MACHINE LEARNING ALGORITHMS FOR FLOW PATTERN CLASSIFICATION IN PULSATING HEAT PIPES

José Loyola-Fuentes[1], Luca Pietrasanta[2,3], Marco Marengo[2,3], Francesco Coletti[1,4*]

[1]Hexxcell Ltd., Foundry Building, 77 Fulham Palace Rd, London W6 8AF, UK
[2]School of Computing, Engineering and Mathematics, University of Brighton, Lewes Rd, Brighton BN2 4AT, UK
[3]AEC, Advanced Engineering Centre, Lewes Road, BN2 4GJ, Brighton, UK
[4]Department of Chemical Engineering, Brunel University London, Kingston Lane, Uxbridge UB8 3PH, UK

ABSTRACT

Owing to their simple construction, along with their cost-effectiveness and performance, Pulsating Heat Pipes (PHPs) have become greatly popular for the cooling of electronics. However, these advantages are limited by the conditions under which PHPs are subjected to. Their operation is strongly related to the existence of a dominant slug-plug flow throughout the required range of operating conditions. Thus, the accurate prediction of flow patterns as a function of operating conditions is of paramount importance to the effective design and deployment of these devices. Predictions of PHPs performance are typically done with semi-empirical correlations that account for operating conditions via dimensionless numbers. However, developing these correlations is a challenging task, as the physical phenomena underlying the operation of PHPs are still to be fully elucidated. In contrast, machine learning offers a convenient alternative that is model-free and needs limited *a priori* knowledge of the system. This work presents a comparative study of three different machine learning classifiers that are trained to predict flow pattern regimes using data from a single-loop PHP that operates with two different working fluids and power input levels. Each observation within the data-set is labelled with respect to the observed flow pattern for the corresponding observation. The most accurate classifier emerging from the comparison is used to build a flow pattern map for the experimental data, where a transition zone from slug-plug to annular flow is clearly identify. The results suggest that well-trained machine learning algorithms could assist in reducing uncertainty when identifying flow regimes in PHP systems.

1. INTRODUCTION

Pulsating Heat Pipes (PHPs) have the potential of playing a pivotal role in reducing cooling costs in electronic components, due to their resulting thermal performance compared to other cooling devices (*e.g.* pure cooper) [1]. In addition, no pumping power is required for the circulation of the working fluid, as the oscillating effect within PHPs is the responsible for the fluid motion. These feature allow to significantly reduce the design complexity of Thermal Control Systems (TCS). When in operation, PHPs are filled with fluid and sealed, so the capillary forces produce liquid slugs and vapor plugs that alternate between each other [2]. By monitoring the variation of flow direction, pressure drop, and liquid film thickness, several flow patterns can be observed [3], showing transitions between slug-plug, semi-annular and annular flow. For a given geometry, flow patterns are highly influenced by filling ratio and power input [4]. In some cases, operating conditions lead to slug-plug transitioning into annular flow which, in the long term, reduces the thermal performance. Moreover, it is known that available heat transfer correlations are very sensitive to the flow pattern conditions [5]. This is why ensuring at the design stage that certain flow patterns perpetuate in PHPs is of great importance.

To overcome the limitations from first-principle models in PHPs (which are still in development), machine learning algorithms provide a compatible solution, as experimental observations can be used to train classification models that can predict flow patterns when unseen or new data are available. This could be integrated to traditional strategies, when developing semi-empirical correlations for relevant

*Corresponding Author: f.coletti@hexxcell.com

values in heat transfer studies, such as heat transfer coefficients and pressure drops. The capability of identifying the flow regime for a set of operating conditions allows for a more accurate estimation of design parameters and for useful insights regarding the behaviour of the system during operation. Within this context, the use of machine learning is beneficial, as it leverages from the abundance of significant sets of data

This work proposes the use of machine learning classifiers to identify flow patterns and flow pattern transition in a single-loop PHP system with two different working fluids and varying gravity conditions, using data from the European Space Agency Parabolic Flight Campaigns [6, 7]. The selection of the most suitable classifier is carried out by comparing the accuracies of such classifiers when predicting the flow regime on unseen data (or testing set). The selected classifier is used for devising flow pattern maps for both working fluids, to identify the location of the flow regime transition zone. It is expected that this capability provides a more systematic approach when identifying flow regimes, reducing observation uncertainty.

