# USING ARTIFICIAL NEURAL NETWORK FOR PREDICTING HEAT TRANSFER COEFFICIENT DURING FLOW BOILING IN AN INCLINED CHANNEL

by

***Adel BOUALI*** [a*], ***Salah HANINI*** [a], ***Brahim MOHAMMEDI*** [b], **and *Mouloud BOUMAHDI*** [a]

[a] Laboratory of Biomaterials and Transport Phenomena (LBMPT), University of Medea, Medea, Algeria
[b] Nuclear Research Center of Birine, Birine, Algeria

Original scientific paper
https://doi.org/10.2298/TSCI200620238B

*The flow and heat transfer characteristics in a nuclear power plant in the event of a serious accident are simulated by boiling water in an inclined rectangular channel. In this study an artificial neural network model was developed with the aim of predicting heat transfer coefficient for flow boiling of water in inclined channel, the network was designed and trained by means of 520 experimental data points that were selected from within the literature. Orientation,mass flux, quality and heat flow which were employed to serve as variables of input of multiple layer perceptron neural network, whereas the analogous heat transfer coefficient was selected to be its output. Via the method of trial-and-error, multiple layer perceptron network with 30 neurons in the hidden layer was attained as optimal arteficial neural network structure. The fact that is was enabled to predict accurately the heat transfer coefficient. For the training set, the mean relative absolute error is about 0.68 % and the correlation coefficient, is about 0.9997. As for the testing and validation set they are, respectively, about 0.60 % and 0.9998 and about 0.79 % and 0.9996. The comparison of the developed arteficial neural network model with experimental data and empirical correlations in vertical channel under the low flow rate and low quality shows a good agreement.*

Key words: *inclined channel, flow boiling, heat transfer coefficient, artificial neural networks*

## Introduction

Flow boiling is a very efficient mode of heat transfer, it is applied in the cooling systems of the nuclear core, the key parameters of this phenomenon are the critical heat flow and the heat transfer coefficient (HTC), many researchers have investigated on these two parameters during the past years.

Gang *et al.* [1] studied experimentally the orientation effect on HTC of a downward surface for flow boiling in a rectangular channel under low flow rate. they developed a new HTC correlation based on Liu and Winterton [2] by considering the orientation effect, another new correlation has been developed by Kouidri *et al.* [3] for the average HTC during flow boiling in a rectangular channel valid for Reynolds number between 380 and 1522 and for heat flux between 9 and 137 KW/m$^2$. The orientation effect on flow boiling HTC for FC-72 in a one side

* Corresponding author, e-mail: boualiadelgm2020@gmail.com

heated micro-channel has been studied by Piasecka [4], they showed that the HTC is higher for an orientation angle equal to 90° they showed also that for lower quality the orientation effect is important. For the vertical tube Chen [5] developed a new model for the estimation of the HTC for saturated flow boiling, the model is based on the combination of the convective heat transfer and nucleate boiling heat transfer, their model is essentially based on the correlations of Forster and Zuber [6]. Shah [7] proposed a correlation for the vertical and horizontal tubes, he considered convective and nucleate boiling as fundamental process of heat transfer. Gungor and Winterton [8] used a large database for water and other fluids to give another form of the Chen correlation's. Kandlikar [9] developed a general correlation for the HTC on the basis of a database with 5246 experimental data. Kim and Sohn [10] developed a correlation for HTC after an experimental study of the flow boiling in a rectangular channel with large range of Reynolds number and heat flux. Ozdemir *et al.* [11] studied experimentally the flow boiling of water in single rectangular micro-channels.

Artificial intelligence is a tool used for modelling the complex phenomenon of heat transfer, the artificial neural networks (ANN) is one of the techniques of artificial intelligence that can provide useful tools for modelling and correlating practical heat transfer problems, ANN technique has been used by Mohamedi *et al.* [12] for prediction of the transport and thermodynamic properties on saturated vapor and saturated liquid of the water, which are used also for prediction of thermal conductivity of liquid and vapor refrigerants for pure and their binary, ternary mixtures [13], ANN has been used for the prediction of flow boiling of $Al_2O_3$ and $TiO_2$ nanofluids in horizontal tube [14] prediction of pool boiling HTC for various nanorefrigerants [15], prediction of flow boiling curves [16], prediction of the normal boiling point temperature and relative liquid density of petroleum fractions and pure hydrocarbons [17].

The great advantages of ANN is their ability to learn, generalize, or extract automatically rules from complex data, but the great disadvantage of ANN technique is that it can be used only in the range in which it has been trained as it is empirical in nature [18].

