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Application of machine learning for prediction of critical heat flux: Support vector machine for data-driven CHF look-up table construction based on sparingly distributed training data points

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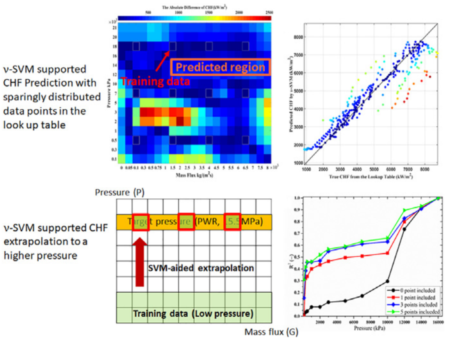
GRAPHICAL ABSTRACT



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ABSTRACT

In this study, ν-Support Vector Machine (ν-SVM) is used to explore strategies for the data-driven CHF look-up table construction, based on sparingly distributed experimental data points. The CHF look-up table of Groeneveld et al. (2007) was used as the reference CHF data bank. In the data bank, the subcooled flow ($Xe < 0$) is selected to focus on the PWR steady-state condition. The results demonstrate that ν-SVM trained with well distributed training data in the parametric space of interest (pressure and mass flux) can give an acceptable level of CHF prediction accuracy. Procurement of training data points that can imply the parametric behavior of CHF with respect to pressure and mass flux is the key to achieving a high level of CHF prediction accuracy. For the pressure-variant CHF behavior, data in the proximity of the inflection point significantly contribute to the prediction accuracy. Hence, physics-informed training data preparation with knowledge of CHF inflection points could enhance the prediction accuracy. The linearizability of CHF with respect to pressure and mass flux determines the level of prediction accuracy, in the absence of a good spread of training data points. CHF extrapolation to a higher pressure with data points collected at low pressure can be effectively achieved by ν-SVM if a few data points are available in the high pressure. This speaks to a possibility of strategically integrating high pressure and low pressure experiments, with a reduced experimental cost associated with the high pressure testing. The presented methodology provides engineering strategies to support the look-up table construction for advanced cladding materials.

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1. Introduction

Critical Heat Flux (CHF) limits the maximum attainable heat flux of fuel pins in the pressurized water reactor (PWR), thereby determining the achievable thermal power. As a way to ensure a sufficient margin to CHF, nuclear power regulation enforces the compliance with Departure from Nucleate Boiling Ratio (DNBR) – the ratio of the heat flux needed to cause departure from nucleate boiling to the actual local heat flux. CHF is a complex phenomenon affected various parameters including flow rate, pressure, quality, geometry and surface characteristics (Bruder et al., 2017). Because of its importance and phenomenological complexities, the CHF phenomena have received considerable attention thus far, with myriads of modeling framework, approach, and perspectives. Today, empirical correlations or tabulated look-up tables based on extensive experiments covering wide ranges of operating conditions are used in nuclear reactor thermal hydraulics codes such as *RELAP5 3D*, *COBRA-TF*, and *TRACE*.

The high costs associated with the CHF investigation conducted in a manner compatible with the current correlations or look-up table developments prevent many experimental CHF studies from being applied for the aforementioned thermal hydraulics system codes. This has become even more evident recently with the developments of Accident Tolerant Fuel (ATF) cladding (Brown et al., 2013, 2015; Carmack et al., 2015; Lee and Kazimi, 2015; Lee et al., 2015a,b, 2017, 2016a,b, 2013; Terrani et al., 2014a,b). Past studies that demonstrated the influence of the material surfaces on boiling (Seo et al., 2015, 2016) make the nuclear community believe that CHF of ATF clad fuels is likely to be different from that of Zirconium-based alloys, or steel materials used for the W-3 correlation or look-up table (Bruder et al., 2017). The high cost associated with procuring CHF measurements covering a wide range of operating conditions motivates us to explore an enabling technology to effectively interpolate and extrapolate experimentally measured points. With enabling inter/extrapolation techniques, we can establish a modeling foundation upon which construction of look-up tables can be expedited to support the application of experimentally measured CHF points for the system codes.

It is noteworthy that the parametric trends of CHF with respect to dominant operating conditions – pressure (P), equilibrium quality (X_e), and mass flux (G) – are relatively simple, despite of the complexity of the phenomena. CHF monotonically decreases, and increases with increasing X_e, and G, respectively (Fig. 1(a), and (b)). The pressure sensitivity of CHF can be parameterized by a simple function that gives a local maximum value at a certain pressure (Fig. 1(c)).

The simple parametric trends of CHF respect to the three major flow conditions (X_e, G, and P) imply that CHF look up tables can be effectively obtained if an enabling fitting method is applied with a suitable set of data.