2. METHODOLOGY

This work was carried out in two stages: first, the experiments were performed, where the data used for the machine learning implementation were generated. Second, these data were pre-processed and prepared for the deployment of machine learning tests and analyses. Velocity measurements were used to estimate acceleration, and the length of bubbles were measured as well. Pressure measurements also took place in both thermal terminals of the device (*i.e.* condenser and evaporator). These measurements were used to estimate physical properties such as surface tension, and for the calculation of dimensionless numbers such as Reynolds (Re), Weber (We), Froude (Fr) and Bond (Bo) numbers, as defined in Pietrasanta *et al.*[8]. The labelling of flow patterns was done visually while analysing the high-speed images.

2.1 Experimental setup

The experimental campaign was conducted on a simplified passive heat transfer loop under varying gravity levels and power inputs. Ethanol and FC-72 were selected as working fluid, given their significant difference in surface tension, density, and latent heat of vaporisation. The main fluid properties are listed in Table 1.

Table 1: Physical properties for Ethanol and FC-72 at 20°C

Fluid	σ [N/m]	ρ_l [kg/m^3]	$h_{l,v}$ [kJ/kg]	μ [Pa s]
Ethanol	0.0224	789.59	927.57	$1.22 \cdot 10^{-3}$
FC-72	0.0118	1701.6	94.024	$0.72 \cdot 10^{-3}$

The experimental device is a hybrid pulsating heat pipe. The setup is equipped with wall-side thermocouples, a glass tube for high-speed shadowgraph, pressure transducers and a power input that is supplied to three heaters coiled around three sections of the evaporator. The temperature at the condenser is kept constant with an external cooling loop. A detailed schematics of the equipment is depicted in Figure 1.

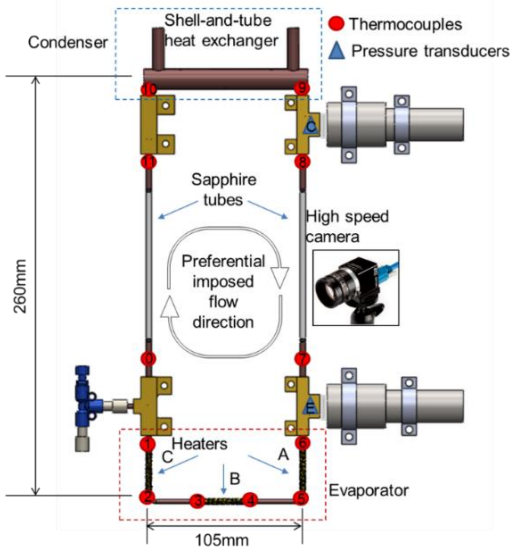

Figure 1: Single loop PHP with position of sensors and camera [8].

2.2 Classification algorithms

Classification is defined as a supervised learning algorithm, where a set of relevant features is associated to a set of categories (*i.e.* categorical data), which are already labelled (hence the name supervised). This provides a more assertive training stage, and accurate predictions. When doing so, different approaches are available, and the specific mechanism for classifying features varies from algorithm to algorithm. Thus, choosing the most suitable alternative mainly depends on the type of data, and the performance that the algorithm exhibits when classifying unseen features. In order to cover a wide range of methods, three different classification algorithms are selected in this work, namely K-nearest Neighbours (KNN), Random Forest (RF) and Multi-layer Perceptron (MLP). Each of these methods present distinct characteristics that make them unique from each other, representing different classification mechanisms. The main attributes these algorithms have are summarised in **Table 2**.

