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NEURAL NETWORK ANALYSIS OF BOILING HEAT TRANSFER IN POOL BOILING OF SINGLE COMPONENT LIQUIDS

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ABSTRACT

The objective of this study is to use Artificial Neural Network for boiling heat transfer at various operating conditions using the experimental data for different liquids. For training the networks, the standard feed forward back propagation algorithm was used and several types of structures were tested to obtain the most suitable network for the prediction of boiling curves. In this study four network structures were used with the variation of neurons and hidden layers. The suitability of the network depends upon the type of system and data chosen for training. It was observed that the predicted results were close to the actual experimental data for all liquids. The predictability of the network is extremely good if the training data are chosen appropriately. When all the data of the system were considered together for the training of the network, the performance was extremely good. The prediction of ANN results was very close to the actual experimental values with a mean absolute relative error less than 2.0 %.

INTRODUCTION

Boiling is one of the efficient means of heat transfer that finds application in variety of industrial appliances such as kettle reboilers, flooded evaporators, steam generators and other chemical process equipment. A substantial amount of work [1-8] has been carried out by many workers on different aspects of nucleate pool boiling heat transfer with a variety of liquids. In a number of experimental work efforts have been made to investigate the effect of governing parameters on heat transfer coefficient.

Artificial neural networks (ANNs) have been used in many industrial applications because providing better and more reasonable solutions. Some typical examples are: analysis of thermosiphon solar water heaters, heat transfer data analysis among others. Cladio et al. [9] used NN approach for optimization of industrial chemical proceeses. 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, Dasguta et al. [17] trained ANN controller with steady state input-output data for a heat exchanger, Pandharipande et al. [18,19] for optimizing ANN network for shell and tube heat exchanger and modeling of packed column, Farshad et al. [20] for predicting temperature profiles in producing oil wells used an ANN algorithm. Cabassud and LeLann [21], .Islamoglu and Kurt [22] used ANNs for heat transfer analysis in corrugated channels. Tianqing Liu et al. [23] developed a model to evaluate and predict boiling heat transfer enhancement using additives. The proposed model is based on the molecular structures of the additives and uses ANN technology. Heydari et al. [24] predicted hydrate formation temperature for natural gas using artificial neural network. Other applications of ANNs is reported by Chouai et al. [25]. Recently Hakeem and Kamil [26-29] predicted temperature profiles, circulation rate, heat transfer and wall superheat for water in a vertical thermosiphon reboiler using ANNs. Sreekanth et al. [30] used NN approach for evaluation of surface heat transfer coefficient at the liquid solid interface. Diaz et al. [31] used ANN for simulation of heat exchanger performance. 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 its optimum value. It is usually determined through trial and error procedure. However, not much work has been reported on the application of ANN methods for heat transfer analysis in a pool boiling system. Therefore present study has been carried out on the applicability of ANNs for predicting boiling curves choosing training data obtained from the experimentation on a pool boiling apparatus.

ARTIFICIAL NEURAL NETWORKS APPROACH

To train and test the neural networks, input data patterns and corresponding targets are required. In developing an ANNs model, the available data [6,7] 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 accomplished 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 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 wall superheat in a pool boiling apparatus . The modified form of Newton Raphson optimization technique is employed to minimize the error. For training the networks, the goal was fixed based on SSE and errors built in the updating the weight and biases. For input and hidden layers, tanh sigmoidal function and linear function for the output layer was taken.

EXPERIMENTAL

The experimental set up consisted mainly of vessel, test section and other necessary accessories as per details given elsewhere [6,7]. A cylindrical vessel of 196 mm i.d. and 305 mm height with a flat bottom and flanged top cover, was used to hold the pool of test liquids. An auxiliary heater was fitted near the bottom to raise the liquid temperature to the desired value and to boil off the dissolved air form the test liquids before conducting the experimental runs. The test section was held horizontally in the vessel at a height of 80 mm from the bottom. Two diametrically opposite view ports were provided in the vessel wall at the level of test section for visual observation of bubbles formation and their dynamics on and around the heat transfer surface. In order to observe and maintain the liquid level in the vessel a level indicator was provided. Pressure guage, feeding connections, condensers and thermocouple probes were fitted in the top cover while a gate valve was provided in the bottom of the vessel. The vessel was thoroughly lagged with glass wool insulation which was finally covered by an aluminium sheet to minimize the heat losses to the surroundings.

