Proceedings of the 18th UK Heat Transfer Conference
9-11 September 2024, Birmingham
UKHTC2024

A NOVEL FEED-FORWARD NEURAL NETWORK FOR FLOW BOILING PATTERN PREDICTION

Joseph J. Widgington[1*], Fang Wang[2], Atanas Ivanov[1], Tassos G. Karayiannis[1]

[1] Department of Mechanical and Aerospace Engineering, Brunel University London, Uxbridge UB8 3PH, United Kingdom

[2] Department of Computer Science, Brunel University London, Uxbridge UB8 3PH, United Kingdom

1. ABSTRACT

Microscale flow boiling presents a promising solution to emerging cooling requirements in many applications. Predicting flow boiling patterns could play a key role in the development of new engineering design tools for predicting heat transfer rates and pressure drops. A novel feed-forward neural network architecture was developed to classify flow boiling patterns in the microscale, in which each transition boundary was considered with its own Forward Neural Network within the overall architecture. The network was then compared to new flow boiling pattern data using HFE-7100 for heat fluxes and mass fluxes between 3.2-132.4 kW/m^2 and 100-1000 kg/m^{2}s, respectively.

2. INTRODUCTION

Studies investigating flow boiling in microchannels have shown capabilities of dissipating high heat fluxes in the order of 1 kW/cm^2 [1]. The high heat flux dissipating capabilities of flow boiling lead to show promise in applications such as data centre cooling, fusion blanket reactor cooling, avionics cooling, satellite electronics cooling, hybrid and battery electric vehicle cooling and as potential uses in heat exchangers for hydrogen storage [2]. However, there is a need to conclude on predictive tools for heat transfer rates and pressure drops. The heat transfer rates and pressure drops are intrinsically linked to the prevailing flow boiling patterns. Consequently, the ability to predict transition boundaries of flow boiling patterns would allow the development of more accurate flow pattern-based heat transfer and pressure drop tools, which currently rely solely on empirical fits of data [3]. Machine learning is now a tool that is currently being utilised in almost every application that requires technological solutions [4]. Various types of neural networks have been utilised in the study of microscale flow boiling patterns; however, their use is often limited to the application of flow pattern image recognition. This work attempts to develop a novel feed-forward neural network architecture that is capable of predicting prevailing flow patterns using algorithm inputs that include operating parameters, fluid thermophysical properties and channel geometry. The algorithm success was compared to new experimental flow pattern data for HFE-7100.

3. METHDOLOGY

The novelty of the developed neural network is in the architecture, where each flow pattern transition boundary is considered using individual feed-forward neural networks to form the larger novel multiple feed-forward neural network (M-FNN) architecture. The flow pattern transition boundaries considered included the bubble to slug, slug to churn and churn to annular transition boundaries for the four generic flow pattern categorisations presented in Fig. 1. A diagram representation of the architecture is presented in Fig. 2.

*Corresponding Author: Joseph.Widgington@brunel.ac.uk

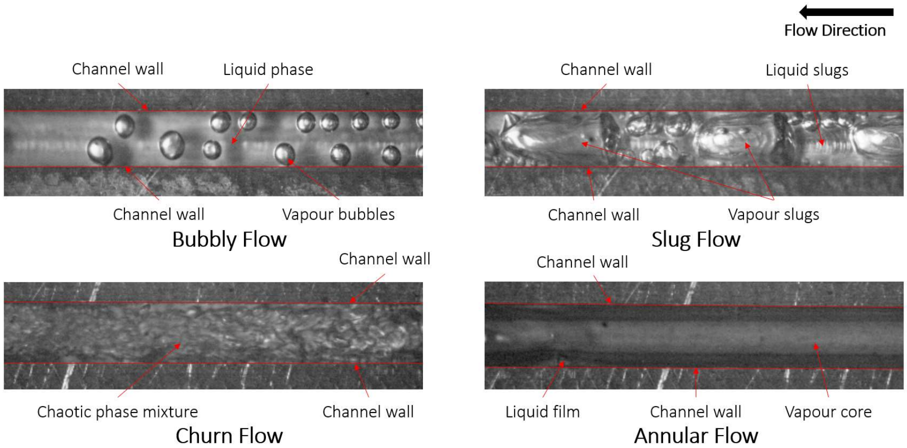

Fig. 1 Flow boiling patterns in small-micro scale passages: Single channel with for HFE-7100.

The use of three individual FNNs for each transition boundary allowed for feature selection to be conducted in each boundary network, thus providing some insight into the physical parameters that are relevant to each transition. Overall, 11,349 data points were extracted and interpolated from the Brunel two-phase high-fidelity data bank to train and test the algorithm. The final data split was 80% used for training and 20% used for testing, with a K=10-fold cross validation. The training data included water, HFE-7100, HFE-7200, R-134a, R-245fa, R1234yf, for flow boiling in vertical tubes and horizontal single and multichannel geometries. Each transition boundary FNN was trained using data that was only relevant to that transition, e.g. only data for bubbly and slug flows was used to train the bubbly to slug transition boundary, which permitted the individual feature selection process. A final FNN, labelled as the results network in Fig. 2, was placed after the transition boundary FNNs to account for any unexpected predictions for data that was outside the training range of the individual FNNs. The final algorithm architecture was developed through tuning of hyperparameters such as the number of hidden layers, the number of neurons in the hidden layers, activation functions, batch size, number of epochs, optimiser types and dropout rates.

