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Performance measurement of plate fin heat exchanger by exploration: ANN, ANFIS, GA, and SA

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Abstract

An experimental work is conducted on counter flow plate fin compact heat exchanger using offset strip fin under different mass flow rates. The training, testing, and validation set of data has been collected by conducting experiments. Next, artificial neural network merged with Genetic Algorithm (GA) utilized to measure the performance of plate-fin compact heat exchanger. The main aim of present research is to measure the performance of plate-fin compact heat exchanger and to provide full explanations. An artificial neural network predicted simulated data, which verified with experimental data under 10–20% error. Then, the authors examined two well-known global search techniques, simulated annealing and the genetic algorithm. The proposed genetic algorithm and Simulated Annealing (SA) results have been summarized. The parameters are impartially important for good results. With the emergence of a new data-driven modeling technique, Neuro-fuzzy based systems are established in academic and practical applications. The neuro-fuzzy interference system (ANFIS) has also been examined to undertake the problem related to plate-fin heat exchanger performance measurement under various parameters. Moreover, Parallel with ANFIS model and Artificial Neural Network (ANN) model has been created with emphasizing the accuracy of the different techniques. A wide range of statistical indicators used to assess the performance of the models. Based on the comparison, it was revealed that technical ANFIS improve the accuracy of estimates in the small pool and tropical ANN.

Keyword: Plate fin heat exchanger; Performance; Flow rate; Methods

1. Introduction

The compactness of heat exchanger is the index of progress in the present day scenario of industrial growth [1]. Especially with increasing the need for developing the cryogenics field. Usually, plate fin heat exchanger is suitable for numerous type of heat exchanger application for a wide range of industry [2–5]. Plate fin units are normally arranged for counter flow heat exchanger. Plate fin heat exchanger has thin corrugated fins or corrugated heat transfer surface of the plates. Compact heat exchanger surface density is very high that means large surface area per unit volume it could be as high as 1800 m^2/m^3, the plate fin heat exchanger is suitable for a close approach temperature as low as 2 °C, Two or more streams can be used by changing the section. Plate fin heat exchanger is significant nowadays and most widely used due to high heat transfer rate. It is investigated that compact heat exchangers such as plain fin strip, offset fin, wavy fin, perforated fin,etc the pressure drop decrease with respect to increasing the turbulence in working fluid. Onwards 1942 by Norris and Spofford [6] provide the first experimental report they draw out the effect of heat transfer coefficient on the basis of length, thickness and pitch of fins and also reduced the friction factor and Colburn modules. As the practical demand of plate fin heat exchanger has increased experimental studies, have been made by London and Shah [7] in 1967 they been brought to a conclusion that small offset spacing

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(length/dh), fin thickness and a large number of fins per inch gives better heat transfer. In 1975 Wieting [8] set up a statically relationship between the variables from earlier experimental heat transfer and fluid flow friction. Data for a plate-fin heat exchanger of offset fin and by using this statically relationship (untested offset fin geometries can be predicted realistically and accurately within the parameter range of the correlation). So that one can predict virtually and correctly within the parametric range of newest offset plate-fin heat exchanger having no previous tested data. Experimental validation of numerical simulation and also provides a comparison of experimental result in computationally obtained results from the effects of fin thickness and free stream turbulence. In 1977, a set of experiments was performed by Sparrow [9] to observe the heat transfer for a mass flow rate with varying the Reynolds number. The thickness ratio and the spacing ratio are the other factors establish that the Nusselt number varies while changing the plate thickness and also come upon after searching that it is not necessarily equal spacing, and length gives optimal results. Cru and Sparrow [10] again in 1979 analysis the heat transfer effectiveness 'ε' of staggered plate arrange is higher than in plate line channel. In 1985 Joshi and Webb [11] expressed an analytical framework to predict the j and f factor for laminar and turbulent flow from experimental and analytical work. In 1994 Hu and Herold [12] suggested a liquid coolant instead of using previous air cooled models in an experimental set up to evaluate heat transfer and pressure drop of offset fin heat exchanger. It shows that the liquid cooled apparatus Prandtl number has a large effect on Nusselt number, and numerical analysis examines the surface temperature distribution. Related to CFD work in 2007 Peng and Ling [13] calculates the Colburn factor j and friction factor f for an Aluminum- oil-air Plate Fin Heat Exchanger (PFHE) with serrated fins at low Reynolds No. (Between10-200) Both experimentally, with constant air flow rate and six different oil flow rates and numerically, with 3D geometric analysis. One of the objectives of this paper is also to propose a procedure for the ANFIS model and an Artificial Neural Network (ANN) model alongside a few experiments so as to predict the performance of fins with the new configuration in PFHE. Again in 2007 Peng and Ling [14] developed the successful utilization of Genetic Algorithm (GA) combined with the Back Propagation (BP) algorithm of Artificial Neural Network.That is more efficient and advanced than the traditional GA method for the optimal design of PFHE and showed that this method is also applicable to various PFHEs. In the same year, Xie and Wang [15] applied genetic algorithm to optimize the design of plain plate triangular fin compact heat exchanger, where fins standards and offset strip design adapted as referred Kays and London [1].

