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TO EVALUATE THE PERFORMANCE OF HEAT EXCHANGER THROUGH ARTIFICIAL NEURAL NETWORKS APPROACH

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Abstract

The performance of heat exchanger deteriorates with time due to fouling on the heat transfer surface. It is necessary to assess periodically the heat exchanger performance, in order to maintain at high efficiency level. In this paper, we have evaluated the performance of parallel flow heat exchanger using artificial neural networks (ANNs). Experiments are conducted based on full factorial design of experiments to develop a model using the parameters such as temperatures, capacity ratio and constant value of optimum NTU. ANN model for efficiency, entropy generation number and overall heat transfer coefficient multiplied with area of a theoretical/clean heat exchanger is developed using a feed forward back propagation neural network and trained. The developed model is validated and tested by comparing the results with the experimental results. This model is used to assess the performance of the heat exchanger with the real/fouled system. It supports the system to improve the performance by asset utilization, energy efficient and cost reduction in terms of production loss.
Keywords: Heat exchanger; Artificial neural networks(ANNs); Modeling; Efficiency; Entropy generation number; Overall heat transfer coefficient multiplied with area.

I. INTRODUCTION

Heat exchanger process is complex due to its non- linear dynamics and particularly the variable steady state gain and time constant with the process fluid[]. Heat exchanger are used to transfer the heat between two fluids across a solid surface that are at different temperatures. In this paper we have taken counter and parallel flow heat exchanger for the evaluation of the performance. The performance of heat exchanger deteriorates with time due to formation of fouling. It is a very complicated phenomenon and can be broadly categorized into particulate, corrosion, biological, crystallization, chemical reaction and freeze[1]. Conventionally, all the books have used overall heat transfer coefficient to determine the performance. But in this paper, we are using 'efficiency', 'entropy generation number' and overall heat transfer coefficient multiplied with area for evaluating the performance.

The concept of efficiency has only recently been identified for heat exchanger. Earlier LMTD-method; and effectiveness NTU (ε-NTU) method is used for analysis. The heat exchanger efficiency is the ratio of actual heat transfer in a heat exchanger to the optimum heat transfer rate. A. Fakheri has given efficiency of parallel flow heat exchanger with the introduction of non-dimensional parameter called fin analogy number.[2]

From the viewpoint of second law of thermodynamics, it is impossible to have reversible heat exchanger. To reduce the irreversibility of heat exchanger 'Bejan' has introduced the concept of entropy generation number. This concept provides a common conceptual basis for thermal optimization of heat exchanger.[3]

ANN is one of the most powerful computer modelling techniques, based on statistical approach currently being used in many fields of engineering, for modelling complex relationships which are difficult to describe with physical models. It only needs input/output samples for training the network and learn complex non-linear relationships.[22]

In recent years, ANNs have been used in thermal systems for heat transfer analysis, performance prediction and dynamic control [4,6]. Sen and Yang [7] discusses in general the applications of ANN and genetic algorithms in thermal engineering. ANN is applied in heat transfer data analysis [8], evaluating heat transfer coefficients from experimental data [9], identifying and controlling heat exchangers [10], simulation of heat exchanger performance using limited experimental data [11], modelling of heat exchanger dynamic characteristics [12], dynamic modelling and controlling of heat exchangers with GA [13], dynamic prediction and neuro controller design for heat exchangers [14,15], neuro predictive controller design of heat exchangers [16], determining fin-and-tube heat exchangers performance with limited experimental data using soft computing and global regression[17,18], predicting heat transfer rate of a wire-on-tube heat exchanger [19], heat transfer analysis of air flowing in corrugated channels [20] and modelling the thermal performance of compact heat exchanger [21]. From the above mentioned successful applications, ANNs are well suitable for thermal analysis in engineering systems, especially in heat exchangers. In this paper, an online monitoring system is developed for a shell-and-tube heat exchanger using.

II. ANALYTICAL ANALYSIS

For theoretical/clean values we have use the analytical formulas. We need to determine 100 values for training neurons with the help of these formulas. Considering hot fluid capacity ratio as minimum.

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1. EFFICIENCY (η):- The heat exchanger efficiency is defined as the ratio of the actual heat transfer to the optimal heat transfer.

$$\eta = \frac{q}{q_{opt}} = \frac{\tanh(fa)}{fa} = \frac{C_h(T_{hi} - T_{ho})}{UA(\frac{T_{hi} + T_{ho}}{2} - \frac{T_{ci} + T_{co}}{2})}$$

where, fa is fin analogy number.

