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Studies on Artificial Neural Network Based Prediction of Wall Temperature Profiles for Methanol-Water System in a Natural Circulation Thermosiphon Reboiler

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Abstract

The present study was undertaken to predict the temperature profiles for a binary system (methanol-water) at various operating conditions using artificial neural network in a natural circulation vertical tube thermosiphon reboiler. The heat flux values ranged from about 4.1 to 43.0 kW/ m^2. The liquid submergence levels were maintained around 100, 75, 50 and 30%. Two main operating parameters namely heat flux and liquid submergence affecting the wall temperature profiles were considered as inputs, while the output parameter was temperature profiles. The network was then trained to predict the wall temperature profiles as outputs. A feed-forward back-propagation network was developed and trained using experimental data from the literature. It was observed that the predicted values are in very good agreement with the measured ones indicating that the developed model is fairly accurate and has the great ability for predicting the temperature profiles. If more exhaustive input data are fed: heat flux, submergence and mass percent then the capability of the network to predict the temperature profile would had been better. The predicted temperature profiles yielded the relative error of the order of 0.1% in majority of the cases.

Keywords: *Artificial neural network; Temperature profiles; Natural circulation loop; Thermosiphon reboiler; Methanol-Water*

1. Introduction

Vertical tube thermosiphon reboilers are most widely used in chemical, petroleum and petrochemical industry. These are characterized by high heat transfer rate and low fouling tendencies. Such type of reboiler is very reliable, easy to setup, lower operating costs and has compact dimensions. Few studies have been conducted to investigate the hydrodynamics and heat transfer aspect of natural circulation boiling of single component liquids/ binary liquid mixtures in vertical tubes. Most of the studies reported are under the conditions of uniform wall temperature heating with saturated liquids. Few studies for constant wall flux heating are also reported in the literature. Prediction of boiling incipience, circulation rate and heat transfer to boiling liquids are important parameters in the design and operation of vertical thermosiphon reboilers [1-8].

Artificial neural network like humans, learn by example and past experience. ANNs are being applied to an increasing number of real world problems of large complexity and offer ideal solutions to a variety of problems such as signal recognition, function prediction and system modeling where the physical processes are not understood or are highly complex. ANNs are relatively crude electronic models based on the neural structure of the human brain. These models

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may take the form of mathematical equations as created by both scientist and engineers. ANNs represent a complex configuration, which includes many simple processors (artificial neurons), arranged in layers (input, hidden and output layers) connected in a particular fashion. The proper transformation of information is possible as a result of a correctly prepared matrix of weights (which are numbers) attributed to all inter-neuron connections. In Multi Layer Perceptron (MLP) feed forward networks, each neuron simply sums up (properly amplifies or weakens) the weighted signals from all neurons of the previous layer with some threshold value called biases. The resulting values are transformed through suitable activation functions which are known as signum functions. Thus in order to prepare a network for solving a task, values of the weight of each connection must be adjusted. The adjustment of these values is the main and most important part of modeling with ANN's, which is called as 'learning procedure' and is carried out by means of an algorithm. The learning process is executed on the basis of input data sets associated with the output sets. During the learning process, the computer software compares the calculated values with the expected ones, and adjusts the values of the weights and biases to reach the best agreement between the input and output in a step by step approach. The non-linear optimization is used for updating the weights and biases till the output values for each pattern become close to the target values. After extensive training, the network will eventually establish the input-output relationships through the adjusted weights and biases of the network.