Almost through with their studies the various other fin geometries louvered fin, perforated fin,etc. In 2009, Peng and Ling [16] set up an artificial neural network for prediction of j and f factors from experimental data for five different types of plate fin heat exchangers. In 2009, Mishra et al. [17] developed optimization of cross flow PFHE using GA method and showed the importance of design approach based on the second law of thermodynamics. The conclusion drawn shows the effect of an additional constraint on the optimum solution and power requirement regarding pressure drops.

Zhu and Li [18] 2009 carried out and investigated the three-dimensional numerical simulations on the flow and heat transfer in the four types of fins after that Wang and Liu 2008 carried out a numerical study of plate-fin heat exchangers with plain fins and serrated fins.Regarding work is done in the field of Artificial Neural Network (ANN), in 2009, Tan et al. [19] developed an Artificial Neural Network (ANN).To represent the overall behavior of the heat exchanger over the whole range of flow rates, inlet temperatures, liquid compositions and blockage ratios in experiments. Thus demonstrating that an ANN was able to predict the overall heat transfer rate between the liquid and air streams in a compact fin-tube heat exchanger with a high degree of accuracy.In 2010, Sanaye purposed multi-objective optimization with the objective function effectiveness and total cost using a genetic algorithm and on suggesting a close form expression between the variables and the objective functions estimate the total annual cost and effectiveness.

In recent years, work related to serrated plate fin heat exchanger was in 2011 by Yusef and Darus [20] employed genetic algorithm with particle swarm optimization technique to optimize the plate-fin heat exchanger design. Another paper in 2011 [21] applied Neural Network Model (NNM) upon data collected by CFD simulation to measure the accuracy of j and f factors of NNM. The result displayed that NNM embrace the accuracy in between 1.3% and 1% which is higher than applications of other models (embace the accuracy in between 3.8% and 8.2%) for analysing the same data of CFD simulation. However, for a precise response neural network has to be supplied with well- defined factors. Also in 2011, Kim et al. [21] proposed new correlations for j & f factor for offset strip fins with blockage ratios of greater than 20%, with the j correlations suggested as functions of the Prandtl number. Resulted in the enhancement of j and f factor (by 24%) for the optimized offset strip fin compared to the referenced non-optimized offset strip fin. To understand the uniform distribution in PFHE, Saad et al. [2] in 2011 investigated the hydrodynamics of a single phase flow in offset strip fins deducing new correlations for the friction factor (f) from laminar to turbulent ranges. Their deductions of the new correlations were in agreement with the numerical results of that from CFD simulations, thus enabling the experimental observation of uniform distribution that is crucial to obtain high performance in compact heat exchangers. In an another paper from Saad et al. in 2011, they performed single-phase CFD simulations for the determination of pressure drop characteristics in an offset strip fin H.E that achieved good agreement between experimental data and numerical prediction of friction factor. They also showed that distribution of two-phase flow in CHEs' depends on gas and liquid superficial velocities concerning the design of the distributor. The multi-objectives formulated problems always aid the industrial sectors to solve their several problems and in case of multi-objectives problems, the criterion are considered as objectives [22–26]. The authors too suggested the role of fuzzy logic applications in industrial realms [3].

In 2012 Yosefi and Mohammadi applied a different technique to optimize plate-fin heat exchanger by using a competitive algorithm (ICA). Seven optimized variable exploit to minimize the total weight and total annual cost. In 2013, Buyruk et al. investigated ways to increase the efficiency of PFHE by optimization of fin angles, fin intervals, and heights, offsetting fins along a horizontal direction that has a potential for direct application to heat exchanger design data.

