HEFAT 2008
6th International Conference on Heat Transfer, Fluid Mechanics and Thermodynamics
30 June to 2 July 2008
Pretoria, South Africa
Paper number: KM2

ARTIFICIAL NEURAL NETWORK BASED PREDICTION OF HEAT TRANSFER IN A VERTICAL THERMOSIPHON REBOILER

Hakeem M.A.* and Kamil M.+
* Author for correspondence
Department of Chemical Engineering
Aligarh Muslim University
Aligarh – 202 002
U.P., India
E-mail:mahakim@rediffmail.com
+Department of Petroleum Studies
Aligarh Muslim University
Aligarh – 202 002
U.P., India
E-mail:sm_kamil@rediffmail.com

ABSTRACT

The present study deals with the prediction of heat transfer coefficients for water and benzene using ANN in a vertical thermosiphon reboiler. The experimental data from the literature were used for training of feed forward artificial neural network with error back propagation technique. Different training algorithms have been applied with different hidden layers and nodes to train the network. It was observed that the heat transfer coefficients predicted was close to the experimental data within the maximum error of ± 20 %. If more exhaustive input data were fed then error would have become still lesser. It has been observed that some algorithms are very efficient with respect to training time in comparison to other algorithms.

Keywords: Neural networks, heat transfer coefficient, thermosiphon reboiler.

INTRODUCTION

Vertical tube thermosiphon reboilers with a horizontal or vertical tube configuration are widely used in petroleum, chemical, petrochemical and power plant industries. The vertical tube units consist essentially of a 1-1 shell and tube heat exchanger placed vertically as one limb of U shaped circulation system. The lower end tube channel is connected through a short tube to another vertical down flow pipe while the upper end channel to a vapor-liquid separator. The flow of liquid is induced under the density difference of liquid at the reboiler inlet and liquid vapor mixture at the outlet, which is strongly influenced by heat transfer. A number of experimental studies have been carried out to investigate the effect of important parameters such as heat flux, inlet liquid subcooling and liquid submergence on heat transfer coefficient and circulation rate in a reboiler tube. Thus there exist a strong interaction between the heat transfer and fluid circulation in a thermosiphon reboiler. The process fluid entering the vertical tubes of the heat exchanger receives the heat from the heating medium (usually steam). Due to vaporization in the tube, the specific volume of the fluid is increased resulting in its upward movement while the liquid is siphoned from the adjoining cold leg. Thus a net flow through the circulation loop is generated. As the sub-cooled liquid enters the heated section and moves up, it undergoes a change in its flow pattern. It has been observed that the various flow patterns developed along the vertical tube of thermosiphon reboiler depend upon several parameters such as heat flux, inlet liquid subcooling, liquid level in cold leg (submergence) and the physical properties of the fluids. These flow patterns affect the hydrostatic conditions near the heated wall, resulting in different modes of heat transfer. Thus hydrodynamics and heat transfer interact with each other, making the process quite complex.

The heat transfer to the liquid in the reboiler tube in effect generates a changing two-phase flow with various regimes spread along the tube length. The difference between the hydrostatic head of the liquid in the cold leg and that of the two-phase mixture in the reboiler tube is responsible for the circulation rate of the liquid through the reboiler. The prediction of rate of liquid circulation and heat transfer is the primary requirement for the design and efficient operation of the thermosiphon reboiler. Several studies [1-13] have been made to predict the heat transfer during the last two decades, but little information is available for the application of ANN in a vertical thermosiphon reboiler [14-17]. There exist two distinct regions of heat transfer over the tube length of a vertical thermosiphon reboiler such as single phase convection and/or subcooled boiling followed by saturated boiling. Some of the investigators have developed empirical /semi empirical correlations for the prediction of heat transfer coefficients in the subcooled and saturated boiling regimes

ANN is information –processing paradigm that is inspired by the way, the biological nervous systems such as the brain processes information. It is composed of large number of highly interconnected processing elements (neurons) working in unison to solve specific problem. It has been used in many engineering applications [14-29] because of providing better and more reasonable solutions. Some examples are: Analysis of thermosiphon solar water heaters, prediction of wall superheat and circulation rate in a reboiler tube, heat transfer data analysis among others. In view of the above it is planned to carry out a systematic study to predict the heat transfer coefficients using ANN in a vertical thermosiphon reboiler using the data from the literature [13]. Different training algorithms (BFGS and SCG) have been applied with different hidden layers and nodes to train the network. It was observed that the heat transfer coefficients predicted was close to the experimental data. If more exhaustive input data were fed then error would have become still lesser. It is observed that some algorithms are very efficient with respect to training time in comparison to other algorithms.

