Journal of Engineering and Sustainable Development
Vol. 21, No. 5, September 2017
ISSN 2520-0917
www.jeasd.org

# PREDICTION OF TWO-PHASE FLOW BOILING CHARACTERESTICS IN MICROCHANNELS HEAT SINK BY ARTIFICIAL NEURAL NETWORK

Dr. Adnan A. Abdulrasool [1], Dr. Ekhlas M. Fayyadh [2], * Adil Abbas Mohammed [3]

1) Prof., Mechanical Engineering Department, Al-Mustansiriayah University, Baghdad, Iraq.
2) Assist Prof., Mechanical Engineering Department, University of Technology , Baghdad, Iraq.
3) Lect., Mechanical Engineering Department, Al-Mustansiriayah University, Baghdad, Iraq

**Abstract:** The current study investigated flow boiling heat transfer, pressure drop in a copper multi parallel microchannels heat sink using R134a as a working fluid. The evaporator consisted of 25 micro channels with dimensions of 300 µm wide, 700 µm deep and 209 µm separating wall thickness. It was made of oxygen free copper by CNC machining and was 20 mm long and 15 mm wide and hydraulic diameter of 420 µm. Experimental operating conditions spanned the following ranges: wall heat flux (5–120) kW/m$^2$, mass flux 50–300 kg/m$^2$s and system pressure 8.5–12.5 bar. The heat transfer coefficient increases with heat flux and system pressure but there is insignificant mass flux. This could be interpreted as a nucleate boiling dominant mechanism. The measured two phase flow pressure drop increases with increasing heat flux and mass flux but decreases with increasing system pressure. The effect of system pressure depends on mass flux, therefore. no pressure effect was found at low mass flux while the heat transfer coefficient increased with pressure at the high mass flux values. Pressure drop was investigated as a variation of heat flux. Simulation with Artificial Neural Network (ANN) was performed to predict heat transfer coefficient and pressure drop using MATLAB- version R2014a software, at mass flux G (75, 125, 175, 225, 275) kg/m$^2$.s and pressure $P_s$ (8.5, 10.5, 12.5) bar .The predicted results were compared with the experimental data and showed a good agreements.

**Keywords**: *Two-phase, Heat transfer, Pressure drop, Heat sink, Microchannels, Neural Net Work.*

# الخصائص التنبؤية لجريان الغليان ثنائي الطور باستخدام الشبكة العصبية الاصطناعية

**الخلاصة:** تتضمن الدراسة الحالية التحقق من انتقال الحرارة وهبوط الضغط خلال جريان الغليان في مجاري متوازية متناهية المقطع داخل تصريف حراري نحاسي مستخدما R134a كمائع الجريان المقطع النحاسي ذو ابعاد بعرض 0.15 متر وطول 0.2 متر. يحتوي المقطع غلى 25 مجرى دقيق بعرض 700 مايكرومتر وارتفاع 300 مايكرومتر وبقطر هيدروديناميكي 420 مايكروميتر. الظروف التشغيلية تتضمن الفيض الحراري للسطح يتراوح بين 5-120 كيلوواط/ متر مربع و معدل الجريان بين 50-300 كيلوغرام/مترمربع ثانية تحت ضغط من 8.5-12.5 بار . يزداد معدل انتقال الحرارة مع ازدياد معدل الفيض الحراري ومع ضغط المنظومة وليس هناك تاثير لمعدل الجريان. هذه الحالة تفسر على هيمنة نظام بداية الغليان. فرق الضغط المقاس لحالة الجريان ثنائي الطور يزداد مع زيادة معدل الفيض الحراري وكذلك مع معدل الجريان وينخفظ مع زيادة ضغط المنظومة. يعتمد ضغط المنظومة على معدل الجريان يعني التاثير قليل عند معدل الجريان الواطئ بينما معامل انتقال الحرارة يزداد مع الضغط عند معدل الجريان العالي تم اجراء محاكاة باستخدام نظام الشبكة العصبية من خلال برنامج MATLAB- version R2014a. عند معدل جريان (75, 125, 175, 225, 275) kg/m$^2$.s وضغط المنظومة عند (8.5, 10.5, 12.5) bar. واظهرت النتائج تطابقا معقولا مع النتائج العملية.

* adekef@yahoo.com

## 1. Introduction

Two-phase flow parallel multi-microchannels are the cutting-edge technologies for high heat flux components cooling devices in recent years. The two-phase flow is considered as an optimum option to be applied in microchannels because of its extremely high heat transfer coefficients, so it keeps the wall at acceptable temperature rises.

