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Prediction of Critical Heat Flux (CHF) Using Artificial Neural Network

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1. Introduction

Data-driven models using artificial intelligence (AI) have been proven successful in a multitude of applications as being a cost effective tool especially for design and optimization problems. In this work, it is proposed to develop an AI algorithm to assess the critical heat flux for water flowing in a circular channel at different flowrates, pressure, and quality. A multi-layer artificial neural network (ANN) is developed using Python to deduce the functional relationship between those parameters, solely based on a pre-existing database without actually solving the underlying physics. The ANN consists of three hidden layers with 4 input parameters: quality, x, hydraulic diameter, D_h, mass flux, G and pressure, P and a single output, the critical heat flux, *CHF*. The forward propagation structure iteratively sets the strengths of the relationship between the output and input parameters via weight factors, while the back propagation allows the ANN to undergo learning process by adjusting the weights.

2. Database

As a preliminary step a single Groeneveld's database is used. The database report the critical heat flux for different flow conditions as a function of pipe diameter (mm), pressure (MPa), mass flux (kg/m^2. s) and quality. Table 1 summarizes the applicable range for each variable.

Table 1: Groeneveld's database Range

Variables	Range
Hydraulic diameter (mm)	1- 8
Pressure (MPa)	0.1-2.0
Mass flux(kg/m2.s)	0-8000.0
Quality	-0.5 – 1.0

The ANN is automatically trained using the available parameters from the database. No correlation coefficient is conducted in selecting the highest contributing parameters using the non-linear correlation coefficient analysis, as the Groeneveld's database itself has been extensively studied[1][4] under the large influence of the variables: hydraulic diameter, pressure, mass flow rate and quality. As such, each variables are vital for the CHF predictions purpose.

3. ANN Model Development

Introduced back in 1943 by Mcculloch and Pitts, the artificial neural networks (ANNs) [2] are biologically inspired classification algorithms that allow the machine to learn from the input data. The ANN is a self-adaptive method that is able to generalize the connection between the input parameters and the target value. An ANN model is characterized by:

1. The network architecture,
2. The learning algorithm, and
3. The activation function.

For the ANN architecture , there is no definite structure that can provide the best results rather, its architecture(number of neuron, number of hidden layer) depend on the user experience and the characteristic of the problems itself.

Two different sets of ANN architecture algorithm has been setup to test the prediction capability of both model which are: the deep learning neural network (DLNN) and the convolutional neural network (CNN). Both ANN's algorithms are trained and validated using Groeneveld's data. For both models, the data is split by the ratio of 1:2:2. These data were divided into four subsets respectively; training set, validation set, test set and the predictions set. The performance of the ANN will be mainly decided by the fourth independent datasets which is the prediction datasets.

For ANN, the number of hidden layer can be varied depending on the size of the database which can influence the model accuracy. However in this study, a tuning process using Talos python library is implemented to find the optimum hyperparameters and architecture for the ANN model. The random quantum search method is used instead of the grid search method for the computational efficiency. At the same time, a fraction limit of 0.1 is used to limit the Talos searching process in finding the best model combinations with respect to the given search space parameters. The results suggested that ANN of 3 hidden layers were the optimal ones and as such it is used to train the networks for both models.

The DLNN is a multilayer feed – forwards neural network that used back propagation algorithm. 1000 epochs and the batch size of 1 is used. The input layer is made up of 4 neurons whereby, each hidden layer possess 15 neurons and a single output layer. The mean squared error (MSE) is used as the loss function during the network training process.

For each layer, the ReLU activation function is used to prevent gradient diminishing problems while simultaneously increase the computation speed. A dropout layer is applied for the input layer and the first hidden layer with the value of 0.5 and 0.8. Adam optimizer is used for its accuracy and faster convergence.

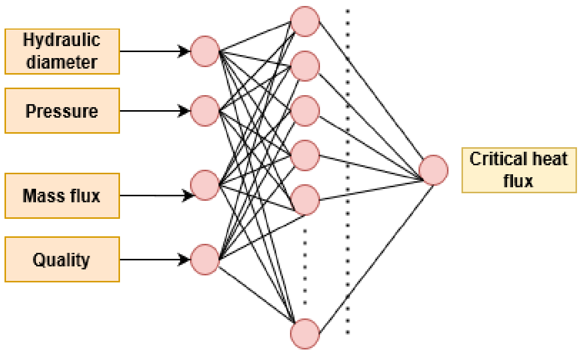

Figure 1: DLNN schematic architecture

For the CNN model, 1-D convolutional layer is used instead of 2-D convolutional layer since the input data is a continuous value. The CNN architecture used in this work, follows the sequence summarize in Table 2:

Table 2: CNN layer architecture.

No	Layer (type)	Descriptions
1	Conv1D	1-D Convolutional layer
2	MaxPooling	Feature extraction layer
3	Conv1D	1-D convolutional layer
4	MaxPooling	Feature extraction layer
5	Conv1D	1-D convolutional layer
6	Flatten	1-D flatten layer
7	Dense	Hidden layer
8	Dense	Output layer

The number of batch, epochs, type of activation function, type of optimizer and the loss function is the same as the DLNN. No pooling layer is placed for the final convolutional layer in order to reduce the model complexity and computation load. The pooling layer is necessary after the convolutional layer for the first input layer only to extract features information from the input data using the sliding kernel window techniques.