NOMENCLATURE

BFGS	[-]	Broyden, Fletcher, Goldfarb and Shanno update
C	[J/kg ^oC]	Heat capacity
d	[m]	inside diameter of the tube
F	[kg/s]	cooling water flow rate
h	[W/m^2 ^oC]	Heat transfer coefficient
k	[W/m ^oC]	Thermal conductivity
L	[m]	Total length of heated tube
m	[kg/s]	Circulation rate
M_V	[kg/s]	Liquid flow rate from condenser
q	[W/m^2]	Heat flux
S	[%]	Submergence
SCG	[-]	Scaled conjugate gradient
T	[^oC]	Temperature
Tc_1	[^oC]	Inlet temperature of cooling water
Tc_2	[^oC]	Outlet temperature of cooling water
T_{L1}	[^oC]	Inlet liquid temperature to the tube
T_{L2}	[^oC]	Outlet liquid temperature from the tube
T_V	[^oC]	Liquid condensate temperature in condenser vessel
T_S	[^oC]	Liquid saturation temperature in the tube
ΔT_{sub}	[^oC]	Degree of subcooling
Z	[m]	Distance along the test section

Special characters

λ	[J / kg]	Latent heat of vaporization
ρ	[Kg/m3]	Density
μ	[N s / m^2]	Dynamic viscosity
σ	[N / m]	surface tension

EXPERIMENTAL APPARATUS

The experimental facility consisted of a natural circulation reboiler loop with a condenser and cooling system, power supply system and required instrumentation as shown in Fig. 1. The liquid enters the tube at its bottom end, get heated and rises upwards with subsequent boiling. The vapour liquid mixture enters the separator from where the vapors go to the condenser for total condensation. The vapor liquid separator is a cylindrical vessel with a tangential entry of the two-phase mixture in the middle. The level of the test liquid in the down flow pipe (submergence) is indicated by a glass tube level indicator. Further details of reboiler loop and operating procedure can be seen elsewhere [7, 8,13].

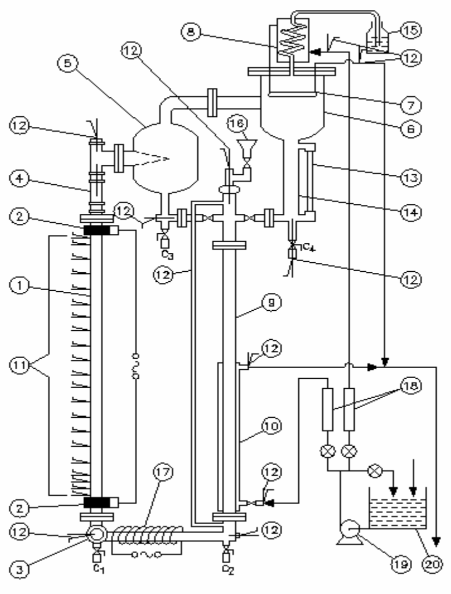

Figure 1 Schematic diagram of the experimental setup [13]

1	Test section
2	Copper clamps
3	View-port for inlet liquid
4	Glass tube section
5	Vapor-liquid separator
6	Primary condenser
7	Spiral coil
8	Secondary condenser
9	Liquid down-flow pipe
10	Cooling jacket
11	Wall thermocouples
12	Liquid thermocouple probes
13	Liquid level indicator
14	Condenser down-flow pipe
15	Removable screwed cap
16	Feeding funnel
17	Auxiliary heater
18	Rotameters
19	Centrifugal pump
20	Cold Water Tank
V1-V3	Control Valves
C1-C5	Drain Cocks

The main unit is a U shaped circulation loop made up of two long vertical tubes connected together with the bottom by a short horizontal stainless tube, while the upper ends are connected to a vapor liquid separator and the condenser. One of the vertical tubes is electrically heated and served as the test section. The liquid enters the tube at its bottom end, get

DATA REDUCTION AND ARTIFICIAL NEURAL NETWORKS APPROACH

For determining the circulation rate it is necessary to know the effective length of the non-boiling or sensible heating region over which the liquid temperature varies linearly. The lengths of the effective boiling and non-boiling zones over the entire heated tube are determined from the quantity of net vapor generation as obtained from the amount of vapor condensed in the condenser. A heat balance around the condenser gives.

$$M_V = \frac{\left[FC_{LC}(T_{C2} - T_{C1})\right]}{\left[\lambda + C_S(T_S - T_V)\right]} \tag{1}$$

