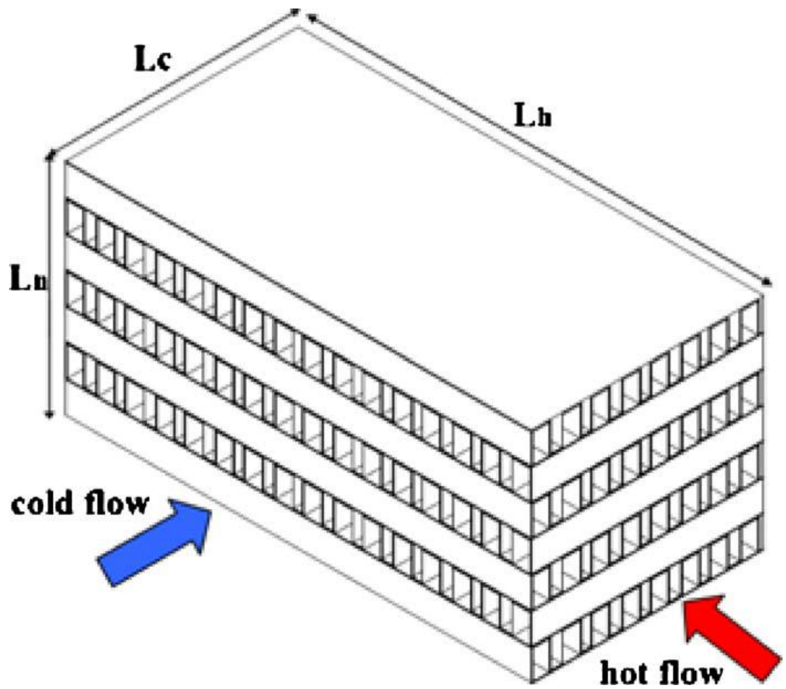


Figure 3-6 Crossflow Plate Fin Heat Exchanger

3.2.2 Aspen EDR Model

Simple crossflow heat exchanger was designed in Aspen with stream by stream simulation. Two number of streams and two number of layer types are used. The input data and heat exchanger design parameters are considered of a heat exchanger designed for tiles furnace [18]. Flue gases from tiles furnace is used as hot stream to heat up the ambient air in order to increase the efficiency of tiles furnace. The optimum design parameters proposed by Sepehr Sanaye [18] are considered for modeling of heat exchanger. The heat exchanger diagram and the flow direction specified in Aspen EDR is shown in Figure 4-1 and the snapshot of Aspen EDR is also shown in this figure. Fin thickness is 0.1mm. The input operation data and optimum design parameters are shown in Table 4-1 and Table 4-2.

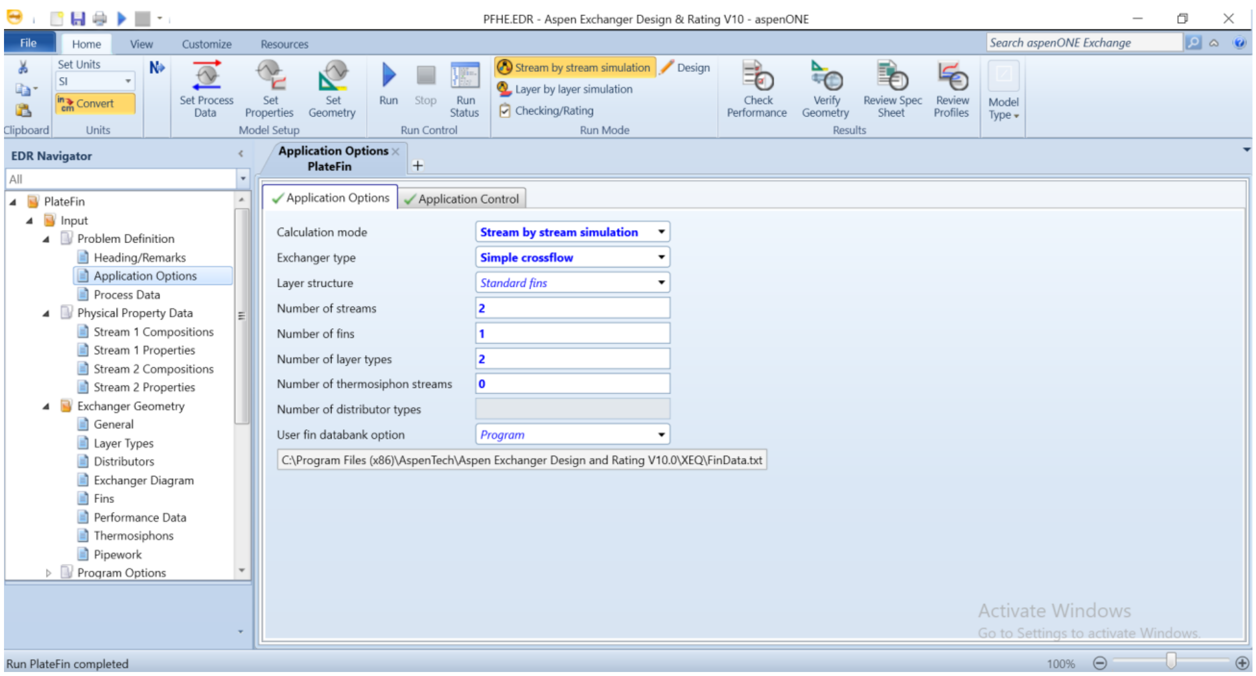


Figure 3-7 ASPEN EDR

3.2.3 Genetic Algorithm for optimization

A genetic algorithm (GA) is a technique for resolving equally forced and unrestrained optimization difficulties dependent on a natural choice measure that mirrors biological evolution. The algorithm over and over changes a population of individual solutions. At each progression, the GA haphazardly chooses characters from the current population and utilizations them as parentages to deliver the children for the future. Over successive generations, the population "evolves" toward an optimal solution.

3.2.4 Genetic Algorithm MATLAB

Three important types of guidelines are used by genetic algorithm for each step to produce the subsequent generation from present population.

