Neural Network Analysis of Void Fraction in Subcooled Flow Boiling Of Water in Horizontal Annulus at High Pressures

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Abstract — *Feed forward back propagation neural network has been used to predict void fraction in subcooled flow boiling of water in horizontal annulus at different pressures. The data bank contains experimental measurement of void fraction for subcooled flow boiling of distilled water in horizontal annulus at mass fluxes from 400 to 1200 kg/m^2-s, heat fluxes from 0.1 to 1 MW/m^2 and pressures varying from 1 to 4 bar at constant subcooling of 20° C through a horizontal annulus. A comparison between the experimental and predicted data reveals RMS error of 2.656 for training and 1.081 for testing data. The value of absolute fraction of variance (R) is 0.998 for training and 0.999 for testing. In addition, the trend of both predicted results and experimental data are qualitatively consistent.*

Keywords — ***Artificial Neural Network (ANN), Subcooled Flow Boiling, Void Fraction***

I. INTRODUCTION

The void fraction in subcooled flow boiling describes the part of the channel which is occupied by the vapor phase at any instant. Prediction of void fraction along the flow direction during subcooled flow boiling is very important for nuclear reactor safety. As the void fraction increases, the reactivity in the reactor core decreases and vice versa. The accurate prediction of the void fraction axial profile, which logically depend on inlet flow conditions like velocity, pressure, subcooling and on the applied heat flux. Various experimental techniques used for measuring void fraction have been discussed elsewhere [1&2].

The experimental results demonstrate that void fraction is a complicated parameter at higher temperature. Some of the independent variables that influence the prediction of void fraction are gas and liquid flow rates, bulk temperature, liquid and gas properties (including vapor pressure), surface tension, bubble size and shape and coalescence mechanism. This complexity leads to a highly non-linear behavior with poorly understood interaction between the independent variables.

The main advantage of neural networks is their ability to handle complicated and non-linear systems, without detailed knowledge of the underlying process.

Radial basis function neural network architecture was used by [3] to predict cross-sectional and time-averaged void fraction at different temperatures for a wide range of operational conditions for upward two phase air/water flows pass through a vertical pipe of 2.42 cm diameter.

The objective of this work is to correlate the experimental data by the use of a neural network. In this study, the well-established feed forward back propagation neural network architecture is used. Finally, attempts are made to compare qualitatively the trend of the resultant network with those of experiments.

II. EXPERIMENTAL EQUIPMENT AND PROCEDURE

The details of the test rig and analysis of the errors associated with experiments have been fully reported elsewhere [4-5], however a brief description of the experimentation is as follows. The experimental apparatus is shown schematically in Fig. 1. The closed loop facility has a capacity of 5 m^3 and is fitted with a horizontal, electrically heated annular test section made of Pyrex glass. Prior to entering the test section the flowing medium, distilled water is circulated from a storage reservoir through a filter and a turbine type flow meter. The liquid vapor mixture coming out of test section passes through a condenser and heat exchanger before returning to the reservoir. The loop allows for varying the heat supply, flow, pressure and inlet temperature of the liquid. The test section is 0.78 m long and consists of an electrically heated rod and an outer borosilicate glass tube of 21.8 mm inner diameter. The heater is 12.7 mm diameter hollow stainless steel rod welded to solid copper rods at both ends. The heated length of 0.48 m is located 0.22 m downstream of the inlet plenum and thus allowing for the flow to fully develop. An input 415 V, three phase AC power is stepped down to 0–32 V DC power by using 64 kVA DC regulated power supply by which a large range of heat fluxes was applied to the test section. The whole test rig, excepting for those areas which need to be accessed for the experiments, was insulated in order to minimize heat losses.

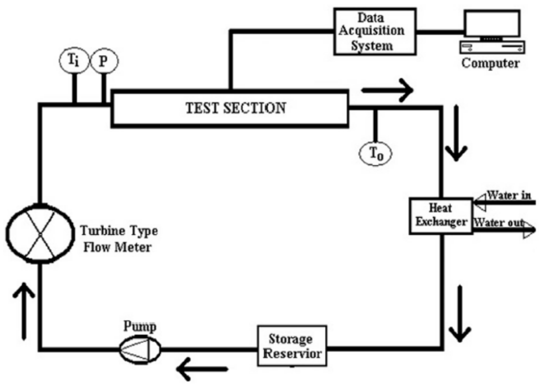

Fig. 1 Experimental Set Up

Details of image acquisition and image processing are reported elsewhere [1-2]. Void fraction at different pressures, mass fluxes and heat fluxes were measured experimentally by using suitable image processing operations and tabulated in Table-1.

III.NEURAL NETWORK APPLICATION

Recently, there has been an increasing interest in the application of artificial neural networks for solving complex problems. The ability of a neural network to analyze any complex functional relationship makes the selection of a suitable regression method unnecessary. Solution of a neural network should generally undergo two phases which lead to final solution, namely training and generalisation. Training is equivalent to finding a surface in a multidimensional space that provides a best fit to the training data. Generalisation is equivalent to the use of this multidimensional solution to interpolate data unseen by the network. The ability to learn non-linear relationships which may exist between a set of inputs and outputs, and the possibility of handling multiple inputs and outputs of the process are the main advantages. However, in general, neural networks are significantly limited by the slow rate of learning and relatively poor extrapolation.

