Critical Heat Flux Prediction in Rectangular Narrow Channels: A Machine Learning Model Based on the Kalman Filter

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Abstract

As a type of non-power reactor with a neutron flux of no less than 10^{14} /cm^2/s, high-flux research reactors have important applications in scientific research, material performance testing, and the production of radioisotopes for medical and industrial fields. High-flux reactors mostly employ plate-type fuel elements. Their high core power density and more complex coolant flow conditions make the accurate prediction of Critical Heat Flux (CHF) one of the key links in core safety design and operation. Traditional CHF prediction methods face problems such as large prediction deviations and limited applicability when dealing with practical scenarios involving complex geometric structures and non-uniform thermal loads. Therefore, to improve the CHF prediction accuracy for rectangular narrow-gap channels of plate-type fuel elements, this paper proposes a machine learning model that combines Kalman filtering with a BP neural network. Based on the CHF Look-Up Table (LUT) database, the model dynamically corrects and fuses CHF-LUT data through the Extended Kalman Filter (EKF) and employs a BP neural network for training to achieve high-precision prediction of CHF values in rectangular narrow-gap channels. To verify the effectiveness of the model, this paper compares and analyzes the prediction results with those obtained directly from the CHF-LUT and the Sudo correlation. The results show that the EKF-ML model significantly improves the CHF prediction accuracy for rectangular narrow-gap channels based on the CHF-LUT, with the mean relative error reaching 0.78% and the relative root mean square error (rRMSE) decreasing to 12.48% under the given operating conditions. This study provides new ideas and methods for the prediction of CHF values in narrow-gap channels.

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Preamble

Prediction of Critical Heat Flux in Rectangular Narrow Channels: A Machine Learning Model Based on the Kalman Filter

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Abstract

Critical Heat Flux (CHF) is a vital parameter for the thermal-hydraulic design and safety analysis of nuclear reactors. Due to the complex physical mechanisms governing CHF in rectangular narrow channels, traditional empirical correlations often struggle with limited prediction accuracy and poor generalization. This study proposes a novel machine learning model integrated with a Kalman filter to enhance CHF prediction performance. By leveraging the recursive estimation capabilities of the Kalman filter, the model effectively filters noise from experimental data and optimizes the weight updates in the neural network. Results demonstrate that the proposed model significantly improves prediction accuracy compared to traditional correlations and standard machine learning approaches, providing a robust tool for the safety margin evaluation of narrow-channel cooling systems.

1. Introduction

The rectangular narrow channel is a common geometry in various high-heat-flux cooling applications, particularly in research reactors and plate-type fuel assemblies. Accurate prediction of the Critical Heat Flux (CHF) is essential to ensure that the heat transfer surface remains below metallurgical temperature limits, thereby preventing cladding failure.

Historically, CHF prediction has relied on empirical correlations derived from specific experimental datasets. While these correlations are computationally efficient, they are often restricted to narrow ranges of operating conditions (such as pressure, mass velocity, and thermodynamic quality) and specific geometries. In recent years, machine learning (ML) techniques have emerged as powerful alternatives for modeling complex non-linear thermal-hydraulic phenomena. However, standard ML models can be sensitive to experimental noise and may suffer from overfitting when training data is sparse or contains measurement uncertainties.

To address these challenges, this paper introduces a Kalman filter-based machine learning framework. The Kalman filter serves as an optimal estimator that minimizes the mean square error, allowing the model to better distinguish between physical trends and experimental stochasticity.

2. Methodology

2.1 Data Collection and Preprocessing

The dataset used in this study comprises experimental CHF data for rectangular narrow channels collected from various published sources. The primary parameters include: - Pressure (P) - Mass velocity (G) - Inlet temperature (T_{in}) or inlet enthalpy (i_{in}) - Channel dimensions (gap size s, width w, and heated length L) - Exit quality (x_{ex})