In an another paper from Peng et al. in 2014, they investigated the flow and heat transfer characteristics of an innovative offset strip fin both experimentally and numerically in the Reynolds Number range of 500–5000.Results showed the dependence of fin length, fin pitch and fin is the bent distance on the performance of the compact heat exchanger (CHE) and how these results could directly be used to design CHEs'. Also in the same year, Aliabadi et al. performed experiments to compare between the seven common types of channels of PFHE. The conclusions showed that better heat transfer obtained from the vortex generator, wavy, offset strip, and pin, perforated, louvered, and plain channels, respectively. The same order followed for the maximum ability to reduce the surface area of the PFHE in comparison to the plain one.

Along with the gathered information above we emphasis on other literature regarding ANFIS.Model for PFHX about the prediction of heat transfer and pressure drop using adaptive neuro-fuzzy inference system and results forecast. Average Nusselt number and dimensionless pressure showed good agreement with the work available by Tahseen Ahmadin 2013 another in ANFIS related to thermal work. Moon [22] implemented two logic such as ANFIS-based (Adaptive Neuro-Fuzzy Inference System-based control) ANN-based (Artificial Neural Network-based control) except artificial intelligence to determine that how much do the buildings have temperature control systems.

Due to increasing demand of plate fin heat exchanger in industry and research work every user is interested in high efficient plate fin heat exchanger and this objective can be achieved with different approaches. Heat exchange efficiency, increase or decrease depending on outlet cold and hot fluid temperature and which is reliant on other factors, i.e. by controlling mass flow rate on a specified heat exchanger. However, as mass flow rate increase the pressure drops also increases, so a sensible compromise is needed.

In this paper, the first purpose is to present a structured Neural Network Model, produced based on experimentally observed data and a simulated annealing (SA) algorithm to search the high-quality optimal process parameter conditions. Simulated annealing optimization scheme is schematic to solve the multi-objective formulation. The objectives to achieve maximum efficiency are (i) cold fluid outlet temperature and (ii) hot fluid outlet temperature. The variable parameters during experiments are

Flow rate 'Q' (lit/min),
Pressure at cold inlet '$P1$.'
Pressure at hot inlet '$P2$',
Pressure drop cold fluid mm of Hg,
Pressure drop hot fluid mm of Hg
the inlet temperature of cold and hot fluid
These are usually the actual performance parameter to evaluate the outlet performance.

2. Experimental investigation, modeling and learning procedure

A serialized set of experiments is conducted by Alur [4]. The experimental setup adopted for the study of plate fin heat exchanger is the steady state experiment. Measurement of temperature and mass flow rate in the two sides provides the required information to compute the heat exchanger effectiveness for the flow rate of liter/min operating between 315k to 365k, the calculations of the performance parameter has carried out by the effectiveness from Shah [7] are given below.

$$\varepsilon = \frac{C_c(T_2 - T_1)}{C_{\min}(T_3 - T_1)} = \frac{C_h(T_3 - T_4)}{C_{\min}(T_3 - T_1)} \tag{1}$$

where,

$T_1 =$ Temperature at inlet of cold fluid
$T_2 =$ Temperature at outlet of cold fluid
$T_3 =$ Temperature at inlet of hot fluid
$T_4 =$ Temperature at outlet of hot fluid.

Based on the previous Experiment, we gleaned objective data; depicted in Table 1; it is decided to assess the behavior of plate fin heat exchanger regarding flow properties before recommending for Industrial applications. Experimental data were used to determine contact between the parameters. The experiment conducted at different mass flow rates (5.7 g/s to 14.2 g/s) and different hot fluid inlet temperature between 315k to 365k. To study the variation of the performance parameters and finally the data tabulated into two categories for training and testing which are applied for modeling and learning procedure:

where,

Q (liters /min)is the flow rate
$P1$(kg/cm^2) Pressure at cold inlet
$P2$(kg/cm^2) Pressure at hot inlet
Pcd (mm of Hg) cold fluid Pressure drop
Phd(mm of Hg) hot fluid Pressure drop
$T1$(k) Cold fluid inlet temperature
$T2$(k) Cold fluid outlet temperature
$T3$(k) Hold fluid inlet temperature
$T4$(k) Hold fluid outlet temperature

3. Implementation of Neural Network Model

The purpose of the developed is working purpose neural network. The network is a feed structure after the first Levenberg–Marquardt propagation training algorithm applied presented by (Eq. (2)). Network with neural network technology, part of the software MATLAB models. Unsubscribe

Table 1
Heat exchanger dataset for the neural network model.