Thus,

$$Z_B = \frac{M_V \lambda}{\pi q d} \tag{2}$$

$$Z_{NB} = L - Z_B \tag{3}$$

The rate of liquid circulation caused by buoyancy-induced flow is evaluated by making a heat balance over the non-boiling section.

$$Q = \pi d Z_{NB} q = m C_L \left(T_S - T_{L1}\right) \tag{4}$$

Or,

$$m = \frac{\pi d q Z_{NB}}{C_{L1}(T_S - T_{L1})} \tag{5}$$

The liquid temperature distribution along the length of the tube in the non-boiling zone is calculated assuming a linear relationship as mentioned below.

$$T_L = T_{L1} + \frac{(T_S - T_{L1})Z}{Z_{NB}} \tag{6}$$

Where, $Z \leq Z_{NB}$

The heat transfer coefficients and Nusselt numbers were calculated as per details given in the literature [8].

RESULTS AND DISCUSSION

There are several classes of neural network architectures, classified according to their learning mechanisms in the literature such as: single layer feed forward networks, multilayer feed forward networks and recurrent networks. A multilayer feed forward network as shown in Fig. 2 have three input neurons and one output neuron. The first and last hidden layer comprises of four and two neurons respectively. The nodes

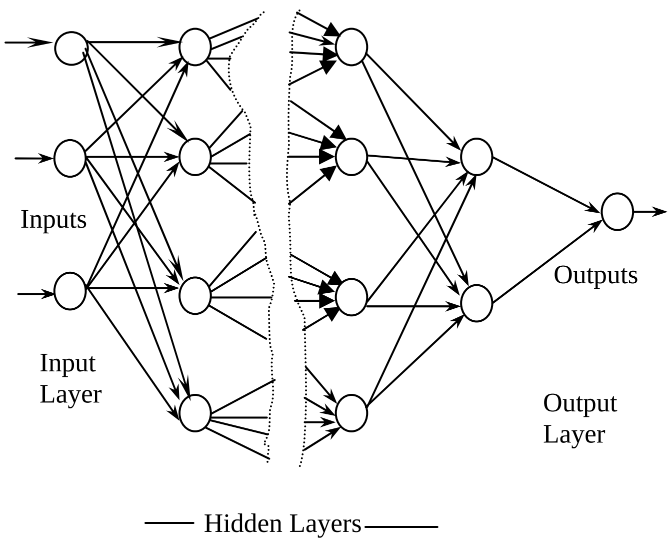

Figure 2 Schematic diagram of multi layer feed forward neural network.

perform non-linear input-output transformations by means of sigmoid activation function. The procedures for training and testing the ANN and its history can be found in the text by Haykin and others [20-29]. Such non-linear mapping enables the ANNs to estimate any function without the need of an explicit mathematical model of the physical phenomenon. To train and test the neural networks, input data patterns and corresponding targets are required. In developing an ANNs model, the available data from the literature are divided into two sets: the network is trained using the first data set and then it is validated with the remaining data as given in the Table 1 and 2. The training of the network is carried out by comparing the output with the target by continuously updating the weights and biases of the same. Thus the configuration of the ANNs is set by selecting the number of hidden layers and the number of nodes in it. The number

Table 1: Training Data for the different ANN topologies for water and benzene

S.No.	Input			Output
	Pe	Pr	Xtt	Nu
	Water			
1	64.76	1.615	0.6378	100.67
2	162.93	1.585	0.0768	127.52
3	284.85	1.588	0.2490	177.60
4	488.35	1.554	0.2479	217.81
5	64.87	1.647	0.0968	78.27
6	163.18	1.611	0.0601	130.76
7	284.78	1.585	0.0834	118.55
8	334.10	1.644	0.1950	159.17
9	65.22	1.651	0.0571	110.98
10	163.46	1.644	0.0607	145.15
11	285.80	1.651	0.0521	150.00
12	486.23	1.665	0.1695	209.59
13	64.98	1.690	0.3261	132.60
14	163.70	1.679	0.1393	177.36
15	286.20	1.686	0.2027	174.40
16	371.02	1.690	0.1676	170.79
	Benzene			
17	85.00	5.146	0.1588	82.65
18	546.88	5.169	0.4891	282.25
19	612.89	5.183	0.2806	330.53
20	142.06	5.156	0.1922	173.01
21	371.55	5.171	0.0259	287.80
22	446.00	5.179	0.0730	286.29
23	546.47	5.168	0.1819	348.27
24	143.21	5.179	0.0325	229.29
25	370.89	5.167	0.1329	374.56
26	442.55	5.160	0.1708	402.89
27	546.51	5.168	0.0600	464.31
28	143.74	5.188	0.0149	289.02
29	257.36	5.180	0.0444	292.59
30	445.48	5.175	0.0206	353.86
31	549.23	5.181	0.0265	383.54