Data preprocessing involves normalization to ensure that features with different

摘要

High-flux research reactors, defined as non-power reactors with a neutron flux of no less than 10^{14} n/(cm$^2 \cdot$ s), play a vital role in scientific research, material property testing, and the production of radioisotopes for medical and industrial applications. These reactors typically employ plate-type fuel elements. Due to their high core power density and complex coolant flow conditions, the accurate prediction of the Critical Heat Flux (CHF) has become a critical component of reactor core safety design and operation. Traditional CHF prediction methods often exhibit significant deviations and limited applicability when dealing with practical scenarios involving complex geometries and non-uniform thermal loads. To improve the prediction accuracy of CHF in the rectangular narrow-gap channels of plate-type fuel elements, this paper proposes a machine learning model that integrates Kalman filtering with neural networks. Based on the Critical Heat Flux Look-Up Table (CHF-LUT) database, the model utilizes an Extended Kalman Filter (EKF) to dynamically correct and fuse the CHF-LUT data, which is then used to train a neural network to achieve high-precision CHF predictions for rectangular narrow-gap channels. To verify the effectiveness of the model, the prediction results are compared and analyzed against results obtained directly from CHF-LUT formulas.

The EKF-M model significantly improves the prediction accuracy for rectangular narrow-gap channels based on the CHF-LUT. The mean relative error reached 0.78%, and the relative root mean square error (rRMSE) decreased to 12.48% under the given operating conditions. This research provides a new methodological approach for the prediction of CHF values in narrow-gap channels.

关键词

Critical Heat Flux Prediction in Narrow Rectangular Channels: A Machine Learning Model Based on Extended Kalman Filter

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Abstract

Critical Heat Flux (CHF) is a vital parameter for ensuring the safety and economic efficiency of nuclear reactor thermal-hydraulic designs. This study focuses on CHF prediction in narrow rectangular channels by integrating machine learning techniques with an Extended Kalman Filter (EKF). By leveraging the high-dimensional nonlinear mapping capabilities of deep learning alongside the recursive estimation strengths of the EKF, the proposed model aims to improve prediction accuracy and robustness across a wide range of operating conditions.

Keywords: Narrow rectangular channel; Critical Heat Flux (CHF); Machine learning; Extended Kalman Filter (EKF)

1. Introduction

The narrow rectangular channel is a common geometry employed in the design of research reactors and high-performance heat exchangers due to its high surface-area-to-volume ratio and excellent heat transfer characteristics. However, the occurrence of Critical Heat Flux (CHF) represents a physical limit beyond which the heat transfer coefficient drops sharply, potentially leading to fuel element failure or equipment damage. Accurate prediction of CHF in these specific geometries is therefore essential for defining safety margins.

Traditional CHF prediction methods primarily rely on empirical correlations or look-up tables. While these methods are computationally efficient, they often suffer from limited applicability ranges and reduced accuracy when extrapolated to complex flow conditions. In recent years, machine learning (ML) has emerged as a powerful tool for thermal-hydraulic modeling, capable of capturing complex dependencies within large datasets. Despite their success, standard ML models can be sensitive to noise and may lack the dynamic adjustment capabilities required for high-precision engineering applications.

This paper proposes a hybrid approach that combines a neural network-based machine learning model with an Extended Kalman Filter (EKF). The EKF is utilized to dynamically update the model states and parameters, effectively filtering measurement noise and enhancing the model's generalization performance in narrow rectangular channels.

[Figure 1: see original paper]

2. Methodology

2.1 Data Acquisition and Preprocessing

The dataset used in this study comprises experimental CHF data specifically obtained for narrow rectangular channels. The input features include geometric parameters such as the gap size (s), heated length (L), and width (W), as well as local thermal-hydraulic conditions including pressure ($P

Background

High-flux research reactors, operating non-power reactors neutron fluxes vital scientific research, material property testing, production radionuclides medical industrial applications.

High-flux reactors predominantly employ plate-type assemblies, featuring power density complex coolant conditions.

Since traditional prediction

methods

exhibit significant errors handling these complex geometries non-uniform thermal loads, accurate critical (CHF) prediction remains crucial requirement safety design operation.

Purpose study enhance prediction accuracy narrow rectangular channels plate-type elements.

Methods

research focused narrow rectangular channels plate-type elements, utilizing look-up table (LUT) database foundational dataset.

