Steady-state CHF prediction using machine learning technique

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1. Introduction

Machine learning is a representative "data-driven" approach for analyzing phenomena or building inference models. In order to train a machine learning model, the quality of the data for the learning is prime important. When a machine learning model is trained with high-quality data, the trained model can simulate the input data as well as extra-prediction capability. This characteristic of the machine learning is useful to predict the critical heat flux (CHF) for wide range of flow condition.

The CHF for the narrow rectangular channel has been investigated by some previous researchers. And empirical correlations have been proposed to predict the CHF. However, applicable conditions of those are different each correlation. Therefore, it is necessary to apply machine learning technology for the prediction of CHF over a wide range of flow conditions. For this purpose, datasets corresponding to a wide range of flow conditions are required. The objectives of present study are to produce pseudo dataset to be used in the machine learning for the development of prediction model and correlation of CHF for narrow rectangular channel.

2. Methods and results

2.1. Study of CHF using machine learning

The dataset for the machine learning should be sufficient to represent the whole thermal-hydraulic phenomenon. However, there is few available experimental CHF dataset in the open literature. Instead, there are many correlations that have been developed for each flow condition. These correlations or models can be applied to produce pseudo dataset for the wide range flow conditions to be used in machine learning. In the case of machine learning using such pseudo dataset, the model including the characteristics of each correlation can be trained. The model trained by following above method requires verification because only the pseudo datasets are utilized. Validation of the developed machine learning method is performed with experimental CHF data. If the experimental CHF data are well predicted by the machine learning model, the trained model can predict CHF for narrow rectangular channel over a wide range of thermal hydraulic condition.

2.2. Establishment of pseudo dataset

The pseudo dataset can be produced from existing CHF correlations applicable to narrow rectangular channel. Mirshak[1] , Kaminaga et al.[2] , Kureta & Akimoto[3] and Tanaka et al.[4] correlations are chosen in this study. The flow conditions of each correlation are summarized in Table 1. The number of pseudo data is 200K for each correlation and 800K for all pseudo data.

Table I: Flow conditions of each correlation

	Mirshak	Kaminaga	Kureta-Akimoto	Tanaka
Mass flux (kg/m^2s)	-12000 ~ -4460	-25800 ~ 6250	53 ~ 19740	0 ~ 4000
Pressure (kPa)	168 ~ 590	100 ~ 400	101	101
Inlet subcooling (K)	28 ~ 106	0 ~ 78	10 ~ 70	20 ~ 80
Gap size (mm)	3.3 ~ 6.6	2.25, 2.80, 5.00	0.2, 0.5, 1.0, 3.0	1.0 ~ 2.8
Length (mm)	489	375, 750	50, 100, 200	10 ~ 375

2.3. Development of machine learning model

The machine learning model for the CHF is composed of pre-training part consisting of deep belief networks (DBNs) [5] structure and prediction part consisting of convolution neural networks (CNNs) [6].

The DBN is a stacked structure of restricted Boltzmann machines (RBMs). RBM, which is one of the unsupervised learning networks, obtains the value of the hidden layer by applying weights between the input data and the hidden layer. And it is learned by the contrastive divergence method which repeats the process of predicting the input data again from the hidden layer. The training of the DBN is performed from a layer closest to the input layer until each RBM shows a sufficient performance.

In this DBN learning method, since each hidden layer can predict the data of the previous layer, the weights between the layers are adjusted to distinguish and convey the information of the previous layer. The proposed model is expected to improve the learning performance of the model through pre-training with DBN. In addition, through the learning of the hidden layer which has more nodes than the number of nodes of the input layer, it is expected that the relevance of the factors constituting the input data will be transferred to the next layer. The output layer of the DBN composed of more nodes than the number of nodes of the input layer is necessary for the

CNN-based prediction part to perform a meaningful operation later.

The CNN is a stacked structure of convolution operation. The CNN includes convolution, batch normalization [7], rectified linear unit (ReLU), and the last layer is a fully connected(FC) layer for prediction of CHF. Information about each layer of the learning model used in this study is listed in Table II.

