Gated Recurrent Unit Model for Fault Diagnosis of Nuclear Reactor Coolant System in Nuclear Power Plants

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Abstract

Traditional data-driven fault diagnosis methods encounter difficulties in accurately diagnosing faults in the Reactor Coolant System (RCS) of nuclear power plants under noisy environments. To address this challenge, the following technical approach was employed to construct a Gated Recurrent Unit (GRU) model for RCS fault diagnosis in nuclear power plants: initially, a preliminary GRU-based fault diagnosis model for nuclear power plant RCS was established using the Gated Recurrent Unit methodology; subsequently, the model's initialization parameters were refined through backpropagation through time and the Adaptive Moment Estimation (Adam) optimization algorithm, thereby constructing the GRU-based fault diagnosis model for nuclear power plant RCS; this model was then applied to RCS fault diagnosis; finally, the effectiveness of the constructed GRU-based fault diagnosis model for nuclear power plant RCS was validated by comparatively analyzing its diagnostic accuracy and robustness against Backpropagation Neural Network (BPNN), Support Vector Machine (SVM), and eXtreme Gradient Boosting (XGBoost) models. The study demonstrates that the constructed GRU-based fault diagnosis model for nuclear power plant RCS is capable of accurately diagnosing RCS faults in noisy environments.

Full Text

Preamble

Gated Recurrent Unit Model for Fault Diagnosis of Reactor Coolant System in Nuclear Power Plants

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Abstract: Traditional data-driven fault diagnosis methods struggle to accurately diagnose faults in nuclear power plant reactor coolant systems (RCS) under noisy conditions. To address this challenge, this study establishes a gated recurrent unit (GRU) model for RCS fault diagnosis through the following technical approach: First, an initial GRU model for nuclear power plant RCS fault diagnosis is constructed using the GRU method. Next, the model's initialization parameters are refined using backpropagation through time and the adaptive moment estimation optimization algorithm, yielding the final RCS fault diagnosis GRU model. The developed model is then applied to RCS fault diagnosis scenarios. Finally, the effectiveness of the proposed GRU model is validated through comparative analysis of diagnostic accuracy and robustness against back propagation neural network (BPNN), support vector machine (SVM), and extreme gradient boosting (XGBoost) models. The results demonstrate that the developed GRU model can accurately diagnose RCS faults in noisy environments.

Keywords: nuclear power plant; reactor coolant system; fault diagnosis; gated recurrent unit model

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1 Introduction

The nuclear reactor, as the "heart" of a nuclear power plant, is a critical device for controlling and sustaining nuclear reactions. Within the reactor, the nuclear fission rate can be precisely controlled, and the released energy can be effectively harnessed to generate electricity for human use [?].

The Reactor Coolant System (RCS) of a nuclear power plant, also known as the primary loop system, constitutes the core component of the entire nuclear island. The RCS is a complex system comprising four main components—the nuclear reactor, steam generator, pressurizer, and main coolant pumps—along with interconnecting pipes and valves [?]. Its primary functions are to remove heat generated by the reactor core through nuclear fission during plant operation and to limit the release of radioactive materials [?]. Historically, multiple nuclear accidents have been triggered by RCS failures, including the Fukushima, Chernobyl, and Three Mile Island accidents [?]. Consequently, the RCS is essential for ensuring the safe and stable operation of nuclear reactors.

RCS fault diagnosis refers to the process of identifying, analyzing, and resolving potential faults within the system. Through effective fault diagnosis, latent problems in the RCS can be detected promptly, enabling appropriate measures to prevent fault propagation and thereby safeguarding the secure and stable operation of the nuclear power plant. Thus, RCS fault diagnosis is directly critical to nuclear power plant safety.

Fault diagnosis methods are primarily categorized into model-driven and data-driven approaches [?]. Model-driven methods rely on expert knowledge and precise physical models, making them difficult to apply to complex industrial processes [?]. In contrast, data-driven methods depend on machine learning techniques that extract features from datasets rather than relying on expert knowledge or mechanistic interpretations [?].