Artificial neural networks (ANNs) have been used in many engineering applications because of providing better and more reasonable solutions. Most chemical engineering problems are nonlinear and complex with conventional modeling and simulation techniques relying often on certain simplifying transport, kinetic and /or thermodynamic assumptions. ANN process models are more cost effective and eliminate the need for detailed effort. These have been successfully employed in solving problems in areas such as: analysis of thermosiphon solar water heaters, heat transfer data analysis, HVAC computations and prediction of critical heat flux among others. Cladio et al. [9] used neural network approach for optimization of industrial chemical processes. The procedures for training and testing the ANN and its history can be found in the text by Haykin and others [10-14]. Such non-linear mapping enables the ANNs to estimate any function without the need of an explicit mathematical model of the physical phenomenon. Kalogirou [15] used ANNs for performance prediction of forced circulation type solar domestic water heating, Lin and Tseng [16] for optimal design using ANN by taking the example of bicycle derailler system. Pandharipande et al. [17] studied for optimizing ANN network for shell and tube heat exchanger. Farshad et al. [18] used an ANN algorithm for predicting temperature profiles in producing oil wells. Cabassud and Le Lann [19], Islamoglu and Kurt [20] used ANNs for heat transfer analysis in corrugated channels. Tianqing Liu et al. [21] developed a model to evaluate and predict boiling heat transfer enhancement using additives. The proposed model was based on the molecular structures of the additives and uses ANN technology. Heydari et al. [22] predicted hydrate formation temperature for natural gas using artificial neural network. Recently Hakeem and Kamil [23-27] predicted temperature profiles, circulation rate; heat transfer and wall superheat for water in a vertical thermosiphon reboiler using ANN. Sreekanth et al. [28] used neural network approach for evaluation of surface heat transfer coefficient at the liquid solid interface. Pouraliakbar et al. [29] used a neural network with feed forward topology and back propagation algorithm to predict the effects of chemical composition and tensile test parameters on hardness of heat affected zone (HAZ) in X70 pipeline steels. Khalaj et al. [30] developed an artificial neural network-based model (ANNs) to predict the layer thickness of pre-nitride steels using seventeen parameters affecting the layer thickness were considered as inputs, including the pre-nit riding time, salt bath compositions ratio, salt bath aging time, ferrochromium particle size, ferrochromium weight percent, salt bath temperature, coating time, and different chemical compositions of steels. The network was then trained to predict the layer thickness amounts as outputs. A 2-feed-forward back-propagation network was developed and trained using experimental data form literature. Faizabadi et al. [31] applied the artificial neural networks with multilayer feed forward topology and back propagation algorithm containing two hidden layers to predict the effect of chemical composition and tensile properties on the both impact toughness and hardness of microalloyed API X70 line pipe steels. Further Khalaj et al. [32] presented some results of the research connected with the development of new approach based on the artificial neural network (ANN) of predicting the transformation start temperature of the phase constituents occurring in five steels after continuous cooling. Nazari et al. [33] predicted compressive strength of geopolymers made from seeded fly ash and rice husk–bark ash by adaptive network-based fuzzy inference systems (ANFIS). Different specimens, made from a mixture of fly ash and rice husk–bark ash in fine and coarse forms and a mixture of water glass and NaOH mixture as alkali activator, were subjected to compressive strength tests at 7 and 28 days of curing. According to input parameters in the ANFIS models, the compressive strength of each specimen was predicted. The training and testing results in ANFIS models showed a strong potential for predicting the compressive strength of the geopolymeric specimens. Chakrabarti and Sastry [34] used an artificial neural network (ANN)-based novel technique to determine the liquid-liquid flow regime. This approach uses phase superficial velocities as input parameters, which are obtained from a specific set of data obtained from experimental investigations. Both experimental and ANN-based determinations of liquid-liquid flow pattern have been undertaken for a common data set and the results are compared to prove the effectiveness of ANNs in pattern recognition. A unique ANN architecture is identified with three hidden layers, and the inputs and outputs are modeled into binary form. Levenberg-Marquardt (LM) learning algorithm is used for training neural network. Azizi and Karimi [35] developed a three–layer artificial neural network (ANN) model to predict the pressure gradient in horizontal liquid–liquid separated flow. A total of 455 data points were collected from 13 data sources to develop the ANN model. Superficial velocities, viscosity ratio and density ratio of oil to water, and roughness and inner diameter of pipe were used as input parameters of the network while corresponding pressure gradient was selected as its output. Levenberg–Marquardt back–propagation algorithm was applied to train the ANN. The optimal topology of the ANN was achieved with 16 neurons in hidden layer, which made it possible to estimate the pressure gradient with a good accuracy. In addition, the results of the developed ANN model were compared to Al–Wahaibi correlation and it is found that the proposed ANN model has higher accuracy. Finally, a sensitivity analysis was carried out to investigate the relative importance of each input parameter on the ANN output. Shirley and Chakrabarti [36] used ANN in liquid-liquid two phase flow. Further few workers [37, 38] employed ANN for the prediction of surface tensions of binary mixtures, estimating sulphur content of hydrogen sulphide at elevated temperatures and pressures.

Thus it is understood from the literature that ANNs better serve to thermal analysis in engineering applications.

Thus it is clear that limited work has been reported in the literature on the application of artificial neural networks to boiling heat transfer in analysis in a vertical thermosiphon reboiler. Therefore, present study has been carried out on the applicability of ANNs for predicting temperature profiles in a vertical thermosiphon reboiler. In view of the above it has been planned to undertake a systematic study to develop a new model based on ANNs for the prediction of wall temperature profiles for a binary liquid mixture in a vertical thermosiphon reboiler. The experimental data from literature was first preprocessed. Using this data, the formulation of an ANN model was made.

2. Experimental Apparatus and Procedure

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 the schematic diagram in Fig. 1. The main unit was 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 heated and rises upwards with subsequent boiling. The vapor liquid mixture enters the separator from where the vapors go to the condenser for total condensation. The condensate and the liquid from the separator were directed towards the top of the other tube serving as down flow cold leg. The entire liquid from the cold leg ultimately entered the test section through a view port. The vapor liquid separator was a cylindrical vessel with a tangential entry of the two-phase mixture in the middle. The vapors were condensed by means of two water-cooled condensers used in series. The primary condenser was a spiral coil fitted just below the top cover of the condenser vessel. The condensation took place at the outer surface of the coil and condensed liquid drained down the bottom of the condenser vessel through a vertical tube fitted with a liquid level indicator. A thermocouple was also inserted in this tube to measure the condensate temperature. The uncondensables, if any, from the primary condenser entered the helical coil of the secondary condenser. The exit of the condenser was connected to a glass tube with its free end dipped into a bottle containing the test liquid so as to provide effective visual observation of the removal of traces of dissolved air from the test liquids during initial boil off. A centrifugal pump and storage tank arrangement connected to freshwater supply was used for circulating water in the condensers.

To measure the total rise in temperature of the cooling water, thermocouple probes of copper-constantan were located at the inlet of the secondary condenser and the outlet of the primary condenser. In order to control the inlet liquid temperature to the test section, the liquid down flow pipe was jacketed from the lower end up to a height of 1000 mm, using a pipe of 80 mm I.D. in which cooling water was passed as and when needed. The inlet and outlet temperatures of the water in the jacket were measured by means of thermocouple probes fitted therein. The temperature of the test liquid exiting from the down flow pipe and entering the horizontal pipe was measured by another thermocouple probe inserted at the bottom of the down flow pipe. The level of the test liquid in the down flow pipe (submergence) was indicated by a glass tube level indicator. This level acted as the driving force for the circulation of liquid through the loop.

