Deep Ensemble Algorithm for CHF Prediction under Uniform/Nonuniform Axial Profile Conditions

Chan Yeong Yoon, Kyung Mo Kim*
Department of Energy Engineering,
Korea Institute of Energy Technology (KENTCH)
21 KENTECH-gil, Naju, Jeonnam, Republic of Korea
Chanyoung3351@kentech.ac.kr, kmokim@kentech.ac.kr

***Keywords : CHF, Deep Ensemble, Tong's F-factor, non uniform.**

1. Introduction

Critical Heat Flux (CHF) represents a critical thermal limit encountered in systems featuring boiling heat transfer. It is defined as the maximum heat flux that can be transferred from a heated surface to a boiling liquid. If this limit is exceeded, the boiling mechanism undergoes a critical transition, leading to a severe degradation in heat transfer performance—a phenomenon known as the "boiling crisis." [1] Consequently, the accurate prediction of CHF is a crucial task for the safe design and operation of many heat transfer systems.

Due to the complex and highly non-linear nature of the CHF phenomenon, Artificial Neural Networks (ANNs) have been widely adopted for its prediction. However, conventional deterministic ANNs suffer from significant limitations, including a restrictive application scope dependent on the training data and their inherent "black-box" nature. To address these limitations, this study employs Probabilistic Neural Networks (PNNs). While PNNs demand greater computational resources than their deterministic counterparts, they offer the distinct advantage of being able to predict CHF while simultaneously quantifying the associated prediction uncertainty. Specifically, developed deep ensemble model [2] decomposes this uncertainty into its aleatoric and epistemic components, which arise from inherent data noise and model ignorance, respectively. [3] This uncertainty quantification provides a direct measure of the model's predictive reliability.

A key limitation of the current framework, however, is that it was trained exclusively on data from uniformly heated cylinders. Consequently, it is not applicable to the non-uniformly heated conditions found in most industrial applications. To overcome this problem, we propose a unified framework that extends the PNN's capability by introducing additional models to correct for the C and F-factors, thereby enabling accurate CHF prediction in non-uniformly heated cylinder conditions.

2. Deep Ensemble model

2.1. Probabilistic Neural Network Architecture

Due to the algorithms inferring the output as a feature of probability distribution, mean and standard deviation, i.e., log variance, can be obtained from the constructed models. The β-Negative Log Likelihood (β -NLL) [4] is used as a loss function of the deep ensemble model:

$$\mathcal{L}_\beta \coloneqq E_{X,Y}\left[\left|\widehat{\sigma^{2\beta}}(X)\right|\left(\frac{1}{2}\log\widehat{\sigma^2}(X)+\frac{\left(Y-\hat{\mu}(X)\right)^2}{2\widehat{\sigma^2}(X)}+\text{const}\right)\right] \tag{1}$$

By adjusting the error penalty according to the predictive variance, the effect of error is mitigated when uncertainty is high. As the variance increases, the loss itself also increases; if the uncertainty estimation is inaccurate, an additional penalty is imposed. Consequently, the model learns to increase the variance to reduce the loss when predictions are difficult, and to decrease the variance when the predictions are accurate. To mitigate the self-amplifying characteristic of the heteroscedastic-NLL, β-NLL introduces a parameter β (beta coefficient) that interpolates between NLL and completely uniform data point importance. [4] As the β-NLL consists of regression (residual between the predictions and actual data) and regularization, the model can provide the prediction results in the form of probability distribution.

The stop gradient operation, denoted by |·|, is applied to the variance-weighting term. This operation is crucial as it ensures that this term functions as an adaptive, input-dependent learning rate, rather than directly influencing the variance prediction itself. As a result, the optimization process behaves as if it were sampling data points with a probability proportional to their inverse variance ($\frac{1}{\sigma^2}$) [4].

2.2. Model summary (Deep ensemble)

Deep Ensemble (DE) model is trained on 20,000 CHF data generated under uniform heat flux conditions along the axial direction of a circular-type heated channel.

The ensemble architecture consists of 20 independent deep neural networks, each constructed with 13 layers (5-63-51-26-44-41-41-41-22-39-36-2 nodes per layer).

'Deep' refers to the multiple layers forming complex nonlinear relationships, which enable high performance in regression tasks.

'Ensemble' denotes the methodology of combining outputs from various models, thereby enhancing predictive accuracy and enabling robust uncertainty quantification in regression problems.