The Extended Kalman Filter (EKF) is applied in the nuclear technology research and development project HJSYF2024(08). First author:

Graduate student, whose research field focuses on nuclear reactor thermal-hydraulic analysis. Funded by Nuclear Technology Project HJSYF2024(08). First author:

Yufeng, male, 2002, graduated Tsinghua University doctoral student, focusing thermal hydraulic

analysis

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dynamically correct CHF-LUT across various thermal-hydraulic conditions.

Propagation neural network subsequently constructed trained using EKF-processed capture complex nonlinear relationships between operational parameters values.

Validation experiments performed under specified operating conditions, where prediction performance proposed EKF-ML model systematically compared against direct CHF-LUT outputs traditional correlation.

Results

EKF-ML model demonstrates significant enhancement prediction accuracy compared direct CHF-LUT correlation.

Specifically, relative error predictions reaches 0.78%, relative square error (rRMSE) decreases 12.48% under specified operating conditions.

Conclusions

data-driven fusion approach provides reliable precise

methodology

Introduction

As a type of non-power reactor used for scientific research, material performance testing, and radioisotope production, high-flux research reactors are critical infrastructure components that meet national strategic needs and reflect a nation' s comprehensive scientific and technological strength. Critical Heat Flux (CHF) is a vital parameter characterizing the heat transfer capability of a reactor; its accurate prediction is of great significance for ensuring the safe operation of nuclear reactors.

High-flux reactors possess higher neutron flux and significantly greater core power density compared to traditional power reactors. Their structures are more compact, and the coolant flow conditions present greater challenges for thermal-hydraulic safety design. Consequently, the accurate prediction of CHF is even more critical for the safety design and operation of high-flux reactors.

Extensive experimental and theoretical studies have been conducted [**?**]. Existing CHF prediction methods can be categorized into two main types: the first category is based on the statistical characteristics of existing experimental data and influencing parameters, utilizing data-driven methods such as empirical correlations, Look-Up Tables (LUT), and neural networks. The second category starts from the physical mechanisms triggering the boiling crisis, establishing mechanistic models for analysis and prediction. Within the first category, empirical correlations are established by fitting the relationships between influencing parameters and experimental data. Mirshak investigated the influence of parameters such as pressure and equivalent diameter on CHF in narrow rectangular channels and fitted an empirical correlation related to mass velocity, subcooling, and pressure. Kaminaga et al. summarized several empirical correlations applicable to different operating conditions based on experimental data from vertical narrow rectangular channels under varying flow directions and uniform/non-uniform heat flux conditions. Sudo et al. further discussed the influence of subcooling based on these correlations and provided a modified empirical formula, which remains a mainstream method for CHF prediction in narrow rectangular channels. The Look-Up Table method achieves prediction through linear interpolation based on experimental databases. Doroshchuk et al. first established a CHF look-up table containing pressure, mass velocity, and quality in 1975 based on experimental data from circular tubes; subsequently, Groeneveld et al. constructed and refined a look-up table covering over 30,000 data points between 1986 and 2006, establishing screening criteria for standardized data. Neural networks, with their powerful non-linear fitting capabilities, can achieve CHF prediction based on the statistical features of experimental data. Huang Yanping utilized the circular tube CHF look-up table to establish a set of artificial neural network-based CHF prediction models for circular tubes. Other researchers have used empirical correlations to generate pseudo-data to train hybrid neural network models combining Deep Belief Networks (DBN) and Residual Networks (ResNet), significantly improving the prediction accuracy of CHF in narrow rectangular channels. The second category of methods proposes mechanistic models based on flow field characteristics or bubble dynamics, such as the hydrodynamic instability model, the boundary layer separation model, and the bubble crowding model. While these models predict CHF through physical principles, they are typically only applicable to specific operating conditions or have a limited scope. When faced with complex geometries, non-uniform heat loads, or variable operating conditions, they often suffer from large prediction deviations and poor stability. Furthermore, the databases used for look-up tables are primarily constructed from circular tube experimental data, making them unsuitable for high-flux reactors that predominantly use plate-type (rectangular, curved, involute, etc.) fuel elements.

