# ON THE USE OF AI FOR TWO-PHASE FLOW IN BPHE

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## ABSTRACT

This paper presents how it is possible to develop and implement AI based models to accurately predict the refrigerant boiling and condensation heat transfer coefficients as well as frictional pressure drops inside Brazed Plate Heat Exchangers (BPHEs). Two Artificial Neural Networks (ANNs) were developed, trained and validated against two large experimental databases consisting of: 1760 data points comprising 15 plate geometries and 16 refrigerants for boiling and 1884 data points comprising 12 plate geometries and 16 refrigerants for condensation. Differently, a Gradient Boosting Machines (GBM) model for predicting refrigerant two-phase frictional pressure drops in BPHEs based on an extensive database that includes 1624 boiling data-points, 925 condensation data-points, 16 different plate geometries, and 16 different refrigerants. The results demonstrates that the AI tools presented herein are capable of better predictive capability than most of the state-of-the-art BPHE analytical-computational models presented in the open literature.

## 1. INTRODUCTION

Thanks to the overall effectiveness, compactness, flexibility and ease of maintenance of Plate Heat Exchangers (PHE), they are widely used in food engineering, process industries, energy generation and conversion systems, and air conditioning and refrigeration applications. Regarding air conditioning and refrigeration applications, PHE are mainly used to realize highly-effective two-phase heat transfer of refrigerants in condensers and evaporators, including in lower temperature refrigeration applications, in medium temperature air conditioning applications and in higher temperature heat pumping applications. In many of these applications, high-pressure refrigerants are employed. In such applications, a specific type of PHE is required, namely, the Brazed Plate Heat Exchanger (BPHE). In this latter type of heat exchanger, the plates are typically joined by either copper or nickel brazing, rather than being joined by gaskets (GPHE) as is the case for low-pressure working fluid applications.

Despite the widespread use of brazed plate heat exchangers (BPHEs), the quantity of experimental data for the two-phase heat transfer of refrigerants inside BPHE available in the open literature is rather scarce. Furthermore, heat transfer and pressure drop correlations are not as numerous or as well established for BPHE as they are for tubular heat exchangers. However, the design of any heat transfer equipment must take into account two different concurrent issues: the increase of the heat transfer coefficients, which involves a reduction of size and direct costs of the heat exchanger for a set thermal effectiveness, and the reduction of pressure drops, which increases the global efficiency of the system reducing also pumping indirect costs. The final optimum solution derives from the balance between these two contrasting aspects.

For example, considering only herringbone- type BPHE, the prediction of two-phase heat transfer and pressure drop of refrigerants is a function of the plate geometry (flow length $L$ and width $W$ of the plate, inclination angle $\beta$, amplitude $e$ and wavelength $p$ of the corrugation), the operating conditions (mass flux $G$ , heat flux $q$ , vapour quality $X$ , saturation temperature $T$ / pressure $P$, saturated / superheated vapour conditions), and the fluid properties of the refrigerant (vapour / liquid density $\rho$, thermal conductivity $\lambda$, dynamic viscosity $\mu$, surface tension $\sigma$, latent heat of phase-change $J_{LG}$ ). Moreover, nowadays, the substitution of more conventional HydroFluoroCarbon (HFC) refrigerants, many of which possess unacceptably high Global Warming Potential (GWP) values, involves the use of newer low-GWP refrigerants, mainly HydroFluoroOlefin (HFO) and HydroChloroFluroOlefin (HCFO) refrigerants. Unfortunately for a number of potential HFO and HCFO refrigerants, the thermophysical properties have not yet been sufficiently characterized in the open literature.

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The traditional models proposed for refrigerant: condensation heat transfer [1], boiling heat transfer [2-4] and for the two-phase frictional pressure drops [3-5] in BPHE are able to reproduce the different available databases with a mean absolute average deviation ranging between ±15% and ±25%. In general, it can be stated that it is difficult to obtain substantially better predictive capability than is currently possible by employing, or building directly upon, conventional analytical-computational methodologies available in the open literature mainly because of the complexity of two-phase heat transfer inside BPHE as already described above. In fact, analytical-computational methodologies are not able to accurately account for the many different parameters and mechanisms affecting two-phase heat transfer in BPHE which require more complex analysis techniques such as, for example, the Machine Learning techniques. Furthermore, for models to be able to reliably capture the complex heat transfer and pressure drop processes, large databases of high-quality experimental data are required to aid in the model development.
This work presents the results obtained by implementing different machine learning methods to develop accurate predicting models for condensation, boiling, two-phase frictional pressure drops of refrigerants inside BPHE.