This work extends the application of ANN to develop a model for prediction of HTC for flow boiling of water in inclined channel as a function of orientation heat flux, mass flux, and equilibrium quality. The first novelty of this study is the highest accuracy of the developed ANN model compared to the empirical correlations for the prediction of HTC, the second novelty is the determination of the effect of each input parameters on HTC, especially the effect of the orientation on HTC.

## Artificial neural networks model

A neural network is a computer model whose layered structure is similar to the network structure of neurons in the brain, with layers of connected nodes. A neural network can learn from data, it can thus be trained to recognize trends, classify data and predict future events [19].

A neural network breaks your data down into abstraction layers. It can be trained on many examples in order to recognize patterns in speech or images, the behavior of the ANN is defined by the way its individual elements are connected and by the weights of those links [20].

These weights are automatically adjusted during training according to a specified learning rule until the neural network performs the desired task correctly. The ANN approach is thought to be the perfect solution of any kind of problem in which the associations between variables are not linear and complex. In the multiple layer perceptron structure, the neurons are gathered into layers, one layer of input neurons, another layer of output neurons and one or more hidden layers. They are created by many interconnected neurons [12].

The number of neuron in the input layer is equal to the number of input variables and the number of neuron in the output layer is equal to the number of variables in targets, but the number of neuron in the hidden layer is chosen for the best performance. Each neuron should be connected with every neuron in an adjacent layer, the initial synaptic weights are given randomly to all of the connections, the normalized input data are entered at the input layer to be transmitted to hidden layers through synaptic connections, knowing that the output layer as their final destination [21].

This study aims at building an ANN model, capable of predicting the HTC during flow boiling of water in inclined rectangular channel as a function of orientation, $\theta$, heat flux, $q$, mass-flow, $G$, and equilibrium quality, $Xe$.

The number of experimental data used in the ANN is 520, which are divided into three sections: the training set (312 data), the test set (104 data), and the validation set (104 data). Table 1 shows the range of variables.

**Table 1. Range of variables**

| | Measure | Unit | Min | Max | Uncertainty |
|---|---|---|---|---|---|
| Orientation | $\theta$ | [ ° ] | 0 | 90 | – |
| Mass flux | $G$ | [Kgm$^{-2}$S$^{-1}$] | 110 | 208 | 0.5% |
| Heat flux | $q$ | [MWm$^{-2}$] | 0.1 | 1.6 | 1.7% |
| Quality | $Xe$ | – | 0.003 | 0.036 | 2.3% |
| Heat transfer coefficient | $HTC$ | [KWm$^{-2}$K$^{-1}$] | 8.315 | 46.55 | 6.2% |

To normalize the input data in the range of [–1, 1] we used the mapminmax algorithm given by eq. (1), but for the normalization of the output data we used the logarithmic function and the $map_{\text{minmax}}$ function, eq. (2):

$$y_n = map_{\min\max}(X) = \frac{2(X - X_{\min})}{(X_{\max} - X_{\min})} - 1 \tag{1}$$

where $X$ is the original vector value, $X_{\max}$ and $X_{\min}$ are the maximum and minimum values corresponding to $X$, respectively, and $y_n$ is the vector value normalized by the $X$ vector:

$$HTC_n = map_{\min\max}\left[\ln\left(HTC\right)\right] \tag{2}$$

where $HTC_n$ is the normalized value of the output, the network is trained by the normalized input and output values.

Finding an optimal ANN architecture is very important due to its major effects on the results [12]. After the examination of a significant number of differently structured neural networks, the optimization of ANN parameters is performed by minimizing the mean relative absolute error (MRAE), the adequate ANN structure that was selected in this investigation has a 30 neurons in the hidden layer. The hidden layer has a tangent sigmoid transfer function. The output layer has a linear transfer function and the Levenberg-Marquardt as a learning algorithm. The optimal ANN structure is presented in tab. 2.

**Table 2. Architecture of the optimized ANN model**

| Training algorithm | Input layer | Hidden layer | | Output layer | |
|---|---|---|---|---|---|
| | Numbre of neurons | Numbre of neurons | Activation function | Numbre of neurons | Activation function |
| Levenberg-Marquardt backpropagation | 4 | 30 | Hyperbolic tangent sigmoid | 1 | Linear |

The developed ANN model is given:

$$HTC_n = \sum_{j=1}^{j=N_h} \left( V_j \left\{ \frac{2}{1+\exp\left[ -2\left( b_j + \sum_{i=1}^{i=N_p} W_{ij} y_{n_i} \right) \right]} - 1 \right\} \right) + b_{\text{out}} \tag{3}$$

where $W_{ij}$ and $V_j$ are the synaptic weights between the input laye and the hidden layer and between the hidden layer and the output layer successively and $b_j$ and $b_{\text{out}}$ are the bias vectors of the hidden layer and output layer.