Numerous scholars have applied data-driven methods to RCS fault diagnosis research. Chen Chao [?] employed kernel principal component analysis and support vector machine (SVM) methods for RCS fault diagnosis, achieving fitting of coolant flow rates during small cold-leg break accidents and predicting their variation trends. Ai Xin [?] developed an adaptive boosting-based model to assess RCS fault severity and estimated coolant leakage flow rates and the number of ruptured steam generator tubes. Peng et al. [?] proposed a deep belief network-based RCS fault diagnosis method, calculating RCS pressure and coolant leakage flow rates to diagnose loss-of-coolant accidents and steam generator tube ruptures. Deng Qiang et al. [?] combined temporal convolutional networks with capsule networks to establish a fault diagnosis model for RCS and other systems, verifying that the model could achieve rapid convergence and high diagnostic accuracy even with limited data samples.

Traditional data-driven fault diagnosis methods include back propagation neural network (BPNN), SVM, and extreme gradient boosting (XGBoost). While BPNN can handle complex nonlinear relationships and is suitable for large-scale data training, it struggles to mine temporal sequence data [?]. SVM and XGBoost offer unique advantages for small-sample data processing, yet their computational complexity increases significantly when facing large-scale datasets [?, ?]. Since nuclear power plant RCS data are massive, nonlinear time-series data, BPNN, SVM, and XGBoost models all face difficulties in accurately diagnosing RCS faults.

The gated recurrent unit (GRU) model is a specialized form of recurrent neural network designed primarily to mitigate the gradient vanishing problem that occurs when traditional RNNs process long sequences [?]. The gating mechanism of GRU models enables effective handling of temporal data [?], and GRU models exhibit strong nonlinear fitting capabilities with relatively fast training speeds, allowing efficient processing of massive input data [?].

Furthermore, data collected by RCS sensors during normal operation or accident conditions typically contain a certain degree of noise [?], while traditional data-driven fault diagnosis methods struggle to accurately diagnose RCS faults in noisy environments. Research has shown that GRU models can effectively address system noise issues [?].

Based on these considerations, this study constructs a GRU model for nuclear power plant RCS fault diagnosis to accurately diagnose RCS faults in noisy environments, and compares the developed model against BPNN, SVM, and XGBoost models in terms of diagnostic accuracy and robustness.

2.1 GRU Model Introduction

The GRU model controls information flow between different time steps through reset and update gates, thereby capturing both short-term critical features and long-term dependencies in time-series data [?]. Equations (1) and (2) [?] define the reset gate state and update gate state, which respectively limit and determine the influence of the previous hidden state on the current candidate hidden state.

$$r_t = \varphi(W_{rx}x_t + U_{rh}h_{t-1} + b_r) \tag{1}$$

$$z_t = \varphi(W_{zx}x_t + U_{zh}h_{t-1} + b_z) \tag{2}$$

where r_t is the reset gate state, z_t is the update gate state, φ is the sigmoid function, W_{rx} and U_{rh} are weight parameters for the reset gate, W_{zx} and U_{zh} are weight parameters for the update gate, x_t is the model input at the current time step, h_{t-1} is the hidden state from the previous time step, and b_r and b_z are biases for the reset and update gates, respectively.

Equations (3) and (4) define the candidate hidden state and hidden state of the GRU model [?]:

$$\tilde{h}_t = \tanh(W_{hx}x_t + U_{hh}(r_t \circ h_{t-1}) + b_h) \tag{3}$$

$$h_t = z_t \circ h_{t-1} + (1 - z_t) \circ \tilde{h}_t \tag{4}$$

where $\tilde{h}_t$ is the candidate hidden state, h_t is the hidden state, tanh is the hyperbolic tangent function, W_{hx} and U_{hh} are weight parameters for the candidate hidden state, $\circ$ denotes element-wise multiplication, and b_h is the bias for the candidate hidden state.

Equation (5) defines the output value of the GRU model [?]:

$$y_t = \rho(V \cdot h_t) \tag{5}$$

where y_t is the model output, ρ is the softmax function expressed in Equation (6), and V is the connection weight matrix from the hidden layer to the output layer.

$$\rho(y_i) = \frac{e^{y_i}}{\sum_{k=1}^{K} e^{y_k}} \tag{6}$$

where y_i is the i-th output value of the GRU model and K is the total number of output values.

2.2 GRU Model Parameter Correction

Backpropagation through time and the adaptive moment estimation optimization algorithm are employed to correct GRU model parameters, including weight parameters for the reset gate, update gate, candidate hidden state, and connection weights from the hidden layer to the output layer.