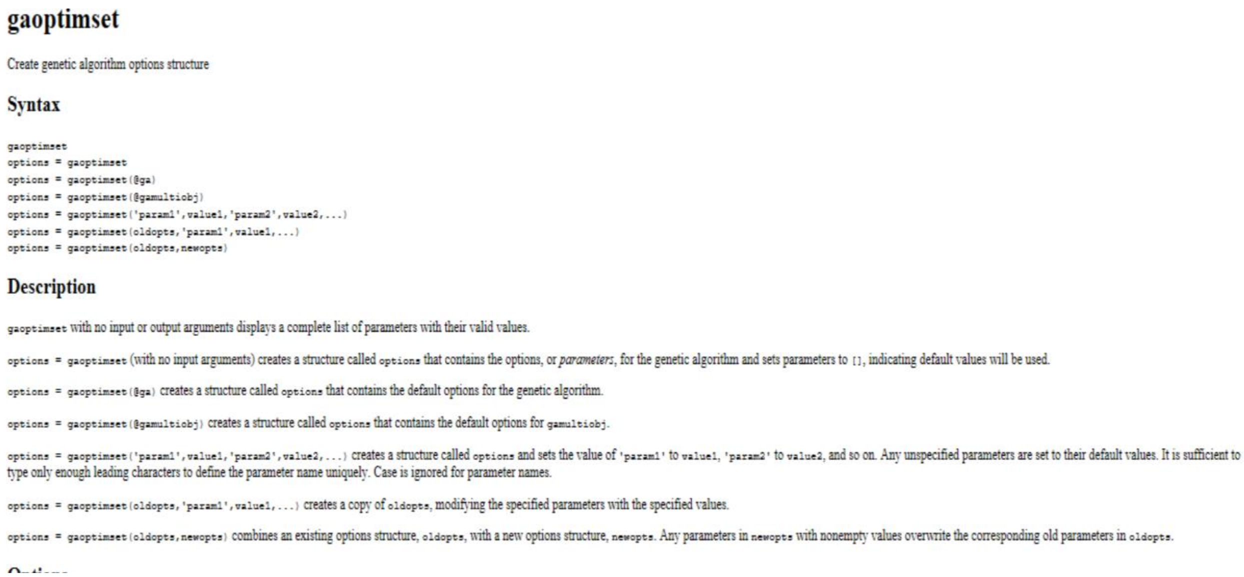
- First Selection rules select the individuals, called parents, that add to the population at the next generation.
- Then Crossover rules combine two parents to form children for the next generation.
- And finally, Mutation rules apply random changes to individual parents to form children.

The genetic algorithm contrasts from a classical, derivative-based, optimization algorithm in two primary ways as summed up in the accompanying table.

Classical Algorithm	Genetic Algorithm
Generates a single point at each iteration. The sequence of points approaches an optimal solution.	Generates a population of points at each iteration. The best point in the population approaches an optimal solution.
Selects the next point in the sequence by a deterministic computation.	Selects the next population by computation which uses random number generators.

In this work MATLAB was used for optimization using gaoptimset function in MATLAB. This MATLAB function with no output or input arguments displays a complete list of parameters with their valid values.

3.2.5 GAOPTIMSET



gaoptimset

Create genetic algorithm options structure

Syntax

```
gaoptimset
options = gaoptimset
options = gaoptimset(@ga)
options = gaoptimset(@gamultiobj)
options = gaoptimset('param1',value1,'param2',value2,...)
options = gaoptimset(oldopts,'param1',value1,...)
options = gaoptimset(oldopts,newopts)
```

Description

`gaoptimset` with no input or output arguments displays a complete list of parameters with their valid values.

`options = gaoptimset` (with no input arguments) creates a structure called `options` that contains the options, or *parameters*, for the genetic algorithm and sets parameters to `[]`, indicating default values will be used.

`options = gaoptimset(@ga)` creates a structure called `options` that contains the default options for the genetic algorithm.

`options = gaoptimset(@gamultiobj)` creates a structure called `options` that contains the default options for `gamultiobj`.

`options = gaoptimset('param1',value1,'param2',value2,...)` creates a structure called `options` and sets the value of `'param1'` to `value1`, `'param2'` to `value2`, and so on. Any unspecified parameters are set to their default values. It is sufficient to type only enough leading characters to define the parameter name uniquely. Case is ignored for parameter names.

`options = gaoptimset(oldopts,'param1',value1,...)` creates a copy of `oldopts`, modifying the specified parameters with the specified values.

`options = gaoptimset(oldopts,newopts)` combines an existing options structure, `oldopts`, with a new options structure, `newopts`. Any parameters in `newopts` with nonempty values overwrite the corresponding old parameters in `oldopts`.

Figure 3-8 GA MATLAB function

3.2.6 Interfacing of Aspen EDR-Excel-MATLAB

The Aspen EDR was linked with excel sheet and MATLAB to transform the model from steady state to a dynamic mode. Plate fin heat exchanger was modelled in Aspen EDR. The proposed modelling framework is shown in Figure 3-9. 200 data sets are generated through inserting variations in steady-state values of process variables by the interfacing of Aspen EDR, Excel and MATLAB for creating the possible scenarios of streams condition and their resulting output. List of two process inputs which are inlet flow rate of hot and cold stream. Generated data is used to provide optimum input variables through genetic algorithm.

Figure 3-9 Simplified Block Diagram of PFHE Optimization Model

3.2.7 Data Generation

The random data was generated using MATLAB function Randi in order to create uncertainties in the process. Uncertainty in Inlet hot stream temperature, Inlet cold stream temperature and fouling resistance were considered. As these three variables are not in control of the process and uncertainty is caused from ambient air and from the flue gases. Now in order to overcome these uncertainties we are using inlet flowrates of both fluids to achieve higher effectiveness value. So, at different uncertain condition Genetic Algorithm was applied to get optimum inlet flowrates for a greater effectiveness. Around 200 cases were generated randomly with 5 percent uncertainty in all the three variables (Inlet temperature Hot, Inlet temperature Cold, Fouling resistance).

3.2.8 ANN Model Simulation

Artificial neural network was trained using the data obtained after GA optimization which gives optimum values of two input operating variables (Inlet flowrate of hot stream, Inlet flowrate of cold stream) at uncertain conditions. In the beginning ANN model was feeded with three input variables i-e Inlet hot stream temperature, Inlet cold stream temperature and fouling resistance. After the simulation of ANN the outputs that were displayed by the network are, Inlet hot stream flowrate and inlet cold stream flowrate. The ANN was capable of predicting optimum inlets flowrates of the streams for high energy efficient operation. 200 cases were generated in order to obtain optimum operating variables at each case for maximum effectiveness.

3.2.9 ANN Model Validation Vs Genetic Algorithm

The predicted and targeted output values of model based effectiveness of PFHE is plotted against test samples. Regression plot shows the accuracy of ANN predicted and targeted output values. The graphs obtained are shown in results section.