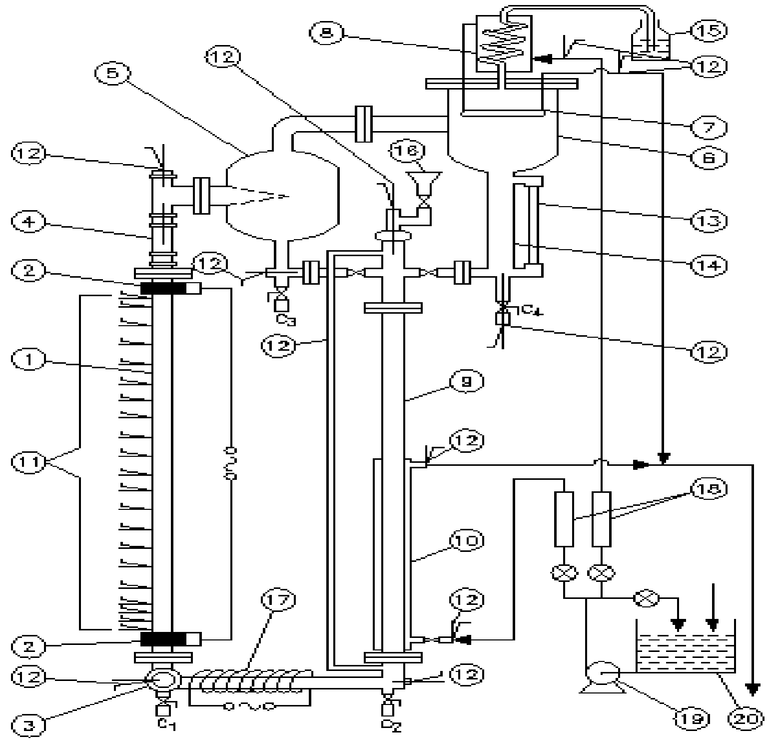
Prior to the start of the experimentation, the setup was hydraulically tested for leaks. It was flushed with distilled water for through cleaning and finally filled with it upto the top of the test section. The connections to the power supply, thermocouples and various measuring instruments were made and checking their calibration ensured the satisfactory performance of these. Power was supplied to the test section and circulation system. Simultaneously, cooling water supply was activated thereby ensuring adequate amount of cooling water to the condensers. Drain cocks were provided at the inlet of test section and exit of the separator and condenser. The entire set up was thoroughly lagged with asbestos rope and glass wool and finally covered with a thin aluminum sheet to reduce the heat losses, which were less than ± 2.5%. This step was essential for the reproducibility of data. Extreme care was taken that once the tube wall got stabilized, it must remain fully submerged with the liquid as the dry surface was very liable to entrap a thin film of air. This air on heating leaves the surface as tiny bubbles and joins the liquid, thereby setting up micro convection near the surface, resulting in additional extraneous turbulence causing error. During startup for conducting a series of runs, the test liquid was boiled off for about 6-8 hours to remove the last traces of dissolved air that was indicated by the cessation of air bubbles in the bubbler. After this, the desired heat flux was impressed upon the test section by proper adjustment and cooling water flow rate was maintained. Adding or draining the necessary amount of test liquid maintained the liquid level in the down flow pipe. When steady state conditions were established, reading of thermocouples, various electrical instruments and rotameters were recorded. The liquid level in the down flow pipe was observed and noted from the glass tube level indicator. While keeping the inlet liquid level and submergence unchanged, readings were taken for different heat fluxes in increasing order. Other details of reboiler and cooling system along with its operating procedure are described in detail elsewhere in literature [39].

The thermocouples were connected to a multi-logger (Model 56-7501 Iwatsu, Japan), through two selector switches of 24 and 12 points each. The temperatures were read directly from the multilogger. It had a built in arrangement for reference point temperature compensation, accuracy of $\pm$ 0.5 (23 ^{o}C $\pm$ 5 ^{o}C, 80% RH) and $\pm$ 1.5 ^{o}C (0 to 50 ^{o}C) below 60% RH). Worst resolution for copper constantan thermocouple was 0.1 ^{o}C and accuracy was $\pm$ 0.2 of full scale. Flow rates of cooling water to the condenser and the jacket were measured by two calibrated rotameters of 0-15 lit/min range.

3. ANN Methodology

ANNs are able to produce a set of outputs for a given set of inputs according to some mapping relationship. During training period such relationship is coded into the network structure depending upon the network parameters. The number of hidden layers and nodes may vary in different applications and depend on the user specifications. No specific technique is available to decide the optimum number and it is usually carried out through trial and error procedure.

To train and test the neural networks, input data patterns and corresponding targets are required. In developing an ANNs model, the available data [39] are divided into two sets: the network is trained using the first data set and then it is validated with the remaining data. 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 of nodes in the input and output layer are governed by the input and target data. The main advantage of neural network over conventional regression analysis is: free of linear supposition, large degrees of freedom and more effectively deal with nonlinear functional forms. Therefore, in the present work multi layered feed forward network with the back propagation algorithm have been used for the prediction of temperature profiles in a vertical thermosiphon reboiler. The Newton-Raphson optimization technique is employed to minimize the error. For training the networks, the goal was fixed based on MSEREG as 1. For input and hidden layers, tanh sigmoidal function and linear function for the output layer was taken. It is evident from the data that the temperature profile is highly dependent on heat flux, submergence and mass percent.