However, these benefits cannot pass without penalty. The narrow passages for fluid flow cause an increase in pressure drop. The comprehensive understanding of heat transfer and pressure drop presents valuable considerations for evaluation of these heat exchangers to get the design approach. The popular approach to analyse the unsteady and steady heat transfer problems is associated with the availability of non-linear empirical modeling methodologies, such as neural networks, inspired by the biological network of neurons in the brain, Ou and Achenie [1]. The large number of published researches reflect the great effort that have been collected for two-phase flow boiling and pressure drop characteristics in microchannels.

The heat transfer and pressure drop results of saturated flow boiling heat transfer coefficient in oxygen-free copper micro-channel heat sinks were investigated by Qu and Mudawar (2003) and Lee and Mudawar [2,3], the heat sink consisted of 21 rectangular micro-channels with 231 µm wide and 713 µm deep , fitted with a polycarbonate plastic cover plate, the deionized water and R134a were used as a working fluids. They compared the results and showed a good agreement with the corresponding numerical predictions.

Chen et al. [4] investigated experimentally and theoretically flow boiling and heat transfer characteristics of Methanol in silicon based multi microchannel heat sink with different hydraulic diameters ranging from (57−267)µm. Experimental results indicated that the critical nucleate heat flux condition appeared, flow mechanism changed into fully developed nucleate boiling and accompanied with wall temperature decreased rapidly and pressure drop increased sharply. Steinke and Kandlikar [5] focused on obtaining the fundamental heat transfer data and two phase flow patterns presented during flow boiling of water in microchannels in six parallel, horizontal microchannels with a hydraulic diameter of 207 $\mu$m.

The local flow boiling heat transfer coefficient exhibits a decreasing trend with increasing quality. Agostini et al. [6] investigated high heat flux flow boiling of R236fa and R245fa in silicon multi-microchannels with 67 parallel channels, which are 223 µm wide, 680 µm high and 20 mm long with 80 µm thick fins. The heat transfer coefficient increased with heat flux and was almost independent of vapour quality and mass velocity. Zhang [7] developed a correlation of two-phase frictional pressure drop and flow pattern in mini-channels with refers to 13 sets of data collected from literatures. Neural network algorithm was used to propose the Chisholm parameter (C) for mini-channel. An extensive evaluation was presented of existing correlations with a collected database covering a wide range of running parameters, and proposed alternative correlations. Artificial Neural Network (ANN) has become a modeling tool frequently used in applications and analyzing the complex problems in different disciplines.

Particularly, its usage has increased in engineering applications such as heat transfer analysis. ANN has been successfully used in the analysis of heat transfer data and the heat transfer coefficient by algorithm for training and testing steps of neural network configurations. Picanço et al. [8] proposed using of genetic algorithms to correlate the derived functional relation between dimensionless numbers in convective and nucleate boiling heat transfer.

Shokouhmand et al. [9] used an artificial neural network (ANN) to simulate the heat sink having laminar flow, the best geometry and volume fraction of nanofluid could be found based on minimum thermal resistance. By applying the artificial neural network. Mehta [10] presented prediction of two phase air and water flow patterns in a 2.1 mm horizontal circular Y-junction minichannel using (ANN). The experimental results are predicted and compared using different artificial neural network models such as feed forward back propagation, cascade-feed forward back propagation, non-linear autoregressive exogenous model and radial basis functions. The comparison is performed by considering statistical parameters like mean bias error and root mean square error .

## 2. The Objectives.

**2.1.** This work aimed to predict the values of heat transfer coefficients and pressure drop as a function of exit vapour quality and wall heat flux by using ANN algorithm based on the experimental results which performed at working pressure (8.5, 10.5, 12.5) bar, with mass fluxes G (50, 100, 150, 200, 250, 300) kg/m$^2$.s, with respect of the experiment inlet paramters G, $P_s$, $x_e$, $DT_{sup}$ , $q''_w$ .

**2.2.** Predict values of heat transfer coefficients and pressure drop at fluxes G (75, 125, 175, 225, 275) kg/m$^2$.s. and working pressure (8.5, 10.5, 12.5) bar.

## 3. Experimental Work.

To perform the experimental tests, the test section is established for the experimental investigation as shown in "Fig. 1". The heat transfer performance of two-phase flow in horizontal copper multi microchannels has been investigated in the mechanical engineering laboratories of Brunel University-London, United Kingdom. The refrigerant R134a is used, initially saturated liquid, as the working fluid, to test forced convection heat transfer. The effects of heat flux, mass flux and operating pressure on boiling heat transfer and pressure drop characterization in multi microchannels.