Table 2: Testing data for the different ANN topologies for water and benzene

S.No.	Input			Output
	Pe	Pr	Xtt	Nu
	Water			
1	196.78	1.565	0.1390	135.57
2	428.70	1.554	0.0576	213.30
3	450.53	1.647	0.1658	168.41
4	347.92	1.637	0.0793	188.21
5	431.82	1.693	0.2505	186.89
	Benzene			
6	256.24	5.163	0.3306	204.71
7	443.76	5.166	0.5384	265.14
8	255.90	5.162	0.0814	226.55
9	257.34	5.177	0.0117	313.16
10	373.55	5.186	0.0460	393.57

of nodes in the input and output layer are governed by the input and target data.

Among the various kinds of ANNs, the feed forward neural network has become very popular in engineering applications. Therefore in the present work multi layered feed forward network with the back propagation algorithm have been used. Two different training algorithms have been applied with different hidden layers and nodes to train the network.

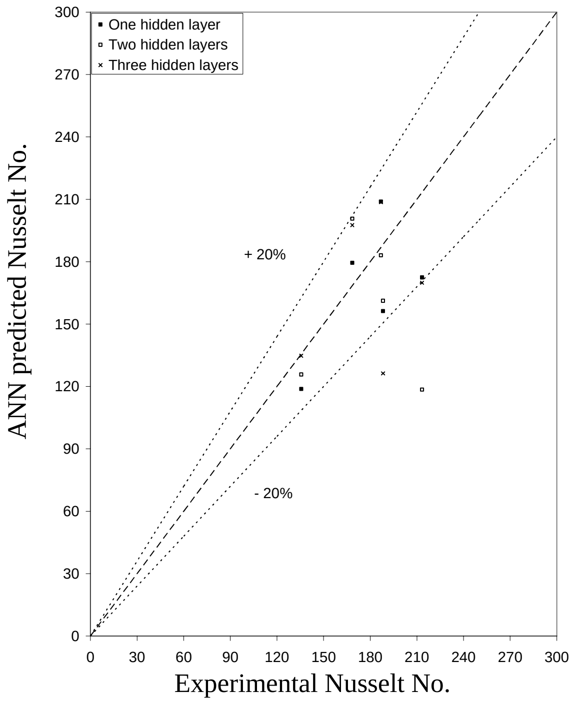

Figure 3 Experimental Nusselt No. versus ANN predicted Nusselt No. for 10 nodes in different number of the hidden layers for water

Figures 3 to 9 represent comparison between experimental and predicted values of Nusselt number. As can be seen in Figures 3 and 4 that a comparison of predicted versus experimental Nu has been made with one, two and three hidden layers respectively for 10 nodes in each hidden layers. Most of the predicted values are very close to the desired line. Around 95 % data are with in maximum error of ± 20 %. A similar comparison is made in Fig. 5 but with 20 nodes in all the hidden layers. Thus it is clear that if the number of nodes increases in different hidden layers than the maximum deviation is less. Figures 6 and 7 shows the capability of the network to predict the heat transfer coefficient by varying the number of nodes for three hidden layers architecture for water and benzene respectively. The maximum deviation is

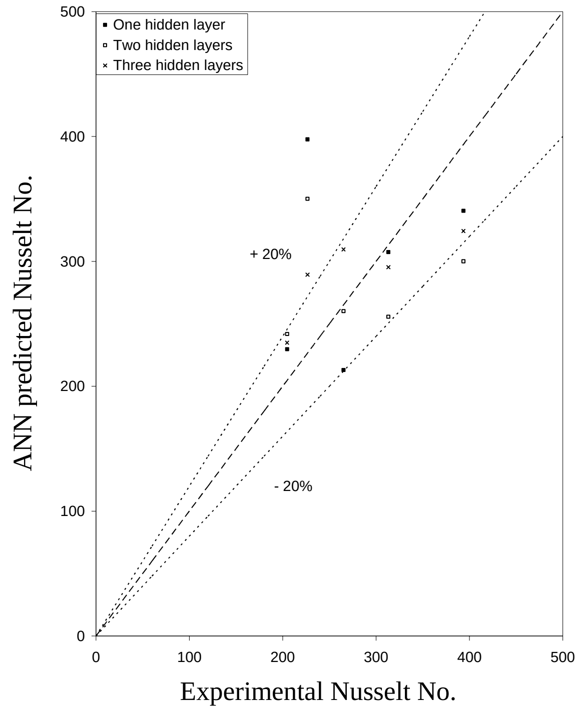

Figure 4 Experimental Nusselt No.versus ANN predicted Nusselt No. for 10 nodes in different number of the hidden layers for benzene