1	Test section	12	Liquid thermocouple probes
2	Copper clamps	13	Liquid level indicator
3	View-port for inlet liquid	14	Condenser down-flow pipe
4	Glass tube section	15	Removable screwed cap
5	Vapor-liquid separator	16	Feeding funnel
6	Primary condenser	17	Auxiliary heater
7	Spiral coil	18	Rotameters
8	Secondary condenser	20	Cold water tank
9	Liquid down-flow pipe	V_1-V_3	Control valves
10	Cooling jacket	C_1-C4	Drain cock valves
11	Wall thermocouples		

Figure 1. Schematic diagram of the experimental setup

4. Modeling by Artificial Neural Networks (ANN)

In the first step, inputs and outputs must be specified, such that inputs must have a theoretical relation to outputs; otherwise there will be problems encountered in the training procedure.

A reliable database is critically important for training and testing of an ANN. Experimental data on wall temperature profiles of methanol-water system has been taken from the literature [39]. In order to avoid over-fitting problems that threaten the generalization capabilities of ANNs, the experimental data have been categorized into training and testing sets. The training set has been used for determination of optimum weight factors as well as biases leading to minimum error. In order to check the prediction ability of the trained ANN, a number of the experimental data have been randomly excluded from the training sets better known as testing sets. The testing set (25% of remaining experimental data) has been used to gauge the efficacy of the training. In the next step, the type of network, the number of layers and the activation function of each layer must be defined; this step is the most important and challenging step in designing and training an ANN. Generally, it is done through a trial and error procedure. Broyden, Fletcher, Goldfarb and Shanno (BFGS), has been used for the training procedure. The specifications of the selected ANN have been presented in the results and discussion section.

There are several classes of neural network architectures, classified according to number of layers, neurons and their interconnections 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 hidden layers having five neurons each, one input layer of three neurons and one output layer of single neuron. Number of neurons in input and output layer is governed by type of input and target fed to the network. The nodes perform non-linear input-output transformations by means of sigmoid activation function. These are given in the following equations:

$$O_{21}=\frac{1-\exp\left[-2\left(\left(\sum_{i=1}^{3}W_{2,1j}*i_j\right)+b_{21}\right)\right]}{1+\exp\left[-2\left(\left(\sum_{i=1}^{3}W_{2,1j}*i_j\right)+b_{21}\right)\right]} \quad O_{32}=\frac{1-\exp\left[-2\left(\left(\sum_{j=1}^{5}W_{3,2j}*O_{2j}\right)+b_{32}\right)\right]}{1+\exp\left[-2\left(\left(\sum_{j=1}^{5}W_{2,2j}*O_{2j}\right)+b_{32}\right)\right]}$$

$$O_{44}=\frac{1-\exp\left[-2\left(\left(\sum_{j=1}^{5}W_{4,4j}*O_{3j}\right)+b_{44}\right)\right]}{1+\exp\left[-2\left(\left(\sum_{j=1}^{5}W_{4,4j}*O_{3j}\right)+b_{44}\right)\right]} \quad O5=\left[\left(\sum_{j=1}^{5}W_{5,1j}*O_{4j}\right)+b_5\right]$$

MATLAB 6P5 was used to perform ANN calculations.

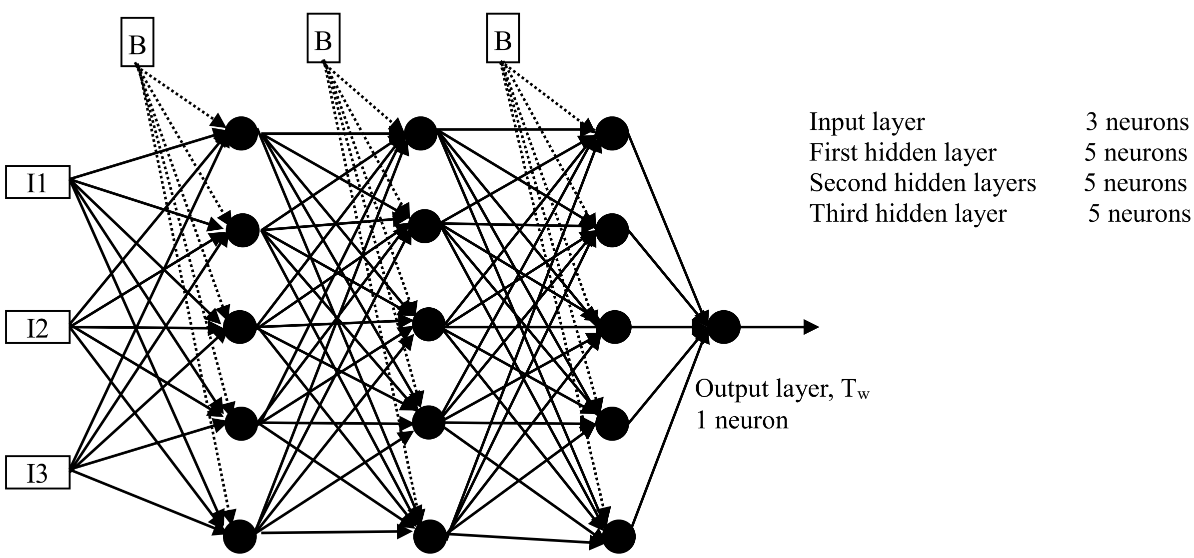


Figure 2. A typical architecture of ANN

Table 1 show the range of experimental values in the present study. There are 99 temperature profiles corresponding to different values of heat flux submergence and mass percent of methanol. The training was done for three types of ANN structures. The experimental data at these parameters show the variation of wall temperature along the length of test section [39]. For a particular mass percent of methanol and submergence levels the network was trained with heat flux as input and temperature profile as an output.