### 3.1. *Test sections.*

The test section consists of a polycarbonate housing with dimensions 0.132m length, 0.06m width and 0.074m high, have inlet/outlet rectangular plenums and converging inlet, diverging outlet manifolds., top covered by transparent quartz glass top cover plates for visualizations as shown in "Fig. 1a". An oxygen free copper block with twenty-five rectangular micro channels were cut into the top surface.

The copper block has overall dimensions of 15mm width, 20mm length, and 74mm height have three cartridge heaters of 175W heating power each. The nominal dimensions of the micro channel, are 300μm width, 700μm depth, 200μm fin thickness and 2cm length.

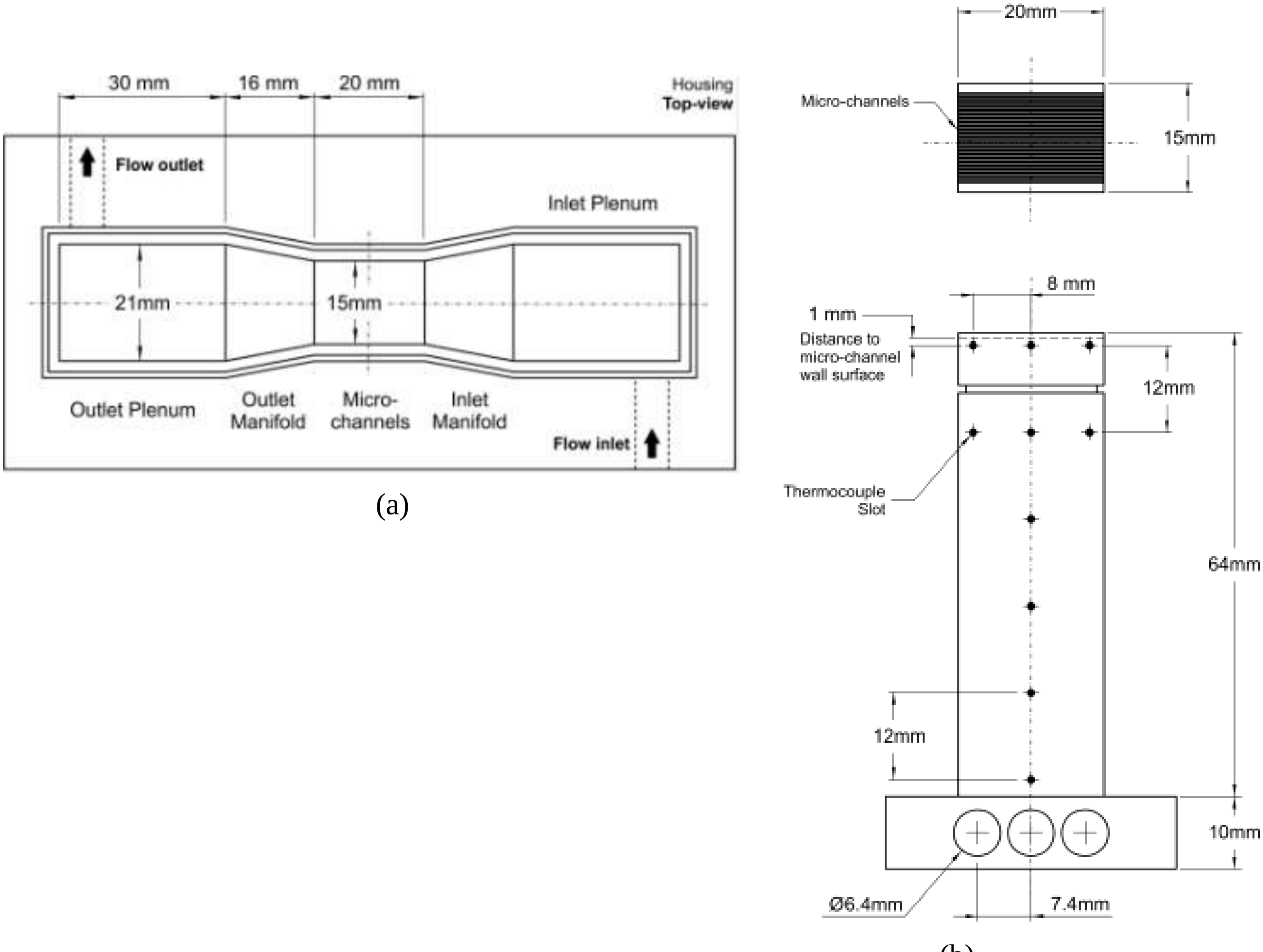


Figure 1. Schematic diagram of the test section components, (a) Housing Polycarbonate, (b) Microchannels copper part.

