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Report On

Critical Heat Flux Prediction For Safety Analysis of Nuclear Reactors Using Machine Learning

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Abstract

Prediction of the critical fuel temperature (CHF) is important for high-energy products because it is an important indicator of the economic performance and reliability of the nuclear power plant. It is also very important to evaluate the safety of nuclear power plants, as there are limits used in the design and operation of nuclear power plants. The method to accurately predict CHF is not easy as there is no decision for its prediction. This article establishes an intelligent tool for CHF prediction, covering various aspects of pressure, airflow and heat fluxes. Two machine learning (ML) techniques, random forest and neural network, were used to predict CHF. New data was created based on data containing a variety of two-stage flows and was used to train and evaluate the model. The two machine learning methods are then compared to the language commonly used to predict CHF. The results show that two machine learning methods, specifically deep neural networks (DNN), can make better predictions than traditional methods. Parameter trends of these methods were also compared. It can also be used as an online monitoring tool to predict weather conditions in nuclear power plant reactor cores.

Contents

1 Introduction

Boiling Devices which boil refer to those in which a liquid coolant change stages while collecting energy from an extremely warm solid surface. As condensate quality increases in flowing boiling structures, the saturated fluid swings through a variety of flow regimes. The heat transfer rate is much higher in systems that use boiling than it would be in a single phase (i.e., all liquid or all vapours). Heat of vaporising and sensible heat are the results of the heated surface's improved heat transmission. Therefore, industrial heat transfer processes like those in microscopic heat transfer devices and gigantic heat transfer exchangers in atomic and power plants powered by fossil fuels. boiling heat transfer has been essential for A property of water known as critical heat flux (CHF) puts limitations on the use of boiling as a heat removal process. The most serious concern that may occur with CHF is that a significant decrease in transfer of heat might trigger the heated surface's temperature to rise rapidly. The integrity of the device may be compromised in industrial applications wherein temperature such as electronic cooling or space devices. 1.1 Heat Transfer in Two Stages: • Newton's law of cooling governs the transfer of heat through convection between an evenly eate ted and flowing environment. The governing equation 1s q ha(T-Tf), in which h is the proportionate constant referred to as the heat transfer coefficient and a is the flow of heat.

- The convective heat Transfer between the a uniformly heated wall and flowing surrounding is governed by the newtons law of cooling
- The Governing equation is q = h(Tw-Tf), where q represents the heat flux, h represents the proportionally constant called the heat transfer coefficient,Tw represents the wall temperature and Tf represents the fluid temperature. If h decreases significantly due to the occurrence of the CHF condition, Tw will increase for fixed q and Tf while q will decrease for fixed

1.1 Modes Of CHF:

- The critical heat flux (CHF) phenomenon is crucial for the safe and efficient design of various heat transfer systems, including nuclear reactors, fossil fuel boilers, fusion reactors, and electronic chips. Extensive research has been conducted worldwide since its initial characterization by Nukiyama.
- In 1950, Kutateladze proposed the hydrodynamical theory of the burnout crisis, which contributed significantly to our understanding. Substantial progress has been made in recent decades, particularly in the context of water-cooled nuclear reactors, leading to a better comprehension of CHF, and the development of reliable prediction models for various applications.
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- However, there is some inconsistency in the use of the term CHF among different authors. To address this, the United States Nuclear Regulatory Commission has recommended using the term ”critical boiling transition” (CBT) to describe the phenomenon associated with a significant decrease in two-phase heat transfer

1.2 Correlations:

- The critical heat flux (CHF) is a crucial point on the boiling curve, and it can be advantageous to operate a boiling process near this point. However, excessive heat dissipation beyond CHF should be avoided. Zuber developed an expression to approximate CHF through a hydrodynamic stability analysis, aiding in understanding and managing this important phenomenon.