## Results and discussion

In this work the performance and reliability of the ANN model were evaluated by various statistical criteria including the relative absolute error, RAE [%], MRAE, the mean square error (MSE), the correlation coefficient ($R$), and the coefficient of determination ($R^2$) [22] .

Accuracy factor, $A_f$, and bias factor, $B_f$, were proposed by Ross [23] were used as criteria for assessing of model performance. The $B_f$ indicate the overall agreement between estimated and actual values, a $B_f$ of 1 means complete agreement.

Good model: $B_f = 0.9 – 1.05$

Acceptable model: $B_f = 0.7 – 0.9$

Model use with caution: $B_f = 1.06 – 1.15$

Unacceptable model: $B_f < 0.7$ and $B_f > 1.1$

The accuracy factor, $A_f$, value will always be equal to or greater than one as all variances are positive. The $A_f$ value of 1.1 means that the estimated value is 10% different from the target value.

The developed ANN model was also evaluated by the criteria of acceptability, $K$ and $K'$, suggested by researchers [24], the model is acceptable if:

$$0.85 \le K \le 1.15 \text{ and } 0.85 \le K' \le 1.15$$

Table 3 gives the obtained values of the weights and the biases ($W_{ij}$, $V_j$, $b_j$, and $b_{\text{out}}$) for the optimal ANN architecture given in tab. 2. These parameters are used in the developed ANN model given in eq. (3) to calculate the HTC during flow boiling of water in an inclined channel.

**Table 3. Optimal values of weights and biases obtained during training of ANN**

| | Weights between the input layer and the hidden layer | | | | Bias values of hidden layer | Weights between the hidden and the output layer | Bias values of output layer |
|---|---|---|---|---|---|---|---|
| $j$ | $W_{1j}$ | $W_{2j}$ | $W_{3j}$ | $W_{4j}$ | $b_j$ | $V_j$ | $b_{out}$ |
| 1 | –1.3117 | 5.8123 | –2.1972 | 6.0248 | 9.7987 | 0.3510 | |
| 2 | 1.5042 | –0.3139 | –3.1344 | 2.3667 | –4.6555 | –2.3514 | |
| 3 | 1.8579 | –0.9120 | –0.3420 | 2.7751 | –3.1617 | 2.3875 | |
| 4 | 2.7216 | 0.3661 | –28504 | –1.5029 | –2.5968 | –2.1650 | |
| 5 | –2.9503 | –1.7629 | 2.4108 | 3.6133 | 4.4408 | 2.3816 | |
| 6 | 3.6294 | 0.6730 | –3.2475 | –1.0666 | –2.8832 | 1.4117 | |
| 7 | 1.8301 | 1.7327 | –2.6270 | –2.5217 | –3.3098 | 2.9724 | |
| 8 | 0.9541 | –3.4161 | –4.0314 | 0.9683 | 2.2023 | –0.4536 | |
| 9 | 0.4134 | –1.4506 | 1.8620 | –1.0447 | –1.8416 | –1.0716 | –5.3525 |
| 10 | –4.1274 | 0.0097 | –3.6633 | –1.5042 | 2.2696 | 0.2415 | |
| 11 | 1.1978 | -0.8278 | –0.2641 | –2-6551 | –0.7530 | 3.3854 | |
| 12 | 1.8921 | –1.5796 | –0.0382 | –0.4343 | –0.3074 | –1.3913 | |
| 13 | 3.8155 | –1.2136 | –3.2717 | –2.5947 | –2.0447 | –1.2379 | |
| 14 | –3.5888 | 0.2031 | –3.6489 | 0.4966 | –1.1658 | 0.3237 | |
| 15 | –3.7544 | 1.0163 | 0.1521 | 2.0787 | 1.3048 | –1.3724 | |
| 16 | –4.1396 | –5.2211 | –1.9237 | –1.1470 | 1.09778 | –0.0379 | |
| 17 | –5.2853 | 4.2681 | –4.6420 | 2.0188 | –0.4281 | –0.0697 | |
| 18 | 0.7786 | –2.8529 | 2.2165 | 0.9115 | 0.7849 | 2.0610 | |
| 19 | –1.2543 | –0.3848 | –0.9557 | –1.3637 | –0.9165 | –3.5568 | |
| 20 | –1.2442 | 3.9585 | –2.9973 | –1.2225 | –0.8220 | 1.0742 | |
| 21 | 1.0025 | 0.8902 | 0.4770 | –1.7181 | 0.4898 | –0.9678 | |
| 22 | 2.8452 | –0.6413 | –1.6201 | 2.5124 | 1.0015 | –1.7350 | |
| 23 | 3.3238 | 1.9422 | –0.5087 | –1.3597 | 1.9492 | 0.5735 | |
| 24 | 1.5642 | –1.0487 | 2.7174 | –1.2099 | 2.7523 | –4.1343 | |
| 25 | 2.5044 | 1.1520 | –2.8710 | –0.5543 | 1.6281 | –0.9639 | |
| 26 | 0.1314 | 1.9148 | –0.6953 | –2.7528 | 3.5711 | 0.6669 | |
| 27 | –0.6939 | 8.3469 | –0.0274 | –0.4532 | 7.4872 | 0.1112 | |
| 28 | –4.0681 | 2.0208 | 2.7900 | –1.3605 | –4.6937 | –1.6225 | |
| 29 | 0.7754 | –4.0405 | 2.3124 | 3.6029 | 5.8716 | 2.0378 | |
| 30 | –1.8228 | 1.2004 | –1.7758 | 2.1135 | –3.3714 | –2.7929 | |