## 2. CONDENSATION

As fully described in Longo et al. [6], an Artificial Neural Network (ANN) model capable of accurately predicting the condensation heat transfer of refrigerants inside herringbone-type BPHE with a Mean Absolute Percentage Error (MAPE) substantially lower than those of state-of-the-art analytical-computational models is proposed. The model is trained, tested, and validated against a large database consists of 1884 measurements containing 12 plate geometries and 16 refrigerants, including 4 so-called natural refrigerants and 6 other low-GWP refrigerants.
The input variables for the ANN model are driving temperature difference DT, vapour superheat $DT_{sup}$, corrugation enlargement ratio Φ, equivalent Reynolds number $Re_{eq}$ and liquid Prandtl number $Pr_L$. The output of the ANN model is the heat transfer factor $J_H$.
The model development employed a conventional feedforward neural network structure as illustrated in Fig. 1a. The five input neurons were connected to all of the hidden neurons that in turn were connected to the output neuron. Each neuron presented a bias $b_X$ (x = F,G,H...), the activation functions were the hyperbolic tangent for hidden neurons and the linear function for the output neuron. The training of the ANN model was carried out by applying the Levenberg-Marquardt algorithm. This algorithm minimises a cost function defined as the mean squared error through the modification of weights and bias of the network.

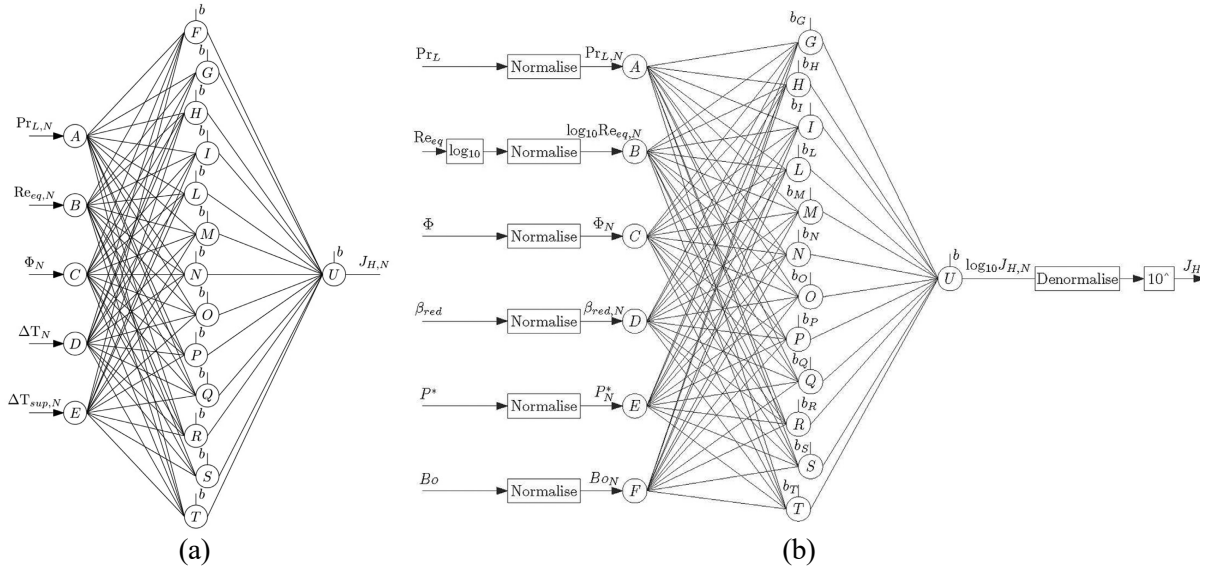


**Figure 1**. ANNs for refrigerants: (a) condensation and (b) boiling heat transfer coefficient inside BPHE

The Levenberg-Marquardt algorithm was chosen because of its fast convergence, even starting from a rather incorrect initial guess. For better neural network training and to avoid over- fitting of the data, the database was randomly split into three parts representing 70%, 15% and 15% of the total data, respectively. The first subset was used for training, the second subset was used for testing and the third subset was used for validating the model. Per standard Levenberg-Marquardt implementation practice, the end of training was determined by the occurrence of one of three conditions. Specifically, (1) reaching a certain number of epochs (10 0 0), (2) the gradient of the cost function below a