S.no.	*Q*	*P1*	*P2*	Pcd	Phd	*T1*	*T2*	*T3*	*T4*	Eff
1.	300	0.08	0.06	9	6	315.24	360.22	368.96	321.1	0.890916
2.	400	0.14	0.12	15	12	311.35	359.94	367.91	316.95	0.90099
3.	500	0.2	0.17	25	22	311.93	361.38	368.88	317	0.910975
4.	550	0.24	0.2	30	26	312.82	361.71	369.45	317.35	0.920007
5.	588	0.28	0.24	31	27	313.41	361.33	368.96	317.86	0.919892
6.	650	0.32	0.26	40	35	314.16	360.74	368.72	318.08	0.928152
7.	300	0.09	0.06	12	10	313.94	352.08	358.83	319.3	0.880597
8.	400	0.14	0.1	15	13	313.6	352.88	358.86	318.43	0.893283
9.	500	0.2	0.16	24	20	312.7	353.05	358.69	317.35	0.898891
10.	550	0.24	0.19	30	26	315.08	353.06	358.86	318.99	0.91069
11.	588	0.28	0.23	34	31	316.55	353.16	358.83	320.3	0.911306
12.	650	0.34	0.28	38	35	315.75	352.39	358.32	319.06	0.922246
13.	300	0.08	0.06	8	7	313.32	343.27	348.86	317.78	0.874508
14.	400	0.13	0.11	15	13	314.13	344.11	348.98	317.85	0.893257
15.	500	0.2	0.16	23	21	316.18	344.66	348.88	319.5	0.898471
16.	550	0.24	0.19	30	26	316.1	344.52	348.71	319.44	0.897577
17.	588	0.28	0.24	33	31	316.62	344.63	348.88	319.59	0.907936
18.	650	0.34	0.28	39	34	316.6	344.16	348.8	319.18	0.919876
19.	300	0.08	0.06	8	6	313.92	335.01	339.31	316.94	0.881056
20.	400	0.14	0.11	16	14	315.77	335.86	339.26	318.45	0.885909
21.	500	0.2	0.16	24	22	312.51	335.42	338.9	315.55	0.884805
22.	550	0.24	0.19	30	26	316.46	336.01	338.83	318.86	0.892713
23.	588	0.28	0.23	33	31	312.99	335.34	338.8	315.57	0.900039
24.	650	0.34	0.28	37	34	315.72	335.67	339.16	317.93	0.905717

sigmoid transfer function is activated, all neurons:

$$\log\ \sin(x) = \frac{x}{1 - e^{-x}} \tag{2}$$

Where x is the input signal. The learning set consisted of 24 cases of the plate-fin heat exchanger.

Results for outlet temperature of cold and hot fluid come from experiments. Many input parameters can be considered to measure the effectiveness of heat exchanger. But, the problem will be so complicated to be solved in case of many input parameters and experimental expenses will also be more, in order to tide over this concerns, the authors conducted relevant literature survey in the context of computations problems pertain to exchangers effectivness and elected few effectual inputs parameters i.e Flow rates are ‘Q’(l/min), the pressure of the cold water inlet ‘P1’ pressure at hot inlet ‘P2’, Pressure drop cold fluid and hot fluid mm of Hg and the inlet temperature of cold and hot fluid.

The Network has an input layer, a hidden layer with 12 neurons and output layer produces results. The structure of the simplified network given in Fig. 1.

The data set was divided up between learning set for determination of network weights and validation and testing data sets which give the independent measure for ability to generalize and the network performance. The regression analysis is giving the information on network performance presented in Fig. 1.Network performance seems good accuracy. It is a matter to optimize the parameters of the systematic changes with learning and processing of the data is ready to shape. An algorithm based on empirical data, primarily designed. The network develops its simplest form. The (Fig. 2a and b) depicted that ANN's accuracy is valid.