Table 1. Range of experimental parameters

System	Heat flux, $q \times 10^{-4}$ [W m^{-2}]	Submergence S [%]	Concentration, X [wt.%]
Distilled water	0.57-4.3	30, 50, 75, 100	100
Methanol	0.41-2.1	30, 50, 75, 100	100
Methanol-water	0.57 2.9	30, 50, 75, 100	5, 10, 18, 26, 30, 38, 58

Table 2 shows the training and test data for 5 mass percent of methanol at 100% submergence Thus for a given mass percent and submergence the temperature profiles were obtained at desired heat flux. This way the 99 networks were trained. The next network in which heat flux and submergence was input; the temperature profile was the output. The versatility of it to predict the temperature profile enhanced significantly. Thus corresponding to each mass percent of methanol, the temperature profile can be deduced by feeding the heat flux and submergence.

Table 2: Training and test data at 100% submergence and 5 mass percent methanol with heat flux as input

Distance along test section Z, m	Training data			Test data		
	Input Heat flux W/m^2			Input Heat flux W/m^2		
	8215	21305	29516	16599		
	Output Temperature ^{0}C			Output Temperature,^{0}C Experimental	Output Temperature,^{0}C AN N simulated	Percentage error
0.05	100.3	103.4	106.5	102.7	103.17	-0.46
0.1	102.2	104.2	107.6	103.9	103.9	0
0.15	103.3	105.4	108.5	104.9	105.52	-0.59
0.2	104.4	107.8	109.5	106.8	107.69	-0.83
0.3	105.1	106.2	110.5	107.3	106.22	1.01
0.4	104.9	106.9	110.2	107.9	106.79	1.03
0.5	104.6	106.4	110.0	107.6	106.36	1.15
0.6	104.7	106.4	108.1	107.0	106.41	0.55
0.7	104.6	105.8	108.4	106.2	105.61	0.56
0.8	104.2	105.8	108.3	105.4	105.98	-0.55
0.9	103.8	105.0	108.3	105.0	104.91	0.09
1.0	103.6	104.6	109.0	104.4	104.58	-0.17
1.1	103.3	104.0	108.3	104.0	103.84	0.15
1.2	103.3	103.4	106.6	103.4	103.45	-0.05
1.3	102.9	103.2	105.7	103.2	103.04	0.16
1.4	101.9	102.8	104.4	102.8	102.84	-0.04
1.5	101.5	102.4	103.2	102.4	102.16	0.23
1.7	100.8	102.4	102.8	101.9	102.48	-0.57
1.8	99.8	102.2	102.9	101.6	102.42	-0.81
1.85	99.7	102.6	102.6	101.6	102.45	-0.84

Table 3(a). Training data at 5 mass percent of methanol with heat flux and percent submergence as input

Input Heat flux W/m^2	8215	21305	29516	16599	21305	29516	8215	16599	21305	21305	29516	Distance along test section, Z, m
Input Submergence, %	100	100	100	75	75	75	50	50	50	30	30	
Output Temperature, °C	100.3	103.4	106.5	103.1	103.6	108.2	101.2	108.7	108.9	113.7	120.7	0.05
	102.2	104.2	107.6	104.0	105.8	109.5	103.5	110.7	114.4	114.1	117.6	0.1
	103.3	105.4	108.5	107.4	106.0	109.8	105.2	117.3	115.5	108.1	116.0	0.15
	104.4	107.8	109.5	108.0	106.8	107.5	106.7	114.5	116.3	106.8	111.9	0.2
	105.1	106.2	110.5	105.4	108.4	107.7	109.1	113.3	117.8	105.8	107.8	0.3
	104.9	106.9	110.2	105.5	109.6	107.6	105.4	108.2	109.6	105.4	107.2	0.4
	104.6	106.4	110.0	106.2	109.4	107.3	103.2	104.4	109.0	105.2	107.0	0.5
	104.7	106.4	108.1	106.4	108.0	107.3	102.5	103.6	106.7	105.4	106.6	0.6
	104.6	105.8	108.4	106.4	108.0	106.4	102.3	103.3	105.2	105.3	106.4	0.7
	104.2	105.8	108.3	106.6	105.9	106.8	102.1	102.9	104.4	105.4	106.4	0.8
	103.8	105.0	108.3	105.2	104.2	105.8	102.1	102.6	103.4	105.3	106.4	0.9
	103.6	104.6	109.0	104.4	103.6	105.2	102.2	102.8	104.0	105.4	106.4	1.0
	103.3	104.0	108.3	104.2	102.9	104.6	102.2	102.6	104.2	105.5	106.6	1.1
	103.3	103.4	106.6	104.4	102.4	103.4	102.2	102.5	103.9	105.5	106.9	1.2
	102.9	103.2	105.7	102.4	101.7	102.6	102.2	102.4	103.8	105.4	106.5	1.3
	101.9	102.8	104.4	101.8	101.6	102.4	102.1	102.3	103.7	105.6	106.8	1.4
	101.5	102.4	103.2	101.4	101.5	102.3	102.1	102.2	103.4	105.8	107.0	1.5
	100.8	102.4	102.8	100.9	101.4	101.9	101.6	101.8	103.6	105.4	106.9	1.7
	99.8	102.2	102.9	100.8	101.2	101.6	101.5	101.7	103.5	105.4	106.6	1.8
	99.7	102.6	102.6	100.4	100.9	101.5	101.4	101.6	103.3	105.2	106.5	1.85

Table 3(b). Test data at 5 mass percent of methanol with heat flux and percent submergence as input