The performance results of the used ANN for training data, testing data, validation data, and all data are shown in tab. 4. The $R$ value of 0.9997 for all data indicated the reliability of the ANN model and confirmed the model is valid. The $R^2$ value of 0.9993 for all data indicated the suitability of the model. The values of bias factor, $B_f$, and accuracy factor, $A_f$, are close to unity, which indicates that the model is valid in the predicting of HTC. The values of $K$ and $K'$ indicates that the model is acceptable. The values of the MRAE demonstrates the accuracy of the ANN model.

**Table 4. Statistical performance of the ANN**

| | Training | Testing | Validation | All |
|---|---|---|---|---|
| $RAE_{min}$ [%] | 0.0002 | 0.0054 | 0.0058 | 0.0002 |
| $RAE_{max}$ [%] | 4.6615 | 4.7273 | 4.5429 | 4.7273 |
| MRAE [%] | 0.6834 | 0.6084 | 0.7910 | 0.6899 |
| MSE | 0.0012 | 0.0263 | 0.0151 | 0.0020 |
| $R$ | 0.9997 | 0.9998 | 0.9996 | 0.9997 |
| $R^2$ | 0.9993 | 0.9995 | 0.9992 | 0.9993 |
| $A_f$ | 1.0069 | 1.0061 | 1.0079 | 1.0069 |
| $B_f$ | 1.0002 | 0.9990 | 1.0002 | 1.0005 |
| $K$ | 1.0003 | 1.0005 | 0.9990 | 1.0001 |
| $K'$ | 0.9996 | 0.9994 | 1.0009 | 0.9998 |

The regression analysis performed between the experimental values and the predicted values of HT*C*. The training, validation, and testing results illustrated in fig. 1. These results confirm the high ability of the used ANN model and demonstrate a good fitting between the predicted and the experimental values of HTC.

The residual of the predicted values of the HTC against the experimental values for the developed ANN model is shown in fig. 2. As most of the calculated residuals are distributed on two sides of the zero line, a conclusion may be drawn that there is no systematic error in the development of the present model.

