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Application of Neural Networks to Predict Changing the Diameters of Bubbles in Pool Boiling Distilled Water

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***Abstract*—**In this research, the capability of neural networks in modeling and learning complicated and nonlinear relations has been used to develop a model for the prediction of changes in the diameter of bubbles in pool boiling distilled water. The input parameters used in the development of this network include element temperature, heat flux, and retention time of bubbles. The test data obtained from the experiment of the pool boiling of distilled water, and the measurement of the bubbles form on the cylindrical element. The model was developed based on training algorithm, which is typologically of back-propagation type. Considering the correlation coefficient obtained from this model is 0.9633. This shows that this model can be trusted for the simulation and modeling of the size of bubble and thermal transfer of boiling.

***Keywords*—**Bubble Diameter, Heat Flux, Neural Network, Training Algorithm.

I. Introduction

BOILING mechanism has been always used as an appropriate mechanism for the transfer of heavy thermal loads in many industrial processes. Nuclear reactors, absorption and distillation towers, as well as boilers are common examples of industries, in which boiling is employed broadly. Pool boiling is a boiling process, in which a hot surface is placed under the free surface of a liquid [1].

A bubble is formed when its internal pressure is less than saturation pressure. Therefore, when bubbles are formed and grown in a liquid, there is certainly a superheated layer in the liquid. As the saturation temperature of the liquid is higher than that of the bubble, the temperature is transferred from the liquid to the vapor.

The diameter of bubbles has been calibrated by a test device made of three main parts: test container, autotransformer, and thermocouple. The element mounted in the middle of the device is heated in different fluxes. The pictures of the bubbles were taken under supersaturated boiling conditions by advanced cameras, and the diameters of the bubbles were determined by related software in different fluxes.

In recent decades, artificial intelligence has been efficiently applied as an instrument for the development of complicated nonlinear models. This instrument has been stimulated based on the biologic neurons of human brain, and it can be used effectively for complicated nonlinear calculations [5].

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II. The Data Used in the Model

The parameters used for the development of this model are the recorded laboratory data. These data are separated based on their adequacy and accuracy. This separation is carried out to develop a practical and appropriate model.

In this model, the input data include the temperature of element's surface, heat fluxes, and retention time of bubbles. The output parameter is the diameter of the bubbles that is provided in form of a digit between 0 and 4.5.

In higher heat fluxes, the bubbles in the process of departure are bigger than those ones in lower flux. This is due the higher cohesion of bubbles that are in higher heat fluxes. Indeed, the molecules of pure water can get closer to each other easily due to the nature of pure water, and therefore, bigger bubbles are formed, however, they are less stable [2], [3].

TABLE I
The Range of the Parameters Used in the Development of Model

Parameter	Range of parameter
Heat flux (kw/m^2)	20-102
Element temperature (m)	96.4-97.1
Present time of bubble (s)	3 – 1.2
Bubble diameter (m)	0.00015- 0.00045

III. Model Description

There are different methods and networks, which have their own capabilities and advantages, and can be used for the development of this model. In this study, a training algorithm was employed for the development of the model. The algorithm is typologically of back-propagation type. Upon calculating prediction error for the first input, the synaptic weights are changed from the last layer towards the first layer in order to reduce prediction error. After reading sufficient samples to the network input, the network becomes converged, and error is minimized. The training rule used in this model is called "trainlm" [4].

The developed model consists of three layers: the input layer with 10 neurons, hidden neuron with 50 neurons, and output layer with one neuron, which is the representative of network output. The number of layers and neurons of each layer are selected optionally [6], [7]. After testing different models with different numbers of neurons, the model with the lowest error was described. The overall structure of the developed network has been provided in the Fig. 1.

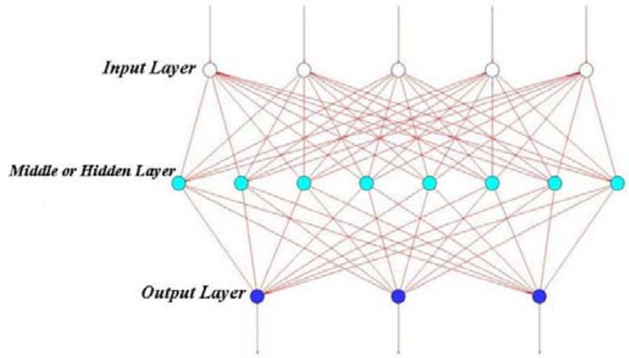

Fig. 1 Overall Structure of the Network with three layers used in the present study

One problem that may occur during the convergence is over-fitting, that is, the system preserves the data instead of analyzing them. In such as case, the developed model can predict similar data that were used in the phase of training, but if new data are inserted into the model, the system functions inappropriately and there will be many prediction errors. To prevent such a condition, cross validation is required. In this method, the total original data are classified into three groups of training, validity, and test. The validity of the network is assessed during training, and whenever the number of errors in the validation data is increased, the training of the network stops [8], [9].