- It is independent of the surface material and is weakly dependent upon the heated surface geometry described by the constant C. For large horizontal cylinders, spheres and large finite heated surfaces, the value of the Zuber constant

- The critical heat flux depends strongly on pressure. At low pressures (including atmospheric pressure), the pressure dependence is mainly through the change in vapor density leading to an increase in the critical heat flux with pressure. However, as pressures approach the critical pressure, both the surface tension and the heat of vaporization converge to zero, making them the dominant sources of pressure dependency 0.131

- $$\frac{q}{A_{max}} = C h_{fg} \rho_v \left[\frac{\sigma g (\rho_L - \rho_v)}{\rho_v^2} \right]^{\frac{1}{4}} (1 + \rho_v / \rho_L)$$

- Here ,

2 Dataset Description For Model Training

Due to advancements in computing capacity and optimization methodologies, predictive approaches based on artificial intelligence have emerged as a possible alternative to conventional data-based tools. The machine learning (ML) method is particularly beneficial in engineering domains where complicated physical processes are hard to describe. Because of its improved performance when interacting with severely non-linear relations, an artificial neural network (ANN) is among the utmost preferred options in this area [6], [7]. ANN consists of multiple layers capable of non-linear mapping through transfer function. It offers a variety of benefits over traditional methods, including non-linear mapping capability, accurate prediction, easiness of training and rapid updating, and a good generalization ability [8]. Tree-based ensemble method, namely random forest (RF), is another prominent supervised ML method for regression. It is highly efficient ML algorithm that requires minimum hyper parameter Tunning.

2.1 Parameters

- In this work, a wide range of nonproprietary CHF experimental data available in the literature is evaluated, and then a data set is created.
- The dataset consists of 4658 samples, covering a wide range of operating conditions. The dataset includes both geometrical and hydraulic parameters for vertical up-flow water in a tube that has been uniformly heated.
- The input variables from raw data include mass flux (G), pressure (P), local equilibrium quality (x), heated tube length (L), and tube equivalent diameter (D). The output/desired target variable is CHF, and the heat flux distribution profile throughout the axis is uniform.
- Table I shows the experimental ranges of the CHF dataset. To increase the prediction accuracy, standardization (i.e., zero arithmetic mean and unity standard deviation) is applied to input variables.
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Author	Mass flow rate [Kg/m²s]	Pressure [MPa]	Exit quality [-]	Heated Length [mm]	Heated Diameter [mm]	CHF [MW/m²]	# of samples
Williams [9]	325-4683	2.75-15.2	-0.03 to 0.92	1800	9.5	0.38-4.1	129
Kim [10]	20-277	0.11-0.95	0.32 to 1.2	300-1700	6-12	0.12-1.6	512
Stein [11]	24-304	1.1-7.1	-0.002 to 1	120-450	9	0.24-4.7	383
Becker [12]	100-5450	0.21-9.9	0 to 0.99	400-3750	3.9-24.9	0.27-7.5	3473
Lowdermilk [13]	59.6-596.7	3.4	0.71 to 0.94	152.4	3	0.47-3.3	21
Clark [14]	28-102	3.4-13.8	0.66 to 0.99	238	4.58	0.23-9.97	67
Reynold [15]	1166-2888	3.5-10.6	0 to 0.47	228	4.6	3.6-9	67
Inasaka [16]	4300-12300	0.29-0.99	-0.17 to -0.05	100	3	7.3-10.1	6
Total	20-12300	0.11-15.2	-0.17 to 1.25	100-3750	3-24.9	0.12-10.1	4658

2.2 Objective of the Work

- The primary aim of this research is to evaluate and compile a comprehensive dataset of CHF experimental data.
- The dataset encompasses a significant number of samples, which provides a broad representation of different operational conditions

2.3 Size Of Dataset and Characteristics

- The dataset comprises a substantial 4658 data samples. This large size is beneficial for statistical analysis and machine learning applications, ensuring a robust and reliable understanding of CHF phenomena.
- The dataset is inclusive, covering various aspects related to the experimental setup and conditions.
- It includes both geometrical parameters (such as heated tube length and tube equivalent diameter) and hydraulic parameters (like mass flux and pressure).
- The use of multiple input variables enhances the dataset ability to capture the complexity of CHF and the factors influencing it.

2.4 Target value and Heat Flux Distribution

- The desired target variable of this dataset is the Critical Heat Flux (CHF). CHF is a crucial parameter in heat transfer studies, representing the point at which a heated surface experiences a transition from nucleate boiling to film boiling.
- Predicting CHF accurately is essential for the design and safety of heat exchange systems
- The dataset is constructed to ensure that the heat flux distribution profile along the tube's axis is uniform. This ensures that the dataset is well-structured and suitable for various modeling and analysis techniques.