IV.FEED FORWARD BACK PROPAGATION (FFBP) NEURAL NETWORK

Feed forward back propagation neural network is one of the active fields of research in numerical analysis recently. This network has a fast rate of learning and high accuracy. Feed forward back propagation neural network is one of the active fields of research in numerical analysis recently. This network has a fast rate of learning and high accuracy.

The construction of a FFBP neural network in its most basic form involves three entirely different layers. The input layer is made of input nodes. The second layer is a hidden layer of sufficient dimensions, and the output layer supplies the response of the network to the activation patterns applied to the input layer. A typical architectural form of a FFBP neural network with multiple inputs and one output is shown in Fig. 2.

The network works in two phases, as follows:

1) The training or learning phase in which a set of known input /output patterns are presented to the network. The weights are adjusted between the nodes until the desired output is provided.

2) The generalisation phase in which the network is subjected to input patterns that it has not seen before, but whose outputs are known and the performance is monitored.

Pressure, mass flux and heat flux are chosen as inputs for the network and void fraction as chosen as desired output from the network. Selection of input and output variables and of the data set for training should be done carefully to cover the whole range of variables, since neural networks cannot be used reliably for extrapolations. In general, the majority of data are be used for training the network, and the remaining part for the generalisation phase.

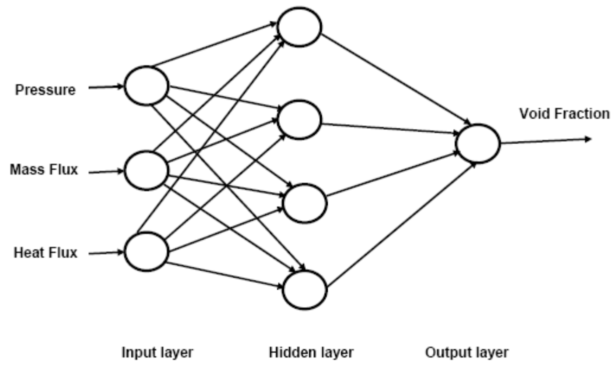

Fig. 2 Network Architecture

V. DATA SOURCE

In this research work, 72 experimental data points, which were reported in [1] are used. They were obtained from experimentation of subcooled flow boiling at varying pressures, heat and mass fluxes in a horizontal tube. The experimental data points are divided into two parts, the training and generalisation phases respectively. In the training phase, 60 experimental data points are presented to the network. The remaining 12 experimental data points are used for the generalisation phase.

VI.TRAINING AND PERFORMANCE OF NETWORK

The training of the network is accomplished by adjusting the weights and is carried out through a large number of training sets and training cycles (epochs). The goal of the learning procedure is to find the optimal set of weights which in the ideal case would produce the right output for any input. The output of the network is compared with a desired response to produce an error. Once the network is adequately trained, it can generalize to similar cases which it has never seen.

The learning algorithm used in the study is Levenberg Marquardt Algorithm (LMA) activation function is logistic sigmoid (logsig) transfer function which try to improve the performance of the neural network by reducing the total error by changing the weights along its gradient. LMA is used to adjust the weights in order to minimize the error. The performance of the network outputs is evaluated by a regression analysis between the network outputs and the actual outputs. The criteria used for measuring the network performance are root-mean square value (RMS) and absolute fraction of variance (R^2) which can be calculated by:

$$E = \frac{1}{2}\left[\sum_{p}\sum_{i}\left(t_{ip} - o_{io}\right)^2\right] ----- (1)$$

$$R^2 = 1 - \left[\frac{\sum_i (t_{ip} - o_{io})^2}{\sum_i o_{io}^2}\right] ----- (2)$$

Where t_{ip} is target value, o_{io} is output value, and p is pattern. If E is zero and R values close to 1 indicates excellent performance of network.

VII. RESULTS AND ANALYSIS

Fig. 3 shows the comparison between the experimental and predicted void fractions for the data used. The resulting neural network predicts the void fraction with RMS error of 2.656 for training and 1.081 for testing data. The value of absolute fraction of variance (R) is 0.998 for training and 0.999 for testing.

VIII. CONCLUSIONS

This paper presents an analysis of experimental void fraction results at various pressures, mass and heat fluxes by using feed forward back propagation neural network architecture. The resultant network accurately predicts the void fraction with RMS error of 2.656 for training and 1.081 for testing data. The value of R is 0.998 for training and 0.999 for testing. The trend of predicted void fractions is also consistent with those of the experiments. This work demonstrates that neural networks in general may be a promising tool to the interpretation and analysis of two-phase flow data. Additional work is presently in progress for other aspects of two-phase flow, such as bubble behavior.

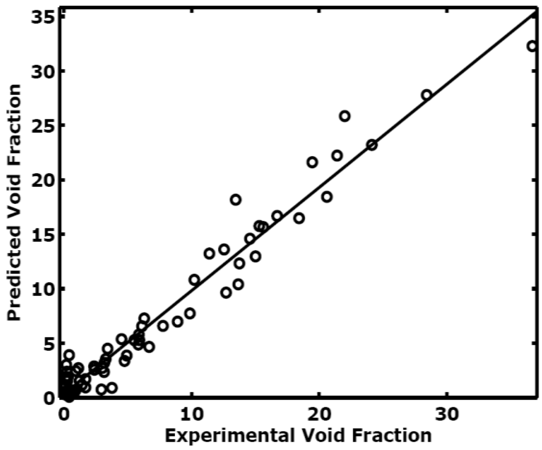

Fig. 3 Pariplot of Experimental Void Fraction Vs Predicted Void Fraction of Ann

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