In developing the intended network, twenty-five percent of the data were validation data, twenty-five percent test data, and the rest are training data that were selected randomly from the total existing data. After thirty times of training, the performance of the eleventh time was selected as the best performance of the network [10], [11].

IV. Discussion

In this study, we developed a neural model that could satisfactorily predict the changes in the diameters of the bubbles in the pool boiling distilled water. Considering the diversity of the data used in the development of this model, it can be considered a practically successful model. The correlation coefficient was 0.97353, and the correlation coefficient of the other data groups used for the test of the network was 0.97609. These have been shown in Figs. 2 and 3.

In Table II, the correlation coefficients and root-mean-square error of each data group have been provided.

TABLE II
Correlation Coefficients And Root-Mean-Square Error

R value	MSE	Sample Percent	Data sets
0.9999	0.0001	50	Training
0.94219	0.0061	25	Validation
0.97609	0.0060	25	Test

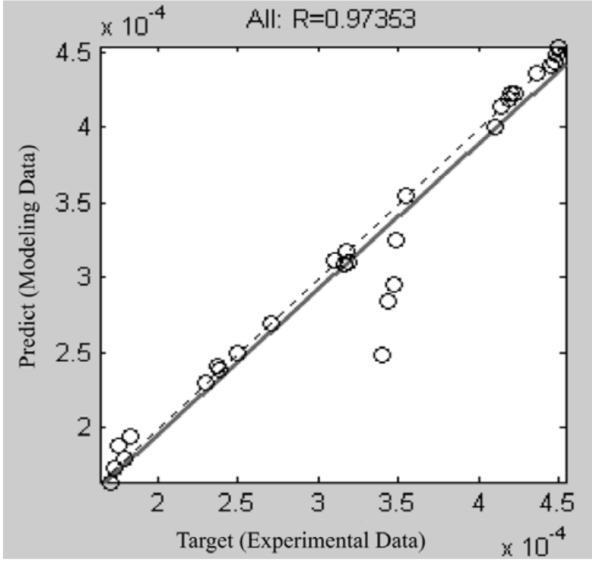

Fig. 2 The Correlation between the actual values and those obtained from the model

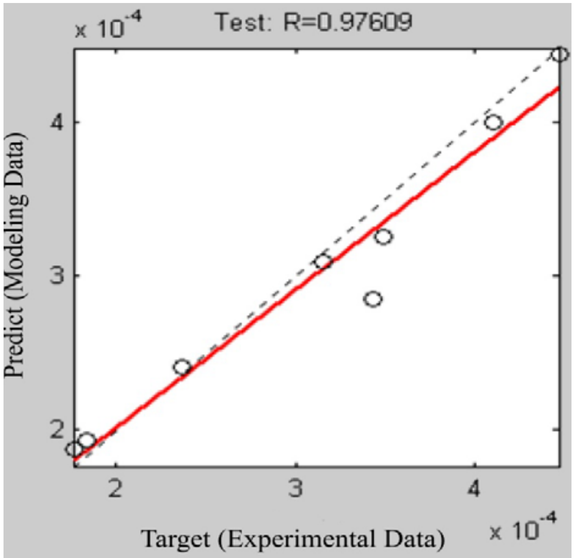

Fig. 3 The Correlation between the actual values and those ones obtained from the model for the test data group

V. Conclusion

Considering the capability of neural networks for the prediction and optimization of the complicated relations between different parameters, a model was developed to predict the changes in the diameters of the bubbles in pool boiling distilled water. The network was developed using the data obtained from laboratory data. The correlation coefficient of this model was more than 0.97, and the room-mean-square error less than 0.006. The results show that this model is an appropriate model for the prediction of bubble diameter in pool boiling distilled water. The application of this model can reduce the costs of heat transfer significantly.

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