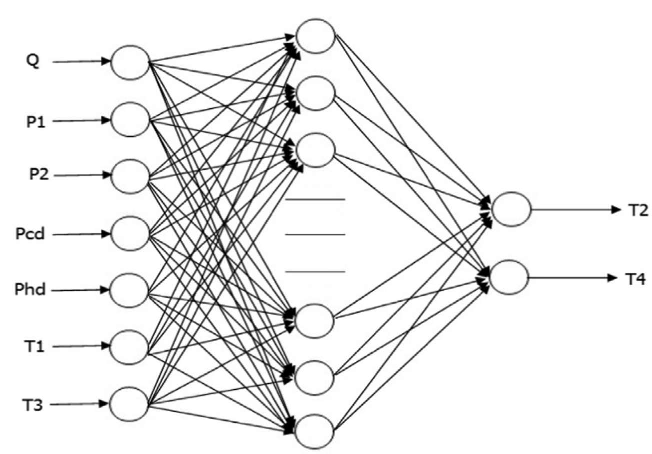

Fig. 1. Simplified network structure designed for the purpose of optimization objective function.

This Plate Fin Heat Exchanger (PFHX) ANN network performance can be obtained directly from the input information that can be seen. In other words, given the mass flow rate in the construction of a plate heat exchanger that is, on the inlet and outlet temperature and the temperature difference and both cold and hot sides of the ribs geometries. Engineers or designers have limited experimental data so to predict the performance Plate-fin heat exchanger ANN approach is useful and convenient. This heat transfer and flow characteristics can express by the mathematical formulas that are a very complex phenomenon, which does not require an understanding of ANN approach.