2.5 Experimental Ranges and Data Standardization

- Table I (not provided in the text) likely presents the experimental ranges of the CHF dataset. These ranges are essential for understanding the scope of the dataset and the diversity of conditions covered.
- This process helps ensure that all input variables are on a similar scale, which is important for certain machine learning algorithms, like neural networks and support vector machines.

3 Methodologies

3.1 Look-Up-table

- In this we will see towards the look up tables Provided in the Nuclear reactor thermal hydraulic those are fequently used.

- For safety Prediction of the CHF in the nuclear power plants LUT are the best data driven tools that are ued to this date.Due to their wide scale applicability in the different scenarios and conditions they are used to this date.

- The LUT which we are using here are designed for an 8 mm water-cooled vertical round tube.It is having a vast amount of data, with more than 30,000 data points.

- The data points span a wide range of parameters, including mass flux, pressure, and exit/local qualities. This broad data coverage ensures the applicability of the CHF LUT to a variety of real-world situations.

- The CHF LUT approach offers several advantages, such as: Comprehensive practical application, making it a valuable tool in reactor safety assessments.Ease of use, making it accessible to a wide range of professionals.Elimination of the need for iterative calculations when predicting CHF.

- Groeneveld proposed a general equation for correcting the diameter of the tube.The purpose of this equation is to account for variations in tube diameter when using CHF LUTs, which are often designed for specific tube dimensions.

- The details of the equation and its application are not provided in the text, but it is implied that this correction is essential for accurate CHF predictions when the tube diameter differs from the standard tube size used in the CHF LUT.

- $$\frac{CHF_d}{CHF_{d=8}} = \left(\frac{8}{d}\right)^{0.5}$$

- To tackle diameter correction of tube, Groeneveld (1996) [18] has proposed following given above general equation

3.2 Arificial Neural Network(ANN)

- ANN is a machine learning technique biologically inspired by the human brain, consisting of many discrete processing components known as neurons. Among the different varieties of ANNs accessible today, in engineering, the feed-forward neural network has become the most popular.

- **Feed Forward Neural Network and its Layers:-**

Among various types of ANNs, the feed-forward neural network is commonly used in engineering.It's a type of neural network where information flows in one direction, from input to output.A typical neural network consists of three layers: the input layer, one or more hidden layers, and the output layer. The input layer receives input parameters and passes them to the hidden layers. The output layer takes information from the hidden layers and produces the final output.

- **Deep Neural Networks and Training Phase:-**

Deep neural networks have multiple hidden layers.These networks, often using non-linear activation functions, can learn both linear and non-linear relationships between input and output.During the training phase, the weights and biases in the neural network are adjusted to improve accuracy, a process often referred to as learning. Since initial weights and biases are set randomly, iterative adjustments are made to minimize the difference between the expected and desired outputs.

- **Backpropagation Learning Technique and Network Architecture:-**

Backpropagation is a widely used learning technique in ANNs.It involves propagating the error backwards through the network to adjust the weights and biases.This iterative process helps the network learn and improve its performance.While not provided in the text, Figure 1 likely illustrates the architecture of an ANN. Visual representations are often used to depict the structure of neural networks.

- **Summary:-**

In summary, ANNs are biologically inspired machine learning models, with feed-forward neural networks being particularly popular in engineering. They consist of layers, including input, hidden, and output layers, and can be deep, enabling them to capture both linear and non-linear relationships. The training phase involves adjusting weights and biases iteratively, with backpropagation being a common learning technique

4 Random Forest Algorithm

4.1 Supervised Machine Learning Technique and Ensemble Learning

- Random Forest is a type of supervised machine learning algorithm. This means it requires labeled data, where the outcomes (targets) are known during training.
- RF belongs to the family of ensemble learning methods. Ensemble learning combines the predictions of multiple machine learning models to make more accurate and robust predictions.In the case of RF, it combines the outputs of multiple decision trees to produce a final prediction.In the case of RF, it combines the outputs of multiple decision trees to produce a final prediction

4.2 Decision Trees and Bagging Technique

- Decision trees are a fundamental building block of the Random Forest algorithm.Each decision tree is a simple, flowchart-like structure that partitions the data based on the input features.
- Decision trees are prone to overfitting, which means they can perform well on the training data but poorly on new, unseen data. Bagging Technique:
- RF employs a technique called bagging (Bootstrap Aggregating) to improve the overall performance and robustness of decision trees.
- Bagging involves creating multiple bootstrap samples (randomly sampled subsets of the training data) and building a decision tree for each sample.By aggregating the results of these multiple decision trees, RF reduces the risk of overfitting and variance in predictions.

