*Project*

# Critical Heat Flux Prediction

## using 2006 Groeneveld Look-up Tables (NUREG)


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# CONTENT: (navigable)

# PROJECT OVERVIEW

## Introduction:

In 2006, Groeneveld et al. developed Look Up Tables (LUT) for predicting Critical Heat Flux (CHF) under various conditions. These tables are based on extensive experimental data and provide a convenient means for engineers to estimate CHF without resorting to complex numerical simulations.

The Groeneveld LUT are based on a range of parameters including fluid properties, system geometry, and operating conditions such as pressure, flow rate, and surface material.

Hence these tables and CHF data are critical for the engineering practices, and offer a valuable tool for designing and analysing thermal systems.

## Objective(s):

- The primary aim of this paper is to **predict CHF values** for a particular set of data **under specified conditions**.
- Ultimately, the goal is to **enhance the design and operation of thermal systems**, particularly those involving boiling heat transfer, by enabling informed decision-making regarding heat transfer limitations and safety margins.

# PROJECT DESCRIPTION

## Theoretical knowledge:

Critical heat flux is the heat flux at which boiling ceases to be an effective form of transferring heat from a solid surface to a liquid. Hence its knowledge determines the power limits for reactors around the world.

Most of the tube CHF correlations have essentially the form:

$$CHF = f(P, G, X\_CHF, D)$$

On this equation, the most recent CHF LUT method (Groeneveld et al., 2007) provides CHF values for water-cooled tubes at discrete values of pressure (P) {0.1 – 20 $MPa$}, mass flux (G) {0 - 7,500 $kg.m^{-2}s^{-1}$}, and thermodynamic quality (X) {(-50) – 100 % (-ve refer to subcooled conditions)}.

## Project Insights:

From the NUREG report (CHF LUT) a database is collected to analyse and predict the values of Critical Heat Flux, especially during boiling heat transfer, based on various parameters, such as

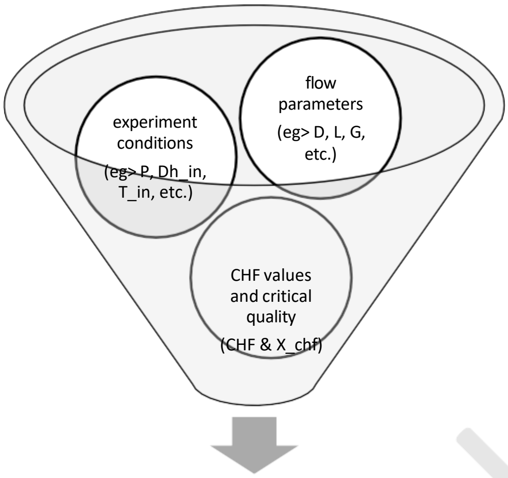
- Tube diameter : D
- Heating length : L
- Pressure : P
- Mass Flux : G
- Critical Quality : X_chf
- Inlet Subcooling : Dh_in
- Inlet Temperature : T_in
- CHF (given) : CHF

  at various conditions.

It also discusses the applicability and validity of the CHF LUT to reactor conditions of interest and a comparison of the range of conditions covered by these primary data and subsequently obtained supplementary data sets.