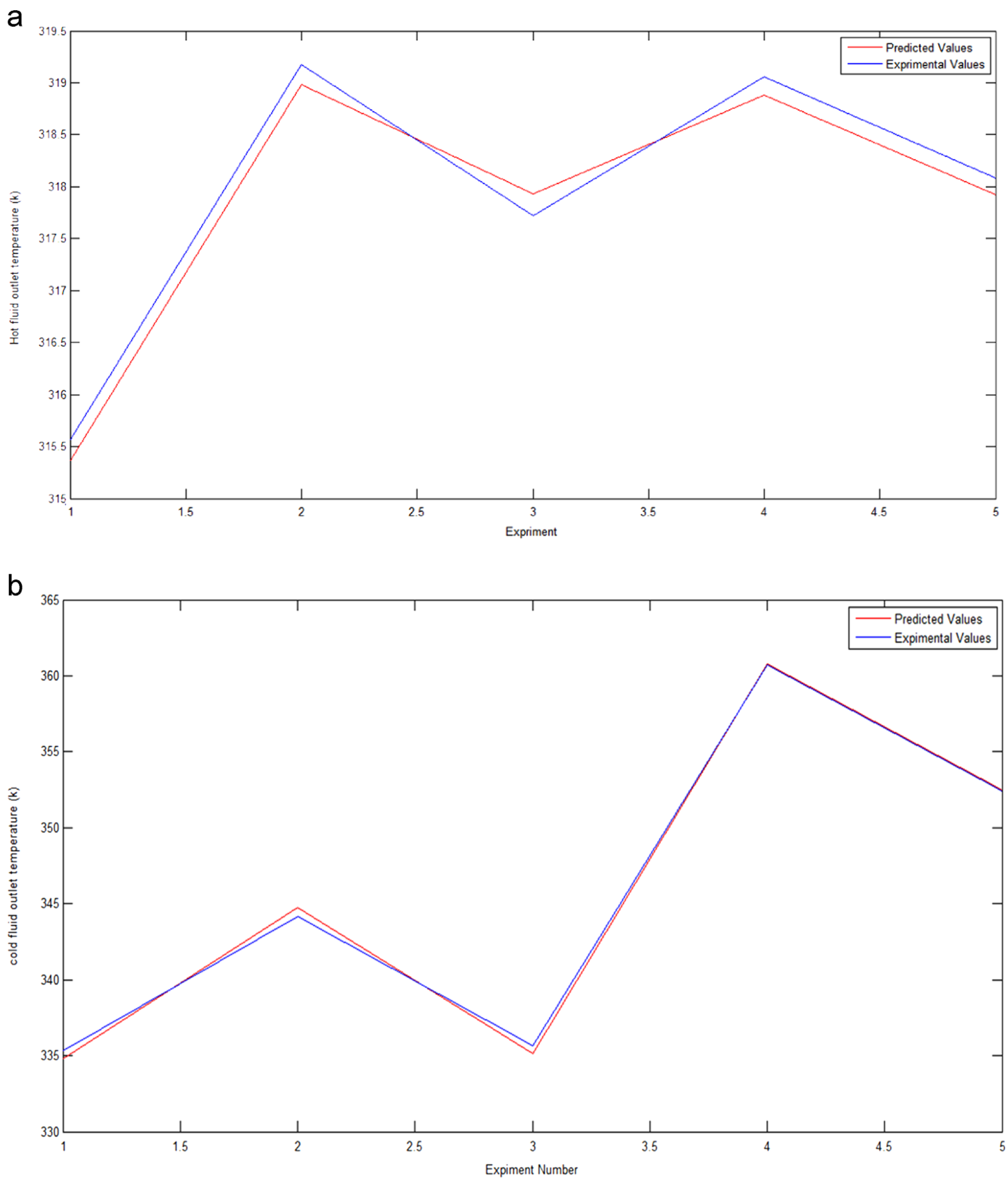

Fig. 2. (a) Network error-1 during learning process. (b) Network error-2 during learning process.

4. Implementation of ANFIS model

Adaptive neuro-fuzzy inference system (ANFIS) is a type Artificial Neural Network (ANN), which based on fuzzy interference system. The name of the fuzzy production system (FIS) is used to provide ANFIS with the start of a member of the training activities.

Are shown in Table 3. As the raw data collected by the MATLAB software with a specific structure and format converted into a data file. Model to produce accurate information about the system (neural model input and output parameters mentioned) is important to the quality of the training database. This data is not so easy for the manual pre-treatment, therefore, a fuzzy clustering method without human intervention used for this task.

For Plate Fin Heat Exchanger (PFHX) two separate fuzzy system have been generated for T2 and T4 i.e. outlet temperature of cold and hot fluid separately with the same inputs, and as shown in Fig. 3(a–d)**.**

Fig. 3(a and d)**,** both controllers (ANN and ANFIS) is used to evaluate the performance of the plate fin heat exchanger. ANFIS and ANN both depicted the corresponding results. In Fig. 3(a), ANN showed that output changes as changes in input variable, while in Fig. 3(c), ANFIS showed the relationship between input and output variable.

a

b

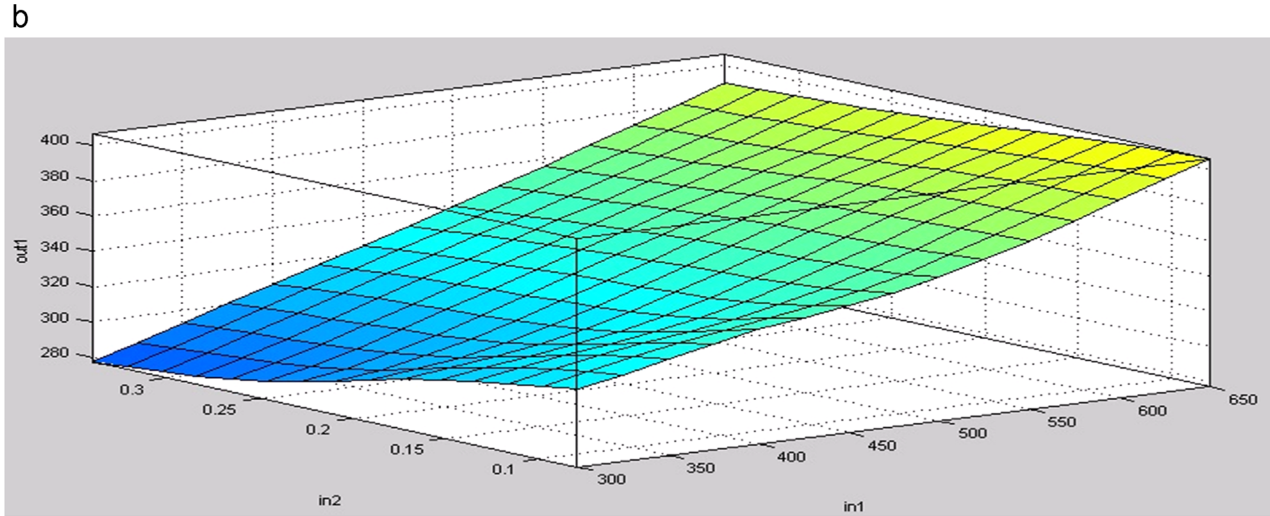

Fig. 3. (a) ANN shows that output changes as changes in input variables. (b) Surface viewer-1 show that output changes as changes in input variables. (c) ANFIS shows that relationship between input and output variable. (d) Surface viewer-2 show that relationship between input and output variable.

