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.

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- Control Valves
V3
C1- Drain Cocks
C5

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:

\[
M_L = \frac{FC_L(T_{c2} - T_{c1})}{\lambda + C_L(T_s - T_y)}
\]  

(1)

Thus,

\[
Z_B = \frac{M_L \lambda}{\pi q d}
\]  

(2)

\[
Z_{NB} = L - Z_B
\]  

(3)

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

\[
Q = \pi d Z_{NB} q = m C_L \left( T_s - T_{l1} \right)
\]  

(4)

Or,

\[
m = \frac{\pi d q Z_{NB}}{C_L(T_s - T_{l1})}
\]  

(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.

\[
T_L = T_{l1} + \frac{(T_s - T_{l1})Z}{Z_{NB}}
\]  

(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 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

![Figure 2](https://example.com/figure2.png)

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

| 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 | 0.0834 | 118.55 |
| 12 | 486.23 | 1.665 | 0.1695 | 209.59 |
| 13 | 64.98 | 1.690 | 0.3261 | 132.60 |
| 14 | 163.70 | 1.644 | 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 | 150.00 |
| 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 6: Experimental Nusselt No. versus ANN predicted Nusselt No. for different number of nodes in three hidden layers for water.

Figure 7: 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 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, 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 10** Mean absolute deviation of the test data for the different training scheme for water

**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 output 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**