The heat transfer section was a horizontal 158.84 mm long stainless steel tube of 31.9 mm outside diameter and 5.95 mm thickness having an effective heat transfer area of 1.59×10^{-2} m^2. The outer surface of the test section was made smooth by turning and polishing with emery paper. The test section was heated by an electric heater made of nichrome wire wound uniformly on a porcelain rod. The heater was carefully wrapped with thin mica sheet placed inside the test section. In order to accommodate the thermocouples for measuring the wall temperatures, axial holes of 4 mm diameter were drilled in the wall thickness upto a distance of 75 mm from one end. Five such holes were drilled at the angles of $^-84$, $^-39$, $^-8$, 33 and 90^0 from the horizontal plane passing through the axis, in order to obtain the variation in wall temperature along the circumference.

A water cooled spiral coil condenser fitted just below the top cover and helical coil condenser above the cover of the vessel condensed the vapours generated during boiling and returned the condensate back to the pool of the liquid. The condensers were connected in series with counter current arrangement of cooling water. The condensate drips are likely to generate additional turbulence in the vicinity of the heat transfer surface. To safeguard against this source of error a clearnance of about 140 mm. between the condenser and the top of the pool liquid was maintained in order to heat up the descending condensate drips, by the ascending vapors, before joining the pool of liquid. This was essential for maintaining the liquid temperature and composition constant. Besides this the test section was submerged to a depth of 150 mm from the top of the pool to keep apart, the vicinity of heat transfer surface from the region which was affected by the condensate joining the liquid pool. A vent cock was fitted at outlet of condenser tube and then to a plastic tubing with its free end kept submerged in the test liquid placed in a glass bottle. This arrangement was found to be useful for visual observation of the removal of traces of dissolved air from the test liquid.

The stabilized electrical power input to the test section heater was regulated by means of an autotransformer and measured by a calibrated precision wattmeter. Five copper constantan thermocouples, placed in the axial holes of the test section wall thickness, sensed the heat transfer surface temperature. The liquid temperature was measured by a copper-constantan thermocouple probe. The bead of the probe was placed at a distance of 30 mm from the test section surface in the horizontal plane passing through the axis of the test section. All t he six thermocouples were connected, through a six point selector switch to a high precision multilogger with a built in arrangement for reference point temperature compensation. The resolution was 0.1 ^{0}c and the accuracy of measurement was + 0.2 percent.

After the fabrication and installation of the experimental facility, the tube wall boiling characteristics were stabilized by boiling of liquid for several hours followed by aging. This ensured the reproducibility of data. The experiments were conducted wherein for each run a heat flux was adjusted, and boiling was allowed to take place. The readings of wattmeter and thermocouples were recorded after the steady state of about 15 min duration was attained. The data were generated with decreasing heat flux at atmospheric pressure. The condenser water was always kept flowing throughout the experimentation. The ranges of parameter covered during the experimentation are given in Table 1.

The temperatures at the outer surface of the tube corresponding to various thermocouple locations were obtained by correcting the thermocouple readings for temperature drop across the wall thickness between the bead and the outer surface. There existed a circumferential variation in the tube surface temperatures which may be attributed to the turbulence produced by nucleation, growth and detachment of vapor bubbles accompanied by the movement of colder liquid towards the surface. The temperature indicated by the wall thermocouple lying in the horizontal plane passing through the axis of the tube was found to be almost equal to the average value of other four thermocouples and hence was chosen to represent the wall temperature in all calculations. The liquid thermocouple probe also lies in the same plane.

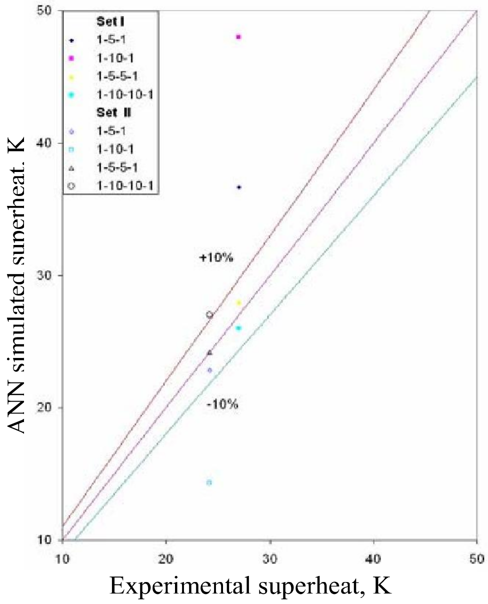

Fig. 1 ANN predicted superheat vs. experimental superheat for ethanol at 25700 and 19000 W/m^2