On other hand, it is found by Fig. 3b and d showing surface viewer, established the relationship between input and output variable (output changes as changes in input variables). In Fig. 3(b), surface viewer-1 showed that output changes as changes in input variable, while in Fig. 3(d), surface viewer-2 showed that relationship between input and output variable c

d

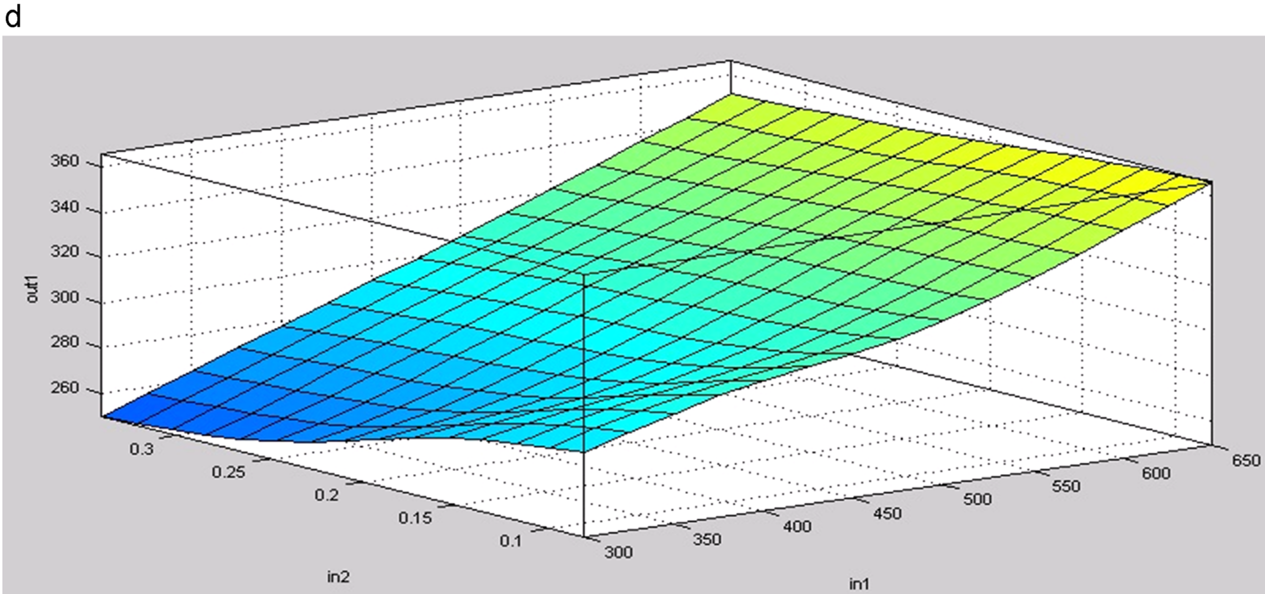

Fig. 3. (*continued*)

5. Implementation of optimization algorithm

The simulated annealing has been applied to reduce labor represented by neural network algorithm. Annealing is a way to solve the problems presented limited and unconstrained and bound. Process models the physical process of heating and then slowly lowering the temperature to reduce defects, whereby the energy system reduced. The way each simulated annealing algorithm generates a new random point. The distance from the new location at the moment or the scope of the search based on the probability distribution of a weight proportional to temperature. Usability has accepted all the points in the new law for the purpose, but also the probability of certain, pointing upwards determined. By the dots to the purposes of the assumption that the supply to avoid trapped in local minima, which is possible in the position to solve the whole world to explore more. Annealing schedule was chosen in order to reduce the logarithm temperature statement systematically. As the temperature decreases, the algorithm reduces the scope of the search to be together at least. Overall, the following elements of the Simulated Annealing algorithm may be distinguished. The representation of possible solutions,

– The generator of random values in the solution,
– Solution assessment function-target function,
– Cooling or annealing method the starting temperature and the rules of its lowering in the process of target function minimum searching. When the annealing algorithm is working it is necessary to adopt a method reducing the probability of transition to the state of worse parameters. Such a rule is called the cooling schedule. For the definition of the cooling schedule the following must be given:
– Starting temperature *T0*,
– Final temperature or the alloy criteria,
– The length of the Markov's chain (depending on the number of variables),
– The rule for the temperature is decreasing.