3.2.10 Sensitivity Analysis

The ANN was used as a surrogate model in Sobol and FAST (Fast Order Sensitivity Test) based sensitivity analysis framework to find hierarchy in the input variables in terms of their impact on the energy efficiency of the heat exchanger. The use of ANN as predictive model and as a surrogate model. The ANN predicted values were validated by applying it on first 20 cases and the results were compared with the results obtained from GA and in

Straight run conditions. The input variables for ANN are Inlet hot temperature, Inlet cold temperature, Fouling resistance while the output variables are the flowrates. Then for validation of the output variables i-e inlet flowrates predicted to be optimum by the ANN was done in order to observe and compare the results i-e Cold out temperature and effectiveness of the heat exchanger under uncertain conditions.

Chapter 4

Results and Discussion

The Table 4-1 shows operating conditions of the PFHE (input data for model). Table 4-2 shows the optimum design parameters. Table 4-3 shows the simulation results obtained from Aspen EDR using the input data mentioned in Table 4-1 **Error! Reference source not found.** and Table 4-2. Analysis of the EDR Model

This section covers the results by Aspen EDR Modelling and simulation. Simple crossflow heat exchanger is designed in Aspen with stream by stream simulation. Two number of streams and two number of layer types are used. The input data and heat exchanger design parameters are considered of a heat exchanger designed for tiles furnace [18]. Flue gases from tiles furnace is used as hot stream to heat up the ambient air in order to increase the efficiency of tiles furnace. The optimum design parameters are considered for modeling of heat exchanger. The heat exchanger diagram and the flow direction specified in Aspen EDR is shown in Figure 4-1. Fin thickness is 0.1mm. The input operation data and optimum design parameters are as follow.

Table 4.1 The operating conditions of the PFHE (input data for the model)

Inlet flow rate (hot stream) (kg/s)	1.45
Inlet flow rate (cold stream) (kg/s)	1.35
Inlet temperature Hot (C)	346.85
Inlet temperature Cold (C)	41.85
Pressure (Inlet Hot side) (kPa)	180
Pressure (Inlet Cold side) (kPa)	120

Table 4.2 PFHE optimum design parameters

Fin Frequency (#/mm)	0.2
Height of Fin (mm)	3.0
Length of Fin (mm)	3.0
Flow length of Hot stream (m)	0.30
Flow length of Cold stream (m)	0.99
No-flow length (m)	0.293

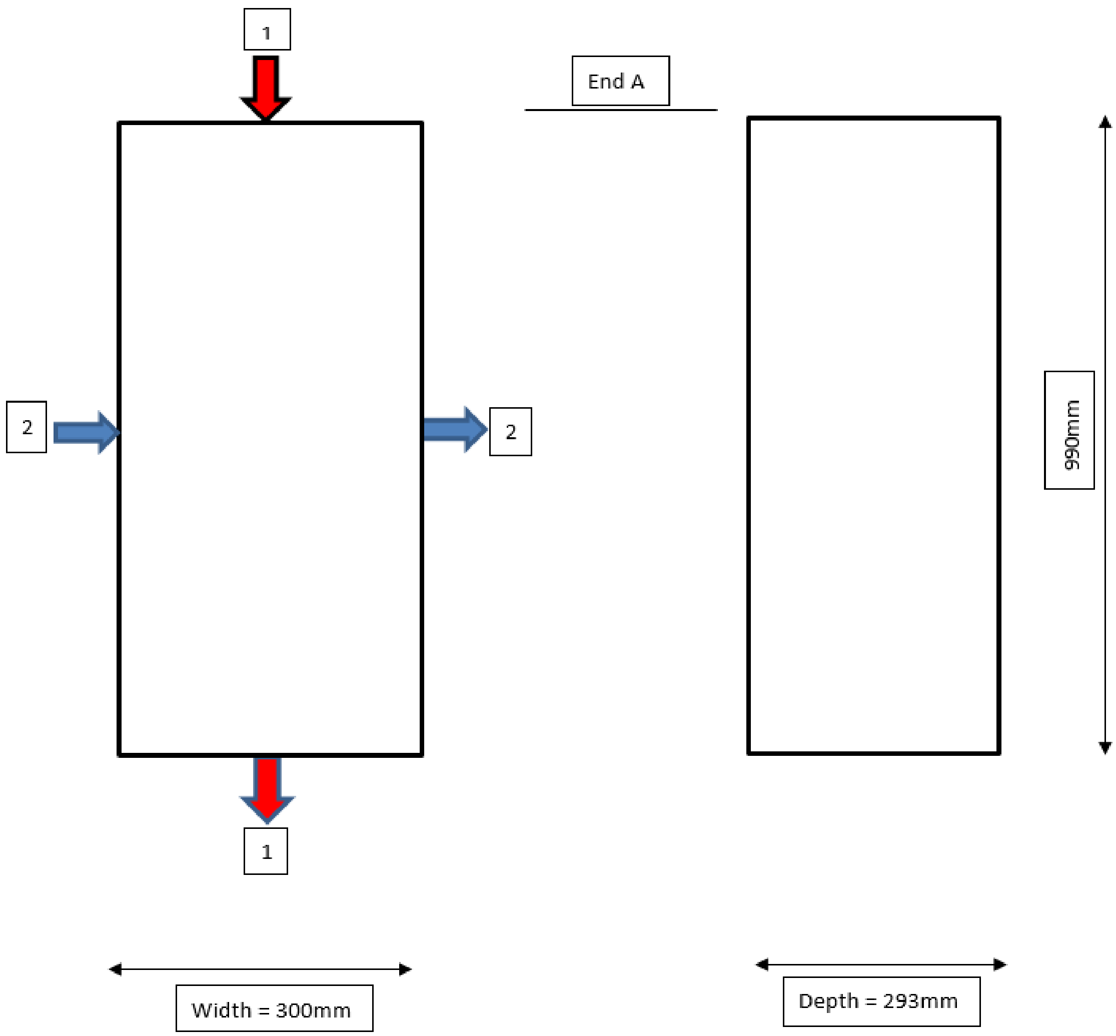


Figure 4-1 PFHE Diagram in Aspen EDR

Table 4.3 Thermal Performance of PFHE (Results from Aspen EDR)

Main stream number		Stream 1	Stream 2
Stream name		Hot Stream	Cold Stream
Flow direction		End A to B (down)	Crossflow
Total mass flow rate	kg/s	1.5	1.26
Heat load	kW	-251	251
Heat load per layer	kW	-9	8.7
Inlet temperature	C	316	53
Outlet temperature	C	206.9	248.74
Inlet quality(vapor mass fraction)	-	1	1
Outlet quality(vapor mass fraction)	-	1	1
Inlet specific enthalpy	kJ/kg	771.7	11.2
Outlet specific enthalpy	kJ/kg	604.4	210.4
Fouling resistance	m2*K/W	0.00101	0.00101
Minimum [T-Twall]	C	9.47	16.44
Mean [T-Twall]	C	34.54	-66.52
Mean heat transfer coefficient	W/(m2*K)	409.5	200.1
Mean fin efficiency	-	0.77	0.86
Solution method		Standard	Standard
Heat load as fraction of maximum	-	0.7399	0.7399
Theoretical maximum heat load	kW	-339.2	339.2

In Table 4-4 the results obtained from Aspen EDR after running the simulation are given.