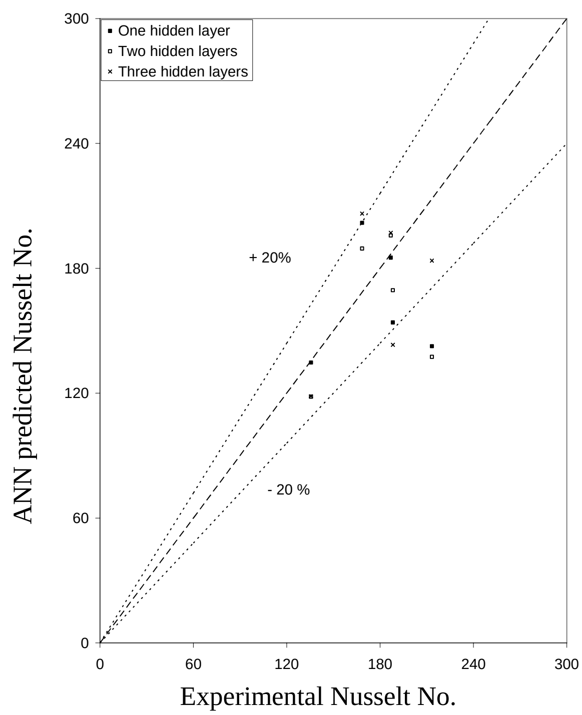

Figure 5 Experimental Nusselt No. versus ANN predicted Nusselt No. for 20 nodes in different number of the hidden layers for water

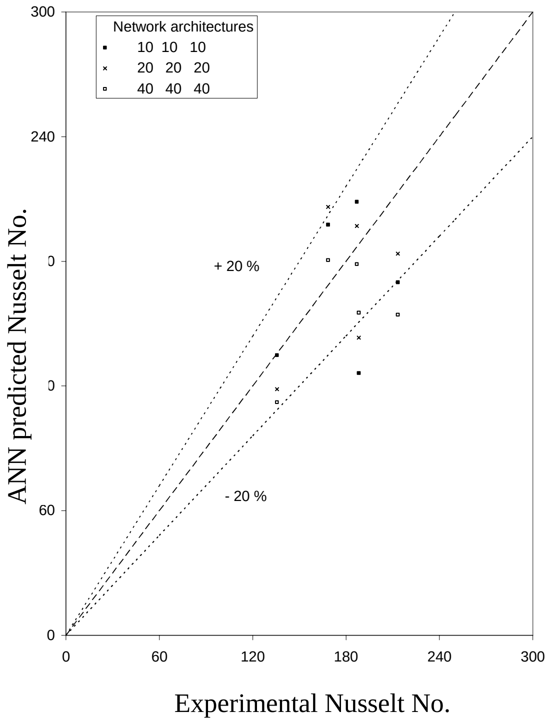

Figure 6 Experimental Nusselt No. versus ANN predicted Nusselt No. for different number of nodes in three hidden layers for water

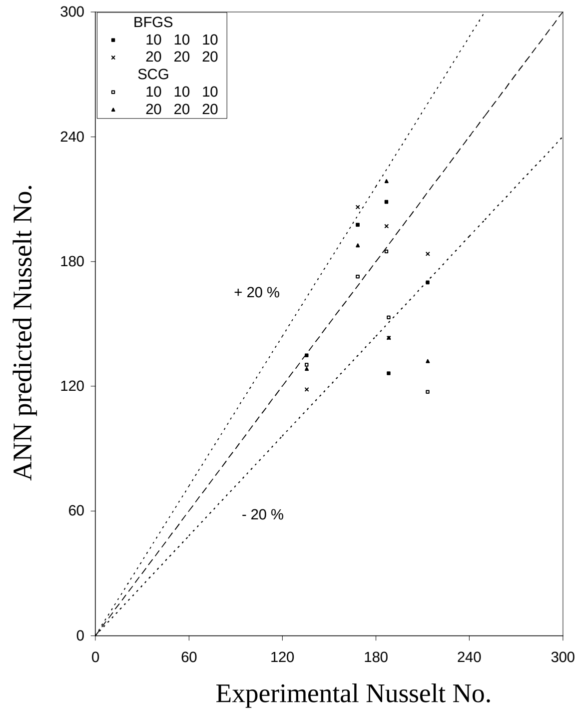

Figure 8 Experimental Nusselt No.versus ANN predicted Nusselt No. using different training algorithm and network architectures for water

