Enhancing CHF Prediction of AECL Look-Up Table Along with Machine Learning

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1. Introduction

A critical heat flux (CHF) is a key safety parameter. For the CHF prediction, artificial neural network has been also applied and showed good performances [1, 2]. However, it is hardly accepted in the nuclear community due to a drawback of '*Explainability*'.

A machine learning, as a subset of the artificial intelligence, can play a supplementary role for a more robust domain knowledge-based model. AECL Look-up Table (LUT) is widely used for the CHF prediction in reactor thermal-hydraulic design and safety analyses [3]. This domain knowledge model can predict the CHF by two schemes such as DSM (Direct Substitute Method) and HBM (Heat Balance Method). The uncertainty is much large in the DSM relative to the HBM. But the DSM is practically used in the nuclear engineering since HBM requires iterations to reach the heat balance in the CHF prediction.

The purpose of this study is to show a feasibility that a machine learning-aided CHF LUT model enhances considerably the accuracy of the CHF prediction.

2. Methods

2.1 Architecture of machine learning-aided Model

An architecture of the machine learning-aided CHF LUT model is constructed as shown in Fig. 1.
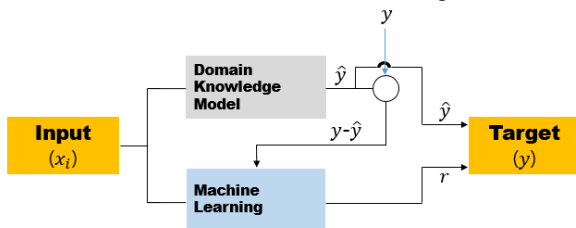

Figure 1 Structure of Domain Knowledge and Machine Learning model

The input x_i are the variables of CHF: pressure, mass flux, equilibrium quality, tube diameter. The domain knowledge model $\hat{y}$ is the 1995 AECL LUT. A machine learning algorism for residual r is a tree-base model of Extreme Gradient Boosting (XGBoost). More specifically, a regression model of XGBRegressor in Scikit-learn library is implemented to fit the residuals r between the measured CHFs y and the predicted CHFs $\hat{y}$. The target y is the measured CHF data.

2.2 CHF Data

The CHF data examined here cover almost a full range of AECL LUT as follows:

P: Pressure, bar	1 – 190.
G: mass flux, kg/m^{2}s	5 – 7,700
x_{eq} : local equilibrium quality	-0.5 – 1.0
Δh_{in}: inlet subcooling, kJ/kg	0 – 1,600
q″: critical heat flux, kW/m^2	30 – 15,000
D: tube diameter, m	0.001 – 0.038
L/D: tube length to diameter	4.5 – 1,000

A total number of the data is 12,209. The data distributions and histograms of the major parameters are displayed in Fig 2. The mass flux data are mostly placed in the lower part of its range, and others properly distributed.
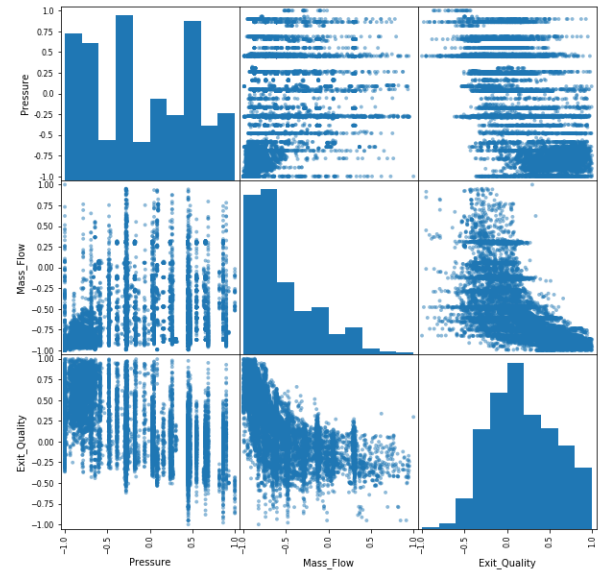

Figure 2 CHF data distributions and histograms

2.3 LUT Standalone Predictions

As a reference, the predictability of LUT for the above CHF data is assessed using HBM and DSM. The DSM is a simple scheme applying the local conditions of pressure, mass flux and local equilibrium quality directly to the LUT. The HBM is a heat balance scheme satisfying the energy conservation of heating system on the given inlet conditions. The statistics of HBM prediction are Mean of 1.002 and Standard deviation of 0.108, while the statistics of DSM Mean of 1.015 and standard deviation of 0.385. In terms of the uncertainty,

DSM is approximately three times larger than the HBM.