Distance along test section Z, m	Input, Heat flux, W/m^2	16599	16599	8215	8215	29516	29516	25241	25241
	Input submergence, %	100	100	75	75	50	50	30	30
		Exp.	ANN	Exp.	ANN	Exp.	ANN	Exp.	ANN
0.05	Output Temperature T, ^{0}C	102.7	101	110.9	117.6	103.9	99.8	110.5	118.1
0.1		103.9	103.3	115.4	115.6	104.8	100.5	114.7	116.4
0.15		104.9	105.2	116	109.2	108.6	102.5	117	112.9
0.2		106.8	107.2	117.2	107.4	109.4	103.7	116.2	109.9
0.3		107.3	107.8	118.4	106.4	107.4	104.3	117.9	107.1
0.4		107.9	108.2	115.6	106	106.7	105	110.5	106.6
0.5		107.6	105.5	111.5	105.8	106.5	104.2	108.6	106.4
0.6		107	105.6	109.9	105.8	106.1	104.3	106.3	106.3
0.7		106.2	104.4	108.6	105.7	106.4	104.2	105.1	106
0.8		105.4	104.1	107	105.9	106.6	104	104.5	106
0.9		105	105.4	105.4	106.1	106.4	103.6	103.9	106.1
1.0		104.4	104.3	105.4	106.1	106.5	103	104.6	106.1
1.1		104	104.2	105.1	106.3	106.2	102.7	104.6	106.3
1.2		103.4	103.8	105	106.1	106	102.6	103.6	106.4
1.3		103.2	101.7	105.2	106	104.3	102	103.7	106.1
1.4		102.8	101	105.2	106.5	103.2	101.4	103.8	106.4
1.5		102.4	101.2	105.2	106.7	102.2	101.3	103.4	106.5
1.7		101.9	100.9	105.1	106.1	101.6	100.6	103.6	106.3
1.8		101.6	100.4	104.9	106	101.4	100	103.6	106.2
1.85		101.6	100.4	104.8	105.9	101.1	99.9	103.5	106

Table 3(a) and 3(b) give the training and test data at 5 mass percent of methanol, with input and output as mentioned above. In the third network, heat flux, mass percent and submergence were chosen as input while yielding the temperature profile as output. Hence only one network training was sufficient for whole range of data. Table 4 represents the test data with three variables as input. The single hidden layer was chosen with the number of nodes 40 for the entire three networks. In the network 1, heat flux was input and temperature profile was output, hence the number of neurons in input and output layer was 1 and 20 where as in the network 2, heat flux and submergence were input and the temperature profile was the output (so the number of neurons in input and output layer were 2 and 20). In the network 3, heat flux, submergence and mass percent were input and temperature profile was output, hence the number of neurons in input and output layer was 3 and 20 respectively.

Figure 3 shows the comparison of predicted and experimental temperature profiles with heat flux as input at 5 mass percent of methanol. In this plot the heat flux of is a test data, while the remaining three were taken as training data at 100% submergence level. This figure shows very good prediction with maximum error of the order of 1.0 %. The training data and test data are shown in Table 2.

Figure 4 shows the comparison of temperature profiles with heat flux 21305 W/m^2 as input at 5 mass percent methanol and S=50%.

Figures 5 and 6 were drawn on the same premise except the mass percent of methanol which was taken as 17. The prediction in figure 5 yielded unsatisfactory performance due to extrapolated value of test data. This has the maximum error of around 15%. While in figure 6 the prediction was satisfactory due to test value were in training range.

Table 4. Test data with heat flux, percent submergence and mass percent of methanol as input and temperature profile as output

Distance along test section Z, m	Input																
	Heat flux , W/m^2	16599	16599	25241	25241	12289	12289	12289	12289	21305	21305	25241	25241	8215	8215	21305	21305
	Percent Submergence,	100	100	75	75	50	50	100	100	50	50	30	30	100	100	50	50
	Methanol mass fraction, X	5	5	10	10	17	17	26	26	26	26	30	30	38	38	58	58
		Output Temperature, ^{0}C															
		Exp.	ANN	Exp.	ANN	Exp.	ANN	Exp.	ANN	Exp.	ANN	Exp.	ANN	Exp.	ANN	Exp.	ANN
0.05		102.7	103.2	105.8	105.9	102.2	100.3	92.5	93.5	97.4	103.7	99	103.4	88.5	91.6	103	101.7
0.1		103.9	104.4	108.4	108.5	105.4	101.7	93.8	94.2	98	105.6	99.3	104.3	89	93.1	104.8	105
0.15		104.9	105.3	111.8	109.8	107.9	103.4	95.4	95.4	99.8	107.2	99.4	104.6	89.9	93.7	107.2	107.2
0.2		106.8	106.1	112.2	110.8	107.4	102.9	96.7	96.5	98.2	106.1	99.5	106.1	91.6	94.5	108.9	106.5
0.3		107.3	106.4	108.3	111.9	103.2	102.8	98.5	97.9	98	104.2	99.8	107.1	92.4	95.7	108	104.9
0.4		107.9	106.6	108.2	113.4	97.1	99.9	98.9	99.3	97.4	102.2	100	108.1	93.9	97.4	103.6	102.2
0.5		107.6	107.4	108.6	113.7	96.4	97.5	100.2	101.9	96.7	99.4	100.1	107.9	94.4	98	93.9	93.3
0.6		107	107.5	115.2	114.1	96.6	96.7	103.3	104	96.6	97.2	100.4	105	95.2	98.8	87.6	88.6
0.7		106.2	107.6	110.8	114.2	96.9	96.5	106	105.5	96.5	96.7	100.6	104.7	95.4	99.6	86.4	85.9
0.8		105.4	107.9	109.2	113.4	96.8	97.2	106.6	107	96.3	96.4	100.8	105.5	95.9	100.3	85.7	84.7
0.9		105	107.1	107.1	111.5	96.8	96.3	108.2	106.4	95.2	95.3	100.8	104.4	96	101.2	85.6	84.4
1.0		104.4	107.2	106.9	110.4	96.6	95.8	108.7	106.5	93.5	94.2	101.1	104.9	96.2	102	85.4	84.9
1.1		104	106.5	106.3	107.2	96.7	96.8	108.1	106.5	93.1	94.8	101.2	104.2	95.1	99.6	85.2	84.3
1.2		103.4	105.7	103	105.1	96.9	96.6	95	103.7	93	94.4	101.4	104.6	95	98.6	85.2	85.2
1.3		103.2	104.5	102.2	103.9	96.8	95.8	92.2	99.2	93.2	93.5	101.6	105.6	93.8	97.3	85.1	85.6
1.4		102.8	103.8	102.1	104.3	97.1	95.5	91.1	97.6	93.6	93.3	101.8	105.4	92.4	95.6	85.1	85.5
1.5		102.4	103.2	101.9	102.3	97.2	95.7	90.3	96.1	94.8	93.9	102	105.5	88.8	95.2	85.2	85.7
1.7		101.9	101.6	101.3	100.7	97.1	95.7	89.1	92.2	93.7	94.3	101.8	104.1	87.7	90.5	85.7	86.1
1.8		101.6	101.3	101.2	100.5	97	95.5	88.9	92	93.6	94.2	101.7	103.9	87.4	90.3	85.6	86.1
1.85		101.6	101.1	101	100.4	97	95.4	88.8	91.7	93.5	94.1	101.6	103.6	87.2	90.1	85.4	85.9