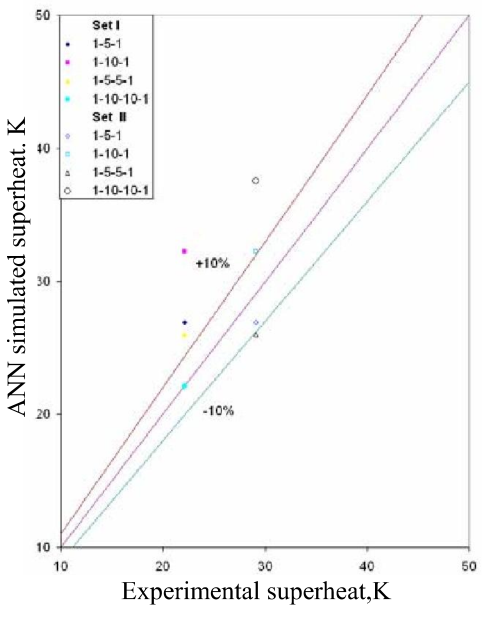

Fig.2 ANN predicted superheat vs. experimental superheat for kerosene at 9400 and 16500 W/m^2

RESULTS AND DISCUSSION

During nucleate pool boiling of liquids, the rate of heat transfer is mainly dependent upon the number of active sites for bubble nucleation on the heat transfer surface. The radius of a cavity becoming active on which thermal and mechanical equilibrium exist is expressed in terms of degree of superheat, slope of the vapor pressure curve and surface tension as discussed by earlier workers. As the heat flux is increased, the heat transfer surface temperature rises resulting in increased wall superheat and hence the value of radius of cavity gets reduced. This enables smaller size cavities becoming active thus the site density increases enhancing the heat transfer coefficient.

Training and test data are given in Table 1 for cyclohexane. Figure 1 shows ANN predicted results of wall superheat for ethanol at two heat fluxes of 25700 and 19000 W/m^2.respectively. Four ANN structures have been used .for all the training . All the results lie within the maximum error of 10 %. Similarly Fig. 2 shows the comparison of superheat for Kerosene at two heat fluxes of 9400 and 15600 W/m^2.respectively. Similar results have been shown for cyclohexane and water at different values of heat fluxes. For all these systems the simulated results are quite well In Figures 1-4 input and output layers have one neuron and one or two hidden layers with 5 and 10 neurons. Figure shows the comparison of predicted superheat vs. experimental superheat for all the components with heat flux and Prandtl number as inputs. In this Figure 5 input layers have two neurons corresponding to the heat flux and Prandtl number representative of the physical properties of the components. ANN structure 1-10-10-1 stands for input and output layers with one neuron each and two hidden layers each having 10 neurons. Except for this Figure all others have more value of error. Less error in it may be attributed to the large number of training data hence very comprehensive training is established as is evident in the Table2. Except few data all lies in the acceptable limits. For all predictions the mean absolute deviation was found to be less than 0.8%. All the simulation was done using MATLAB 6.5 with ANN toolbox.

CONCLUSIONS

In the present study ANN model was developed for the prediction of boiling curves for the pool boiling of different liquids. The boiling curves wee predicted and compared with experimental data for all the four liquids. There is large error for the prediction of boiling curves for individual systems However, in case of all the systems together the small error was observed as discussed earlier. The values so obtained can be used to predict the pool boiling heat transfer coefficients. For all predictions the mean absolute deviation was found to be less than 2.0 %.

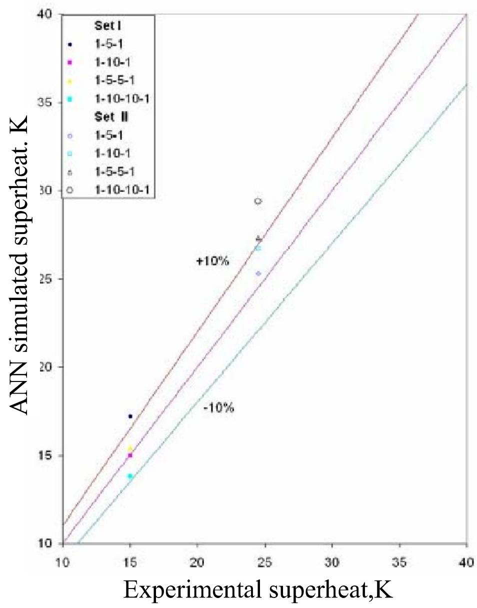

Fig.3 ANN predicted superheat vs. experimental superheat for cyclohexane at 9600 and 31700 W/m^2