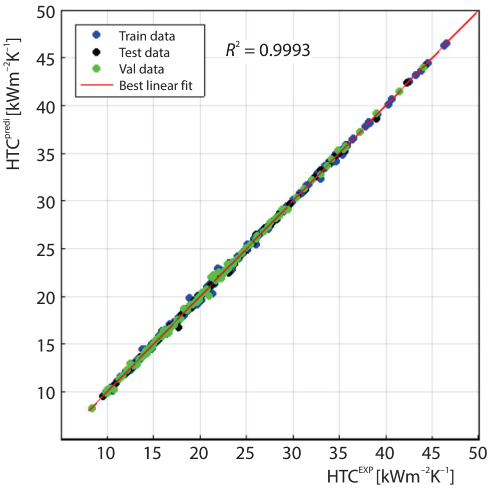


**Figure 1. Regression plots of ANN for prediction of HTC (all data sets)**

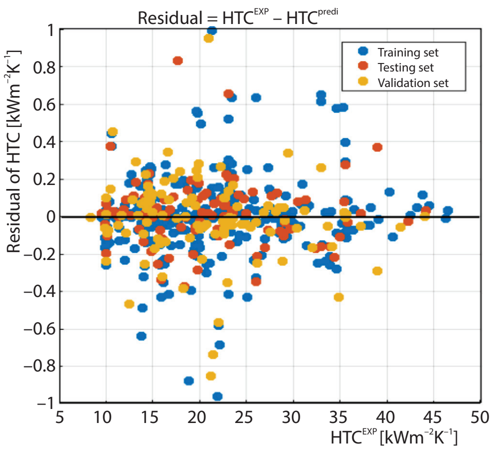


**Figure 2. Plot of the residuals for calculated values of HTC from the ANN model *vs.* their experimental values for the training, test and validation sets**

Normal probability plot of ANN model prediction of HTC is shown in fig. 3. In a normal probability, nearly a straight diagonal line is formed by the data points which shows normally distributed data. As shown in fig. 3, many of the data points are very near to residual value zero which indicates minimum errors in developed ANN model.

Typical prediction results of the developed ANN model regarding the influence of the orientation, $\theta$, and heat flux, $q$, on the HTC are shown in fig. 4, from the figure it is clear that the HTC is almost constant between 0° and 30°, but in the range of 30-70°, the HTC increases enormously and the variation of HTC between 70° and 90° is very small, it is also clear that the increase in heat flux causes the increase in HTC, these results are almost compatible with the results of Gong *et al.* [1].

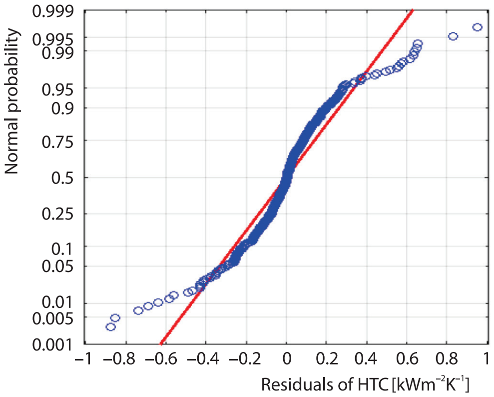


**Figure 3. Normal probability plot of ANN model for predicting HTC**

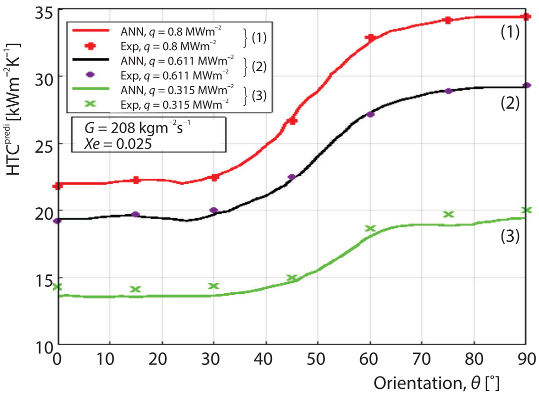


**Figure 4. Model prediction of orientation effect on the HTC**

Typical prediction results of the developed ANN model regarding the influence of the mass flux, $G$, and quality, $Xe$, on the HTC are shown in figs. 5 and 6, from the figures we show that the effect of mass flux and quality on the HTC are weak, these results are similar to results reported in [1].