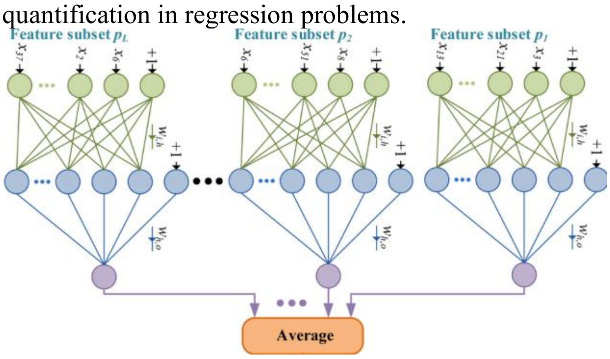

Fig. 1. Deep ensemble model.

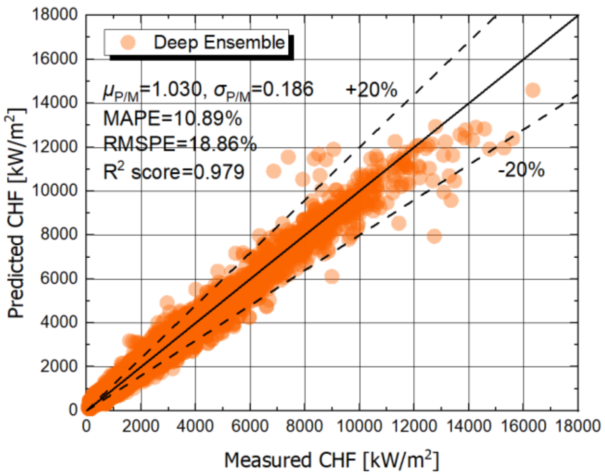

Fig. 2. Comparison of predicted CHF and actual CHF data in a uniformly heated circular tube

In Fig.2. DE model demonstrates 0.979 of R^2 score and outstanding regression ability in CHF prediction.

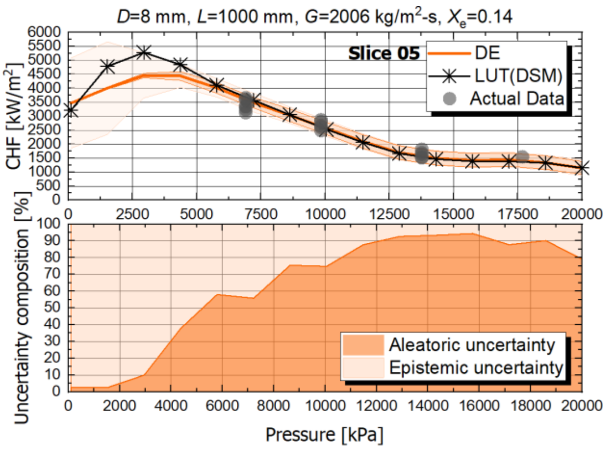

Fig. 3. CHF prediction behaviors with analysis on the epistemic and aleatoric uncertainties of DE.

As shown in Fig. 2. The constructed DE model demonstrates better regression results than conventional LUT also obtains the source of uncertainty. Where data existed aleatoric uncertainty accounts most of the uncertainties. In the opposite, the area where actual data are not existed, uncertainty increased and epistemic (means model ignorance) accounts most of the uncertainties. Thus, CHF prediction, uncertainty quantification, and Investigation of uncertainty sources were successfully operated via developed model.

3. CHF prediction model for axially nonuniform power profile conditions

While the DE model developed in Section 2 can predict the CHF in circular tubes with uniform power distributions, its direct application to practical safety analyses is limited, because actual fuel assemblies in the reactor core exhibit non-uniform axial power profiles. Therefore, this study aims to develop a model capable of predicting CHF under these non-uniform conditions by leveraging the foundational DE model.

3.1. F-factor methodology

The conventional approach to predicting Critical CHF under non-uniform axial power distributions involves applying a correction factor to a CHF model originally derived from uniform heat flux data. This correction factor is designed to account for the influence of the upstream heat flux profile on the CHF location, a phenomenon commonly referred to as the "memory effect." A prominent and widely used correction factor that incorporates this memory effect is the F-factor, as proposed by Tong. [5] The F-factor is defined as follows:

$$F_{NU} \equiv \frac{q''_{CHF,EU}}{q''_{CHF,NU}} = \frac{C}{q''(z_c)(1-e^{-Cz_c})}\int_0^{z_c} q''(z)e^{-C(z_c-z)}\,dz \qquad (2)$$

$$C = 5.906 \times \frac{(1-X)^{4.31}}{\left(\frac{G}{1356}\right)^{0.478}} \qquad (3)$$

$$q''_{\mathrm{CHF,NU}} \equiv \frac{q''_{\mathrm{CHF,EU}}}{F} \qquad (4)$$

3.2. Combination of DE model and F-factor methodology

Therefore, in this study, the previously developed DE model was utilized as a predictive tool for CHF under uniform power distributions. The non-uniform CHF was then predicted by calculating the F-factor and substituting it into Eq. (3). To evaluate the prediction performance for these non-uniform conditions, the CHF database documented in KAERI/TR-1665/2000 was employed.