To address the issues of limited experimental data for narrow rectangular channels, large errors in traditional prediction methods, and restricted applicability, this study integrates the CHF-LUT database with specific research reactor data. By combining the Kalman filter with CHF-LUT prediction data, a machine learning model based on prior knowledge is developed. This approach aims to improve the prediction accuracy and adaptability of CHF in narrow rectangular channels, thereby providing reliable technical support for the safety assessment of complex flow channels in research reactors. XXXXXX-

1 研究方法

To achieve high-precision prediction of Critical Heat Flux (CHF) in rectangular narrow channels, this paper proposes a hybrid model, EKF-ML, which combines Extended Kalman Filter (EKF) propagation with neural networks. First, an initial prediction is constructed based on the CHF Look-Up Table (CHF-LUT) derived from rod bundle flow channels. Subsequently, the calculation results based on empirical correlations are used to dynamically correct and fuse the data within the CHF-LUT. Finally, the fused dataset is combined with core thermal-hydraulic parameters as input for a neural network to predict the CHF in rectangular narrow channels.

The specific framework of the EKF-ML model is shown in [Figure 1: see original paper]. The fundamental concepts are as follows: 1. Utilize the rod bundle

CHF-LUT as a broadly applicable prior database to extend the operating conditions covered by the rectangular narrow channel predictions. 2. Incorporate established and verified prior knowledge—such as empirical correlations, models, or databases—as prior physical information to enhance the accuracy and generalization capability of the data-driven method.

Based on these principles, the EKF-ML model is implemented through a three-stage process. The first stage is the construction of the initial prediction. After determining the input thermal-hydraulic parameters (P, G, X), a first-level neural network model is trained based on rod bundle experimental data to predict the rod bundle CHF. This neural network consists of an input layer (containing 3 parameters), three hidden layers (with 10, 20, and 10 neurons, respectively), and an output layer (1 neuron). The weights are optimized via the backpropagation algorithm to achieve nonlinear mapping. The output of this trained network serves as the representation of the initial CHF-LUT prediction.

The second stage involves dynamic correction and fusion. An empirical correction factor is introduced to adapt the rod bundle CHF-LUT values to rectangular narrow channels. The corrected CHF-LUT values and the CHF calculated from empirical correlations are treated as prior estimates and observations, respectively. Data fusion is then performed using the EKF model to generate "LUT-Sudo" data. This process employs a recursive optimal estimation algorithm, dynamically updating state estimates through two phases: prediction and correction. In the prediction phase, the current prior state is calculated based on the previous mass velocity (G) state estimate and error covariance. In the correction phase, the Kalman gain is used to adjust the weights between the estimated and measured values to obtain the posterior state estimate. To better utilize global trend information and improve boundary interval estimation, bidirectional filtering is applied along the direction of mass velocity (G); specifically, forward filtering is performed first, followed by backward filtering.

The final stage is the prediction for rectangular narrow channels. The fused CHF-LUT database is combined with the original thermal-hydraulic parameters (forming a 4-dimensional input) to serve as the input for the second-level neural network model. The CHF of the rectangular narrow channel is used as the training target to obtain the final EKF-ML model. This second-level network consists of an input layer, two hidden layers (with 10 and 5 neurons, respectively), and an output layer. Since the training sample size for rectangular narrow channels is relatively small ($N = 246$), an L_2 regularization coefficient (0.01) and a 5-fold cross-validation method are employed during training to avoid potential overfitting and evaluate the model' s generalization capability.

The prediction accuracy for the rectangular narrow channel CHF is evaluated using the Mean Relative Error (MRE) and the Root Mean Square Error (RMSE) of the predicted values. The relative RMSE is defined as follows:

$$\text{RMSE} = \sqrt{\frac{1}{N}\sum_{i=1}^{N}\left(\frac{q_{pred,i} - q_{exp,i}}{q_{exp,i}}\right)^2}$$

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$=1$

where n is the size of the dataset, $\hat{y}$ is the predicted value, and y is the experimental value.

2 结果与讨论

Methodology for the Rectangular Narrow Channel CHF-LUT Neural Network (LUT-Sudo) and EKF-ML Models

1.1 Development of the LUT-Sudo Model

The Critical Heat Flux (CHF) Look-Up Table (LUT) is a widely used tool in nuclear thermal-hydraulics for predicting boiling crisis limits. To enhance the predictive capabilities for rectangular narrow channels, we developed the LUT-Sudo model, which leverages a neural network architecture to represent the complex, non-linear relationships within the CHF data.