(i) For cold fluid outlet temperature:

$$T2 = 5.29036 - 0.00302818\ \mathrm{Q} + 13.9982\ P1 - 16.8278 P2 - 0.0849\ \mathrm{Pcd} + 0.0800369\ \mathrm{Phd} + 0.91353\ T1 + 0.0777416\ T3$$

(ii) For hot fluid out let temperature:

$$T4 = -0.138507 + 0.022083\ Q - 10.2438\ P1 - 14.6291\ P2 - 0.150565\mathrm{Pcd} + 0.113141\ \mathrm{Phd} + 0.120165\ T1 + 0.863851\ T3$$

6. Result and discussions

The result of conducted research has summarized below:

The Table 1 predicted data through modeling are intimating near the experimental values. The error shows in Table 2 is within the acceptable circumscribe. Table 3 represented the errors in prediction of responses. The Fig. 3 recapitulates the summarized view of validation and experimental result briefly after the construction the process model conveniently simulated annealing is used for obtaining optimization result. The two objectives of the present study are the maximization of temperature at the cold outlet, and minimization of hot outlet temperature. Table 4 represents the optimal fitness value for the simulated annealing. Similarly, Table 5 represents the optimal fitness value for the genetic algorithm.

Table 2
Comparison of the developed model with experimental data.

S.no.	*Q*	*T1*	*T3*	Experimental		Predicted			
						ANN		ANFIS	
				T2	*T4*	*T2*	*T4*	*T2*	*T4*
1	588	312.99	338.80	335.34	315.57	334.84	315.37	335	315
2	650	316.6	348.80	344.16	319.18	344.76	318.98	344	319
3	650	315.72	339.16	335.67	317.93	335.12	317.72	339	318
4	650	314.16	368.72	360.74	318.08	360.79	317.92	361	318
5	650	315.75	358.32	352.39	319.06	352.44	318.88	352	319

Table 3
Errors in prediction of responses.

% Error in prediction of *T2*		% Error in prediction of *T4*	
ANN	ANFIS	ANN	ANFIS
0.5	0.34	0.2	0.57
−0.6	0.16	0.2	0.18
0.55	−3.33	0.21	−0.07
−0.05	−0.26	0.16	0.08
−0.05	0.39	0.18	0.06

Table 4
Optimization results with best fitness values for simulated annealing.

Output response	Best fitness function value	*Q*	*P1*	*P2*	Pcd	Phd	*T1*	*T3*
T2	312.34	418.19	0.096	0.273	36.779	6.026	315.37	335.85
T4	322.52	300.49	0.34	0.28	33.656	7.314	315.24	335.85

Table 5
Optimization results with best fitness values for genetic algorithm.

Output response	Best fitness function value	Q	*P1*	*P2*	Pcd	Phd	*T1*	*T3*
T2	311.88	438.554	0.081	0.28	36.499	6.188	315.252	335.71
T4	321.86	300	0.34	0.28	37	6	315.24	335.67

7. Conclusion

The purpose of conducted research work is to expose the modern models: ANN and ANFIS, which investigated as a best modern model to prediction the results of compact heat exchanger on input parameters. The ANN and ANFIS modern models have been found valid corresponding to traditional other models i.e Genetic Algorithm and Simulated Annealing.

The first part of paper precede a multi-input output ANN and ANFIS based predictive model for the anticipation of performance parameter such as (i) cold fluid outlet temperature and (ii) hot fluid outlet temperature for experimental studies on plate fin heat exchanger. The model served as a tool to calculate the performance parameter based on the variation of process parameters.

Another part gives an optimal result with best-fit values using simple genetic algorithm and Simulated Annealing, which shown in Tables 4 and 5. It is an experimental investigation into the various parameters affecting these two algorithms and adapting them to our problem.

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