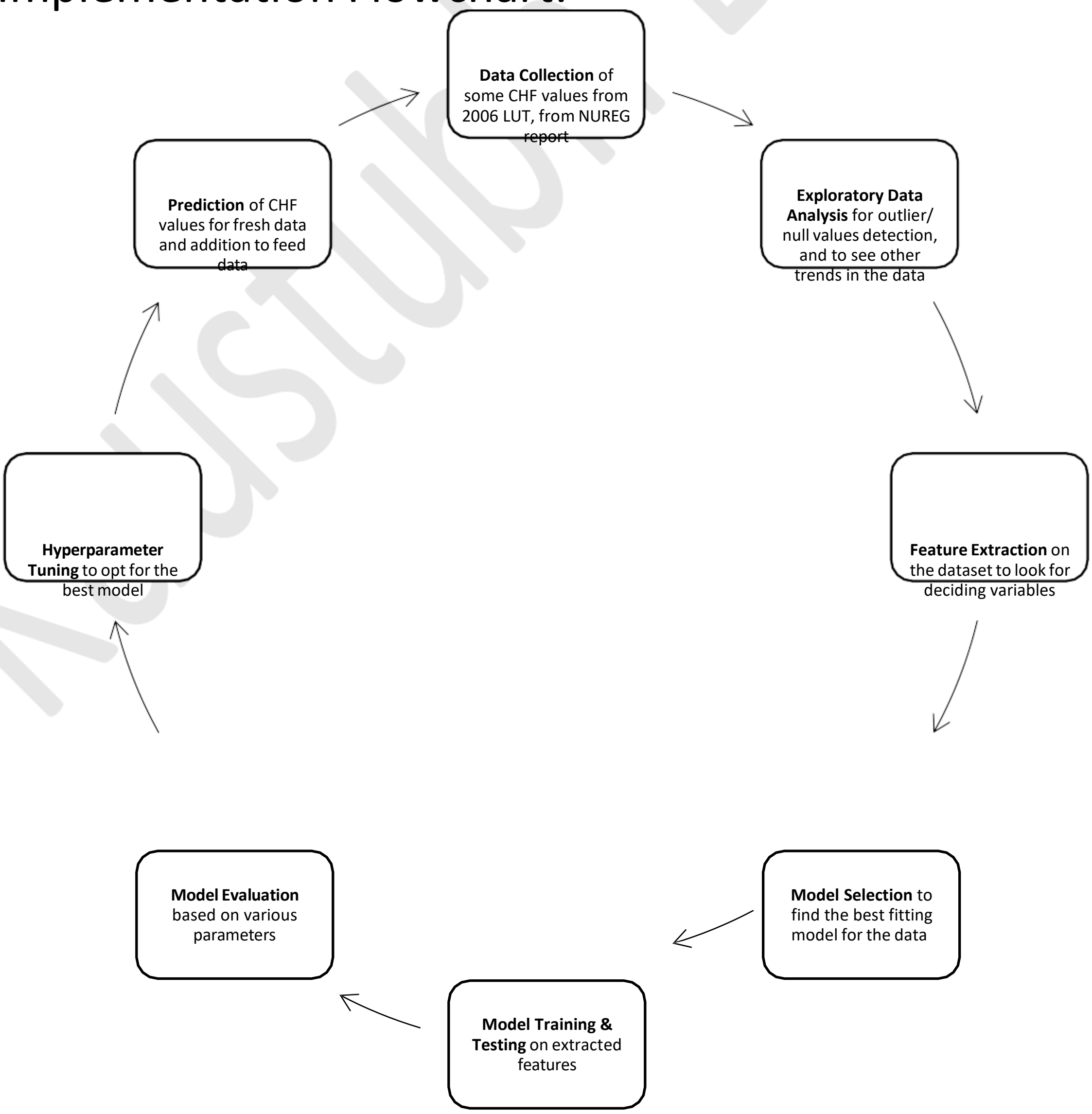
# PROCESS FLOW

## Data collection Parameters:




CHF LUT Data

## Model Implementation Flowchart:



# DATA SOURCE

## Source Description:

- The data is collected from the *United States Nuclear Regulatory Commission (U.S.NRC)* library titled as "**Critical Heat Flux Data Used to Generate the 2006 Groeneveld Lookup Tables (NUREG/KM-0011)**".
- This is a compiled database of CHF values determined experimentally under various conditions. It consists of a data of over **25,000 data points** that were used to derive the 2006 Groeneveld CHF LUT.
- From this dataset, a smaller subset of around **10,000 data points** is chosen for the project.

## Data Characteristics:

- The dataset consists of around 10,000 entries of CHF values at different values of parameters ($D$, $L$, $P$, $G$, $X\_chf$, $Dh\_in$, $T\_in$).
- In all there are 7 distinguishable parameters, that are:
  Tube Diameter (D), Heating Length (L), Pressure (P), Mass Flux (G), Critical Quality (X_chf), Inlet Subcooling (Dh_in), and Inlet Temperature (T_in).
- The references to various data sources are included as well, which provide the year and name of the research paper and people involved.

# DATA DESCRIPTION

## Nature of data:

- While the dataset itself is derived from **steady-state experiments**, it can be used to **predict CHF in dynamic scenarios** based on transient conditions.
- However, it is essential to recognize that the lookup tables primarily represent steady-state behaviour.
- This may have its own limitations when applied to highly dynamic or transient processes.

## Data Preprocessing:

- **Data Description & EDA**: Describe function is used to look for null values, outliers, and other stats via plots, like standard deviation and mean values.
- **Data Cleaning**: Null values, if any are removed and outliers are detected and replaced with mean values. Additional column (named 'Data') is also removed.
- **Normalization**: Fields like Mass Flux and Inlet Subcooling are normalized using scaling methods.
- **Feature Extraction**: Techniques are applied to extract relevant features usefull to develop the model.
- **Data Splitting**: Data is split into training and testing set in a 90:10 ratio, since this is a very large dataset.

# AI/ML MODEL DEVELOPMENT

## Model Selection:

- Their can be various regression models used for the dataset for prediction of CHF values, including Random Forest, Gradient Boosting or Support Vector Machines.
- Neural Networks can also be used to build the model on Tensorflow and Keras.

## Training & Testing:

- A training set of around 9000 data points is taken and rest 1000 data points would be used as testing data.
- K-fold Cross Validation is applied on the training dataset.
- The data is trained on different models simultaneously.

## Evaluation Metric:

- Evaluation Metrices such as MAE, MSE, RMSE, MAPE, $R^2$ score can be used to evaluate the model.

## Validation Strategy:

- Implementation of K-fold Cross Validation ensures robustness of the model.

# MODEL DEPLOYMENT

Once the prediction model is developed, steps are taken to deploy the model. Model deployment involves making the model accessible and usable by integrating it into production systems or applications where CHF predictions are needed.