Initial results at Straight run conditions are shown in **Error! Reference source not found.**. At constant flow rates in different cases the results obtained are also shown in this table.

Table 4.4 Straight run Input Condition simulation results

S.No	Hot Inlet Temp	Cold Inlet Temp	Fouling Resistance	Hot Outlet Temp	Hot Inlet Flowrate	Cold Inlet Flowrate	Effectiveness
Case 1	346.85	41.85	0	277.66	1.45	1.35	0.773
Case 2	347	35	0.00121	253.04	1.45	1.35	0.699
Case 3	346	38	0.00119	253.55	1.45	1.35	0.699
Case 4	344	45	0.00116	254.58	1.45	1.35	0.701
Case 5	345	38	0.00121	252.85	1.45	1.35	0.699
Case 6	353	35	0.0031	228.99	1.45	1.35	0.610
Case 7	359	39	0.0014	259.56	1.45	1.35	0.689
Case 8	349	35	0.00104	257.36	1.45	1.35	0.708
Case 9	350	42	0.00129	256.08	1.45	1.35	0.695
Case 10	359	36	0.00101	264.59	1.45	1.35	0.708
Case 11	359	37	0.00101	265.64	1.45	1.35	0.710
Case 12	354	41	0.00117	260.86	1.45	1.35	0.702
Case 13	359	45	0.00126	264.09	1.45	1.35	0.698
Case 14	356	35	0.00121	259.49	1.45	1.35	0.699
Case 15	349	43	0.00106	259.73	1.45	1.35	0.708
Case 16	354	41	0.00111	261.72	1.45	1.35	0.705
Case 17	347	45	0.00114	257.67	1.45	1.35	0.704
Case 18	348	30	0.00129	257.38	1.45	1.35	0.715
Case 19	354	35	0.00105	260.71	1.45	1.35	0.708
Case 20	352	40	0.00126	249.83	1.45	1.35	0.673

4.1 Optimization through Genetic Algorithm

Single objective maximization Genetic algorithm was applied using MATLAB gaoptimset function. The input variables to be optimized are inlet flowrate of hot and cold stream while the objective to be maximized is outlet cold stream temperature. By increase in outlet cold stream temperature effectiveness of plate and fin type heat exchanger is increased. The upper and lower bounds of input variables are 1.45+0.1,1.35+0.1 and 1.45-0.1,1.35-0.1 respectively. The population size is 10 with 1 set of generation and 20 iterations.

The optimum input variables i-e hot stream inlet flowrate and cold stream inlet flowrate are obtained from Genetic algorithm for each 200 cases. First 20 cases are shown in Table 4-5 and the results i-e outlet cold stream temperature and effectiveness obtained at each case are shown. Table 4-6 shows increase in effectiveness after applying GA as compared to the Straight run initial inputs.

Table 4.5 Genetic Algorithm Results

S.No	Hot Inlet Temp	Cold Inlet Temp	Fouling Resistance	Cold Outlet Temp	Hot Inlet flowrate	Cold Inlet flowrate	Effectiveness
Case 1	346.85	41.85	0	288.02	1.52	1.26	0.81
Case 2	347	35	0.00121	257.71	1.41	1.27	0.71
Case 3	346	38	0.00119	259.69	1.48	1.29	0.72
Case 4	344	45	0.00116	262.86	1.54	1.3	0.73
Case 5	345	38	0.00121	256.48	1.41	1.28	0.71
Case 6	353	35	0.0031	238.98	1.52	1.26	0.64
Case 7	359	39	0.0014	269.75	1.51	1.26	0.72
Case 8	349	35	0.00104	267.9	1.52	1.26	0.74
Case 9	350	42	0.00129	259.63	1.44	1.3	0.69
Case 10	359	36	0.00101	271.5	1.51	1.31	0.73
Case 11	359	37	0.00101	278.6	1.55	1.25	0.75
Case 12	354	41	0.00117	267.5	1.53	1.31	0.72
Case 13	359	45	0.00126	274.4	1.54	1.27	0.73
Case 14	356	35	0.00121	263.8	1.49	1.32	0.71
Case 15	349	43	0.00106	270	1.52	1.26	0.74
Case 16	354	41	0.00111	266.5	1.41	1.27	0.72
Case 17	347	45	0.00114	263.72	1.48	1.29	0.72
Case 18	348	30	0.00129	258.6	1.54	1.3	0.72
Case 19	354	35	0.00105	267	1.55	1.33	0.73
Case 20	352	40	0.00126	268.3	1.51	1.25	0.73

Table 4.6 Comparison of Effectiveness before and after Genetic Algorithm optimization

Case. No	Straight run Condition	GA Results
1	0.77	0.81
2	0.7	0.71
3	0.7	0.72
4	0.7	0.73
5	0.7	0.71
6	0.61	0.64
7	0.69	0.72
8	0.71	0.74
9	0.69	0.69
10	0.71	0.73
11	0.71	0.75
12	0.7	0.72
13	0.7	0.73
14	0.7	0.71
15	0.71	0.74
16	0.71	0.72
17	0.7	0.72
18	0.71	0.72
19	0.71	0.73
20	0.68	0.73

4.2 Prediction through Artificial Neural Network

The simplified structure of ANN obtained from MATLAB with three input values, 5 hidden layers and 2 output layers is shown in Figure 4-2. ANN predicted input values are then used in simulation and the results obtained are shown in Table 4.7. The performance comparison of Straight run conditions, GA results and ANN results are shown in Table 4.8. The change in outlet cold stream temperature before and after applying GA and ANN is shown in Figure 4.3, change in hot stream outlet temperature is shown in Figure 4.4 and the overall performance is plotted in Figure 4.5. The regression analysis is giving the information on network performance presented in Figure 4.6. Network performance seems good accuracy.