Backpropagation through time improves upon traditional backpropagation by treating gradients of model parameters across time steps as a sequence and applying the chain rule to compute gradients of model errors with respect to parameters [**?**]. The adaptive moment estimation optimization algorithm is an adaptive learning rate method based on first-order and second-order moment estimates, which optimizes and corrects model parameters by computing these moment estimates of gradients across different time steps [**?**].

Equation (7) calculates the error between GRU model outputs and actual values [**?**]:

$$E_t = -\sum (y_t \log(\hat{y}_t) + (1 - y_t)\log(1 - \hat{y}_t)) \tag{7}$$

where E_t is the error and $\hat{y}_t$ is the actual value.

According to the chain rule, gradients of the GRU model error with respect to model parameters (W_r, W_z, W_h, V) are computed [**?**]. Equations (8) and (9) [**?**] calculate the first-order and second-order moment estimates of the gradients.

$$m_t = \beta_1 m_{t-1} + (1 - \beta_1) g_t \tag{8}$$

$$n_t = \beta_2 n_{t-1} + (1 - \beta_2) g_t^2 \tag{9}$$

where m_t is the first-order moment estimate, n_t is the second-order moment estimate, β_1 and β_2 are decay rates for the first-order and second-order estimates respectively, with values in $[0, 1)$.

Equations (10) and (11) [**?**] correct the moment estimates:

$$\hat{m}_t = \frac{m_t}{1-\beta_1^t} \tag{10}$$

$$\hat{n}_t = \frac{n_t}{1-\beta_2^t} \tag{11}$$

where $\hat{m}_t$ is the corrected first-order moment estimate and $\hat{n}_t$ is the corrected second-order moment estimate.

Equation (12) computes the learning rate for the adaptive moment estimation optimization algorithm [**?**]:

$$\alpha_t = \alpha \frac{\sqrt{1-\beta_2^t}}{1-\beta_1^t} \tag{12}$$

where α_t is the learning rate and α is the initial learning rate in $[0, 1)$.

Equation (13) calculates the optimized GRU model parameters [**?**]:

$$\theta_{t+1} = \theta_t - \frac{\hat{m}_t}{\sqrt{\hat{n}_t} + \epsilon} \alpha_t \tag{13}$$

where θ represents the parameters (W_r, W_z, W_h, V) and ϵ is a constant, typically a very small non-zero value.

2.3 Construction of Nuclear Power Plant RCS Fault Diagnosis GRU Model

The nuclear power plant RCS fault diagnosis GRU model is constructed through three steps:

Step 1: Determine GRU Model Structure
Based on the parameters of nuclear power plant RCS data samples (including normal and fault parameters) and RCS fault types, the numbers of neurons in the input and output layers are determined. The empirical formula method is applied to determine the number of hidden layers, thereby establishing the GRU model structure.

Step 2: Determine GRU Model Parameters
Random initialization is used to initialize the GRU model parameters. The GRU method is applied to compute the reset and update gate states using Equations (1) and (2), the candidate hidden and hidden states using Equations (3) and (4), and the output values using Equations (5) and (6). Equation (7) calculates the model error. Based on backpropagation through time and the adaptive moment estimation optimization algorithm, gradients of the error with respect to the

reset gate, update gate, candidate hidden state weights, and hidden-to-output connection weights are computed. The first-order and second-order moment estimates of these gradients are calculated and corrected to refine the initialized GRU model parameters.

Step 3: Construct RCS Fault Diagnosis GRU Model
Based on the above steps, the RCS fault diagnosis GRU model is constructed as shown in Figure 1 [Figure 1: see original paper]. The algorithm flowchart for RCS fault diagnosis is presented in Figure 2 [Figure 2: see original paper].

3.1 Description of Nuclear Power Plant RCS Operation and Fault Data

Nuclear power plants operate in safe and stable conditions most of the time, making fault data relatively scarce. Therefore, this study utilizes the Personal Computer TRansient ANalyzer (PCTRAN) software developed by the International Atomic Energy Agency (main interface shown in Figure 3 [Figure 3: see original paper]) as the source for operation and fault data. PCTRAN can simulate RCS operation and fault states under various conditions, and the generated simulation data can accurately reflect actual RCS behavior under real operating conditions.