4. Models Verifications

Verifications for both ANN models are usually judged on the basis of statistical parameters such as the means squared logarithmic error (MSLE), mean absolute error (MAE), the K-fold cross validation accuracy and the prediction scatter plot. The model metrics provide the basis for further model improvement [5]. However, in this study, the error deviation will be used to evaluate the model performance.

On the other hand, the k-fold cross validation is used to measure the model accuracy by continuously running on a smaller k-folded subsets data. The k-fold validation is consider to be the gold standard of the ANN evaluation method when evaluating the estimator performance. In this study, the fold is set to 10 which is the commonly value for ANN evaluation [6].

5. Results and Discussion

In this section, results of the DLNN and the CNN model were evaluated for the critical heat flux (CHF) predictions. Table 3 shows the error for the DLNN and CNN model.

Table 3: ANN error value model

Metrics	ANN Model	
	DLNN	CNN
Lowest under-predicted value (kw/m^2)	-2022.87	-1251.05
Highest over-predicted value (kw/m^2)	871.02	615.74
Average deviation per points (kw/m^2)	136.12	127.59
Model cumulative error (%)	10.72	17.54

Table 4: Accuracy performance

ANN Model	Model Accuracy (%)
DLNN	88.28
CNN	80.46

After training, validating and tuning the model, the scatter plots in Figure 2 and Figure 3 show the predictions versus known value of the CHF. It can be seen that both model demonstrate high prediction capabilities as majority of the data points lie on the 45 degree line. However, the DLNN performance exceeds that of the CNN.

Meanwhile, the CNN perform better at both low and higher CHF value by looking at the scatter plot. However, due to the random sampling, the CNN potential datapoint that can contribute to the error reduction has been not randomly selected when preparing the dataset. In the best of author understanding, controlling the data splitting matrix cannot be done in conventional way and the random sampling method only allows the user to control the split ratio preventing from choosing the specific sample row. Such uncertainty introduce bias if the model has a data dependent performance. Even so, randomness in data allow the model to be trained better through the introduction of bias and uncertainty that can make the model more adaptive and robust.

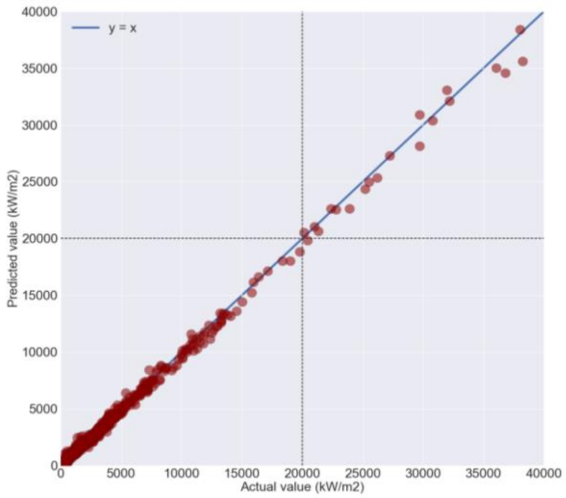

Figure 2 : DLNN scatter plot critical heat flux predictionn

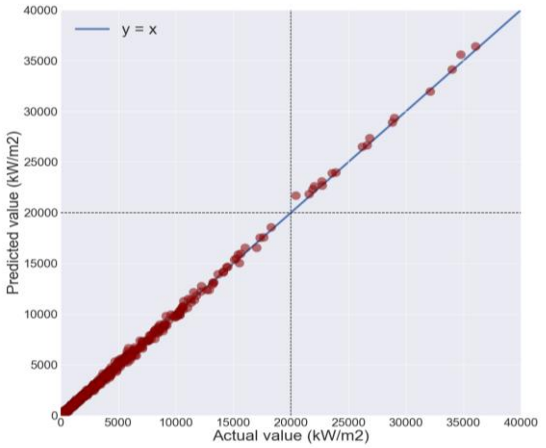

Figure 3: CNN scatter plot critical heat flux predictions

However the CNN has much narrow datapoint line indicating greater accuracy relative to the DLNN that has high degree of data scattering from the diagonal line especially on the large CHF value. Conceptually, the maximum pooling prevent the model from overfitting as such allowing it to continuously learn instead of memorizing the pattern. Increasing the layer and the number of neurons in the ANN may help it overcome the CNN metrics performance with the given database at the same time by reducing the bias and uncertainty in the database when using random sampling. Until now, there is no clear cut indication in determining which DLNN architecture will have the same performance metrics as the CNN architecture.

The author recommend future would should focus on the use of combine recurrent neural network (RNN) with the CNN for the regression problems such as predicting the CHF value.

ENDNOTES

There is no conflict of interest that could influence the work reported in this paper.

ACRONYMS

ANN = Artificial Neural Network
AI = Artificial Intelligence
CHF = Critical Heat Flux
CNN = Convolutional Neural Network
DLNN = Deep Learning Neural Network

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