The surface roughness of the bottom wall was measured and found to be 0.301μm. T-type calibrated thermocouples were inserted vertically along the centerline of the copper block at 12 mm equidistance to measure the heat flux.

### 3.2. *Test Loop and cooling system.*

The main refrigeration system uses R134a as a refrigerant and the cooling systems which uses R404a is illustrated in "Fig. 2". The main loop consists of , gear pump, Coriolis mass flow meters, electric heaters and R134a wall insulated tank. The cooling system consists of compressor, condenser, gear pump, heat exchangers used as evaporators and R404a wall insulated tank. The cooling system is used to carry the heat away from R134a test loop through a cooling coil and heat exchangers.

The system can regulate its cooling capacity automatically to adapt the heating load from the R134a experimental system.

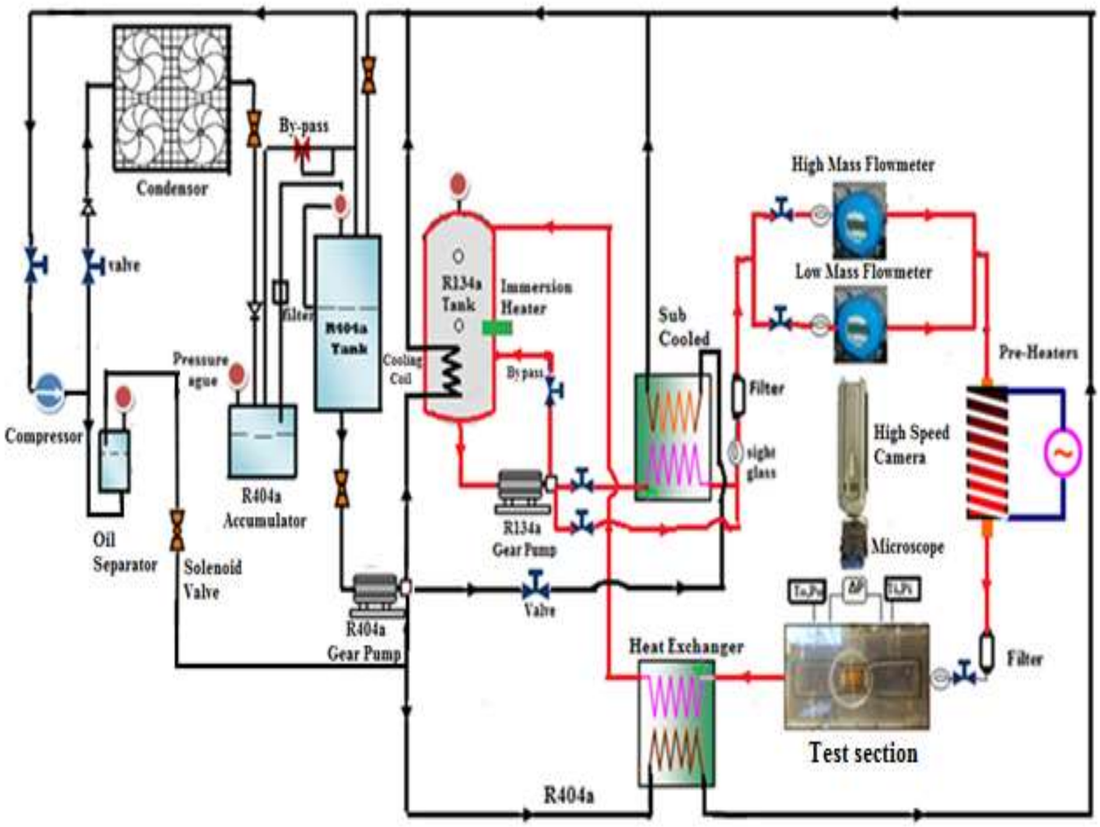


Figure 2. Schematic diagram for test loop and cooling system.

## 4. ANN Modeling of Two-Phase Flow Parameters

Artificial neural network is based on the important rules for classifying the two-phase flow parameters. Neural network stimulate human mind and demonstrate high intelligence and it can be trained to study the correct output and classify training exercises and needs knowledge input for training. After the training, the neural network can classify the similar flow parameters with high accuracy,[11]. ANN mainly grouped into two major type categories:-

- Feed forward in which no loops are formed by network.
- Feedback in which one or more loops are formed.