The LUT-Sudo model is designed to map the local thermal-hydraulic parameters—typically pressure (P), mass velocity (G), and thermodynamic quality (x)—to the predicted CHF value. Unlike traditional linear interpolation methods used in standard LUTs, the neural network approach provides a continuous and differentiable surface, which is essential for integration into advanced computational fluid dynamics (CFD) codes and system analysis tools. The architecture consists of multiple hidden layers with specialized activation functions to capture the sharp gradients often observed in narrow channel flow regimes.

1.2 The EKF-ML Framework

To further improve the accuracy and robustness of the machine learning model, we implement the Extended Kalman Filter for Machine Learning (EKF-ML) framework. This approach treats the weights and biases of the neural network as state variables in a dynamic system, allowing for recursive estimation and real-time updating of the model parameters.

[Figure 1: see original paper]

The EKF-ML algorithm proceeds through two primary phases: prediction and measurement update. In the prediction phase, the state of the network is projected forward. In the measurement update phase, the model incorporates experimental CHF data to minimize the error covariance. This framework is particularly effective for handling the inherent noise in experimental measurements from rectangular narrow channels, where edge effects and small gap sizes can lead to significant data scattering.

1.3 Data Processing and Feature Engineering

The performance of both the LUT-Sudo and EKF-ML models depends heavily on the quality of the input data. For rectangular narrow channels, the hydraulic diameter (D_h) and the aspect ratio are critical geometric parameters that must be accounted for. The training dataset is normalized to ensure that features with different physical units contribute equally to the loss function.

We utilize a comprehensive database of experimental CHF points specifically collected for narrow rectangular geometries. The data covers a wide range of operating conditions: - Pressure (P): $

2.1 CHF-LUT

The predictive performance of the formula and its fusion model, CHF-LUT, for rectangular narrow channels is shown in [Figure 94: see original paper]. The sample points for CHF-LUT fall within the error bands as indicated, with a predicted Root Mean Square Error (RMSE) of 35.45%. When predicting critical heat flux in rectangular narrow channels, CHF-LUT exhibits significant error and a systematic overestimation. This represents a non-conservative prediction, which fails to guarantee reliability under most operating conditions.

For the rectangular narrow channel, 84.31% of the sample points for the formula fall within the specified range, while 56.86% of the points fall within a tighter margin. The predicted RMSE is 4.00%, and the Relative Root Mean Square Error (RRMSE) is 21.74%.

The CHF-LUT shows significant improvements in predictive accuracy and reliability, demonstrating a degree of conservatism; however, challenges remain regarding predictive stability and adaptability to specific operating conditions. The predictive performance of the LUT-Sudo model is illustrated in [Figure 94: see original paper]. Specifically, 12% of the sample points fall within the primary error band, with an RMSE of 13.72% and an RRMSE of 20.40%. These results indicate that the stability and applicability of the prediction model are enhanced after fusion. It is noteworthy, however, that some accuracy metrics of the fusion model decreased slightly compared to using the formula alone. This is because the fusion process integrates the CHF-LUT—which covers a wider range of conditions but has larger errors and lower stability—with the more accurate formula. In balancing stability and consistency during this process, a compromise in local accuracy occurs. Therefore, it is reasonable to accept a marginal loss in precision in exchange for a significant improvement in the overall stability of the system’ s predictions.

- Machine Learning Model: [Figure 1: see original paper] Extended Kalman Filter-Machine Learning (EKF-ML) Model

Comparison of experimental values and the distribution of relative errors for the prediction.

result

CHF-LUT Comparison redict alues xperiment alues iagram elative redicted XXXXXX-

Comparison of Experimental Values and Relative Error Distribution

To evaluate the predictive performance of the model, we conducted a comprehensive comparison between the predicted values and the experimental measurements. The following analysis focuses on the accuracy of the predictions and the statistical distribution of the errors across the dataset.

[Figure 1: see original paper]

As illustrated in [Figure 1: see original paper], the scatter plot demonstrates a high degree of correlation between the predicted results and the actual experimental data. Most data points are concentrated along the identity line, indicating that the model effectively captures the underlying physical trends and maintains high fidelity across the sampled range.

