A Numerical Approach for Prediction of Critical Heat Flux (CHF) utilizing Local Condition Hypotheses

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1. Introduction

The thermally controlled system of forced-convective subcooled or saturated flow boiling is generally used to dissipate the heat from the heat resources effectively. But the optimization of a design in the thermal-controlled system should always consider the thermal limit known as Critical Heat Flux (CHF). CHF represents a limit of heat transfer at which there is a sudden decrease in the value of the heat transfer coefficient. It is an important parameter in the safety design and operation of facilities like nuclear reactors, heat exchangers, very large integrated circuits, etc. [1].

One of the earliest work on CHF is proposed by McAdams et al. [2] for flow boiling in 1949. Since that, Researchers have been studying CHF for more than 70 years, and developing hundreds of CHF empirical correlations in various models; Annular film dryout models, Bubbly layer models, CHF look-up table methods, Upstream Condition Correlation (UCC), and Local Condition Correlation (LCC) etc. [3]. In this study, we focus on the LCC for predicting CHF. For this work, (Dankook University – Process Design Laboratory, DKU-PDL) numerical algorithm is developed and adopted.

2. Local Condition Hypothesis

2.1 Local Condition Correlation

Local Condition Hypothesis concept stipulates that the CHF is determined only by the local variables at the local location; the system pressure (P), tube diameter (D), mass flux (G), and 'True mass quality' of Steam (X_t). Where, X_t is defined as the ratio of the 'true' mass flow rate of steam to the total mass flow rate of the steam-water two-phase mixture. Because it can describe the behavior of vapor generation quantitatively, it captures more of the physical meanings than the thermodynamic equilibrium quality (X_{eq}), especially in the subcooled boiling regime. Thus, a LCC consists of $f(P, D, G, X_t)$ and it is usually calculated by Heat Balance Method (HBM) [4].

In developing the LCC in uniformly heated tubes, three assumptions are adopted. First, a uniformly heated round tube with vertical flow of water is only considered for this correlation. Second, the mass velocity from upstream to downstream in the tube is sufficiently high that the effect of gravity is neglected. And lastly, the inlet flow is stable with no oscillation during detecting pressure, temperature etc.

Jafri [5] suggests a rate equation of true mass quality, X_t, inside a tube from the inlet as the starting point as it can be calculated by X_{OSV} and X. Where, X_{OSV} is thermodynamic equilibrium quality at Onset of Significant Void (OSV). It is calculated values and Saha and Zuber [6] correlation was utilized to estimate it in this study. And X is thermodynamic equilibrium quality through heated length. Thus, X_t can be calculated under the initial condition of Eq. (2).

$$\frac{dX_t}{dX} = \frac{X_t - X}{X_{OSV}(1 - X_t)} \tag{1}$$

Initial condition of X_t is follows:

$$\begin{cases} X_t = 0, & at\ X = X_{OSV} \quad if\ X_{in} < X_{OSV} \\ X_t = 0, & at\ X = X_{in}\ \ if\ X_{OSV} < X_{in} < 0 \\ X_t = X_{in}, & at\ X = X_{in} \qquad if\ 0 < X_{in} \end{cases} \tag{2}$$

2.2 DKU-PDL Algorithm for X_t

The initial value of CHF should be determined before applying Eq. (1) along with Eq. (2). Because X_{OSV} and initial X_t is calculated by initial CHF. So, we construct the HBM algorithm using the rate equation as shown in Fig. 1. This algorithm pursues to "Unsupervised machine learning" technique because independent variables are determined by calculated CHF value for solving rate equations instead of indirect use of the pre-developed CHF correlation. In this study, we choose the CHF correlation by Deng [7] that is utilized as shown in Eq. (3-6). $Z(X_t)$ is a slip factor between steam and water.

$$Z(X_t) = (1 + X_t^2)^3 \tag{3}$$

$$q_c = \frac{\alpha}{\sqrt{D_h}} \exp\left(-\gamma\sqrt{G X_t Z(X_t)}\right) \tag{4}$$

$$\alpha = 1.669 - 6.544\left(\frac{P}{P_c} - 0.448\right)^2 \tag{5}$$

$$\gamma = 0.06523 + \frac{0.1045}{\sqrt{2\pi\left(\ln\left(\frac{P}{P_c}\right)\right)^2}} \exp\left(-5.413\frac{\left(\ln\left(\frac{P}{P_c}\right)+0.4537\right)^2}{\left(\ln\left(\frac{P}{P_c}\right)\right)^2}\right) \tag{6}$$

The rate equation is a differential equation; however, it is difficult to determine the analytic solution. So, the equation at each step is solved by a numerical approach such as Gauss-Seidel, Bisection, or Runge-Kutta method, etc. In this study, the Gauss-Seidel method is adopted to solve the solution. When X_t is converged by the numerical approach in the algorithm, alpha and gamma are re-adjusted and determined by using Eq. (4).