For counter flow, $fa = \frac{1 - C_r}{2}$

For parallel flow, $fa = \frac{1 + C_r}{2}$

2. ENTROPY GENERATION NUMBER (N_S):- It is the ratio of entropy generation to the minimum capacity ratio.

$$N_S = \frac{S_{gen}}{C_{\min}} = \ln\frac{T_{ho}}{T_{hi}} + \frac{1}{C_r}\ln\frac{T_{co}}{T_{ci}}$$

3. OVERALL HEAT TRANSFER COEFFICIENT MULTIPLIED WITH AREA (UA):- To evaluate this we Have used energy balance equation.

$$Q_h = UA * LMTD$$

$$Q_h = C_h(T_{hi} - T_{ho})$$

III. ANN MODEL DEVELOPMENT

1. DATA ACQUISITION:- To develop the ANN training model we, require inputs and outputs to train our network. Therefore, we have used 100 inlet temperatures of hot and cold fluids for parallel flow and evaluated the values of efficiency, entropy generation number and overall heat transfer coefficient multiplied with area.

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Table1. Input and output values for parallel flow for training.

Ti (°C)	ti (°C)	m (hot)(l/	m(cold)(l/	Cr	UA (Kw/°(	NS	η		
120	5	65	100	0.65	0.092892	2.680176	0.5629		
110	5	65	200	0.325	0.125667	4.294715	0.6551		
100	5	65	300	0.2167	0.147345	5.250755	0.6893		
90	5	75	100	0.75	0.100209	2.042438	0.5379		
80	5	75	200	0.375	0.136662	3.182461	0.6398		
120	10	75	300	0.25	0.160964	3.302007	0.6786		
110	10	85	100	0.85	0.106931	1.349021	0.5144		
100	10	85	200	0.425	0.146869	2.063054	0.625		
90	10	85	300	0.2833	0.173683	2.393716	0.6681		
80	10	65	100	0.65	0.092892	1.279489	0.5629		
120	15	65	200	0.325	0.125667	1.983719	0.6551		
110	15	65	300	0.2167	0.147345	2.222269	0.6893		
100	15	75	100	0.75	0.100209	0.977167	0.5379		
90	15	75	200	0.375	0.136662	1.35589	0.6398		
80	15	75	300	0.25	0.160964	1.433242	0.6786		
120	20	85	100	0.85	0.106931	0.804611	0.5144		
110	20	85	200	0.425	0.146869	1.144547	0.625		
100	20	85	300	0.2833	0.173683	1.247624	0.6681		
90	20	65	100	0.65	0.092892	0.694844	0.5629		
80	20	65	200	0.325	0.125667	0.856706	0.6551		

2. NETWORK DESIGN :- Feed forward back propagation (FFBP) NNs model is the best purpose general model and probably the best at generalization. We have developed three networks with the same input and different outputs for parallel flow.The input data in each network is T_{hi}, T_{ci}, C_r, NTU and output is efficiency for network 1 & network 4, entropy generation number for network 2 & network 5 and overall heat transfer coefficient multiplied with area for network 3 & network 6.

3. NETWORK ARCHITECTURE:- Since ANNs model is trial and error method. Therefore, these network architectures gave us the best performance for their respective networks.

Network 1:- for parallel flow
Input:- T_{hi}, T_{ci}, C_r, NTU Output:- efficiency
Transfer fuction: - transig
Algorithm:- trainlm
Adaptation function:-learngdm
No. of neurons:-50
Network 2:- for parallel flow
Input:- T_{hi}, T_{ci}, C_r, NTU Output:- entropy generation no.
Transfer fuction:-transig
Algorithm:-trainr
Adaptation function:-learngdm
No. of neurons:-50
Network 3:- for parallel flow
Input:- T_{hi}, T_{ci}, C_r, NTU Output:- overall heat transfer coefficient multiplied with area
Transfer fuction:- transig
Algorithm:-trainlm
Adaptation function:-learngdm
No. of neurons:-50

IV. PERFORMANCE OF DEVELOPED NETWORK MODEL:-

The performance of the ANN network is evaluated through the mean square error (MSE). Minimum error means our network has been optimized and we can get actual values of our output by giving same inputs.