certain threshold ($1e^{-7}$) and (3) a specific number of consecutive validation checks demonstrating no improvement in error (6). The optimal number N of hidden neurons was investigated first. According to these results, the optimal number N of hidden neurons was set equal to 13, as the MAPE remains almost constant for higher numbers of hidden neurons. Figure 2 shows the results obtained considering the saturated vapour condensation data points, the AI based model exhibits an excellent prediction capability and allows to highlights possible outliers.
The ANN model presented is able to reproduce the entire database presented in this paper with a MAPE of 3.6%; whereas, state-of- the-art analytical-computational models available in the open literature are only able to reproduce the same data with an MAPE value of approximately 13-14%.

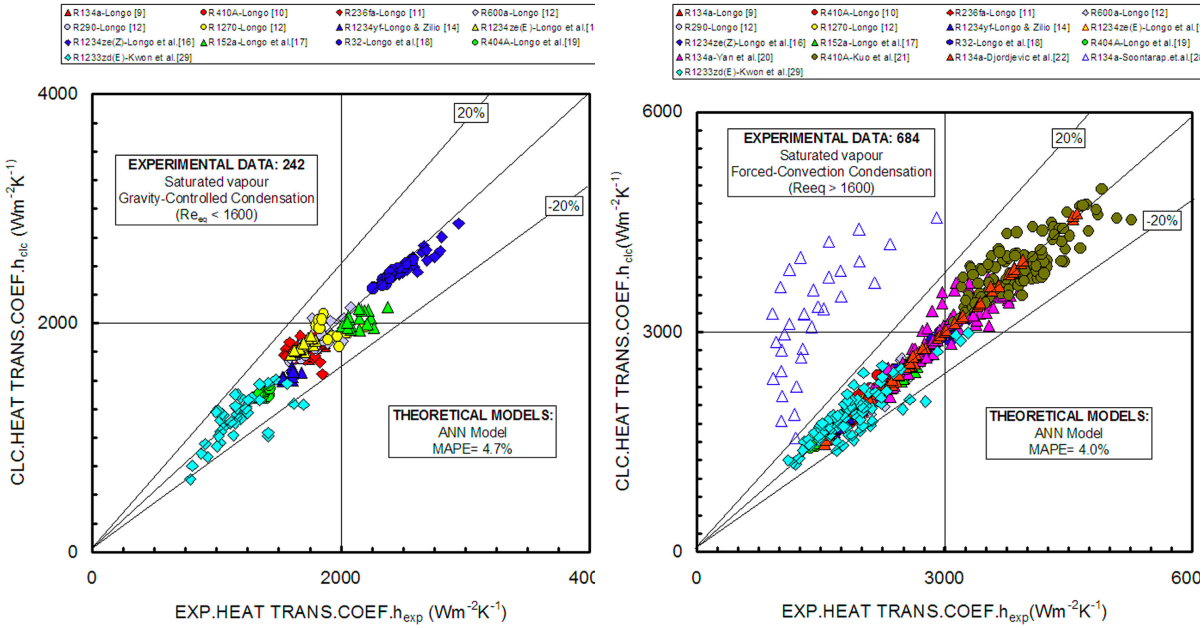


**Figure 2**. Comparison between experimental and calculated condensation heat transfer coefficients by ANN model. Left: saturated vapour gravity-controlled condensation data points - $Re_{eq}$>1600 ; Right: aaturated vapour forced-convection condensation data points - $Re_{eq}$>1600.)

## 3. BOILING

As described in Longo et al. [7], an ANN model for predicting refrigerant boiling heat transfer coefficients inside BPHE is proposed. The model accounts for the effect of plate geometry, operating conditions and refrigerant properties. The model shows a fair agreement with a database of 1760 data points comprising 15 plate geometries and 16 refrigerants (including 4 natural refrigerants and 6 other low-GWP refrigerants). The variables used as input for the ANN model were corrugation enlargement ratio Φ, reduced inclination angle $\beta/\beta_{max}$, liquid Prandtl number $Pr_L$ , equivalent Reynolds number $Re_{eq}$ , boiling number Bo and reduced pressure $P/P_{cr}$ , while the output of the ANN model was the heat transfer factor $J_H$. A similar methodology as described before for condensation is used. The optimal number N of hidden neurons is found to be 12 (Fig. 1b), which leads to a MAPE lower than 5%, that is considered a good predicting performance for the ANN model. The results are shown in Figure 3 where a comparison between experimental and calculated boiling heat transfer coefficients by ANN model is reported.