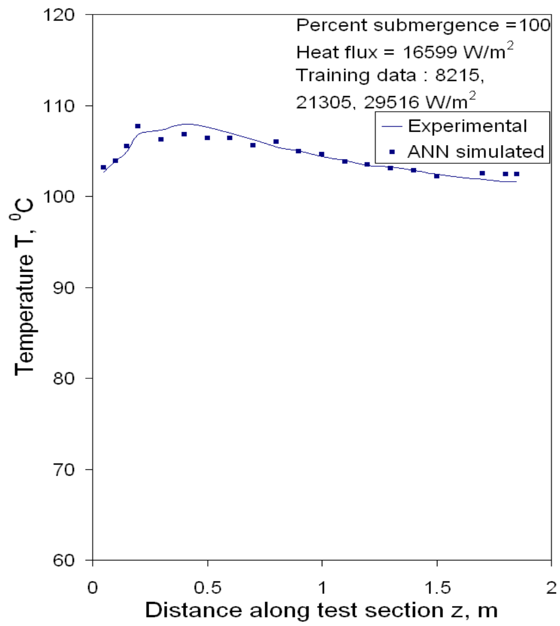


Figure 3. Comparison of experimental and ANN simulated temperature profile at 5 mass percent of methanol

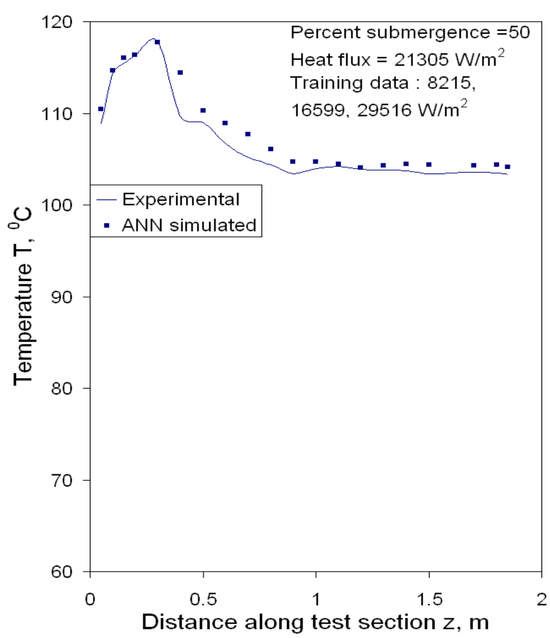


Figure 4. Comparison of experimental and ANN simulated temperature profile at 5 mass percent of methanol

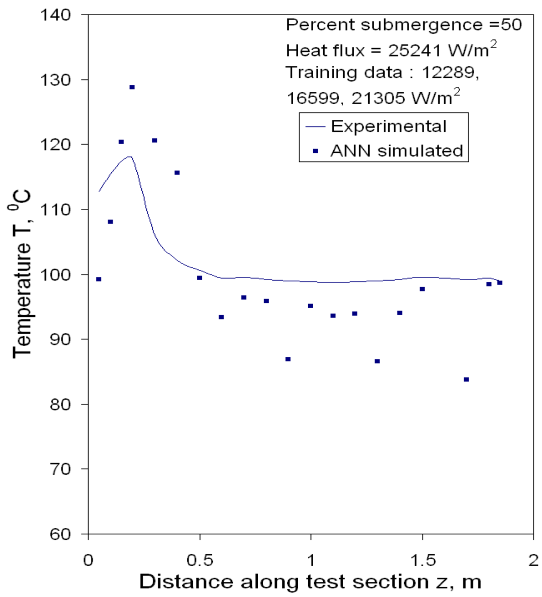


Figure 5. Comparison of experimental and ANN simulated temperature profile at 17 mass percent of methanol