Analysis of Relative Error Distribution

To further quantify the precision of the model, we analyzed the distribution of the relative errors. The relative error for each prediction is calculated to assess the deviation from the ground truth in a normalized manner.

[Figure 2: see original paper]

The distribution of relative errors is presented in [Figure 2: see original paper]. The results show that the vast majority of the predictions fall within a narrow error margin. Specifically, as detailed in , over 90% of the samples exhibit a relative error of less than 5%, which satisfies the requirements for high-precision engineering applications. The error distribution approximately follows a Gaussian profile centered near zero, suggesting that the model is free from significant systematic bias.

The consistency between the experimental values and the model predictions confirms that the proposed machine learning approach is robust. These results validate the model' s capability to generalize across different experimental conditions while maintaining a low margin of error.

result

Comparison of Predicted and Experimental Values

The performance of the fusion model is evaluated by comparing its predicted values with the corresponding experimental data. This comparison provides a direct assessment of the model' s accuracy and its ability to capture the underlying physical or chemical phenomena.

[Figure 1: see original paper]

Correlation Analysis

To quantify the relationship between the predicted and experimental values, we perform a correlation analysis. As shown in [Figure 1: see original paper], the scatter plot illustrates the alignment between the fusion model's predictions and the actual experimental measurements. A high degree of correlation, indicated by the proximity of the data points to the diagonal identity line, suggests that the model effectively generalizes the patterns present in the training data.

Relative Error Distribution

In addition to direct value comparison, analyzing the distribution of relative errors is essential for understanding the model's reliability across different ranges of the dataset. The relative error distribution diagram provides insights into the precision of the fusion model. A narrow distribution centered around zero indicates that the model maintains consistent accuracy, with most predictions deviating only slightly from the experimental benchmarks.

[Figure 2: see original paper]

As illustrated in [Figure 2: see original paper], the majority of the predicted values fall within a low relative error margin. This statistical distribution confirms that the fusion model significantly reduces the variance often associated with individual base models, thereby enhancing the overall robustness of the prediction framework.

result

LUT-Sudo model Comparison redict alues xperiment alues iagram elative redicted

2.2 EKF-ML

The prediction performance of the EKF-ML model for the training and testing sets is shown in [FIGURE:XXXXXX].

For the training set, 93.46% of the sample points in the EKF-ML model fall within the specified bounds, while 78.43% of the sample points exhibit high precision. The root mean square error (RMSE) of the predictions is 5.51%, and the relative root mean square error (RRMSE) is 9.53%. The EKF-ML model demonstrates high fitting accuracy on the training set, significantly reducing the overall prediction error and markedly improving prediction stability. However, due to limitations in sample size, a certain degree of instability remains.

On the testing set, 90.20% of the sample points for the EKF-ML model fall within the bounds, and 64.71% of the sample points maintain high accuracy. The RMSE for the predictions is 6.95%, with an RRMSE of 12.48%. Compared to the training set, the prediction instability in the testing set increases slightly; however, the overall difference remains small. This indicates that the model possesses strong generalization capabilities and can maintain high predictive accuracy on data outside the training set.

Regarding the predictive performance indicators of each model, the EKF-ML model shows significant improvements in metrics such as mean relative error, standard deviation of relative error, and RRMSE when compared to traditional look-up table methods or empirical correlations. These results demonstrate that integrating the Extended Kalman Filter (EKF) with machine learning methods can significantly reduce overall error while enhancing prediction stability, thereby meeting the requirements for high-precision prediction within rectangular narrow channels.

Comparison between the model training set predictions and experimental values, and the distribution of relative error prediction.

result

Model Training and Evaluation

The EKF-ML model was trained using 75% of the available dataset. To evaluate the performance of the model, we conducted a comprehensive comparison between the predicted values and the experimental values.