The ANN approach seems to be completely suitable to the problems where the relations between variables are not linear and complex. In a multi-layer structure, the neurons are grouped into layers, layer of input neurons, layer of output neurons and one or more hidden layers which are made up of many interconnected neurons.

As shown in "Fig. 3", a Multi Layer Preceptron (MLP) has two hidden layers. It consists of input layer which has five neurons. These become input signals to neurons of the hidden layers where input signals are

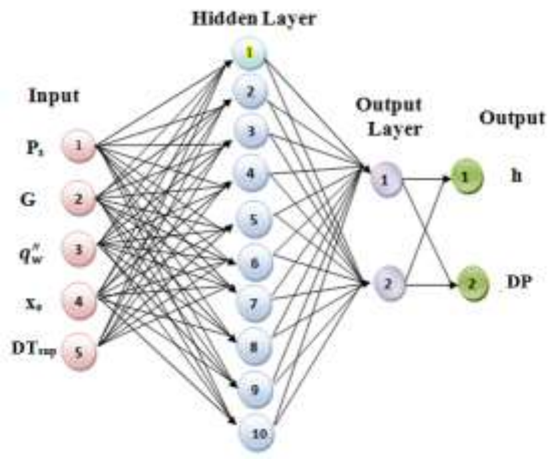


Figure 3. The proposed neural network architected.

summed after weighing and then compute in function. The activation functions under hidden layer considered are Linear (PURELIN), hyperbolic tangent sigmoid (LOGSIG), Logistic sigmoid (TANSIG). The output of output layers are computed in same manner as hidden layer,[10]. The identification of two-phase flow parameters in microchannels using ANN algorithm and consider the G, P, $x_e$, $DT_{sup}$ , $q''_w$ as input parameters while heat transfer coefficient (h), pressure drop (DP) are considered as outputs.

The comparison of different algorithm is based on the statistical parameter squared correlation coefficient (R). The normalization of values is a conclusive step in the ANNs. The input values to the ANN may differ by several orders of magnitude, which may not reflect the relative importance of the input data which normalize the maximum and minimum values of each row within the range of (-1,1). The procedure to predict the output parameters using ANN modeling is summarized as follows:-

a) Determine training patterns from data sets.
b) Define neural network architecture.
c) Determine network parameters.
d) Run feed-forward back propagation program.
e) Comparison and analysis.

The selected ANNs have two hidden layers with 10 neurons and an output layer with 2 neurons. The hidden layer has a TANSIG transfer function. The output layer has a PURELIN transfer function. Each neuron sums the product of each connection weight ($w_{jk}$) from a neuron (j) to the neuron (k) and input ($x_j$ ), and the additional weight called the bias to get the value of sum for the neuron. The $i^{th}$ neuron has a summer that gathers its weighted input ($w_{ij}$,$x_j$) and the bias $b_i$ to form its net input $P_i$

$$P_i = \sum_{j=1}^{n-1} w_{ij} x_j - b_i \qquad (1)$$

where $w_{ij}$ denotes the strength of connection from the $j^{th}$ input to the $i^{th}$ neuron and (n) being the number of input vectors, $x_j$ is the input vector; $b_i$ is the $i^{th}$ neuron bias. An activation function F(Pi), the sigmoid function, is used to calculate the neuron output given the set of neuron inputs. To find suitable $w_s$ and biases for each neuron, a process training is essential; it is the first step to build an ANN. Training means that the weights are corrected to produce prespecified ("correct", known from experiments) target values, and the training requires sets of pairs ($X_S$, $Y_S$) for input: the actual input into the network is a vector ($X_S$), and the corresponding target is labeled ($Y_S$) after successful training. When correct values of $Y_S$ for each vector of $X_S$ from the training set are obtained, it is hoped that the network will give correct predictions of Y for any new object of X according to the ANN model fundamentals and with the use of more data for training the network, better result would be obtained.

The most utilized training method for multilayered neural network is called back propagation, where Levenberg-Marquardt (LM) is applied which is considered the most efficient algorithm in terms of speed and memory usage. The number of observed data used in the ANN is 243 which are divided into three sections: the training set (240 data), test set (33 data) and validation set (30 data). Training, test and validation subsets of the ANN are obtained as selecting 74% of the dataset as training, 12.4% of the dataset as test and 13.6% of the dataset as validation subsets. The differences between observed and predicted values are filtered back through the system and is used to adjust the connections between the layers, thus performance improves.