## Model Deployment Plan:

- Choose Deployment Environment: based on your specific requirements and constraints
- Model Serialization: serializing the trained regression model into a format that can be stored and loaded easily during deployment
- Integration with Production Systems: involves embedding model within existing software infrastructure, incorporating into data pipelines, or connecting to other services through APIs
- Monitoring and Maintenance: Setting up monitoring systems to track the performance of the deployed model over time
- Security Considerations: ensuring proper security measures are implemented to protect sensitive data and prevent unauthorized access to the deployed model
- Documentation and User Support: provide user with comprehensive documentation and user support materials to assist in understanding how to interact with the deployed model

# SCALABILITY & PERFORMANCE

## Scalability:

- Since the model itself is developed using large dataset, it can handle large datasets over real time after its deployment.
- If a neural networking model is chosen, large dataset would although help it with huge amount of data but would increase model complexity with other ML model if deployed.

## Performance Optimization:

The performance of the model can be optimised by the following ways:

- Algorithm Selection: Neural Networks can be chosen if other ML algorithms like Random Forest or Decision Tree, don't provide desired output.
- Feature Selection & Engineering: selecting the most relevant features for CHF prediction to reduce the dimensionality of the dataset and improve model efficiency
- Architecture Optimization: optimizing the architecture by adjusting the number of layers, neurons, and activation functions and considering use of techniques like model pruning, quantization, or model distillation
- Hyperparameter Tuning: Fine-tuning model hyperparameters to achieve optimal performance. Use of techniques like grid search, random search, or Bayesian optimization to search the hyperparameter space efficiently
- Hardware Acceleration: Leveraging hardware accelerators like GPUs or TPUs (Tensor Processing Units) to speed up model training and inference

# OPEN SOURCE

## Use of Open Source Tools & Libraries:

Many Open Source Tools & Libraries are used in the development of the model, such as:

- Numpy: used for data manipulation and numerical computations in machine learning workflows
- Pandas: provides data structures like DataFrame, which are used extensively for data preprocessing, exploration, and manipulation tasks
- MatplotLib / Seaborn: advanced tools used to plot various trends and other data visualisation
- Scikit-learn: comprehensive machine learning library for Python that provides a wide range of algorithms for classification, regression, etc.
- TensorFlow: open-source deep learning framework to provide a flexible ecosystem for building and training deep neural networks
- Flask & Django: web development frameworks for Python commonly used for building web applications and APIs to deploy machine learning models

# PURPOSE & USE CASE

## Application:

- Boiling Heat Transfer Systems: CHF prediction is applicable in various boiling heat transfer systems, including industrial boilers and heat exchangers
- Nuclear Reactor Safety Analysis: CHF prediction is crucial for ensuring the safe and efficient operation of nuclear reactors
- Electronic Cooling Systems: CHF prediction is essential in the design and optimization of electronic cooling systems, such as heat sinks
- Thermal Management in Aerospace and Automotive Industries: where efficient heat dissipation is essential for optimal performance and reliability of critical components

## Impact:

- Safety and Reliability: By accurately predicting CHF values, this paper contributes to enhancing the safety and reliability of critical systems such as nuclear reactors, electronic cooling systems, and industrial boilers
- Efficiency Optimization: The ability to predict CHF values enables engineers to optimize the design and operation of thermal systems, heat exchangers, and electronic cooling devices
- Environmental Impact: Optimizing the thermal efficiency of industrial processes, indirectly contributes to reducing energy consumption and greenhouse gas emissions, which aligns with efforts to promote sustainability
- Cost Reduction: By accurately predicting CHF values, the paper helps minimize the need for costly over-engineering or conservative design approaches in plants
- Emergency Response Planning: Accurate CHF prediction is essential for emergency response planning and preparedness in industries where thermal hazards pose significant risks

# CONCLUSION

The paper encompassing the prediction of Critical Heat Flux (CHF) values from Groeneveld Lookup Tables (LUT) involves several key phases, from data collection to impact assessment:

- Proliferation in CHF correlations (>500) and CHF models (>50)
- Limited range of applicability of the models and correlations
- Therefore, need for a more generalized CHF predictions arose
- Comprehensive data on CHF under various operating conditions collected
- Predictive models are developed to estimate CHF values using ML & DL
- Model performance is assessed through rigorous validation against data
- Trained CHF prediction models needs to be deployed into production systems
- Measures needed to be implemented to enhance scalability of CHF models
- The project's impact spans multiple domains, including safety, efficiency, technological advancement, environmental sustainability

To summarize, this paper involving Critical Heat Flux predictions from Groeneveld Lookup Tables represents a comprehensive effort to harness experimental data, develop predictive models, deploy actionable solutions, ensure scalability, and realize significant impacts on safety, efficiency, innovation, and sustainability in diverse applications.

# REFERENCES


- Description of Topics (U.S.NRC website)
- Article on CHF Data used to Generate Groeneveld LUT, 2006
- CHF Data (complete database)
- CHF Data Extracted and Used in this Paper