Deng [7] pointed that alpha and gamma are a function of pressure; the values can be calculated from the CHF data points of the same pressure. Once α and γ is determined at each pressure, the values of α and γ at whole pressure range can be calculated by non-linear regression form of Eq. (4).

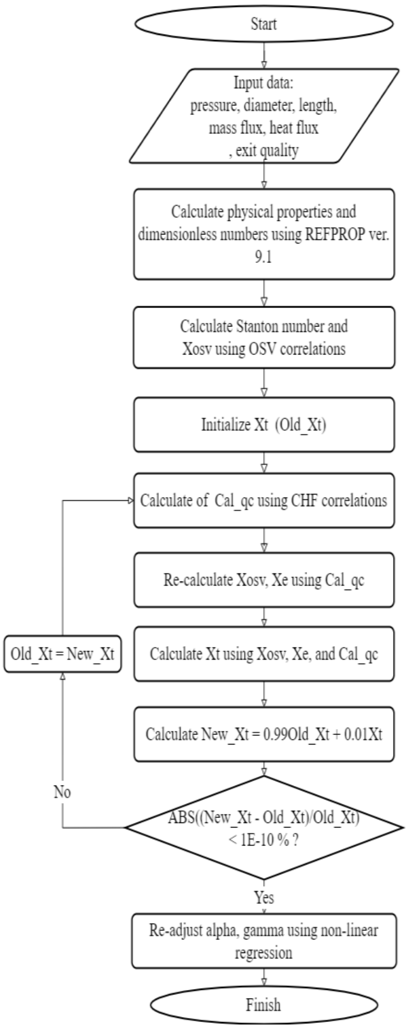

Fig. 1. DKU-PDL algorithm for $\boldsymbol{X_t}$ using calculated CHF by correlations

3. Experimental CHF data

For this study, a total of 9,366 CHF data in uniformly heated vertical round tubes was collected from 13 published report or sources. The detail information on the database is presented by Shim [1]. All data points used in this study were validated within 5% errors, by heat balance. These data have a wide experimental condition. The data with high and low-pressure conditions was as follows:

[High pressure data: 359 data]
Pressure: 100.00 – 104.78 bar
Diameter: 0.0046 – 0.0446 m
Heated length: 0.2286 – 4.9660 m
Mass flux: 28.13 – 9966.60 kg/m^2s
Heat flux: 0.262 – 10.77 MW/m^2

[Low pressure data: 400 data]
Pressure: 1.01 – 4.95 bar
Diameter: 0.0010 – 0.02388 m
Heated length: 0.0254 – 3.1991 m
Mass flux: 27.10 – 3764.65 kg/m^2s
Heat flux: 0.191 – 12.583 MW/m^2

4. Results and Discussion

The low-pressure data discussed and unrestricted to mass flux in the same data points for the evaluating the CHF using the algorithm are shown in Fig. 2. Fig. 2 shows that the low-pressure data, under 3 bar, results in good prediction but the other data near the 5 bar is overpredicted. This result shows that the α and γ are sensitive at low pressures. On the effect of mass flux in low pressure conditions, Fig. **3** shows that the α and γ are less dependent on the mass flux.

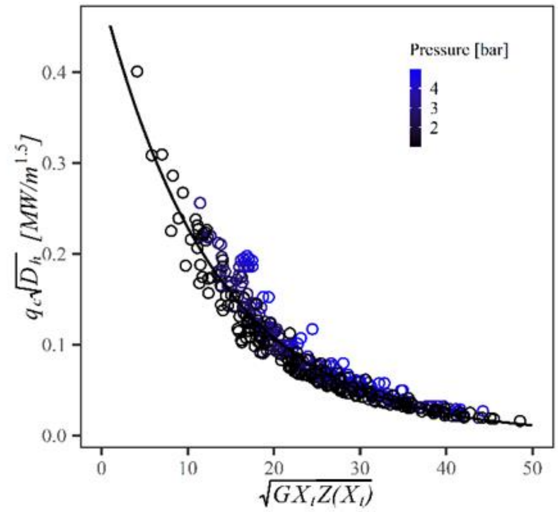

Fig. 2. CHF Trend on a $\boldsymbol{q_c\sqrt{D_h}}$ versus $\sqrt{\boldsymbol{GX_tZ(X_t)}}$ at low pressure

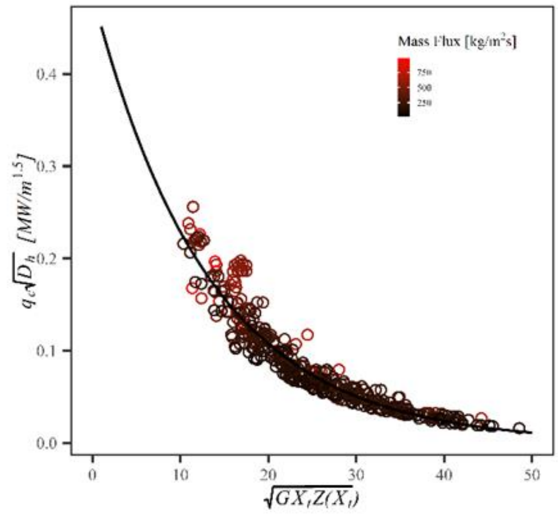

Fig. 3. CHF Trend on a $\boldsymbol{q_c\sqrt{D_h}}$ versus $\sqrt{\boldsymbol{GX_tZ(X_t)}}$ at low pressure with low mass flux