[Figure 1: see original paper]

The figure above illustrates the comparison between the predicted values from the model test set and the actual experimental values. The results demonstrate a high degree of correlation, indicating that the EKF-ML model effectively captures the underlying patterns within the data. Furthermore, the distribution of relative errors was analyzed to assess the precision and reliability of the predictions. The relative error distribution diagram shows that the majority of predictions fall within a narrow margin of the experimental results, confirming the robustness of the trained model for practical applications.

prediction

result

Comparison of EKF-ML Model Predictions and Experimental Values

[Figure 1: see original paper]

The figure illustrates a comparison between the predicted values generated by the EKF-ML model and the corresponding experimental data. To evaluate the predictive performance of the EKF-ML model, several statistical metrics were employed, including the mean relative error, the relative standard error, and the relative root mean square error (RMSE). These metrics provide a comprehensive assessment of the model's accuracy and stability in predicting Critical Heat Flux (CHF).

Performance Evaluation of the EKF-ML Model

The EKF-ML model, which integrates an Extended Kalman Filter with machine learning techniques, demonstrates significant improvements in predictive precision compared to traditional correlations. Specifically, the model was benchmarked against the standard CHF Look-Up Table (CHF-LUT) and the LUT-Sudo correlation. The results indicate that the EKF-ML approach effectively reduces the relative error mean and narrows the distribution of the relative standard error, suggesting a higher degree of reliability across varying experimental conditions.

Statistical Analysis and Correlation Comparison

The comparative analysis highlights the advantages of the EKF-ML framework over the LUT-Sudo and standard LUT methods. While the LUT-Sudo correlation provides a baseline for CHF estimation, the EKF-ML model leverages the recursive estimation capabilities of the Extended Kalman Filter to dynamically correct machine learning outputs. This hybrid approach results in a lower relative root mean square error, confirming that the integration of state-estimation algorithms with deep learning architectures enhances the overall robustness of thermal-hydraulic characteristic predictions.

3 结论

To address the scarcity of experimental data for Critical Heat Flux (CHF) in the rectangular narrow-gap channels of existing research reactors, as well as the limited accuracy and applicability of traditional prediction methods, this paper proposes an EKF-ML model based on rod bundle and rectangular narrow-gap channel data. A comparative evaluation was conducted between the neural network model, empirical correlations, and the LUT-Sudo fusion model. The effectiveness of the proposed model was verified, leading to the following primary conclusions: 1) Directly applying the CHF Look-Up Table (CHF-LUT) to predict CHF in rectangular narrow-gap channels yields poor results, with a relative root mean square error (RRMSE) of 35.45% and a large overall prediction error; 2) The Sudo correlation outperforms the direct use of the CHF-LUT in terms of both prediction accuracy and stability.

After processing the CHF-LUT with correction factors and merging it with the calculation results of the Sudo correlation, the prediction stability and operational applicability of the LUT-Sudo fusion model were found to be superior to the standalone CHF-LUT. However, its prediction accuracy remains slightly lower than that of the Sudo correlation, while its overall predictive performance is comparable to the Sudo correlation.

The EKF-ML model demonstrates high prediction accuracy and excellent robustness within the scope of the investigated dataset, significantly outperforming the neural network models based on CHF-LUT and the Sudo correlation. Compared to the CHF-LUT, the RRMSE is reduced by 60%–65%, and compared to the Sudo correlation, the RRMSE is reduced by 40%–45%. Through systematic comparative experiments with traditional methods such as the CHF-LUT and the Sudo correlation, this study demonstrates the advantages of the EKF-ML model in terms of prediction accuracy and robustness. These results highlight the potential value of data-driven methods for predicting critical parameters in nuclear reactors and provide new insights and references for CHF prediction in narrow-gap channels.

致谢

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Author Contributions Statement

Deng Yufeng was responsible for modeling, analysis, and the drafting and revision of the manuscript, as well as providing overall research guidance. Liu Ruiyang was responsible for the literature review and experimental data collection. Lyu Meng, Yin Huaqiang, Li Jian, Xie Heng, and Shi Lei were responsible for supervision and project management.

1 石磊

Design Features and Application Prospects of the Wide-Spectrum Ultra-High Flux Test Reactor

1 Introduction

The development of advanced nuclear energy systems and the exploration of frontier nuclear science rely heavily on high-performance research reactors. As nuclear technology evolves toward higher safety standards and more efficient fuel cycles, the demand for high-flux neutron sources has become increasingly urgent. The Wide-Spectrum Ultra-High Flux Test Reactor (W-UHFR) represents a significant leap in reactor design, aiming to provide a versatile platform for material irradiation, isotope production, and fundamental physics research. This paper discusses the core design characteristics and the broad application potential of this next-generation facility.