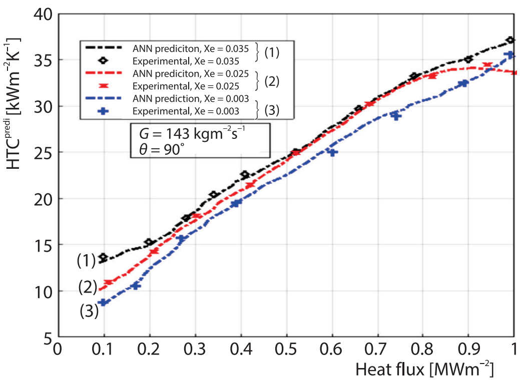


**Figure 5. Model prediction of quality effect on the HTC**

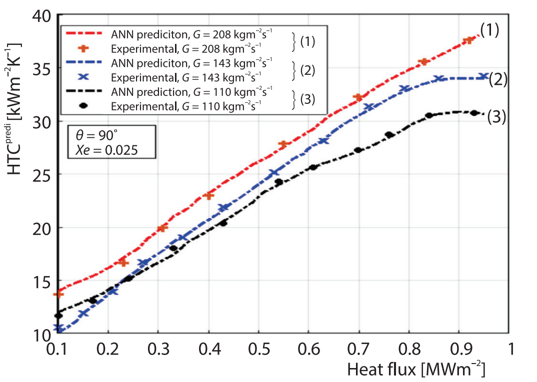


**Figure 6. Model prediction of mass flux effect on the HTC**

*Validation of ANN model*

To validate the developed ANN model, we compared it with the empirical correlations of saturated boiling HTC [2, 7, 8] and experimental data of Gong *et al.* [1] for vertical channel, the comparison is shown in fig. 7, the model was also compared with the Gong *et al.* [1] experimental results for different orientations in fig. 8, from the two figures we can see the precision and the validity of the neural model developed for the prediction of HTC during flow boiling of water in an inclined channel.

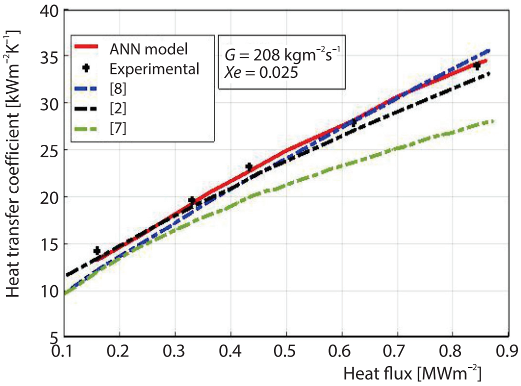


**Figure 7. Comparisons of ANN prediction of HTC with experimental data and empirical correlations in vertical channel**

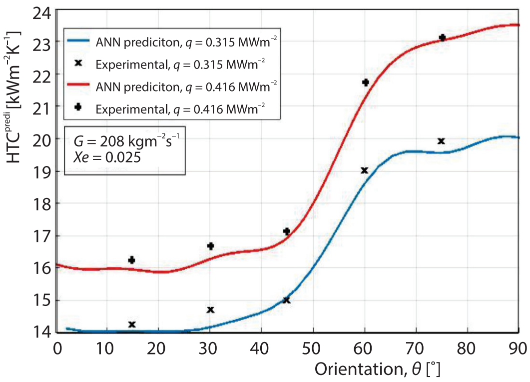


**Figure 8. Comparisons of ANN prediction of orientation effect on HTC with experimental**

*Determination of importance of each input variable*

The values of neural network weights are used to know the relative importance of the different input variables (orientation, mass flux, heat flux, quality) on the output variable (HTC), an equation based on partitioning of connection weights anticipated by [25]:

$$imp_t = \frac{\sum_{j=1}^{N_h}\left(\frac{|W_{tj}|}{\sum_{j=1}^{N_p}|W_{ij}|}|V_j|\right)}{\sum_{i=1}^{N_p}\left[\sum_{j=1}^{N_h}\left(\frac{|W_{tj}|}{\sum_{i=1}^{N_p}|W_{ij}|}|V_j|\right)\right]} \tag{4}$$

where $imp_t$ is the relative importance of the input variable $t$ on the output variable, $N_p$ and $N_h$ are the number of input and hidden neurons, respectively, $W_{ij}$ – the connection weights between the input layer and the hidden layer, and $V_j$ – the connection weights between the hidden layer and the output layer. Note that the numerator in the eq. (4), describes the sum of the products of the absolute weights for each entry. However, the denominator is the total of all the weights feeding the hidden unit, taking the absolute values [26] .

A summary of the obtained results is presented in fig. 9. It can be seen that the orientation has strong effects on the HTC value with importance equal to 27%, but the heat flux and the equilibrium quality and mass flux have almost the same effect on the HTC value with an importance equal to 19 and 25, and 28%, respectively.

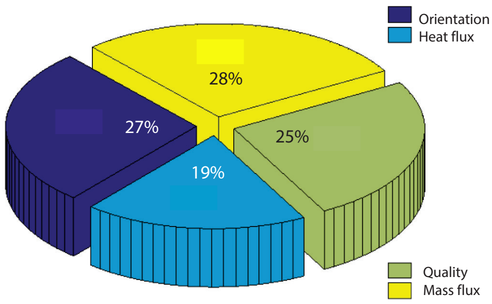


**Figure 9. Relative importance of input variables on outputs**

### *Computer program for calculate heat transfer coefficient*

A computer program has been developed in MATLAB for the purpose of using the neural model with more flexibility. This gives the user all the necessary inputs for the execution of model to predict the HTC during flow boiling of water in inclined rectangular channel, fig. 10.