In Table II, the DBN layer means each RBM layer included in the DBN. In the proposed model, 3-layer DBN is used as pre-training part. The output of the each DBN layer is 1-D data. The output of the pre-training part is reshaped into square 2-D data of size 256×256 in front of the CNN structure. Each output of the convolution layer represents the number of kernels used for convolution operations. All convolution layers use ReLU as an activation function. Also, except for the first convolution layer, the convolution layer applies batch normalization before ReLU is applied.

Table II: Structure of learning model

Layer	Kernel size	Stride	Padding	Output
DBN Layer1	-	-	-	8192
DBN Layer2	-	-	-	4096
DBN Layer3	-	-	-	4096
Reshape	-	-	-	-
CNN Layer1	3	2	same	32
CNN Layer2	3	2	same	64
CNN Layer3	3	2	same	128
CNN Layer4	3	2	same	256
CNN Layer5	4	1	valid	256
FC	-	-	-	1

2.4. Prediction results

To verify the trained model, we need to evaluate the CHF prediction results against pseudo dataset that is not used for training. This dataset is called "test data", and the amount of test data is 10% of pseudo data. Fig. 1 shows the CHF prediction results for the test data. The trained model predicts the test pseudo data within 4.26% of root-mean-squared (RMS) error and shows that the learning was successful.

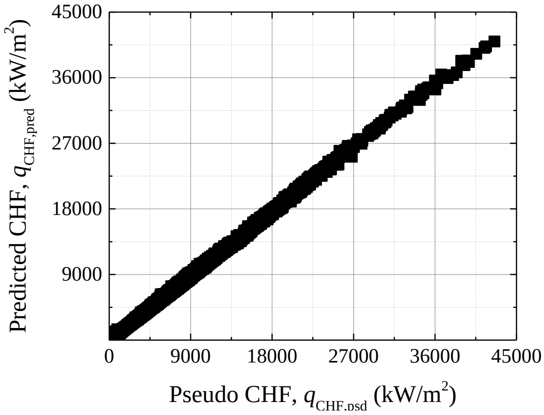

Fig. 1. CHF prediction results of trained model for test data

Even if the trained model is verified, the predictability of the trained model should be validated by predicting the other experimental CHF data that has never been used in the learning and verification. Fig. 2 shows the CHF predicting results of the trained model for experimental CHF data of which experimental conditions is listed in Table III. From the prediction, the trained model predicts the experimental CHF data within 15.28% of RMS error. It indicates that the trained model simulates successfully the CHF in narrow rectangular channel.

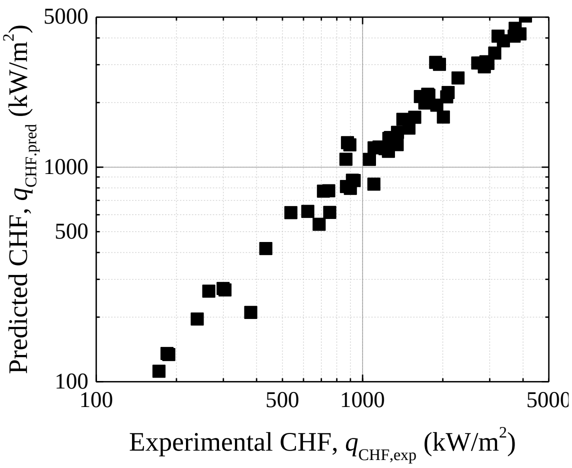

Fig. 2. CHF prediction results of trained model for experimental data

Table III: Flow conditions of experimental data

Parameter	Value
Mass flux (kg/m^{2}s)	-5700 ~ 9000
Pressure (kPa)	120 ~ 320
Inlet subcooling (K)	0 ~ 78
Gap size (mm)	2.35, 2.58
Length (mm)	182, 640

3. Conclusions

In the present study, the machine learning model was developed to predict CHF in narrow rectangular channel. The machine learning model consists of DBNs for pre-training and CNNs for prediction. The dataset used for learning is the pseudo dataset generated from Mirshak, Kaminaga et al., Kureta-Akimoto and Tanaka et al. correlations. The trained model predicts the test pseudo data within 4.26% of root-mean-squared (RMS) error. Finally, the trained machine learning model predicts experimental CHF data within 15.28% of RMS error. It shows that the proposed machine learning model is suitable for the prediction of CHF for narrow rectangular channel.

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