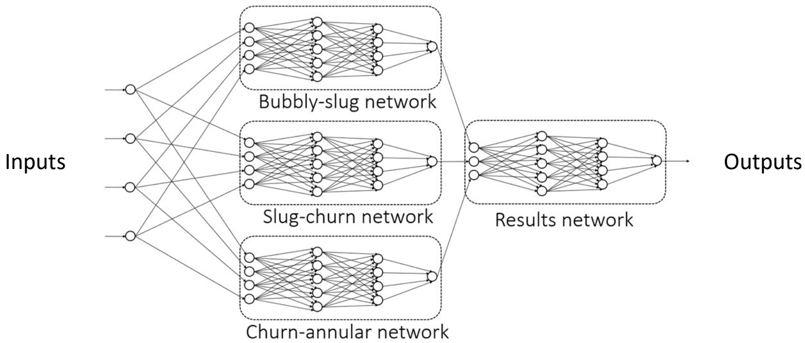

Fig. 2 Diagrammatic representation of M-FNN architecture.

Assessments of algorithm performance based solely on data splits in which data from a single flow boiling experiment exists in both the testing and training data is a potential criticism of many existing publications. The idiosyncrasies that exist in the collected data during physical flow boiling experiments may result in an algorithm that overfits to data collected during that experiment and will perform very poorly when implemented in real world examples. Therefore, a better evaluation of the network is to compare the algorithm predictions to new experimental data. Consequently, new experimental flow boiling pattern data for HFE-7100 in a single microchannel were obtained for heat fluxes and mass fluxes between 3.2-132.4 kW/m² and 100-1000 kg/m²s, respectively.

4. RESULTS

A comparison between the M-FNN algorithm and the new experimental data for HFE-7100 is shown in the flow pattern map presented in Fig. 3. The trends were well captured by the M-FNN algorithm, especially the bubbly to slug transition, although the vapour qualities at which the slug to churn transition and churn to annular transition occurred were under predicted and over predicted, respectively. However, the actual transition can be considered fairly similar to the model predictions when the propagated uncertainties of the vapour quality and mass flux are considered. Furthermore, the model can also be considered successful when the subjectivity in categorising flow patterns between researchers, which is difficult to quantify, is considered.

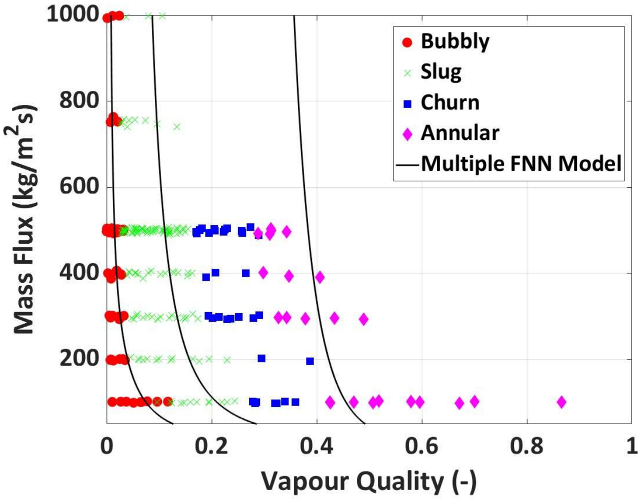

Fig. 3 Comparison of neural network predictions to experimental data.

Further predictions were also made in which all HFE-7100 and HFE-7200 data removed from the training data set to observe if the network is capturing global flow pattern transition mechanisms or if the algorithm is only using patterns taken for fluids with similar properties. The M-FNN was found not to accurately predict the flow pattern transitions for this case, a fairly significant limitation as it is only applicable if predicting for a fluid used during training. However, this is not a limitation of the process adopted here, since the solution is to harvest data from literature and obtain a larger and more continuous data set to enhance the performance of the algorithm.

5. CONCLUSIONS

A new M-FNN type model was developed to predict flow boiling patterns in microchannels using 11,349 data points that were taken and extrapolated from the Brunel University London two-phase high-fidelity data bank. The algorithm was compared to the experimental data and found to perform fairly well, with the caveat that it could only do so whilst some data for HFE-7100 and HFE-7200 existed in the training set. We will be training the algorithm with a wider range of data including different fluids that will help get to a working solution of predicting flow pattern transition boundaries for a range of fluids covering both water and refrigerants. This could be better that currently available methods of predicting transition boundaries. We also expect to present the methodology and the final algorithm in an easy to use package.

ACKNOWLEDGMENT: The support of EPSRC through grant EP/P004709/1 is acknowledged.

REFERENCES

[1] B. Parizad Benam, A. K. Sadaghiani, V. Yağcı, M. Parlak, K. Sefiane, and A. Koşar, "Review on high heat flux flow boiling of refrigerants and water for electronics cooling," Int J Heat Mass Transf, vol. 180, p. 121787, Dec. 2021.

[2] S. M. Kim and I. Mudawar, "Review of databases and predictive methods for heat transfer in condensing and boiling mini/micro-channel flows," Int J Heat Mass Transf, vol. 77, pp. 627–652, Oct. 2014.

[3] M. M. Mahmoud and T. G. Karayiannis, "Flow pattern transition models and correlations for flow boiling in mini-tubes," Exp Therm Fluid Sci, vol. 70, pp. 270–282, Jan. 2016.

[4] B. Ramsundar and R. B. Zadeh, TensorFlow for deep learning: from linear regression to reinforcement learning, 1st ed., vol. 1. O'Reilly, 2018.