Fig. 4 shows CHF data $q_c\sqrt{(D_h)}$ versus $\sqrt{GX_tZ(X_t)}$ at high pressures between 100 and 105 bar. The α and γ are more independent to pressure in this region, which is a contrast to the low-pressure results. Also shown as Fig. 5, the alpha and gamma are relatively independent to high mass flux.

Table I shows the values of α and γ in different pressure condition. α is more sensitive than γ for pressure changes. This can be understood better by natural log-linearization of Eq. (4). If we take the natural logs of both sides of Eq. (4), it consists of $\ln\left(q_c\sqrt{D_h}\right)$ and $\ln(\alpha) - \gamma\sqrt{GX_tZ(X_t)}$. So, $\ln(\alpha)$ represents the bias of linear relationship of $q_c\sqrt{D_h}$ versus $\sqrt{GX_tZ(X_t)}$ If pressure is changed, γ represented coefficients is almost same regardless of pressure, but α is sensitive to changes of pressure.

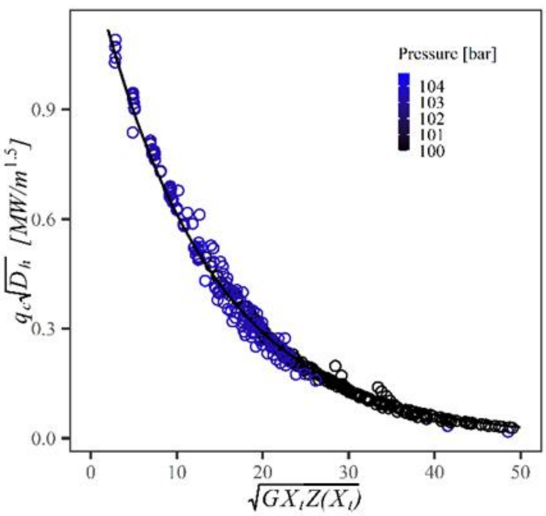

Fig. 4. CHF Trend on a $\boldsymbol{q_c\sqrt{D_h}}$ versus $\boldsymbol{\sqrt{GX_tZ(X_t)}}$ at high pressure

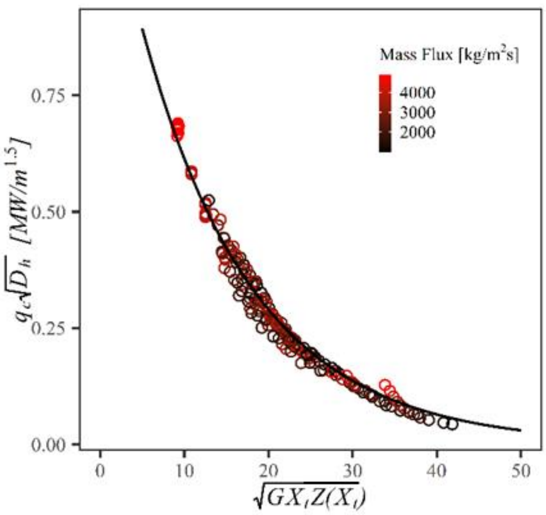

Fig. 5. CHF Trend on a $\boldsymbol{q_c\sqrt{D_h}}$ versus $\boldsymbol{\sqrt{GX_tZ(X_t)}}$ at high pressure with high mass flux

Table I: Re-adjusted value of $\boldsymbol{\alpha}$ and $\boldsymbol{\gamma}$

Pressure [bar]	No. of data	α	γ
5 below	400	0.487	-0.0755
100 – 105	359	1.300	-0.0750

5. Conclusions

A numerical approach using the local condition hypothesis can be useful for predicting CHF. Thus far DKU-PDL algorithm is useful for optimizing X_t using calculated CHF regardless of the experimental value. Once initialized X_t in Eq. (2) and CHF can be determined by the correlation, by the validation of old X_t and new X_t step by step. Saha and Zuber [6] correlation and Deng [7] CHF correlation have been used to calculate the X_t for CHF and the value of α and γ in forced-convective subcooled vertical tubes are re-adjusted. α is the bias in term of natural log linearization of Eq. (4), and it is of a more critical value than γ in predicting CHF.

In the future works, the CHF correlation without α and γ is re-initialized step of X_t and q_c. For the focus on that, the optimization of α and γ for convergence loop is needed. And the other general form instead of $\sqrt{GX_tZ(X_t)}$ is essentially needed because it is slightly insufficient to some of pressure range.

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