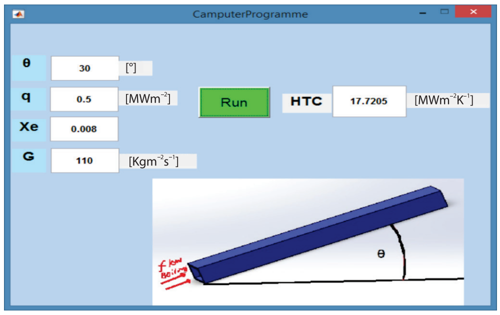


**Figure 10. The MATLAB interface for HTC**

## Conclusions

In this work we developed a neural model prediction of the HTC during flow boiling of water in inclined channel, depending on orientation, heat flux, low equilibrium quality, and low mass flux. The comparison between the experimental data and the data predicted by the neural network shows the performance of the used network architecture.

The optimal training data was attained with 4-30-1 structure considering the Levenberg-Marquardt back propagation training algorithm and the tangent sigmoid transfer function in the hidden layer and linear transfer function in the output layer. A total of 520 experimental data points were collected from the literature resources to employ in the ANN model as training, validation and testing data points. The MRAE of 0.68% and correlation coefficient of 0.9997 were obtained by the ANN model for all data sets.

We conclude that the orientation effect on HTC is very important in the region between 30° and 70°, we also conclude that the effects of low mass flux and low quality on HTC are weak.

The validity of the ANN model is shown in its comparison with some empirical correlations for vertical channel and with the experimental results for various orientations.

## Acknowledgment

We are grateful to the Laboratory of Biomaterials and Transport Phenomena (LBMPT) of the University of Medea for the financial support provided. The authors also express their gratitude for the useful and interesting discussions with researchers at the Birine Nuclear Research Center (CRNB).

## Nomenclature

$A_f$ – accuracy factor
$B_f$ – bias factor
$b_j$ – bias values of hidden layer
$b_{out}$ – bias value of output layer
$G$ – mass-flow rate, [$Kgm^{-2}S^{-1}$]
$HTC$ – heat transfer coefficient, [$KWm^{-2}K^{-1}$]
$imp_t$ – relative importance of the input variable
$K$, $K'$ – criteria of acceptability
$N_h$ – number of neurons in the hidden layer
$N_p$ – number of neurons in the input layer
$q$ – heat flux, [$MWm^{-2}$]
$R$ – coefficient of correlation
$R^2$ – coefficient of determination
$V_j$ – synaptic weights between the hidden layer and the output layer
$W_{ij}$ – synaptic weights between the hidden layer and the output layer
$Xe$ – equilibrium quality

*Subscripts and superscripts*

max – maximum
min – minimum
exp – experimental value
predi – predicted value

*Greek symbols*

$\theta$ – the angle between the inclined channel and the horizontal, [°]

*Acronyms*

ANN – artificial neural network
MRAE – mean relative absolute error
MSE – mean squared error
RAE – relative absolute error