Table1 Training and testing data for cyclohexane

S.No.	Training data for set I		ANN output for set I			
	Input, Heat flux W/m^2	Target, (T_w-T_L) K	ANN Architecture	Input, Heat flux W/m^2	Output, (T_w-T_L) K	Actual, (T_w-T_L) K
1	6300	12	1-5-1	9600	17.2	15
2	13700	17.1	1-10-1		15	
3	29100	22	1-5-5-1		15.4	
4	31700	24.5	1-10-10-1		13.8	
5	36000	33.8				
-	Set II		Set II			
6	6300	12	1-5-1	31700	25.3	24.5
7	9600	15	1-10-1		26.7	
8	13700	17.1	1-5-5-1		27.3	
9	29100	22	1-10-10-1		29.4	
10	36000	33.8				

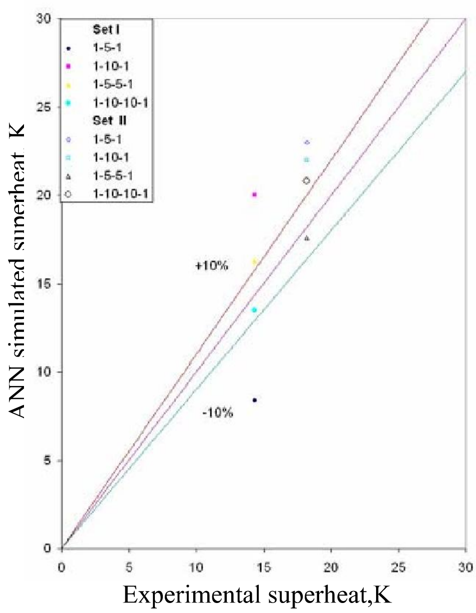

Fig.4 ANN predicted superheat vs. experimental superheat for water at 19500 and 35000 W/m^2

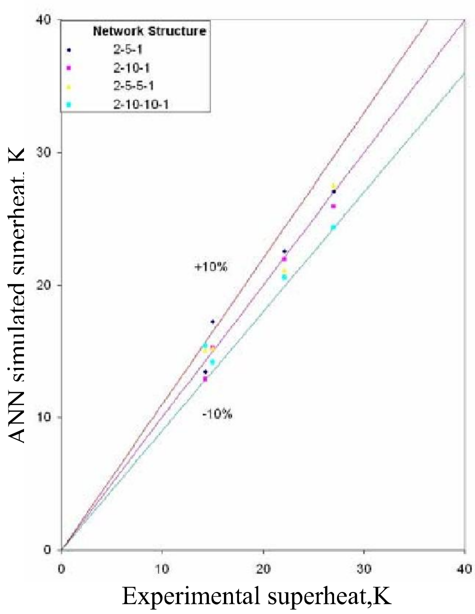

Fig.5 ANN predicted superheat vs. experimental superheat for all the components with heat flux and Prandtl number as inputs

Table2 Training and testing data for all the four components taken together

S.No.	Training Data			ANN simulated result						
	Input		Target	Input		Output, (T_w-T_L) K for architecture				
	Pr	Q W/m^2	(T_w-T_L) K	Pr	Q W/m^2	1-5-1	1-10-1	1-5-5-1	1-10-10-1	Actual value
1	9.18	12200	22.1	9.18	25700	27.03	25.89	27.48	24.34	27
2	9.18	19000	24.2	7.414	9400	22.53	21.91	21.11	20.52	22.1
3	9.18	22000	26.1	9.64	9600	17.21	15.28	15.22	14.15	15
4	9.18	32000	31.5	1.68	19500	13.43	12.89	15.05	15.36	14.3
5	7.414	2300	15							
6	7.414	8800	17.1							
7	7.414	12200	29.1							
8	7.414	16500	29.1							
9	7.414	17200	29.1							
10	9.64	6300	12							
11	9.64	13700	17.1							
12	9.64	29100	22							
13	9.64	31700	24.5							
14	9.64	36000	33.8							
15	1.68	7539	8.3							
16	1.68	15000	12.5							
17	1.68	27300	16.8							
18	1.68	35000	18.2							
19	1.68	38800	20							

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