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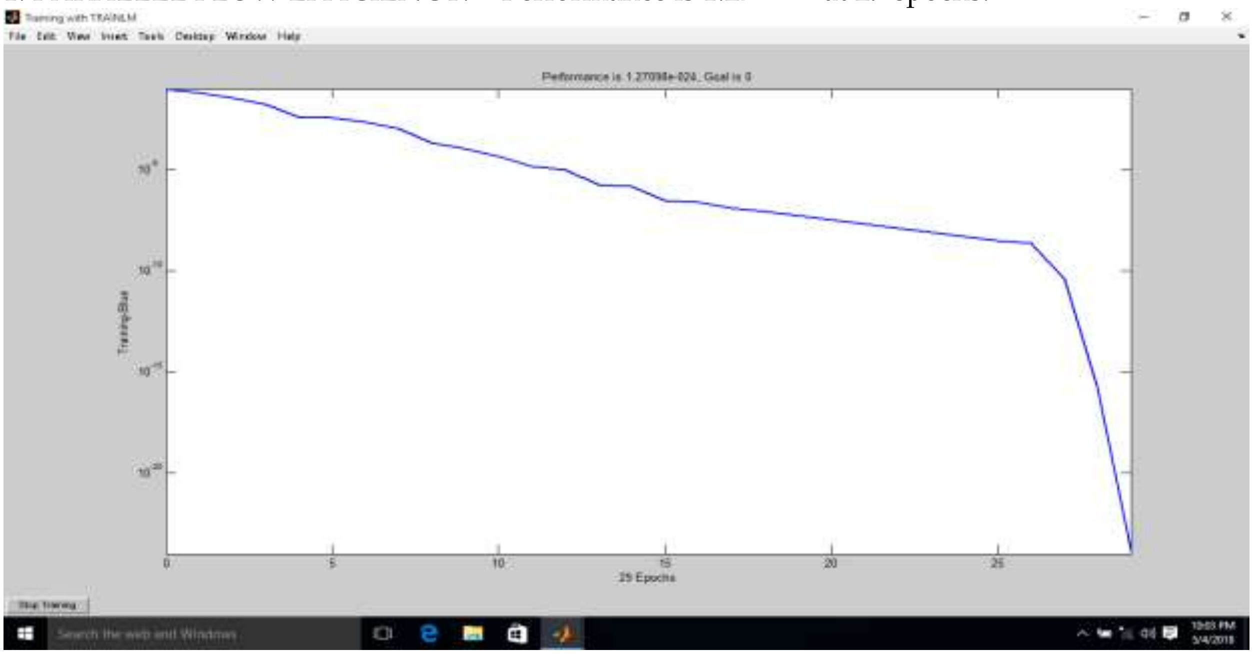
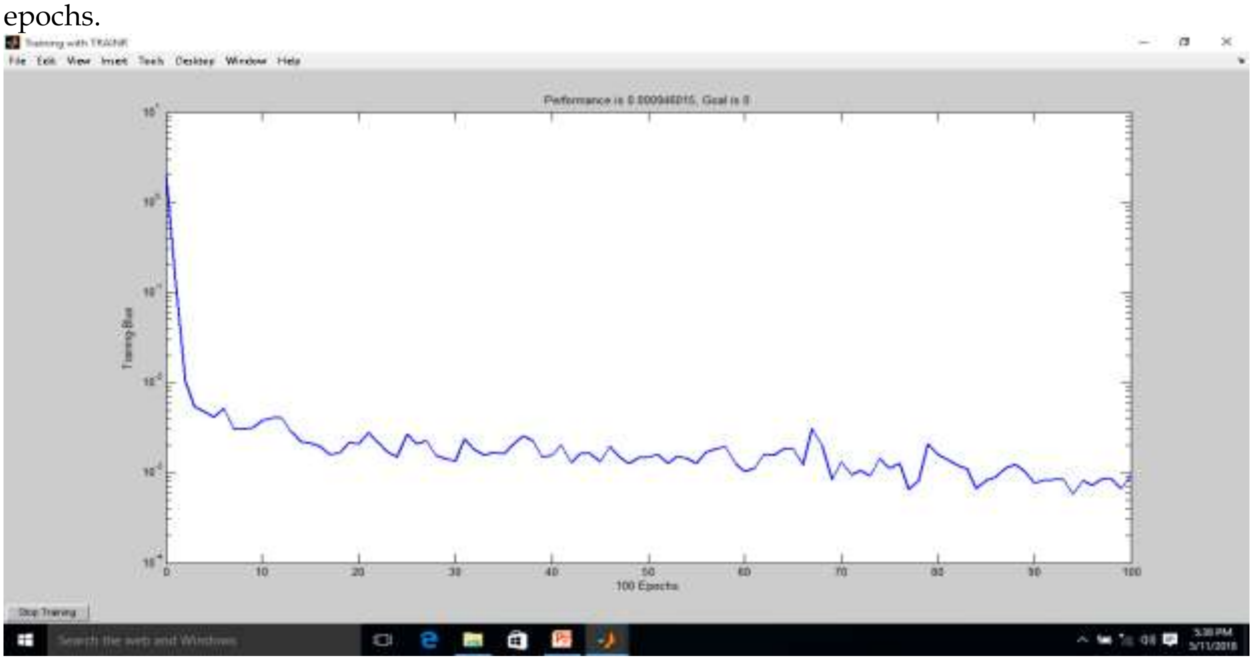
1. PARALLEL FLOW EFFICIENCY:- Performance is $1.27e^{-24}$ at 29 epochs.