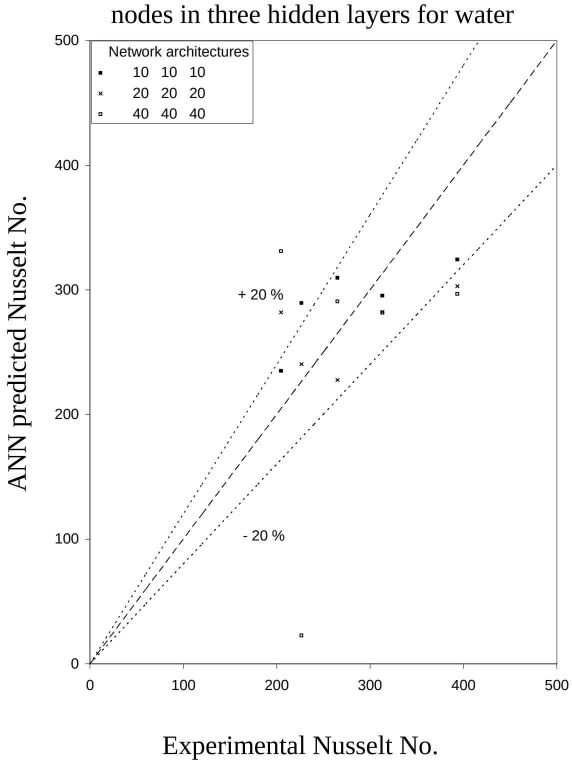

Figure 7 Experimental Nusselt No. versus ANN predicted Nusselt No. for different number of nodes in three hidden layers for

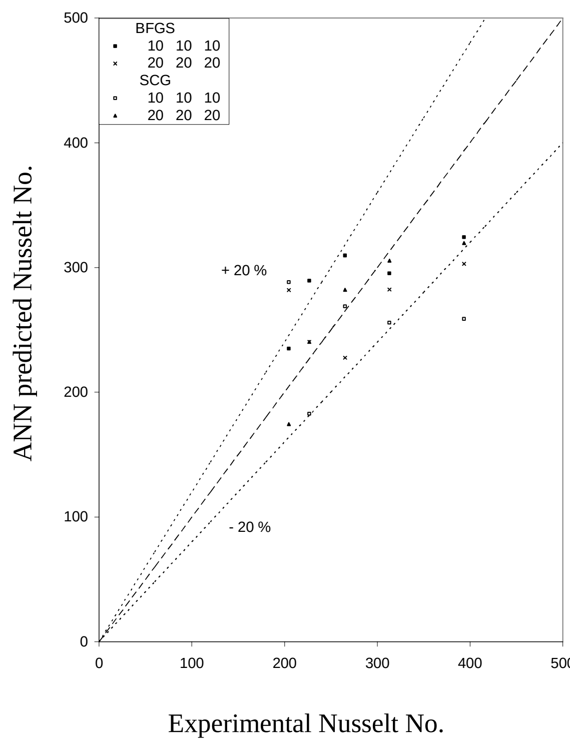

Figure 9 Experimental Nusselt No.versus ANN predicted Nusselt No. using different training algorithm and network architectures for benzene

observed for the architecture of 10-10-10 hidden layers in comparison to other network structures for water. However in case of benzene the maximum deviation was found for 40-40-40 hidden layers architecture. The effect of training algorithm has been shown in Figures 8 and 9. The Scaled conjugate gradient (SCG) algorithm is more error prone in comparison to Broyden, Fletcher, Goldfarb and Shanno update (BFGS) for both systems. However in each algorithm as the number of nodes is increased,