4.3 Prediction Averaging and Hyperparameter Adjustment

- The aggregation strategy in RF typically involves averaging the predictions made by individual decision trees.
- This averaging helps to reduce the impact of noise and increases the model's predictive accuracy.Random Forest is known for its robustness and often provides reliable results with minimal hyperparameter tuning.
- This means that, in many cases, you can use a default set of hyperparameters and still achieve good results. However, fine-tuning hyperparameters can further optimize performance in specific cases.

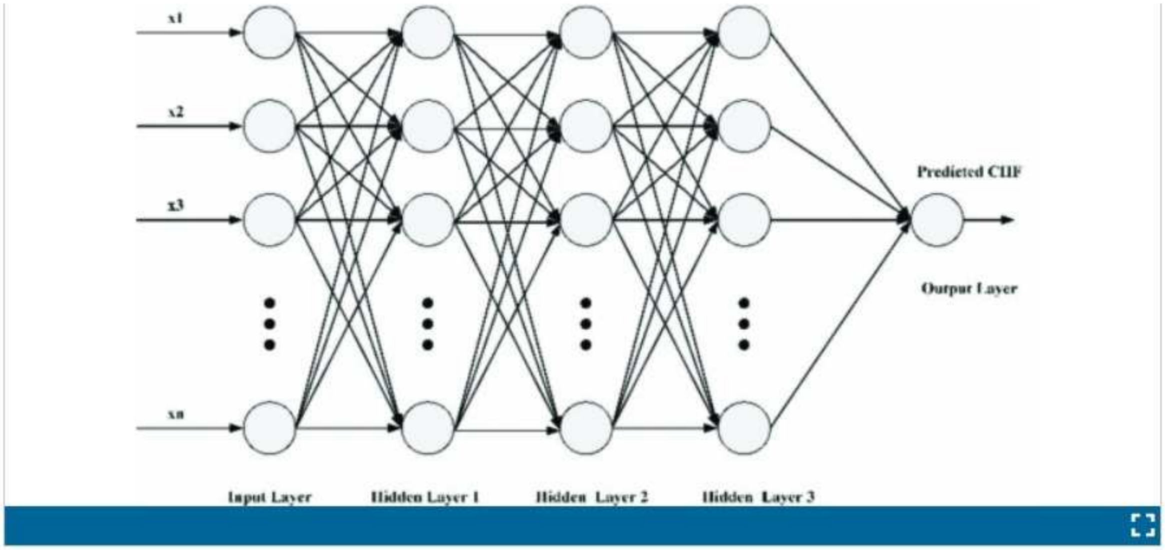
- 

Fig. 1.
ANN Architecture

5 Training and Testing

- Both RF and ANN are used to train and test the data. For this purpose, the deep learning library, i.e., Keras application interface programming backend by tensor flow, is used with the sci-kit-learn library in python 3.9.

- During this process, 80 percentage of data is used for training, and 20 percentage is used to evaluate the performance. The data are randomly distributed to check how well performed on unseen data. The structure of an ANN specifies

- the appropriate number of hidden layers, neurons in the hidden layers, the activation function employed in the layers, and the connection of layers.

- The architecture of a deep neural network has a major impact on the network's generalization and how accurately predicate the output for a given input; therefore, it should be optimized.

- Physical parameters dictate the neurons in the input and output layers. Therefore, hidden layers, neurons in each layer, and activation function in each layer are important for an ANN's architecture.

- It is worth mentioning that there is no universal rule for determining the ideal topology of a deep neural network, and it is often established through the trial and error method [22].

- Optimal network architecture has three hidden layers of 100 neurons in each. The input layer has five neurons corresponding to the input variables, and the output layer has one neuron.