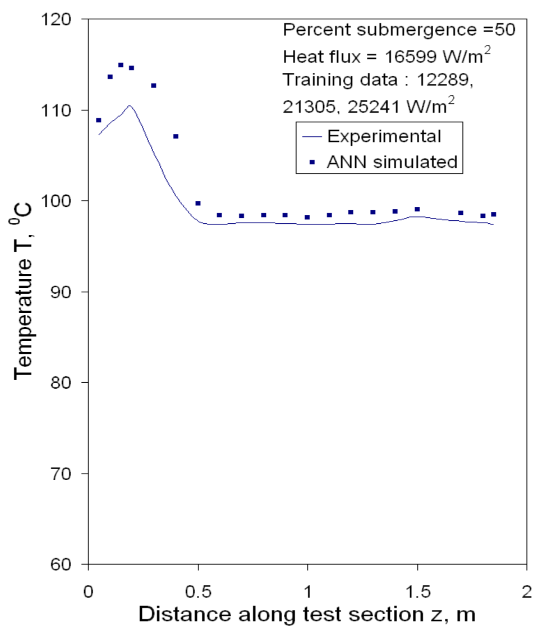


Figure 6. Comparison of experimental and ANN simulated temperature profile at 17 mass percent of methanol

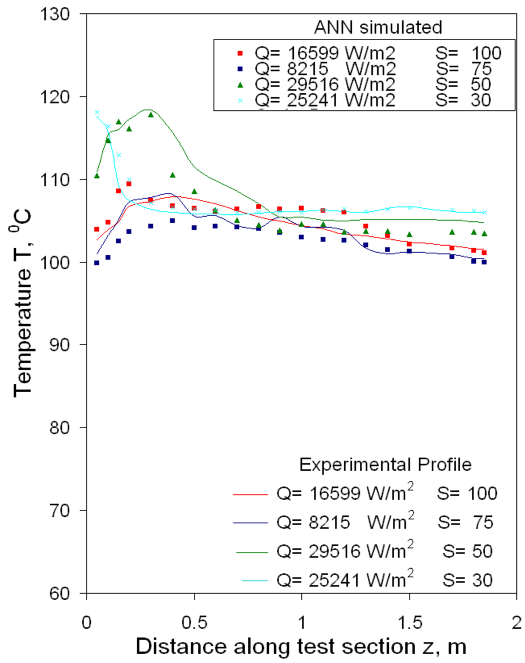


Figure 7. Comparison of experimental and ANN simulated temperature profile at 5 mass percent of methanol with heat flux and submergence as input

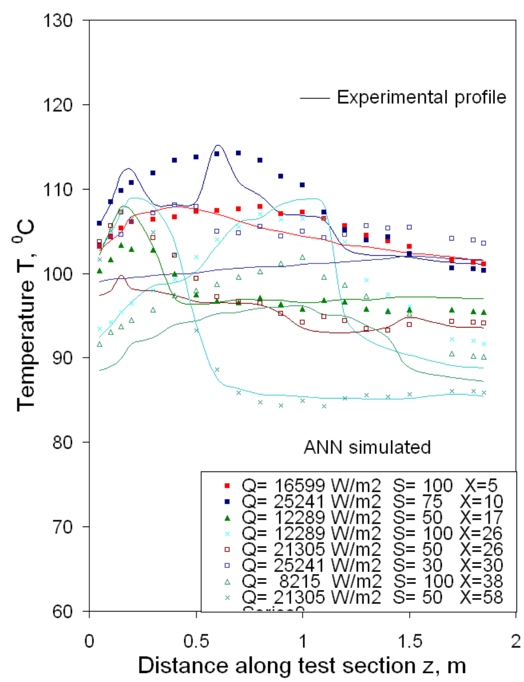


Figure 8. Comparison of experimental and ANN simulated temperature profile with heat flux Submergence and mass percent as input

Figures 7 and 8 show the good matching of the experimental data by using the network 2 with error less than 1% except at the onset of the boiling region.

Tables 3 (a) and 3 (b) show the training and test data to predict the temperature profiles using the network type 2.

Figure 9 shows the plots for third type of network. A good matching is also observed in these plots having maximum error less than 5%. For all predictions the mean absolute deviation was found to be less than 0.8%.

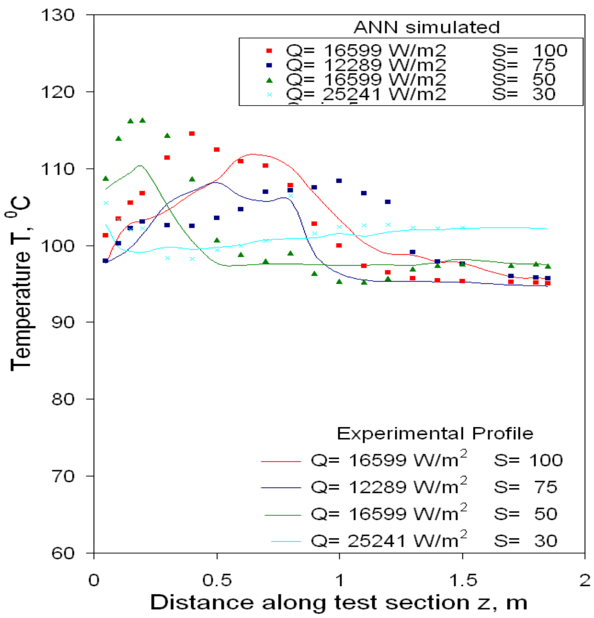


Figure 9. Comparison of experimental and ANN simulated temperature profile at 17 mass percent of methanol with heat flux and submergence as input

5. Conclusions

In the present study, ANN models were developed for the prediction of temperature profile for methanol-water system in a vertical thermosiphon reboiler. The temperature profiles were predicted and compared with experimental data for all the four submergence levels at different methanol concentration. Network 1 has applicability at the particular submergence level while network 2 operates on wider range of data and more versatility. In case of heat flux, submergence and mass percent as input in the network 3, only one training is required for a particular system and hence most robust in nature. For all predictions the mean absolute deviation was found to be less than 0.8%.

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