Table 2: Main characteristic of each selected classification algorithm

KNN	RF	MLP
- Distance-based method. Different distance metrics can be deployed while implementing - Main parameters are the number of neighbours to consider and the distance metric - Normally no training stage is needed, classification is done via the analysis of each data query	- Ensemble method. Predictions are made based on majority vote of a population of decision trees - Main parameters are the number of trees, number of splits and decision criteria - The training stage can be improved using boosting (re-sampling) to randomise data samples	- Artificial neural network (ANN) with feedforward structure - Performs prediction via the minimisation of a cost function - Main parameters are the number of layers, activation function and learning rate

The performance of each algorithm is evaluated via the accuracy score, defined in Equation (1), where n is the number of samples, $\hat{y}_i$ is the predicted categorical value, y_i is the true categorical value and the function $1(x)$ is the *indicator function*, which outputs 1 when $\hat{y}_i = y_i$, and 0 otherwise. Additionally, learning curves are to be built to assess the effect of training sample size on the training and validation performance.

$$score = \frac{1}{n}\sum_{i=1}^{n-1} 1(\hat{y}_i = y_i) \tag{1}$$

3. RESULTS

The entire experimental data set consists of 9841 observations for Ethanol and 8590 for FC-72. For both working fluids, the input features are modified versions of Weber, Froude, and Bond numbers, represented by We_l^*, Fr_l^* and Bo_l^* respectively. For more details on these numbers, please refer to the work done Pietrasanta *et al.*[8]. The categorical output data indicate whether a specific observation is classified as slug-plug flow or semi-annular flow, and it was done visually using the high-speed imaging. To create, train and deploy the classification models for both working fluids, the following steps took place:

i. Data splitting: Data sets are randomly split into training and testing sets. This is done to avoid overfitting problems. The proportion of data into the training stage was fixed to 70%. Note that even though the KNN algorithm does not need a training stage, this splitting step was done to have a consistent comparison among all three classifiers.

ii. Data scaling: Input features in both the training and testing set were scaled (*i.e.* normalised) to avoid issues coming from different orders of magnitude in the feature values. This is done by estimating the expected value and standard deviation of the data sets and applying the normalisation formula shown in Equation (2), where z_i is the normalised data point, x_i is the original data point, μ is the sample's mean or expected value, and σ is the sample's standard deviation.

$$z_i = \frac{x_i - \mu}{\sigma} \tag{2}$$

iii. Classifier setup: The training set is used to train the classifier and then to test it with the testing set. The accuracy score is estimated and stored. At this point, default values for each algorithm's parameters are used. The selection of the most suitable set of parameters for each method is done later.

iv. Cross-validation: The validation step takes place using the training data and the process commonly known as cross-validation. In this work, cross-validation is done via the so-called *k-fold* cross-validation method.

v. Accuracy assessment: The accuracy score of both the initial classifier and the one from the cross-validation are compared to assess the robustness of the initial classifier.

vi. Selection of hyper-parameters: The most suitable set of hyper-parameters is selected via *grid search*. This method aims to perform several training and cross-validation across a grid of candidates for hyper-parameters. The selected set is the one that outputs the highest cross-validation score.

Once all the above-mentioned steps are carried out, the testing set is used to assess the prediction of all three classifiers for both working fluids. These results are presented in the form of confusion matrices, where the proportion of correct predictions for both flow pattern labels and working fluids are reported. Table 3 and Table 4 show such results for Ethanol and FC-72 respectively.

Table 3: Confusion matrix results for Ethanol

		Actual Slug-plug	Actual Semi-annular
KNN	Predicted Slug-plug	0.89	0.32
	Predicted Semi-annular	0.11	0.68
RF	Predicted Slug-plug	0.88	0.32
	Predicted Semi-annular	0.12	0.68
MLP	Predicted Slug-plug	0.90	0.30
	Predicted Semi-annular	0.10	0.70

Table 4: Confusion matrix results for FC-72

		Actual Slug-plug	Actual Semi-annular
KNN	Predicted Slug-plug	0.90	0.33
	Predicted Semi-annular	0.10	0.67
RF	Predicted Slug-plug	0.89	0.34
	Predicted Semi-annular	0.11	0.66
MLP	Predicted Slug-plug	0.91	0.33
	Predicted Semi-annular	0.09	0.67

In general, all algorithms perform similarly, where the classification of slug-plug flow is significantly higher than that of semi-annular flow. This could be due to the increase in observation error when classifying the semi-annular flow, or to the innate nature of this flow pattern. For both working fluids, the MLP classifier shows the best performance, although all three classifiers predict similarly.