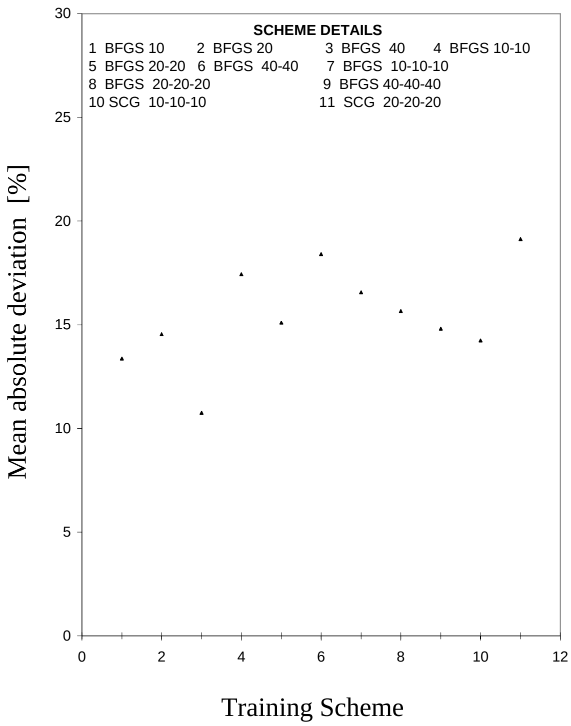

Figure 10 Mean absolute deviation of the test data for the different training scheme for water

the accuracy in the prediction of heat transfer coefficient increases. In Figures 10 and 11 the mean absolute deviation of the predicted results for the various network structures has been shown. The performance of the BFGS is superior over the SCG algorithm for both fluids. The training scheme three (BFGS) with one hidden layer of 40 nodes shows the minimum absolute deviation of around 10 % for water. Other network topology exhibits MAD in the range of 13 to 16 % with the exception of 19 % for SCG training algorithm of 3 hidden layers of 20 nodes each. For benzene the minimum absolute deviation of around 9 % was observed for training algorithm SCG with three hidden layers of 20 each. The maximum MAD is around 39 %

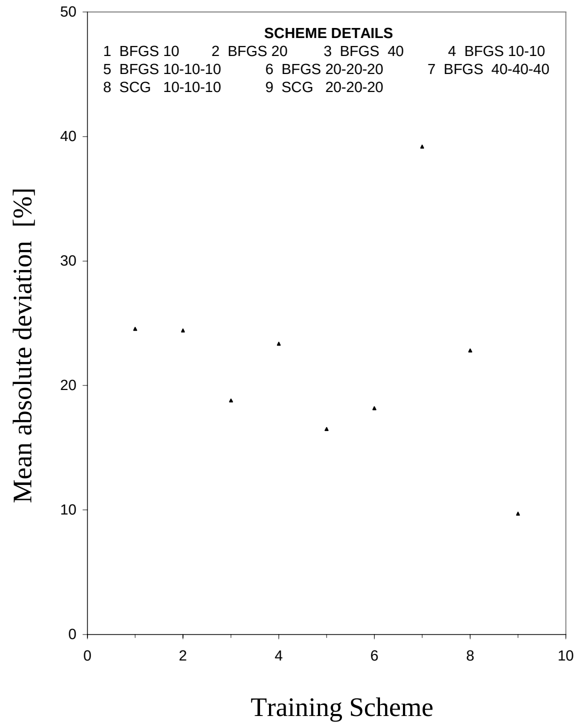

Figure 11 Mean absolute deviation of the test data for the different training scheme for benzene

for BFGS algorithm with three hidden layers of 40 nodes each.

CONCLUSIONS

The following important conclusions can be drawn from the present study.

1. In the prediction of heat transfer coefficient by ANN, the out put from training data gives fairly good matching for water in comparison to benzene.
2. With the increase in the number of hidden layers, the predictability characteristic of the network improves for both systems.
3. As the number of nodes increase, the network performance in general increases.

REFERENCES

[1] P.R. Beaver and G.A.Hughmark, Heat Transfer Coefficients and Circulation

Rates for Thermo siphon Reboiler, *AIChE Journal*, vol. 14, No 5, pp. 746-749, 1968.

[2] K. R. Shellene, C.V. Sternling, D.M. Church and N.H. Synder, Experimental Study of a Vertical Thermosiphon Reboiler, *CEP Symp. Ser*., vol. 64 , No 82, pp. 102-113, 1968.

[3] J. V. Smith, Improving the Performance of Vertical Thermosiphon Reboilers, *CEP*, vol.70, pp.68-70, 1974.

[4] G. C. Shah, Trouble Shooting Reboiler Systems, *CEP*, vol. 75, No 7, pp. 53-58, 1979.

[5] D.L. Johnson and Y. Yukawa, Vertical Thermosiphon Reboilers in Vacuum Service, *CEP*, vol. 75, No 7, pp. 47-42, 1979.

[6] K.P. Hallinan and R. Viskanta, Heat Transfer from a Vertical Tube Bundle under Natural Circulation Conditions, *Int. Journal Heat and Fluid Flow*,vol. 6 No. 4, pp. 256-264, 1985.