Statistical quality of the ANN for the training, test and validation sets is evaluated using the squared correlation coefficient R:

$$R = 1 - \frac{\sum_{i=1}^{n}(y_i - y_i^t)^2}{\sum_{i=1}^{n}(y_i - y_0)^2} \tag{2}$$

$$y_0 = \frac{1}{n}\sum_{i=1}^{n}\left(y_i - y_i^t\right) \tag{3}$$

where $y_i$ represents either the i$^{th}$ trained, test or validation output value and $y_i^t$ is the corresponding target value. [12] ,[13]**.**

## 5. MATLAB Algorithm

The algorithm to predict the experimental data using ANN algorithm by using MATLAB software version R2014a, is summarized as follows:-

a. Experimental data file in EXCEL format and read these data into MATLAB must be prepared also MATLAB M.file to target, train and test the data.

b. In the MATLAB command window, type (nntool) and import inputs and targets data file into the neural network data manager.

c. Set input data, target data.

d. Train the network. On the train tab of the network, network dialog, select inputs and targets: and then press the train network button to start the network training.

e. Obtain the result of the trained data.

f. Hit the export button and test unseen data.

g. It is interesting to note that the performances of the neural networks decrease when overtraining occurs.

h. Input and target data.

The 243 experimental data are considered for modeling, data are trained by feed forward back propagation neural network. The targets, heat transfer coefficient and pressure drop are the predicted flow parameters of testing input data (input pressure, mass flux, exit vapour quality, heat flux, $DT_{sup}$).[10].

## 6. Results and Duscussion

The predictive ability of ANN can give a satisfying output to flow parameters included in the examples of the ANN learned. To determine that predictive ability, cross validation has been used. In this procedure one compound is removed from the data set, the network is trained with the remaining compounds and used to predict the discarded compound. The process is repeated in turn for each compound in the data set. After cross-validation, the predictive ability of different networks was assessed by the cross-validated (R).

The neural network performance is a function of the number of hidden neurons. The relationship between measured and predicted descriptors is expressed by a linear combination. The learning performance of the ANN increases with the number of iterations, but its predictive ability slowly decreases above 1000 iterations. This is known as the overtraining effect, due to a too long learning time. Indeed, the weights obtained after the overtraining contain more information specific to the training set. Therefore, prediction on the test set will not really be satisfying. Thus, when a very low error in the training set is sought, the predictive ability of an ANN is less successful- The ability to predict being an essential quality of an ANN, the overtraining effect must be avoided. The full results of cross validation for 1000 iterations and with the ANN architecture.

### 6.1. *Heat transfer Results.*

"Fig. 4",depicts the prediction of heat transfer coefficient with exit vapour quality and with heat flux at working pressures $P_s$(8.5, 10, 12.5)bar. The predicted data at selected new mass fluxes G(75, 125, 175, 225, 275) kg/m$^2$.s are compared with the experimental data at mass fluxes G(50,100,150,200,250,300) kg/m$^2$.s the curves trend show that the heat transfer coefficient increases as the vapour quality increases "Fig. 4.a,c,e ", and there is a clear mass flux effect this is because of convective heat transfer domination,**[**14**]**. The heat transfer coefficients increase as wall heat flux increase these are illustrated in "Fig. 4.b,d,f ".

### 6.2. *Pressure drop predictive results***.**

The pressure drop DP increases as the exit vapour quality increases and also as the mass flux increases, these results are illustrated in "Fig. 5.a,c,e", at $P_s$(8.5,10,12.5)bar, with selected mass fluxes G(75,125,175,225,275) kg/m$^2$.s. At the same conditions of system pressure and mass flux, $\Delta P$ increases as $q''_w$ increases, these results are depicted in "Fig. 5.b,d,f ". The curves trend agree with the results of experimental data.