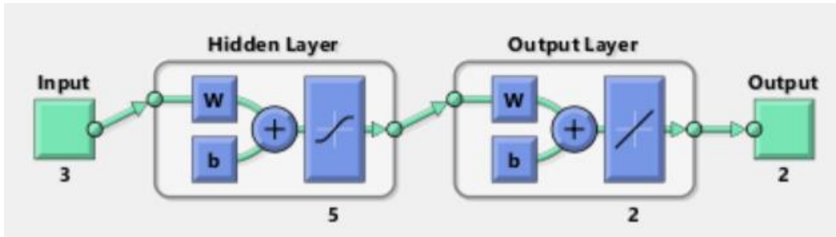


Figure 4-2 ANN Structure

Table 4.7 ANN Results

S.No	Hot Inlet Temp	Cold Inlet Temp	Fouling Resistance	Cold Outlet Temp	Hot Inlet Flowrate	Cold Inlet Flowrate	Effectiveness
Case 1	346.85	41.85	0	283.78	1.478	1.286	0.89
Case 2	347	35	0.00121	263.02	1.513	1.262	0.73
Case 3	346	38	0.00119	262.17	1.503	1.272	0.73
Case 4	344	45	0.00116	263.58	1.505	1.272	0.73
Case 5	345	38	0.00121	261.3	1.503	1.271	0.73
Case 6	353	35	0.0031	237.44	1.503	1.273	0.64
Case 7	359	39	0.0014	268.47	1.504	1.273	0.72
Case 8	349	35	0.00104	266.2	1.509	1.270	0.74
Case 9	350	42	0.00129	264.68	1.507	1.270	0.72
Case 10	359	36	0.00101	273.63	1.503	1.273	0.74
Case 11	359	37	0.00101	274.68	1.495	1.270	0.74
Case 12	354	41	0.00117	269.48	1.501	1.275	0.73
Case 13	359	45	0.00126	272.29	1.494	1.270	0.72
Case 14	356	35	0.00121	268.45	1.499	1.273	0.73
Case 15	349	43	0.00106	268.37	1.502	1.273	0.74
Case 16	354	41	0.00111	270.47	1.499	1.274	0.73
Case 17	347	45	0.00114	265.74	1.489	1.270	0.73
Case 18	348	30	0.00129	259	1.495	1.274	0.72
Case 19	354	35	0.00105	269.72	1.499	1.275	0.74
Case 20	352	40	0.00126	264.94	1.494	1.279	0.72

Table 4.8 Comparison of developed model at Straight run condition, optimized data and ANN predicted data

Case. No	Straight run Condition	GA Results	ANN Results
1	0.77	0.81	0.89
2	0.7	0.71	0.73
3	0.7	0.72	0.73
4	0.7	0.73	0.73
5	0.7	0.71	0.73
6	0.61	0.64	0.64
7	0.69	0.72	0.72
8	0.71	0.74	0.74
9	0.69	0.69	0.72
10	0.71	0.73	0.74
11	0.71	0.75	0.74
12	0.7	0.72	0.73
13	0.7	0.73	0.72
14	0.7	0.71	0.73
15	0.71	0.74	0.74
16	0.71	0.72	0.73
17	0.7	0.72	0.73
18	0.71	0.72	0.72
19	0.71	0.73	0.74
20	0.68	0.73	0.72

Figure 4-3 Cold Stream Outlet Temp (Comparison Graph)

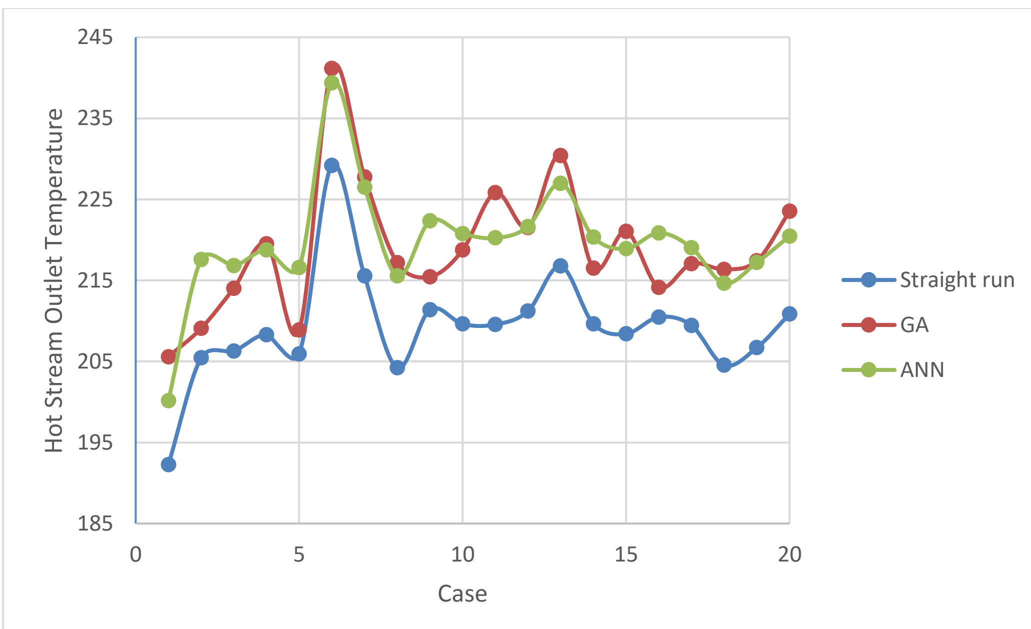


Figure 4-4 Hot Stream Outlet Temp (Comparison Graph)

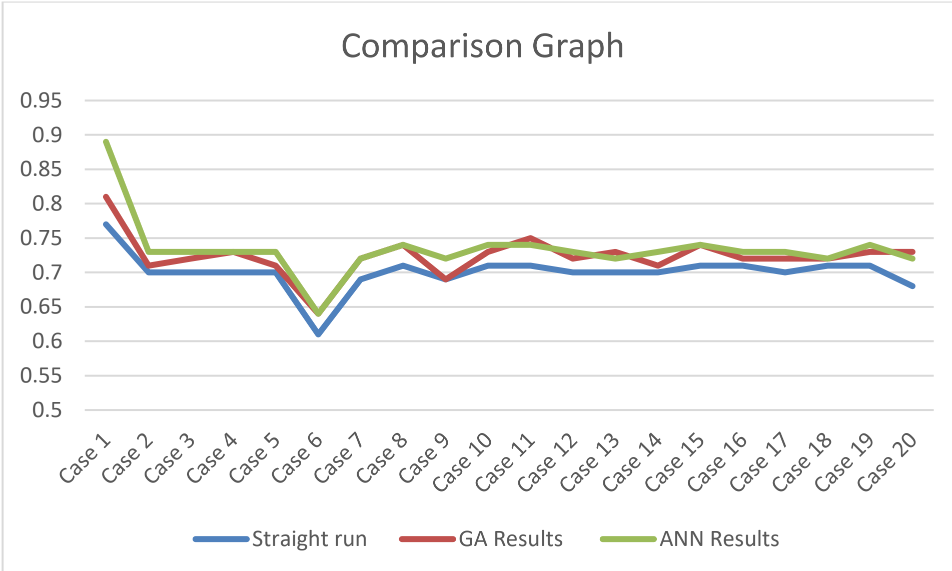


Figure 4-5 Overall Performance Comparison Graph

4.3 ANN Accuracy Vs Genetic Algorithm

The predicted and targeted output values of model-based effectiveness of PFHE is plotted against test samples. The Figure 4.6 shows Target and Prediction Accuracy of Hot Stream Inlet flowrate and Cold Stream Inlet flowrate.