2 Design Features of the W-UHFR

The W-UHFR is distinguished by its unique ability to provide an ultra-high neutron flux across a broad energy spectrum. Unlike traditional research reactors that often optimize for either thermal or fast neutron populations, the W-UHFR utilizes a hybrid moderation approach to achieve high intensities in both regimes.

2.1 Core Configuration and Flux Performance The core design employs high-density low-enriched uranium (LEU) fuel to meet non-proliferation standards while maintaining high power density. By optimizing the geometry of the fuel assemblies and the arrangement of reflectors, the reactor can achieve a peak thermal neutron flux exceeding $\Phi_{th} > 1.0 \times 10^{15}$ n/(cm$^2 \cdot$ s) and a fast neutron flux of comparable magnitude.

[Figure 1: see original paper]

The spatial distribution of the neutron flux is engineered to be highly flexible. The central experimental channels are designed for high-energy neutron irradiation, while the peripheral regions, moderated by heavy water or beryllium, provide high-quality thermal neutron beams for scattering experiments and isotope transmutation.

2.2 Cooling and Safety Systems To manage the extreme power density required for ultra-high flux, the W-UHFR incorporates an advanced forced-convection cooling system. The design emphasizes passive safety features, including natural circulation capabilities for decay heat removal and redundant shutdown systems. The integration of these features ensures that the reactor remains stable even under transient conditions, adhering to the latest IAEA safety standards [**?**, **?**].

3 Key Technical Innovations

The "wide-spectrum"capability is achieved through a modular experimental zone. Researchers can insert specific filter or converter modules into the irradiation positions to tailor the neutron energy distribution. For

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10 黄彦平

Application of Artificial Neural Networks in the Data Analysis of Critical Heat Flux in Circular Tubes

Abstract

Critical Heat Flux (CHF) is a vital parameter in the design and safety analysis of nuclear reactors and heat exchange equipment. This study explores the application of Artificial Neural Networks (ANN) for predicting and analyzing CHF data in circular tubes. By leveraging the non-linear mapping capabilities of deep learning architectures, we developed a predictive model trained on an extensive experimental database. The results demonstrate that the ANN approach provides superior accuracy and a wider range of applicability compared to traditional empirical correlations. This paper details the network architecture, the data preprocessing techniques employed, and a comparative analysis of the model' s performance against standard CHF look-up tables and classical correlations.

1. Introduction

The phenomenon of Critical Heat Flux (CHF) represents the limit of efficient heat transfer in boiling systems. In the context of nuclear thermal-hydraulics, accurately predicting the occurrence of CHF is essential for ensuring the structural integrity of fuel elements and optimizing the thermal margins of the reactor core. Due to the complexity of the two-phase flow patterns and the numerous influencing factors—such as pressure, mass velocity, tube diameter, and quality—developing a universal physical model remains a significant challenge.

Traditionally, CHF prediction has relied on empirical correlations or look-up tables. While these methods are effective within specific parameter ranges, they often suffer from significant errors when extrapolated or applied to complex geometries. Recently, machine learning and artificial neural networks have emerged as powerful tools for modeling complex, multi-variable thermal-hydraulic phenomena. This study aims to utilize the robust interpolation capabilities of ANN to improve the precision of CHF predictions in circular tubes.

2. Methodology

2.1 Data Collection and Preprocessing

The reliability of a neural network depends heavily on the quality and scope of the training data. For this research, a comprehensive dataset of CHF measurements in circular tubes was compiled from various international experimental databases. The parameters considered include: - Pressure (P) - Mass velocity (G) - Tube diameter (D) - Heated length (L) - Inlet subcooling or local quality (x)

To ensure efficient convergence during the training process, all input and output parameters were normalized to a range of $[0, 1]$ using the following transformation:

$$\hat{y} = \frac{y - y_{min}}{y_{max} - y_{min}}$$

where y represents the physical variable,

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Note: Figure translations are in progress. See original paper for figures.