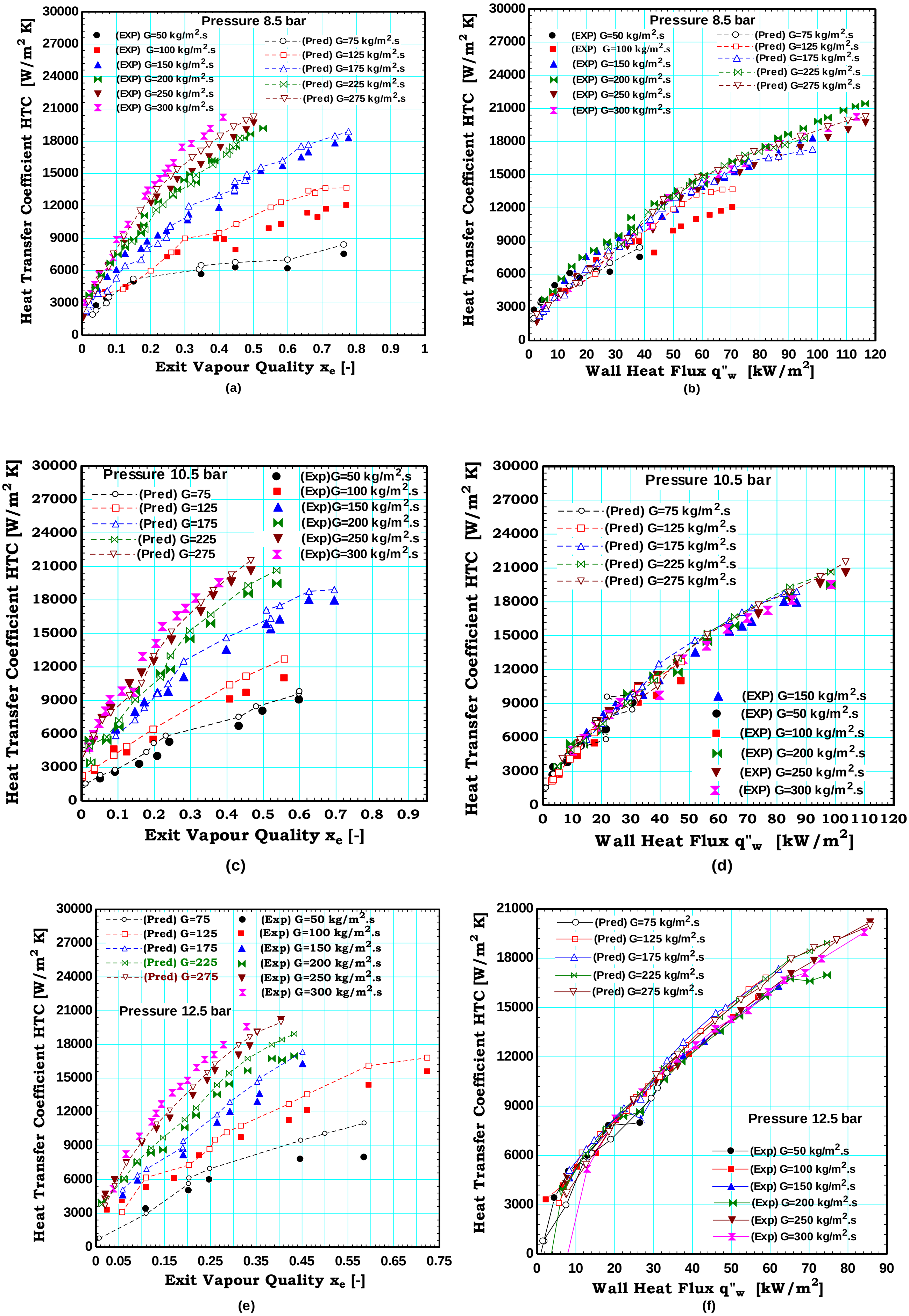


Figure 4. ANN predicted and experimental heat transfer coefficient.