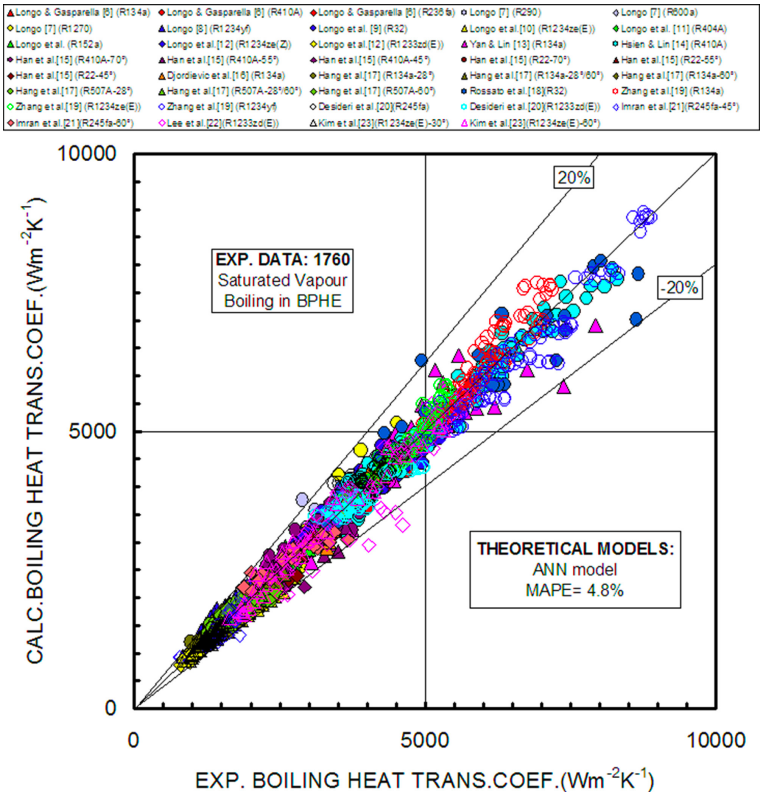


**Figure 3**. Comparison between experimental and calculated boiling heat transfer coefficients by ANN model.

## 3. TWO PHASE FRICTIONAL PRESSURE DROPS

As described in Longo et al. [8], a Gradient Boosting Machines (GBM) model for predicting refrigerant two-phase frictional pressure gradient inside BPHE based on an extensive database that includes 1624 boiling data-points, 925 condensation data-points, 16 different plate geometries, and 16 different refrigerants (including 4 natural refrigerants and 6 other low-GWP refrigerants) is proposed.

The variables used as input for the GBM model were corrugation enlargement ratio Φ, reduced pressure $P/P_{cr}$, and type of two-phase heat transfer process (boiling or condensation) while the output of the GBM model was the frictional pressure gradient $\Delta P_f/L$.

The best predictive performances on the test set were achieved using a Gradient Boosting Machines (GBM) model. GBM is a powerful and flexible machine learning technique, based on a particular ensemble approach, namely boosting. As any other ensemble method, boosting is based on the idea that it is easier to identify several rough prediction rules (i.e. weak learners) than building a single highly accurate rule. A schematic of the applied GBM procedure is reported in Figure 4.

In general, the GBM model shows a good ability in predicting the trends of all the different sets of data, including also those relative to refrigerants for organic Rankine cycle working at high temperature which are not well predicted by the state-of-the-art analytical computational models. The GBM model exhibits only some difficulties in predicting the experimental data-points affected by large experimental uncertainty such as, for example, the boiling data relative to refrigerants for organic Rankine cycles or the condensation data inside GPHE at very low mass flux. The boiling data-points were predicted with a MAPE of 7.1% with 95% of the data within ±20%, while condensation data-points were predicted with a MAPE of 5.8% with 94% of the data within ±20%. The GBM model exhibits a MAPE of 6.6% against the whole database consisting of 2549 pressure drop data-points.