3. Results

In the machine learning, some parameters are explored to see the overfitting problem and optimize the model as follows:

- 5-fold Cross-validation
- n_estimator = 500
- learning rate = 0.1
- Max-depth = 10
- Training and testing split ratio = 0.75 (9156 points/3053 points)
- No regularization

The input variables for the data training are normalized over the range from -1 to 1 in order to minimize the effect of magnitude difference of each variable.

As a result, the CHF prediction by DSM along with the machine learning are compared with the measured CHF in Fig. 3.
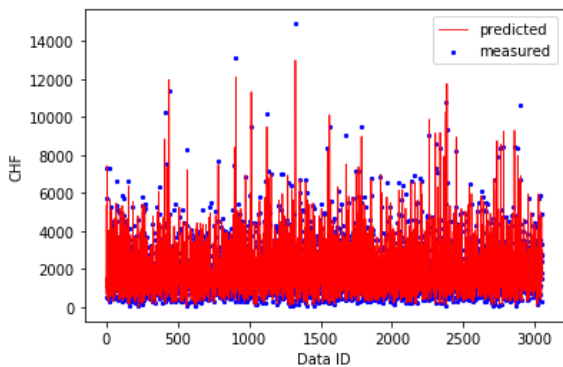

Figure 3 Comparisons of Predicted and Measured CHF

Fig. 4 shows the importance of the input parameters on each CHF prediction with SHAP analysis [4]. Red means an indication of pushing the prediction higher and blue pushing the prediction lower. The effect of exit quality on CHF is dominant particularly in lower quality range.
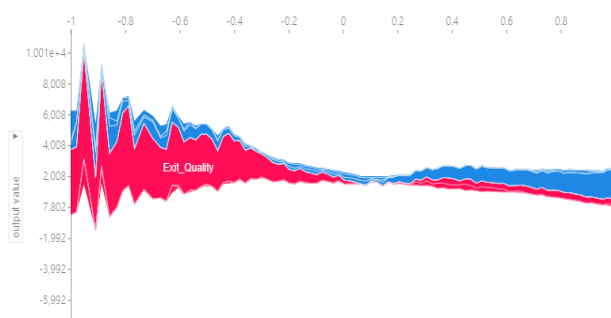

Figure 4 Feature Importance of Exit Quality

The statistics of the machine learning-aided CHF LUT model revealed Mean =1.027, standard deviation = 0.208 for the test data set of 3053 points. So, it is clear that the uncertainty of LUT can greatly decrease about half of that of LUT standalone. The systematic trends of

Predicted CHF/Measured CHF are checked in Fig.4 over the ranges of input variables of Pressure, Mass flux and Local quality. It shows randomly-distributed errors around the mean and there are no systematic errors.
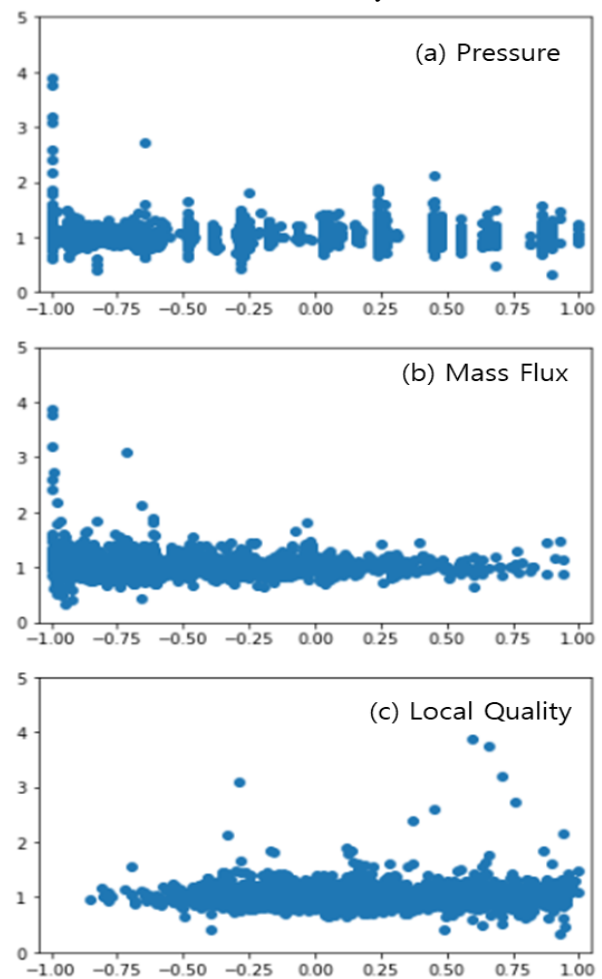

Figure 5 Trends of Input Variables of (a) Pressure, (b) Mass flux and (c) Local Quality in terms of P/M ratio

3. Conclusions

It is demonstrated that a more robust and accurate prediction of CHF could be expected if the domain knowledge-based model is coupled with the machine learning.

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