[7] M. Kamil, S. S. Alam and H.Ali, Prediction of Circulation Rates in a Vertical Tube Thermosiphon Reboiler **,** *Int. Journal of Heat and Mass Transfer*, vol. 38, No. 4, pp. 745-748 , 1995.

[8] M. Kamil, S. S. Alam and H.Ali, Heat Transfer to Liquids in Single Vertical Tube Thermosiphon Reboiler **,** Experimental Thermal and Fluid Science, vol. 10, pp.44-53 , 1995.

[9] Stephan Arneth. and Stichlmair Johann., Characteristics of Thermo siphon Reboilers**,** *Int. Journal of Thermal Sciences*, vol. 40, No 4, pp. 385-391, 2001.

[10] P. Saha and N. Zuber, An Analytical Study of the Thermally Induced Two Phase Flow Instabilities Including the Effect of Thermal Non- Equilibrium, *Int. Journal Heat Mass Transfer*, vol. 21, pp. 415-426, 1978.

[11] M. Kamil, S. S. Alam, H.Ali and C. P. Agarwal, Estimation of Physical Properties of Single Component Liquids and Binary Mixtures, *Chemical Engineering World*, vol. 29, No. 12, pp. 155-170, 1994.

[12] J.H. Perry, Chemical Engineers Handbook, 5th Edition, McGraw Hill Book Co. Inc., 1973.

[13] M. Kamil, Studies on a vertical thermosiphon reboiler, PhD Thesis, A.M.U. Aligarh, 1992.

[14] M. Kamil, M.A. Hakeem, Artificial neural network based prediction of wall superheat in a vertical thermosiphon reboiler, Proc. of ECI International Conference on Boiling Heat Transfer, [CD-ROM], Paper No. 26, May 7-12, 2006, Spoleto, Italy.

[15] I. Arman, ANN based modeling of thermosiphon reboilers, M.Tech. Thesis, Department of Chemical Engineering, A.M.U. Aligarh, India, 2004.

[16] M.A. Hakeem, M. Kamil and I. Arman, Prediction of temperature profiles in a thermosiphon reboiler using artificial neural networks, Applied Themal Engineering, 2007, doi:10.1016/j.applthermaleng.2007.10.002 . (in Press).

[17] M.A. Hakeem and M. Kamil, Circulation for a vertical thermosiphon reboiler using artificial neural networks, Proc. Of 19th National and 8th ISHMT-ASME Heat and Mass Transfer Conference, JNTU Hyderabad, Jan. 3-5, 2008, India.

[18] A.O.N. Cladio, G. Reinaldo, G. Robert, Neural network based approach for optimization of industrial chemical processes, Computers & Chemical Engineering Journal, 24(9-10) (2000) 2303-2314.

[19] R.Neelakantan, J. Guiver, Applying neural networks, Hydrocarbon Processing, (1998) 91-95.

[20] Haykin, Neural networks, A Comprehensive Foundation, New Jersey, 1994.

[21] J.M. Zurada, Introduction to artificial neural systems, Second ed., Jaico publishing house, N. Delhi, 1997.

[22] D.W. Patterson, Artificial neural network theory and application, Prentice Hall, 1995.

[23] S. A. Kalogirou, Applications of artificial neural networks for energy systems, Appl. Energy, 67(1&2) (2000) 17-35.

[24] T.Y. Lin , C. Tseng, Optimum design for artificial neural networks: an example in a bicycle derailleur system, Eng. Appl. Artif. Intell., 13(2000) 3-14.

[25] S.L Pandharipande, M.A. Siddiqui, A. Dubey, S.A.Mandavgane, Optimising ANN architecture for shell and tube heat exchanger modeling, Indian Journal of Chemical Technology, 11(2004) 804-810.

[26] F.F. Farshad, J. D. Garber, J.N. Lorde, Predicting temperature profiles in producing oil wells using artificial neural networks, Eng. Comput. 17 (2000) 735-753.
[27] M. Cabassud, M.V. Le Lann, in: Application of Neural Network and other Learning Technologies in Process Engineering, Mujtaba, I.M. and Hussain, M.A. (eds), 331(Imperial College Press, London, U.K., 2001.
[28] Y. Islamoglu, A. Kurt Heat transfer analysis using ANNs with experimental data for air flowing in corrugated channels, International J. Heat Mass Transfer, 47(2004) 1361-1365.
[29] T. Liu, X. Sun, X. Li, H. Wang, Neural network analysis of boiling heat transfer enhancement using additives, 45(2002) 5083-5089.