## References

[1] Gong, S., *et al*., Orientation Effect on Heat Transfer Coefficient of a Downward Surface for Flow Boiling in a Rectangular Channel under Low Flow Rate, *International Journal of Heat and Mass Transfer, 153* (2020), 119594
[2] Liu, Z., Winterton, R., A General Correlation for Saturated and Subcooled Flow Boiling in Tubes and Annuli, Based on a Nucleate Pool Boiling Equation, *International Journal of Heat and Mass Transfer*, *34* (1991), 11, pp. 2759-2766
[3] Kouidri, A., *et al*., Experimental Investigation of Flow Boiling in Narrow Channel, *International Journal of Thermal Sciences*, *98* (2015), Dec., pp. 90-98
[4] Piasecka, M., Correlations for Flow Boiling Heat Transfer in Minichannels with Various Orientations, *International Journal of Heat and Mass Transfer*, *81* (2015), Feb., pp. 114-121
[5] Chen, J. C., Correlation for Boiling Heat Transfer to Saturated Fluids in cCnvective Flow, *Industrial & Engineering Chemistry Process Design and Development*, *5* (1966), 3, pp. 322-329
[6] Forster, H., Zuber, N., Dynamics of Vapor Bubbles and Boiling Heat Transfer, *AIChE Journal*, *1* (1955), 4, pp. 531-535
[7] Shah, M. M., Chart Correlation for Saturated Boiling Heat Transfer: Equations and Further Study, *ASHRAE Transactions*, *88* (1982), Jan., pp. 185-195
[8] Gungor, K., Winterton, R. S., Simplified General Correlation for Saturated Flow Boiling and Comparisons of Correlations with Data, *Chemical Engineering Research and Design*, *65* (1987), 2, pp. 148-156
[9] Kandlikar, S. G., A General Correlation for Saturated Two-Phase Flow Boiling Heat Transfer Inside Horizontal and Vertical Tubes, *Journal of Heat Transfer*, *112* (1990), 1, pp. 219-228
[10] Kim, B., Sohn, B., An Experimental Study of Flow Boiling in a Rectangular Channel with Offset Strip Fins, *International Journal of Heat and Fluid-Flow*, *27* (2006), 3, pp. 514-521
[11] Ozdemir, M. R., *et al.,* Flow Boiling of Water in a Rectangular Metallic Micro-Channel, *Heat Transfer Engineering*, *42* (2020), 6, pp. 492-516
[12] Mohamedi, B., *et al*., Simulation of Nucleate Boiling under ANSYS-FLUENT Code by Using RPI Model Coupling with Artificial Neural Networks, *Nuclear Science and Techniques*, *26* (2015), 4, pp. 40601-040601
[13] Ghalem, N., *et al*., Prediction of Thermal Conductivity of Liquid and Vapor Refrigerants for Pure and Their Binary, Ternary Mixtures Using Artificial Neural Network, *Thermophysics and Aeromechanics, 26* (2019), 4, pp. 561-579
[14] Dadhich, M., *et al*., Flow Boiling Heat Transfer Analysis of $Al_2O_3$ and $TiO_2$ Nanofluids in Horizontal Tube Using Artificial Neural Network (ANN), *Journal of Thermal Analysis and Calorimetry*, *139* (2020), 5, p p. 3197-3217

[15] Zarei, M., *et al.*, Prediction of Pool Boiling Heat Transfer Coefficient for Various Nanorefrigerants Utilizing Artificial Neural Networks, *Journal of Thermal Analysis and Calorimetry*, *139* (2019), 6, pp. 3757-3768

[16] Su, G., *et al.*, Applications of Artificial Neural Network for the Prediction of Flow Boiling Curves, *Journal of Nuclear Science and Technology*, *39* (2002), 11, pp. 1190-1198

[17] Fissa, M. R., *et al.*,The QSPR Estimation Models of Normal Boiling Point and Relative Liquid Density of Pure Hydrocarbons Using MLR and MLP-ANN Methods, *Journal of Molecular Graphics and Modelling*, *87* (2019), Mar., pp. 109-120

[18] Haykin, S., *Neural Networks: A Comprehensive Foundation,* Prentice Hall PTR, Upper Saddle River, N. J., USA, 1998

[19] Thanikodi, S., *et al*., Teaching Learning Optimization and Neural Network for the Effective Prediction of Heat Transfer Rates in Tube Heat Exchangers, *Thermal Science*, *24* (2019), 1, pp. 575-581

[20] Maouz, H., *et al*., Modelling the Molecular Weight and Number Average Molecular Masses during the Photo-Thermal Oxidation of Polypropylene Using Neural Networks, *Moroccan Journal of Chemistry*, *7* (2019), 1, pp. 17-27

[21] Koyuncu, H., Determination of Positioning Accuracies by Using Fingerprint Localisation and Artificial Neural Networks, *Thermal Science*, *23* (2019), Suppl. 1, pp. S99-1S11

[22] Benimam, H., *et al*., Dragonfly-Support Vector Machine for Regression Modelling of the Activity Coefficient at Infinite Dilution of Solutes in Imidazolium Ionic Liquids Using σ-Profile Descriptors, *Journal of Chemical & Engineering Data*, *65* (2020), 6, pp. 3161-3172

[23] Ross, T., Indices for Performance Evaluation of Predictive Models in Food Microbiology, *Journal of Applied Bacteriology*, *81* (1996), 5, pp. 501-508

[24] Golbraikh, A., Tropsha, A., Beware of $q^2$, *Journal of Molecular Graphics and Modelling*, *20* (2002), 4, pp. 269-276

[25] Garson, D. G., Interpreting Neural Network Connection Weights, *Al Expert*, *6* (1991), 4, pp. 46-91

[26] Hamzaoui, Y. E., *et al*., Optimal Performance of COD Removal during Aqueous Treatment of Alazine and Gesaprim Commercial Herbicides by Direct and Inverse Neural Network, *Desalination*, *277* (2011) 1-3, pp. 325-337

Paper submitted: June 20, 2020
Paper revised: July 27, 2020
Paper accepted: August 17, 2020