The overall performance in the form of accuracy score for all classifiers on the testing set are reported in Table 5 for Ethanol and FC-72 respectively. In accordance with the confusion matrices, the results suggest that the use of MLP provides the highest performance. The lowest performance is shown by the RF algorithm.

Table 5: Accuracy score for all classifiers and working fluids

Classifier	Accuracy (%) - Ethanol	Accuracy (%) – FC-72
KNN	82.8	75.8
RF	82.2	75.6
ANN	83.9	77.1

These results are complemented via the use of learning curves. A learning curve shows the sensitivity of a particular performance metric (accuracy score in this case.) with respect to the size of the training set. This allows to identify whether more data instances are needed and/or a bias/variance error dominates the classifier's performance (*i.e.* bias-variance trade-off). Figure 2 depicts the learning curves for all classifiers and working fluids, showing that the MLP classifier presents the most balanced bias-variance trade-off, given by the small gap between training and validation error curves.

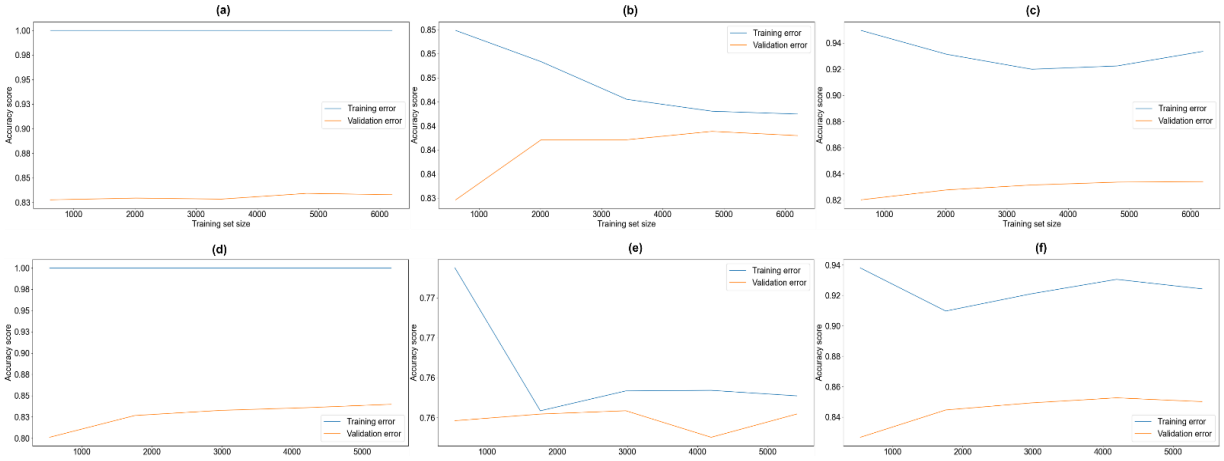

Figure 2: Training and cross-validation curves: (a) - KNN: Ethanol, (b) - MLP: Ethanol, (c) - Random Forest: Ethanol, (d) - KNN: FC-72, (e) - MLP: FC-72, (f) - Random Forest: FC-72

The classification results from the MLP classifier are used to construct a flow pattern map. Based on the concepts used in Pietrasanta *et al.*[8], the x-axis corresponds to $Bo_l^{0.5}$ and the y-axis with $Fr_l^{0.5}We_l^{0.25}$. In addition, to account for the differences in physical properties between both working

fluids, the x-axis values are standarised using the ratio of surface tensions, where that of Ethanol is considered as a reference value. Both flow pattern maps are shown in Figure 3 and Figure 4 for Ethanol and FC-72 respectively.