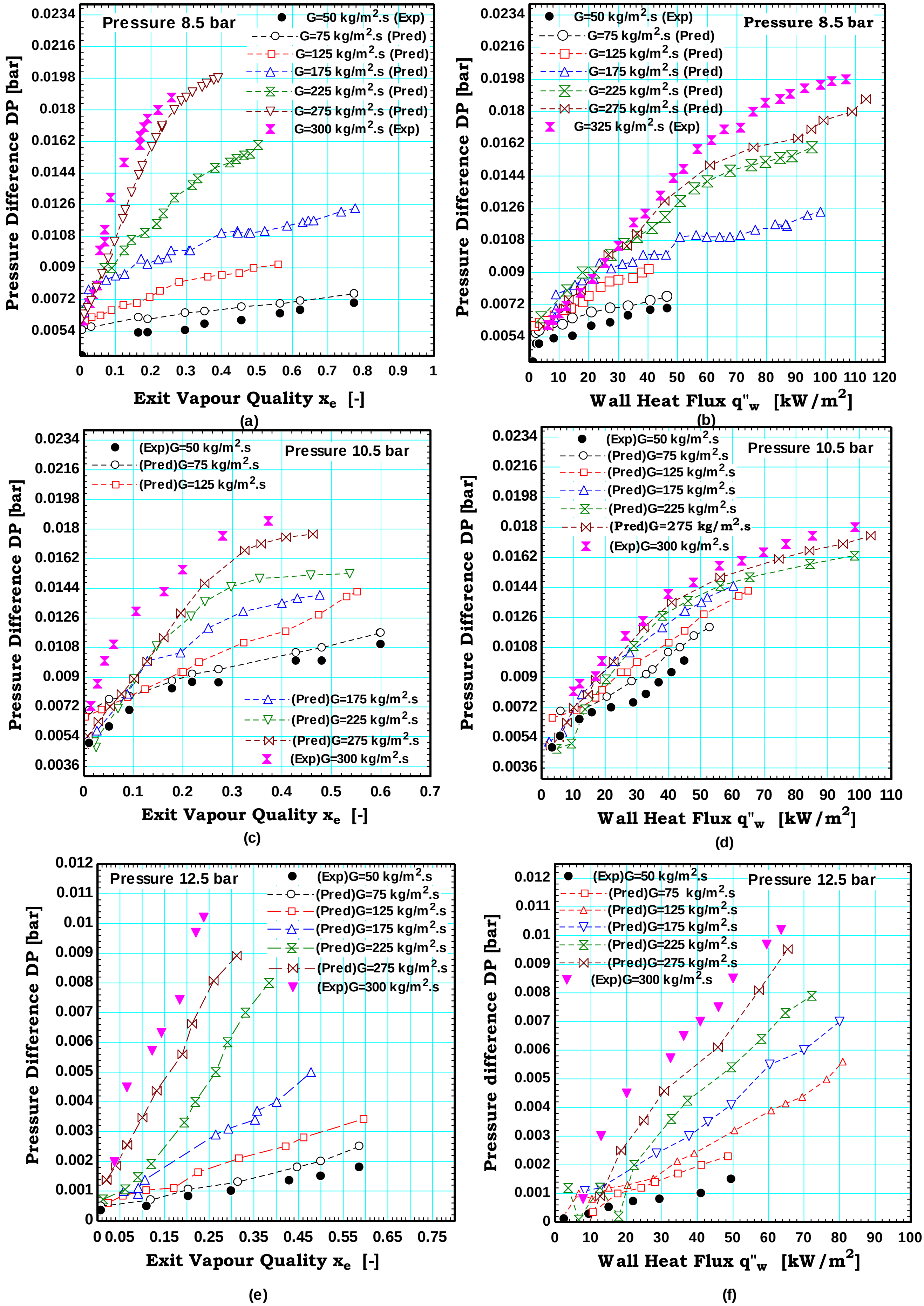


Figure 5. ANN predicted and experimental pressure drop data.

## 7. Conclusions

Flow boiling experiments in a coper multi- microchannels heat sink using R134a were performed for a mass flux range 50-300 $kg/m^2.s$, heat flux range (5-120) $kW/m^2$ and system pressure range 8.5-12.5 bar. The main concluding points can be summarized as follows:-

1- The heat transfer results demonstrated that the heat transfer coefficient depends strongly on heat flux while it is a weak function of mass flux. However, plotting the heat transfer coefficient versus vapour quality indicated dependence on vapour quality and mass flux. Based on that it would be difficult to infer the dominant mechanism using the conventional criteria.

2- The higher inlet pressure resulted in a higher heat transfer coefficient, when the heat transfer coefficient is plotted as a function of heat flux.

3. The two phase pressure drop increases with increasing heat flux, exit vapour quality at a constant mass flux the pressure drop decreased as the system pressure increased.

4. The possibility of using ANN based techniques to identify two-phase flow boiling parameters in multi parallel microchannels. The computing ability with ANN are very flexible and powerful. They are also very well suited for real time systems.

## 8. Nomenclatures

| | |
|---|---|
| $DT_{sup}$ | Super temperature difference ($T_w$-$T_s$) ($^oC$) |
| DP | Pressure drop (bar) |
| G | Mass flux ($kg/m^2.s$) |
| h | Coefficient of heat transfer ($W/m^2.K$) |
| LOGSIG | Hyperbolic tangent sigmoid |
| MLP | Multi Layer Preceptron |
| $P_s$ | System pressure ($N/m^2$). |
| PURELIN | Linear transfer function |
| $q''_w$ | Wall heat flux ($kW/m^2$) |
| R | Squared correlation coefficient |
| $T_s$ | Saturated temperature ($^oC$) |
| $T_w$ | Wall temperature ($^oC$) |
| $x_e$ | Exit vapour quality (-) |

***Abbreviations***

| | |
|---|---|
| ANN | Artificial Neural Network |

***Supscriptions***

| | |
|---|---|
| s | System |
| w | Wall |

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