- The Adam optimization algorithm (optimal learning rate = 0.001) is employed to update synaptic weights and biases. Adam optimizer is famous for deep learning problems and requires minimum tuning.

- It is a stochastic gradient descent optimization algorithm derived from an adaptive estimation of 1st order and 2nd order moments. Non-linearity is added in order to increase predictive capabilities.

- The Rectified Linear Unit (ReLU) transfer function is employed in the hidden layers because of its popularity and performance in the proposed model.

- It is a universal approximator since it can estimate any function using a combination of ReLU. To further validate the results of the proposed model, 10-fold cross-validation is also performed.

6 Results

- In this paper, three different approaches are used to predict the CHF for nuclear reactor safety analysis. One is the most popular approach (LUT approach) among the reactor thermal-hydraulic community for the prediction of CHF during the design and operation of the reactors. The other two are artificial intelligence-based techniques, including ANN and RF.

- The performance of three different models (as depicted in Table III) is compared through relative root-mean-square error (rRMSE), which is defined as:-

- $$rRMSE = \sqrt{1/m \sum_{i=1}^{m} \left(\frac{y_i - y_{p_i}}{y_i} \right)^2}$$

- Given below are the different graphs for implementation

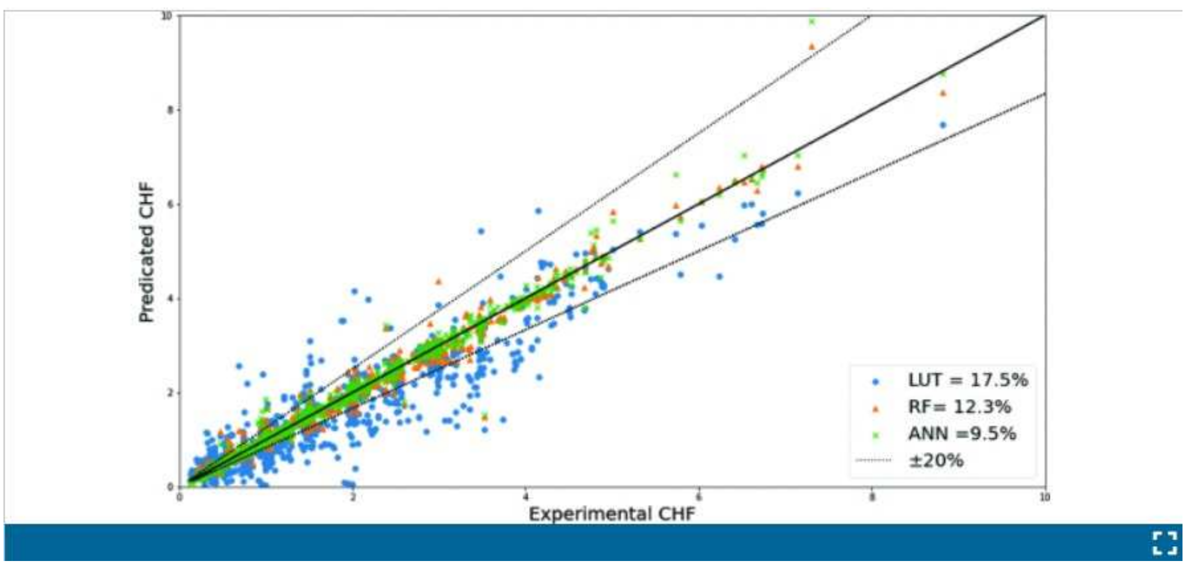
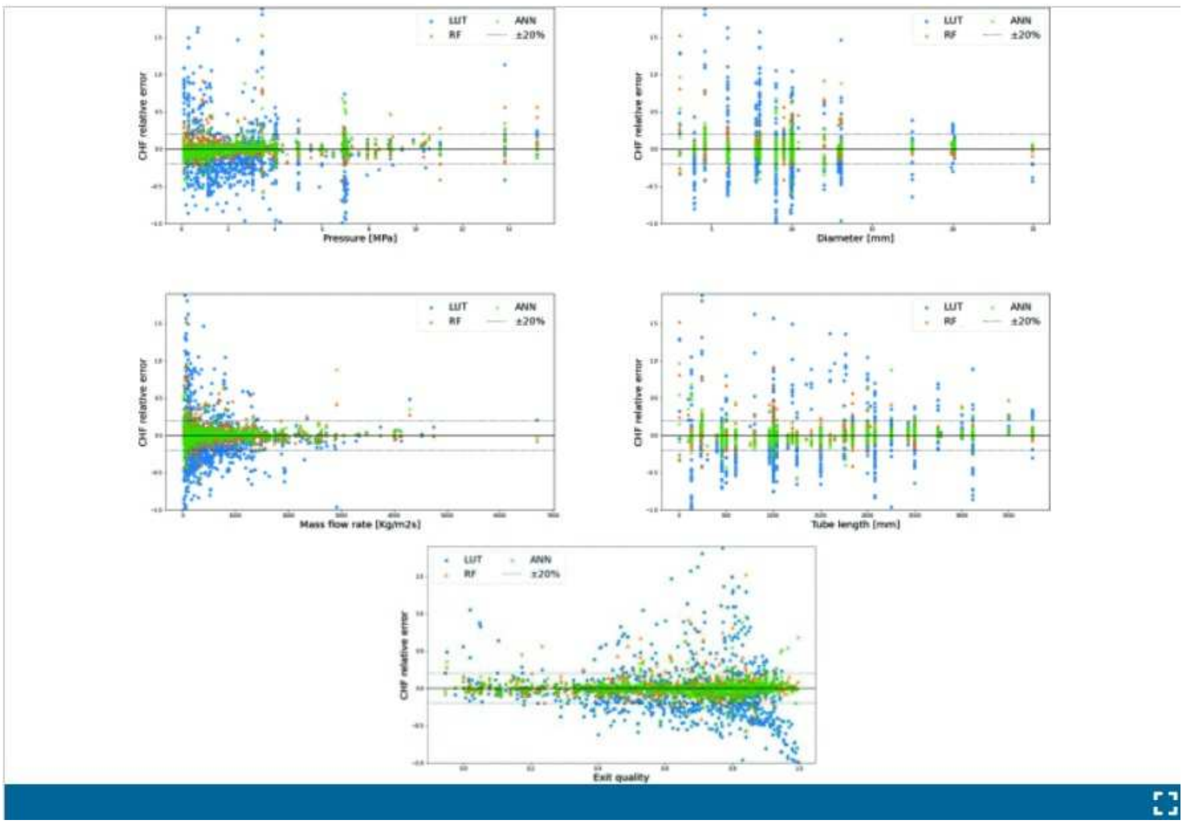
- 