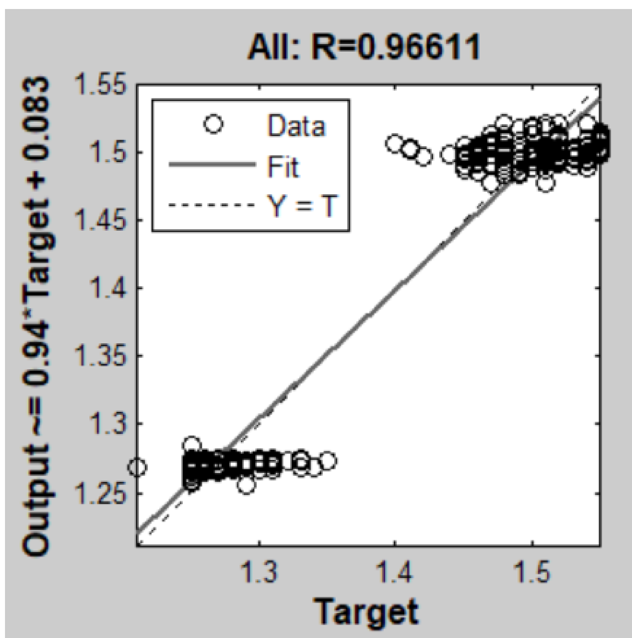


Figure 4-6 ANN Regression Plot

4.4 Sensitivity Analysis

A set of sequences have been established in MATLAB for computing sensitivity indices by SOBOL and FAST as already mentioned in section 3.1.5. This is done by generic user-defined model and given the name GSAT (Global Sensitivity Analysis Toolbox). SO, in MATLAB environment the logical flow, as given in Figure 4.7, to analyze the sensitivity analysis is to create this new project under name of (*Pro_Create*). Then, by using function of (*Pro_AddInput*) every new variable with its characteristics must be added.

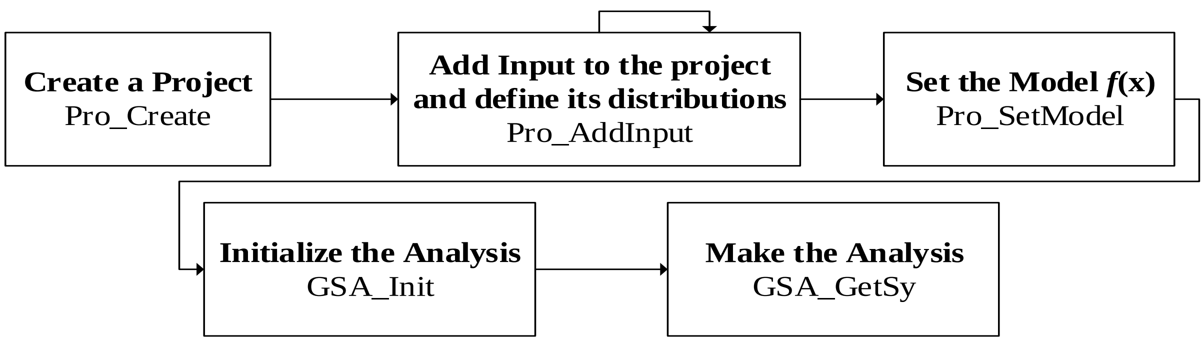


Figure 4-7 Steps to proceed for sensitivity analysis through GSAT

Sensitivity indices of SOBOL and FAST are shown in Figure 4.8 and Figure 4.9 for Hot Inlet Flowrate and Cold Inlet Flowrate respectively. The most sensitive variables for Hot Inlet Flowrate is Hot Inlet Temperature while for Cold Inlet Flowrate according to FAST indices both Hot and Cold Inlet temperature are more sensitive.