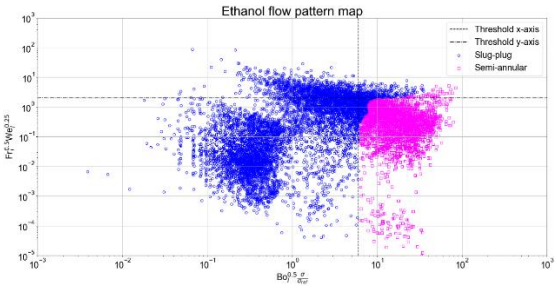

Figure 3: Flow pattern map for Ethanol: Multi-layer Perceptron

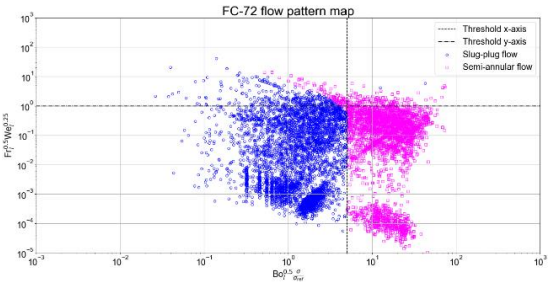

Figure 4: Flow pattern map for FC-72: Multi-layer Perceptron

The flow pattern maps exhibit consistent transition values in both axes and working fluids. In the case of Ethanol, these values are 6 for the x-axis and 2 for the y-axis, whereas for FC-72, 5 for the x-axis and 1 for the y-axis. This set of values allows for more interpretability, as there is only a margin of only ± 1 unit at each axis across both working fluids.

4. CONCLUSIONS

Three different machine learning algorithms were tested to propose a systematic flow pattern classification method for two different working fluids in a PHP system. The output categorical data were defined visually and the input features were embedded in dimensionless numbers that represent the physical forces involved. All three classifiers showed good performance, where the classification in Ethanol data was more accurate than that of FC-72. The use of Multi-layer Perceptron (MLP) exhibited the highest performance for both working fluids. These results were used to build flow pattern maps, where clear transition zones were identified for both working fluids. Further extensions include the use of more diverse data, which will improve the robustness of the classification algorithms. In addition, the use of unsupervised learning could provide a significant upgrade, independent from visual classification.

ACKNOWLEDGEMENTS

The authors acknowledge the financial support of the EPSRC grant HyHP (EP/P013112/1), the European Space Agency MAP projects TOPDESS and Hexxcell Ltd.

REFERENCES

[1] Thome J.R, *Encyclopedia of Two-Phase Heat Transfer and Flow IV*,(2018), World Scientific
[2] Nikolayev V.S., A Dynamic Film Model of the Pulsating Heat Pipe. *J Heat Transfer*, **133** (2011)
[3] Liu S., Li J., Dong X., Chen H. Experimental study of flow patterns and improved configurations for pulsating heat pipes. *J Therm Sci*., **16** (2007) 56–62
[4] Alhuyi M., Ahmadi M.H., Ghasempour R., How to improve the thermal performance of pulsating heat pipes. *A review on working fluid*, **91** (2018) 630–8
[5] Özdemir M.R., Mahmoud M.M., Karayiannis T.G., Flow Boiling of Water in a Rectangular Metallic Microchannel. *Heat Transf Eng*. **0** (2020) 1–25
[6] Ahmad S.W., Lewis J.S., McGlen R.J., Karayiannis T.G., Pool Boiling on Modified Surfaces Using R-123. *Heat Transf Eng*, **35** (2014) 1491–503
[7] Nekrashevych I., Nikolayev V.S., Effect of tube heat conduction on the pulsating heat pipe start-up. *Appl Therm Eng*, **117** (2017) 24–9
[8] Pietrasanta L., Mameli M., Mangini D., Georgoulas A., Michè N., Filippeschi S., Filippeschi S.,. Developing flow pattern maps for accelerated two-phase capillary flows. *Exp Therm Fluid Sci*., **112** (2020) 109981