TABLE III. PERFORMANCE OF LUT, RF AND ANN

Technique	Test rRMSE	Samples within ± 10% error	Samples within ± 20% error
LUT	17.5	60%	70%
RF	12.3	90%	95%
ANN	9.5	94%	99%
ANN (10-fold cross-validation)	9.7	92%	98%



7 Conclusion

- In this work, the predictive capacity of artificial intelligence (AI) techniques is employed to enhance the safety and economy of the nuclear reactor system, which mainly depends on the accurate prediction of CHF.
- A comprehensive assessment has shown superior predictive capabilities of artificial intelligence approaches as compared to the widely used conventional data-driven approach, i.e., LUT.
- Furthermore, deep learning approach is outperformed as compared to other machine learning algorithms i.e., RF. One of the most critical characteristics of AI methods is their capacity to expand their applicability domain on-the-fly.
- The finding of this research provides deep insight into the future development and enhancement of AI techniques, particularly deep learning models for CHF prediction. More experimental data is also vital for CHF prediction through AI approach.
- Other channel geometries will certainly increase the number of input characteristics. For instance, to estimate CHF, if rod bundle data is given, bundle-specific factors such as nonuniform heat flux distribution, grid space layout, and local flow conditions may also be taken into account.
- the research highlights the potential of AI techniques, particularly deep learning, in improving the safety and efficiency of nuclear reactor systems by enhancing CHF prediction.
- AI's adaptability and outperformance compared to conventional methods make it a valuable tool for addressing complex challenges in this domain, with the availability of more experimental data and consideration of diverse input characteristics further enhancing its applicability.

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