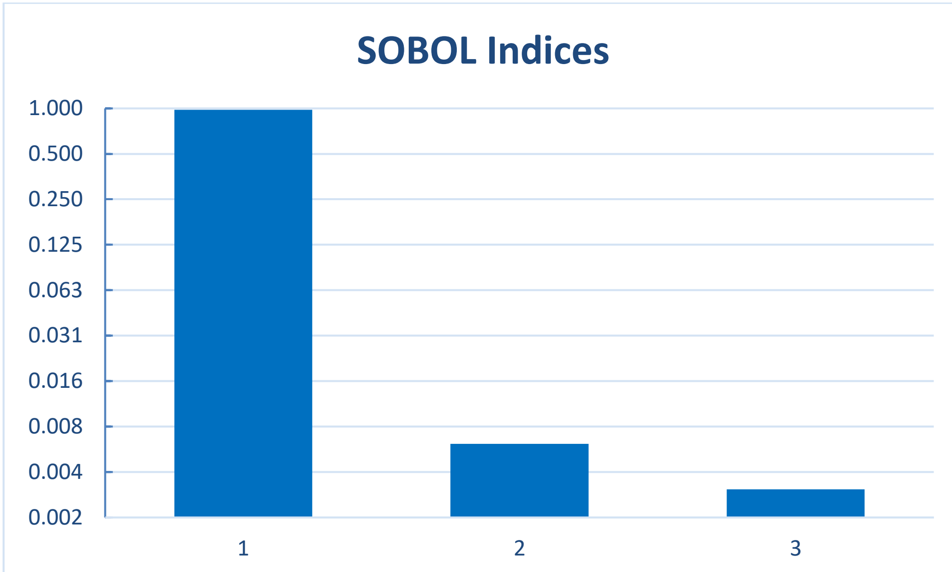


Figure 4-8 SOBOL sensitivity indices of Hot and Cold Inlet Flowrate

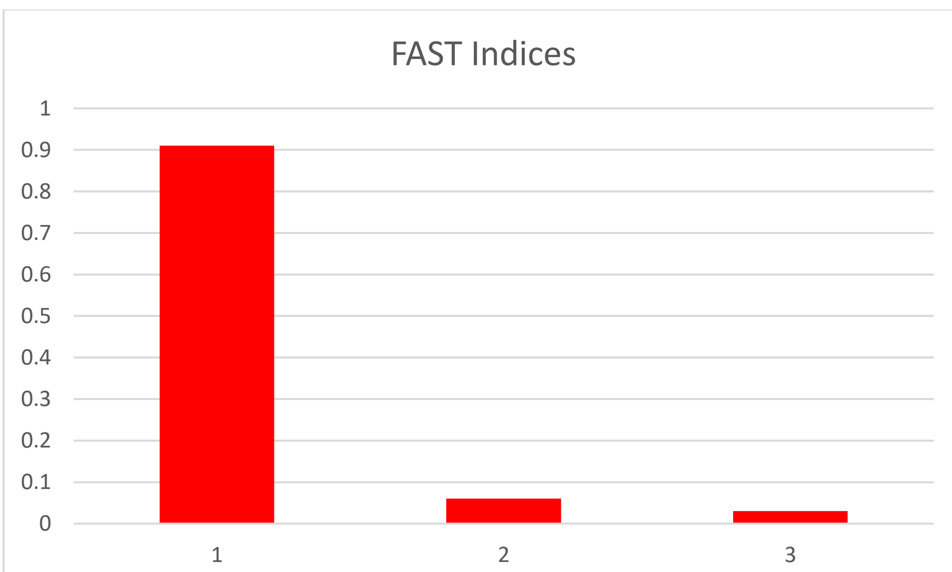


Figure 4-9 FAST sensitivity indices of Hot and Cold Inlet Flowrate

Conclusion

In this study Plate and Fin type heat exchanger was designed in Aspen EDR environment. The model was converted from steady state to dynamic by interfacing of Aspen, Excel and MATLAB. An Aspen EDR based model of Plate fin heat exchanger used in tiles factory was developed. The methodology used for optimization purpose is proposed in this study in order to achieve maximum effectiveness during operation under uncertain condition. 200 random cases were generated in order to create artificial uncertainty in Hot inlet stream temperature, Cold inlet stream temperature and Fouling resistance. Single objective GA was applied on each case to obtain maximum effectiveness (Outlet cold stream temperature) using 2 input variables (Inlet Hot Stream flowrate, Inlet Cold Stream flowrate). During the literature review it was found that the inlet flowrate of both streams are more effective towards heat exchanger performance. The heat exchanger performance is increased after applying GA. The data comprised of 200 samples was used to develop ANN model. The predicted output variables are inlet flowrate of both hot and cold streams. The predicated output variables seem good accuracy. Sensitivity Analysis was performed through the results obtained and it was found that Fouling resistance and Inlet hot stream temperature are the most sensitive variables.

References

[1]. "d — M APPLIED MECHANICS Heat Exchangers," p. 1960, 1960.

[2]. B. Kim and B. Sohn, "An experimental study of flow boiling in a rectangular channel with offset strip fins," *Int. J. Heat Fluid Flow*, vol. 27, no. 3, pp. 514–521, 2006, doi: 10.1016/j.ijheatfluidflow.2005.11.008.

[3]. L. Guo, F. Qin, J. Chen, and Z. Chen, "Lubricant side thermal-hydraulic characteristics of steel offset strip fins with different flow angles," *Appl. Therm. Eng.*, vol. 28, no. 8–9, pp. 907–914, 2008, doi: 10.1016/j.applthermaleng.2007.07.005.

[4]. G. Lihua, C. Jiangping, Q. Feng, and C. Zhijiu, "Geometrical optimization and mould wear effect on HPD type steel offset strip fin performance," *Energy Convers. Manag.*, vol. 48, no. 9, pp. 2473–2480, 2007, doi: 10.1016/j.enconman.2007.04.003.

[5]. Y. Song, M. Asadi, G. Xie, and L. A. O. Rocha, "Constructal wavy-fin channels of a compact heat exchanger with heat transfer rate maximization and pressure losses minimization," *Appl. Therm. Eng.*, vol. 75, pp. 24–32, 2015, doi: 10.1016/j.applthermaleng.2014.05.027.

[6]. C. Liu, W. Bu, and D. Xu, "Multi-objective shape optimization of a plate-fin heat exchanger using CFD and multi-objective genetic algorithm," *Int. J. Heat Mass Transf.*, vol. 111, pp. 65–82, 2017, doi: 10.1016/j.ijheatmasstransfer.2017.03.066.

[7]. G. N. Xie, B. Sunden, and Q. W. Wang, "Optimization of compact heat exchangers by a genetic algorithm," *Appl. Therm. Eng.*, vol. 28, no. 8–9, pp. 895–906, 2008, doi: 10.1016/j.applthermaleng.2007.07.008.

[8]. I. R. de S. Victorino and R. M. Filho, *Application of Genetic Algorithms To the Optimization of an Industrial Reactor*, vol. 39, no. 2. IFAC, 2006.

[9]. H. Najafi and B. Najafi, “Multi-objective optimization of a plate and frame heat exchanger via genetic algorithm,” *Heat Mass Transf. und Stoffuebertragung*, vol. 46, no. 6, pp. 639–647, 2010, doi: 10.1007/s00231-010-0612-8.

[10]. R. V. Rao and V. K. Patel, “Thermodynamic optimization of cross flow plate-fin heat exchanger using a particle swarm optimization algorithm,” *Int. J. Therm. Sci.*, vol. 49, no. 9, pp. 1712–1721, 2010, doi: 10.1016/j.ijthermalsci.2010.04.001.

[11]. J. Janaun, N. H. Kamin, K. H. Wong, H. J. Tham, V. V. Kong, and M. Farajpourlar, “Design and simulation of heat exchangers using Aspen HYSYS, and Aspen exchanger design and rating for paddy drying application,” *IOP Conf. Ser. Earth Environ. Sci.*, vol. 36, no. 1, 2016, doi: 10.1088/1755-1315/36/1/012056.

[12]. S. Sanaye and H. Hajabdollahi, “Multi-objective optimization of rotary regenerator using genetic algorithm,” *Int. J. Therm. Sci.*, vol. 48, no. 10, pp. 1967–1977, 2009, doi: 10.1016/j.ijthermalsci.2009.02.008.

[13]. R. Hilbert, G. Janiga, R. Baron, and D. Thévenin, “Multi-objective shape optimization of a heat exchanger using parallel genetic algorithms,” *Int. J. Heat Mass Transf.*, vol. 49, no. 15–16, pp. 2567–2577, 2006, doi: 10.1016/j.ijheatmasstransfer.2005.12.015.

[14]. J. J. Wang, Y. Y. Jing, and C. F. Zhang, “Optimization of capacity and operation for CCHP system by genetic algorithm,” *Appl. Energy*, vol. 87, no. 4, pp. 1325–1335, 2010, doi: 10.1016/j.apenergy.2009.08.005.