2. PARALLEL FLOW ENTROPY GENERATION NO.:- Performance is 0.00094 at 100 epochs.



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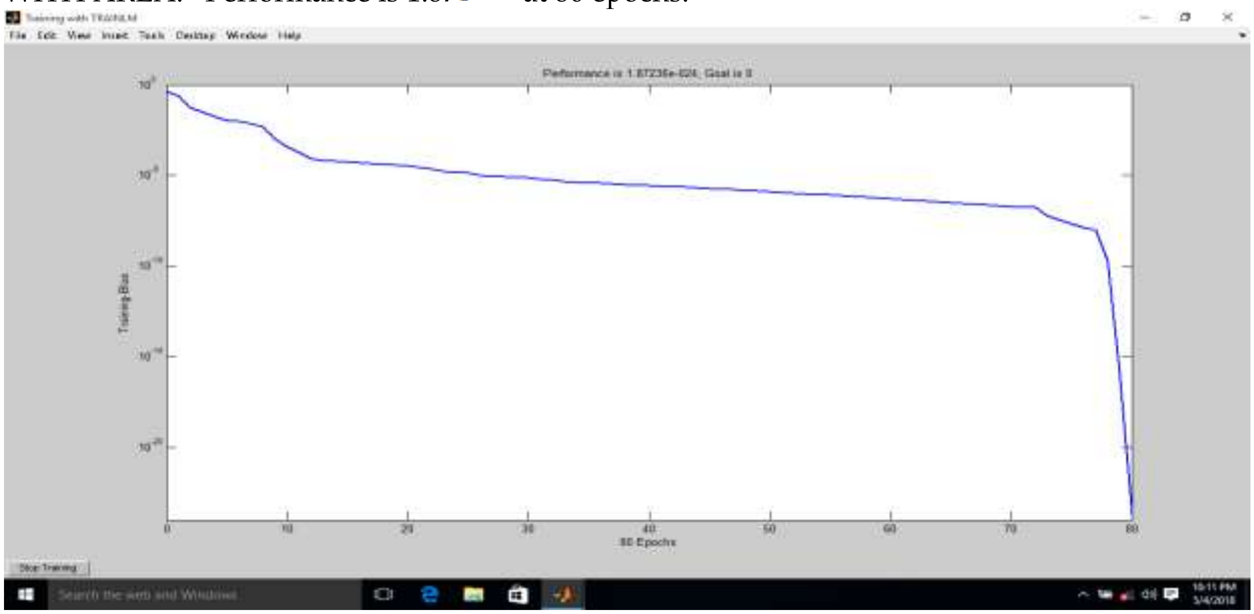
3. PARALLEL FLOW OVERALL HEAT TRANSFER COEFFICIENT MULTIPLIED WITH AREA: - Performance is $1.87e^{-24}$ at 80 epochs.



As we can see the performance is optimized and we can test and validate the results from experiment from the above networks.

V. EXPERIMENTAL VALIDATION:- We have done the experiment to get the real values of the outputs. For that we have used three different values to evaluate the performance.

	Thi(°C)	Tci(°C)	R	Tco(°C)	Tho(°C)	Fhi(LPH)	Fci(LPH)
Y1	40	28.6	0.65	32.5	34	65	100
Y2	50	24.75	0.75	34.5	37	75	100
Y3	60	29.875	0.375	37	41	75	200

Table 3. Experimental values

From the above values we have evaluated the actual values from ANN and real values from the experimental values.

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Table 4. Comparative values of efficiency

	ANN (η)	EXPERIMENTAL (η)
Y1	0.91361	0.4651
Y2	0.95545	0.4684
Y3	0.92322	0.5567

Table 5. comparative values of UA

	ANN (KW)	EXPERIMENTAL(KW)
Y1	0.13127	0.1139
Y2	0.44622	0.1157
Y3	0.12331	0.1039

Table 6. comparative values of entropy generation no.

	ANN	EXPERIMENTAL
Y1	0.03414	0.13398
Y2	0.02287	0.14174
Y3	0.1896	0.22965

VI. RESULTS AND CONCLUSION

- As we can see the ANN values of efficiency are higher whereas the experimental values are less therefore we can conclude that our heat exchanger has been deteriorated over the period of use.
- Reasons for this change could be:-
  Fouling factor
  Thermocouple calibration is wrong.
- Similarly entropy generation number is less for ANN whereas higher for experimental values.
- Thus we can say **efficiency** and **entropy generation** number are the parameters which can be used for the analysis of performance of heat exchanger.

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