A computational framework was established to predict CHF in a nonuniformly heated circular tube. First, a fitting function was developed to approximate the axial power distribution for each experimental case. Based on this function, 50 axial nodes were generated to calculate the local parameters based on geometry (length and diameter) and flow conditions (mass flux, pressure, and inlet subcooling). Since the power distribution at each of the 50 axial nodes is known, the local quality (X) can be calculated from the given mass flux (G), pressure (P), and inlet enthalpy. This provides the complete set of input variables (D, L, P, G, X) for the DE model at each node, enabling the prediction of local CHF as if it were uniform. Subsequently, the C and F-factors are calculated, leading to the final prediction of the non-uniform CHF. This entire workflow is illustrated in Fig.3.

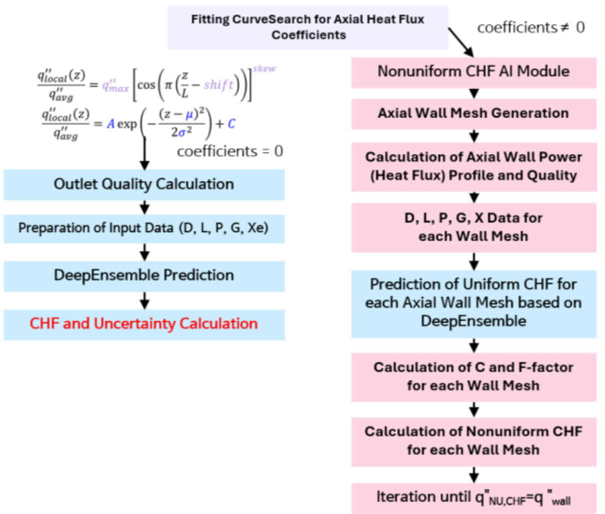

Fig. 4. Entire workflow of framework extending DE model towards nonuniform power profile condition.

The prediction of CHF under non-uniform axial power distribution is carried out through an iterative F-factor based method. Instead of directly using experimental CHF values, the procedure begins with an assumed average heat flux (q''_{Avg}). The axial domain is discretized into wall meshes, and for each mesh, local thermohydraulic parameters and wall heat flux profiles are calculated.

The Deep Ensemble model, previously trained for uniform axial power conditions, is then applied to estimate the baseline CHF for each mesh. Using these baseline results, correction coefficients C and F-factors are computed. The non-uniform CHF distribution ($q''_{NU,CHF}$) is subsequently predicted, and the results are compared with the corresponding local wall heat flux (q''_{local}).

If convergence is not achieved($q''_{NU,CHF} \neq q''_{local}$), the assumed q''_{avg} is incrementally updated, and the process of recalculating C, F-factors, and non-uniform CHF is repeated. This iterative cycle continues until the predicted non-uniform CHF matches the local heat flux profile.

Through this procedure, the iterative F-factor method not only enables accurate prediction of the non-uniform CHF curve but also successfully identifies the CHF occurrence location, which cannot be achieved by the single-pass approach.

By comparing the predicted non-uniform CHF profile with the actual wall heat flux distribution along the axial direction, it is possible to predict both the CHF value and its occurrence location. The predicted CHF is determined as the point of intersection where the non-uniform CHF curve and the wall heat flux profile meet, as illustrated in Fig. 5.

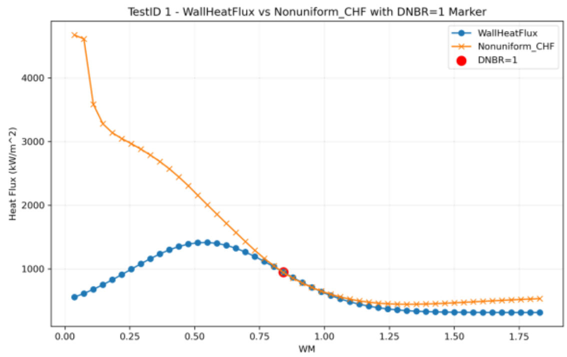

Fig. 5. Nonuniform CHF prediction method based on wall heat flux

By processing CHF prediction under non-uniformly heated conditions, it was found that the combination of F-factor and constructed DE model underestimates the CHF in a nonuniformly heated circular tube. However, CHF underestimation is conservative result. Thereby, it can be utilized in the perspective of safety analysis.