[15]. B. Sahin, K. Yakut, I. Kotcioglu, and C. Celik, “Optimum design parameters of a heat exchanger,” *Appl. Energy*, vol. 82, no. 1, pp. 90–106, 2005, doi: 10.1016/j.apenergy.2004.10.002.

[16]. A. R. Doodman, M. Fesanghary, and R. Hosseini, “A robust stochastic approach for design optimization of air cooled heat exchangers,” *Appl. Energy*, vol. 86, no. 7–8, pp. 1240–1245, 2009, doi: 10.1016/j.apenergy.2008.08.021.

[17]. K. Foli, T. Okabe, M. Olhofer, Y. Jin, and B. Sendhoff, “Optimization of micro

heat exchanger: CFD, analytical approach and multi-objective evolutionary algorithms," *Int. J. Heat Mass Transf.*, vol. 49, no. 5–6, pp. 1090–1099, 2006, doi: 10.1016/j.ijheatmasstransfer.2005.08.032.

[18]. S. Sanaye and H. Hajabdollahi, "Thermal-economic multi-objective optimization of plate fin heat exchanger using genetic algorithm," *Appl. Energy*, vol. 87, no. 6, pp. 1893–1902, 2010, doi: 10.1016/j.apenergy.2009.11.016.

[19]. M. Yousefi, A. N. Darus, and H. Mohammadi, "An imperialist competitive algorithm for optimal design of plate-fin heat exchangers," *Int. J. Heat Mass Transf.*, vol. 55, no. 11–12, pp. 3178–3185, 2012, doi: 10.1016/j.ijheatmasstransfer.2012.02.041.

[20]. S. Ben Saad, P. Clément, C. Gentric, J. F. Fourmigué, and J. P. Leclerc, "Experimental distribution of phases and pressure drop in a two-phase offset strip fin type compact heat exchanger," *Int. J. Multiph. Flow*, vol. 37, no. 6, pp. 576–584, 2011, doi: 10.1016/j.ijmultiphaseflow.2011.03.009.

[21]. M. S. Kim, J. Lee, S. J. Yook, and K. S. Lee, "Correlations and optimization of a heat exchanger with offset-strip fins," *Int. J. Heat Mass Transf.*, vol. 54, no. 9–10, pp. 2073–2079, 2011, doi: 10.1016/j.ijheatmasstransfer.2010.11.056.

[22]. A. K. Sahu, N. K. Sahu, and A. K. Sahu, "Application of modified MULTI-MOORA for CNC machine tool evaluation in IVGTFNS environment: An empirical study," *Int. J. Comput. Aided Eng. Technol.*, vol. 8, no. 3, pp. 234–259, 2016, doi: 10.1504/IJCAET.2016.077603.

[23]. A. Kumar Sahu, N. Kumar Sahu, and A. Kumar Sahu, "Appraisal of CNC machine tool by integrated MULTI-MOORA-IVGN circumferences," *Grey Syst. Theory Appl.*, vol. 4, no. 1, pp. 104–123, 2014, doi: 10.1108/gs-11-2013-0028.

[24]. N. K. Sahu, A. K. Sahu, and A. K. Sahu, "Appraisement and benchmarking of third-party logistic service provider by exploration of risk-based approach," *Cogent Bus. Manag.*, vol. 2, no. 1, pp. 1–21, 2015, doi: 10.1080/23311975.2015.1121637.

[25]. A. K. Sahu, N. K. Sahu, and A. K. Sahu, “Application of integrated TOPSIS in ASC index: partners benchmarking perspective,” *Benchmarking*, vol. 23, no. 3, pp. 540–563, 2016, doi: 10.1108/BIJ-03-2014-0021.

[26]. A. K. Sahu, N. K. Sahu, and A. K. Sahu, “Benchmarking CNC machine tool using hybrid-fuzzy methodology: A multi-indices decision making (MCDM) approach,” *Int. J. Fuzzy Syst. Appl.*, vol. 4, no. 2, pp. 28–46, 2015, doi: 10.4018/IJFSA.2015040103.

[27]. S. N. Sivanandam and S. N. Deepa, “Chapter 2 Genetic Algorithms,” *Introd. to Genet. Algorithms*, pp. 15–37, 2008.

[28]. C. García-Martínez, F. J. Rodriguez, and M. Lozano, “Genetic algorithms,” *Handb. Heuristics*, vol. 1–2, pp. 431–464, 2018, doi: 10.1007/978-3-319-07124-4_28.

[29]. A. Oyama, S. Obayashi, and T. Nakamura, “Real-coded adaptive range genetic algorithm applied to transonic wing optimization,” *Appl. Soft Comput.*, vol. 1, no. 3, pp. 179–187, 2001, doi: 10.1016/S1568-4946(01)00017-5.

[30]. 天津医药肖沉， 孙莉， 曹杉杉， 梁浩， 程焱 - and undefined 2017, “肖沉 1, 2, 孙莉 1, 2Δ, 曹杉杉 1, 2, 梁浩 1, 2, 程焱 1, 2,” *Tjyybjb.Ac.Cn*, vol. 3, no. 2252, pp. 58–66, 1828, [Online]. Available: http://www.tjyybjb.ac.cn/CN/article/downloadArticleFile.do?attachType=PDF&id=9987.

[31]. Z. Zi, Y. Zheng, A. E. Rundell, and E. Klipp, “SBML-SAT: A systems biology markup language (SBML) based sensitivity analysis tool,” *BMC Bioinformatics*, vol. 9, pp. 1–14, 2008, doi: 10.1186/1471-2105-9-342.

[32]. A. Saltelli, K. Chan, M. S.-J. and W. & Sons, N. York, and undefined 2000, “Sensitivity analysis. Probability and statistics series.”

[33]. I. M. Sobol, “Global sensitivity indices for nonlinear mathematical models and their Monte Carlo estimates,” *Math. Comput. Simul.*, vol. 55, no. 1–3, pp. 271–280,

2001, doi: 10.1016/S0378-4754(00)00270-6.

[34]. N. Perrin *et al.*, "Oxycombustion for carbon capture on coal power plants and industrial processes: Advantages, innovative solutions and key projects," *Energy Procedia*, vol. 37, pp. 1389–1404, 2013, doi: 10.1016/j.egypro.2013.06.015.

[35]. F. Cannavó, "Sensitivity analysis for volcanic source modeling quality assessment and model selection," *Comput. Geosci.*, vol. 44, pp. 52–59, 2012, doi: 10.1016/j.cageo.2012.03.008.

[36]. A. Saltelli, S. Tarantola, and K. P. S. Chan, "A quantitative model-independent method for global sensitivity analysis of model output," *Technometrics*, vol. 41, no. 1, pp. 39–56, 1999, doi: 10.1080/00401706.1999.10485594.