The results are shown in Figure 5 where a comparison between the experimental and calculated boiling (left) and condensation (right) pressure gradients inside BPHEs is reported.

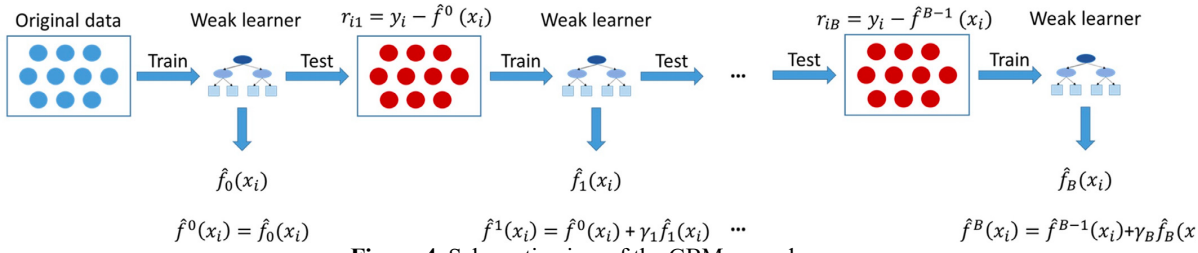


**Figure 4.** Schematic view of the GBM procedure.

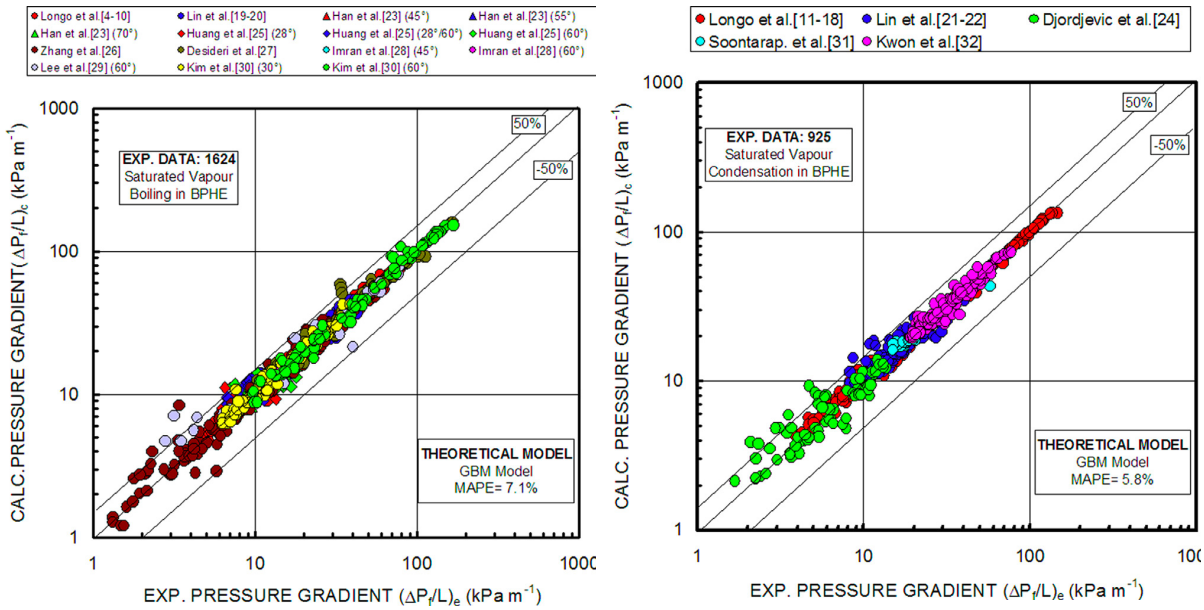


**Figure 5**. Comparison between experimental and calculated boiling (left) and condensation (right) pressure gradients inside BPHEs by the GBM model.

## 4. CONCLUSIONS

This work presents three different applications of machine learning algorithms to predict the two-phase refrigerants heat transfer coefficients during either condensation or boiling as well as the frictional pressure drops inside BPHE. Both the ANN method and GBM procedure show superior predicting capabilities as compared to the traditional methods.

## 5.ACKNOWLEDGMENTS

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