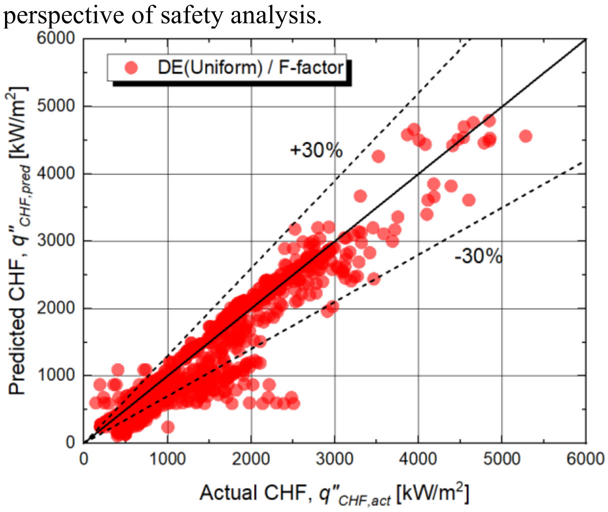

Fig. 6. Predicted CHF vs Actual CHF of DE(Uniform)/F-factor

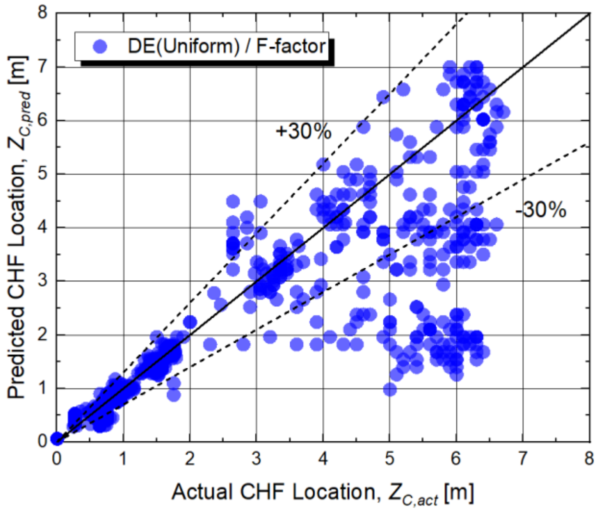

Fig. 7. Predicted CHF Location vs Actual CHF Location of DE(Uniform)/F-factor

3. Conclusion

In this study, a hybrid framework for predicting CHF under non-uniform axial power distribution conditions was successfully developed and validated. The first step of the approach was to construct a DE model using 20,000 CHF data points for uniform heat flux conditions. This base DE model demonstrated high regression performance, with a coefficient of determination $\boldsymbol{R^2}$ of 0.979 and proved its ability to quantify prediction uncertainty by decomposing uncertainty into its aleatoric (inherent data noise) and epistemic (model ignorance) components.

Subsequently, the DE model trained in uniform conditions was extended to non-uniform conditions by integrating it with the physics-based Tong's F-factor methodology. The proposed framework calculates local thermohydraulic parameters at 50 generated axial nodes and computes the C and F-factors based on local CHF predictions obtained from the DE model. Through an iterative process, the framework predicts both the CHF value and its location by finding the point where the predicted non-uniform CHF curve converges with the actual wall heat flux profile.

Validation using a non-uniform condition database revealed that the developed framework tends to underestimate the actual CHF values. This can be positively utilized from a nuclear system safety analysis perspective, as it provides a conservative prediction. This study is significant as it demonstrates the potential of effectively combining a data-driven DE model with physics-based correction factors to predict the complex CHF phenomenon under non-uniform conditions using abundant uniform condition data.

Future work will focus on developing advanced methodologies to address the observed underestimation of CHF in regions with non-uniform axial power distributions, thereby improving the accuracy and reliability of the predictive framework

ACKNOWLEDGEMENT

This work was supported by the Nuclear Safety Research Program through the Regulatory Research Management Agency for SMRs (RMAS) and the Nuclear Safety and Security Commission (NSSC) of the Republic of Korea (No. RS-2025-02309978)

REFERENCES

[1] L. S. Tong, Boiling Crisis and Critical Heat Flux, AEC Critical Review Series, TID-25887, U.S. Atom

[2] Lakshminarayanan, B., Pritzel, A., & Blundell, C. (2017). "Simple and Scalable Predictive Uncertainty Estimation using Deep Ensembles." NeurIPS 2017.

[3] A. Kendall and Y. Gal, What Uncertainties Do We Need in Bayesian Deep Learning for Computer Vision?, *Advances in Neural Information Processing Systems 30 (NIPS 2017)*, pp. 5574-5584, 2017.

[4] Seitzer, M., Wenzel, F., Brox, T., & Mandt, S. (2022). "On the Pitfalls of Heteroscedastic Uncertainty Estimation with Probabilistic Neural Networks." ICLR 2022(OpenReview).

[5] L. S. Tong, H. B. Currin, P. S. Larsen, and O. G. Smith, Influence of Axially Non-uniform Heat Flux on DNB, *Chemical Engineering Progress Symposium Series*, Vol. 62, No. 64, pp. 35-40, 1966.