2. ν-SVM supported CHF prediction with sparingly distributed CHF data points

In contrast to Artificial Neural Network (ANN), Support Vector Machine (SVM) can automatically select its model size and obtain the globally optimal and unique solution. In Cai's study (Cai, 2012a,b), ε-SVM was employed to correlate the geometrical parameters of tubes and the thermal properties of liquids with Kutateladze number. Its comparison with experimental results demonstrated that ε-SVM gives better prediction accuracy than various ANNs. A few past studies investigated CHF prediction using ν-SVM (Jiang et al., 2013; Jiang and Zhao, 2013a,b). Jiang et al. (2013) demonstrated that CHF behavior with respect to the aforementioned flow parameters (G, P, and X_e) can be predicted by ν-SVM. The following investigation by Jiang and Zhao (2013a,b) improved its model by finding optimal coefficients of ν-SVM, with which dryout prediction was conducted using the CHF look-up tables of Groeneveld et al. (2007) and Kim et al. (2000). These investigations focused on how ν-SVM models CHF with more than three parameters, and validated ν-SVM has superiority of CHF prediction over other machine learning techniques, such as radial basis function network (Jiang et al., 2013). It is noteworthy that in their preparation of training datasets (Jiang et al., 2013; Jiang and Zhao, 2013a,b), 75% of the total CHF datasets were used as training datasets with the subtractive clustering scheme. That is, 25% of the CHF dataset are used for the performance evaluation. In light of this, the applied SVM was essentially used as an enabling interpolation method for the closely distributed CHF data points.

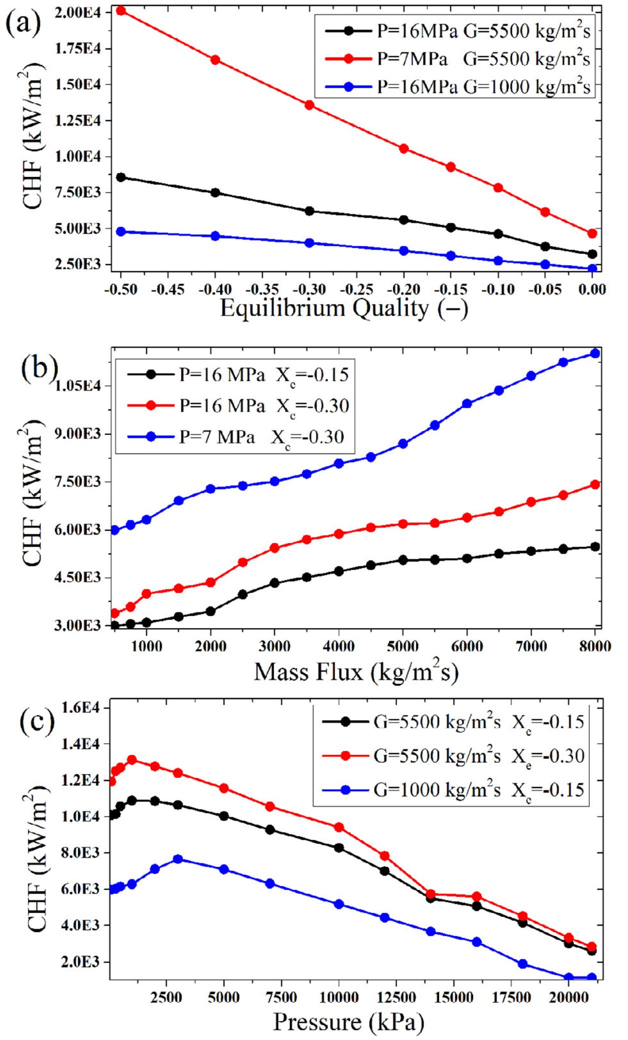

Fig. 1. The parametric trends of CHF in subcooled flow with respect to (a) equilibrium quality (X_e), (b) mass flux (G), and (c) pressure (P).

In reality, the value of SVM application for CHF prediction would be best realized if it successfully captures CHF behavior by interpolating sparingly distributed experimental data. This would imply that the CHF look-up table for various cladding surfaces under investigation, including ATF candidates, can be prepared with a limited number of data points, thereby expediting the system-level simulation of ATF clad fuels. In addition, SVM-supported extrapolation of CHF data beyond the experimental conditions could support the cost reduction of experiments as it may alleviate pressure, heater, and pump requirements. Therefore, the objective of this study is to explore strategies for the data-driven CHF look-up table construction with ν-SVM, based on sparingly distributed experimental data points. In addition, its potential application for the pressure extrapolation for CHF is investigated in this paper.

This study uses the CHF look-up table of Groeneveld et al. (2007) as the reference CHF data bank. The Groeneveld et al. (2007) look-up