PCTRAN software was used to simulate nuclear power plant RCS scenarios including normal operation and typical accident conditions. The typical accident conditions include: reactor coolant loss (hot-leg small break, cold-leg small break, hot-leg large break, and cold-leg large break), steam generator tube rupture (sections A and B), and loss-of-flow conditions [?]. The simulation times and sample quantities for each scenario are listed in Table 1 .

Each data record in Table 1 contains 83 parameters (including normal and fault parameters) such as RCS pressure, RCS average temperature, and steam generator feedwater flow rate, along with corresponding classification labels. Due to differences in parameter magnitudes, min-max normalization is applied using the formula:

$$x' = \frac{x - x_{\min}}{x_{\max} - x_{\min}} \tag{14}$$

where x' is the normalized parameter value, x is the original parameter value, and $x_{\max}$ and $x_{\min}$ are the maximum and minimum values of the original parameter, respectively.

The sliding window method was systematically tested with window step sizes of 1s, 3s, 5s, 7s, 10s, and 12s, and window sizes of 50s, 100s, 180s, and 200s. The highest diagnostic accuracy was achieved with a step size of 10s and window size of 180s. Therefore, these parameters were selected, dividing the operation and fault data into 383 independent datasets across time slices. The data were then partitioned into 70% training and 30% testing sets to serve as input datasets for the fault diagnosis GRU model.

3.2 Nuclear Power Plant RCS Fault Diagnosis

The nuclear power plant RCS fault diagnosis GRU model constructed in Section 2 was applied for fault diagnosis. Since each data record contains 83 parameters, the GRU model input layer was configured with 83 neurons. Using the empirical formula method, the number of hidden layers was set to 90. With eight fault types selected for this study, the output layer was configured with 8 neurons.

Random initialization was employed to initialize the GRU model parameters. The PCTRAN-generated training dataset was used as input, and Equations (1)-(6) were applied to determine the initial GRU model parameters.

Backpropagation through time and the adaptive moment estimation optimization algorithm were used to refine the initial parameters, with hyperparameter settings listed in Table 2 .

Equations (7) and (15) were used to calculate the diagnostic error and accuracy on the training dataset, with corresponding variation curves shown in Figures 4 [Figure 4: see original paper] and 5 [Figure 5: see original paper].

$$\text{Accuracy} = \frac{N_{\text{right}}}{N_{\text{total}}} \tag{15}$$

where N_{right} is the number of correctly diagnosed samples and N_{total} is the total number of samples.

As shown in Figures 4 and 5, after 200 iterations of parameter refinement, the GRU model error on the training dataset decreased from 2.08 to 0.16, while diagnostic accuracy improved from 9.99% to 94.67%. These results demonstrate the high reliability of the constructed GRU model.

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4 Discussion and Analysis

The effectiveness of the nuclear power plant RCS fault diagnosis GRU model is validated through comparative analysis of diagnostic accuracy and robustness against other models.

(1) Diagnostic Accuracy Comparison

The PCTRAN-generated test dataset was used as input for comparative analysis of BPNN, SVM, and XGBoost models against the developed GRU model.

Hyperparameter settings for the comparison models are listed in Table 3 .

Diagnostic accuracy for each model was calculated using Equation (15), with results presented in Table 4 .

For scenarios S1, S5, S6, S7, and S8, the GRU model achieved higher accuracy than BPNN, SVM, and XGBoost. For scenario S2, GRU accuracy matched SVM at 99.50% (exceeding XGBoost's 99.16% but slightly below BPNN's 100.00%). For scenario S3, GRU accuracy was 98.60% (higher than SVM's 98.20% and XGBoost's 98.50%, but slightly below BPNN's 99.30%). For scenario S4, GRU accuracy was 98.10% (higher than XGBoost's 96.47% but slightly below the other two models). The average diagnostic accuracy across all eight scenarios ranked as: GRU (99.04%) > XGBoost (98.15%) > BPNN (97.33%) > SVM (96.66%).

To further validate the high diagnostic accuracy, misdiagnosis rates were analyzed. The developed RCS fault diagnosis GRU model was applied to diagnose faults in each time slice, with results shown in Figure 6 [Figure 6: see original paper].

Across the 383 time slices in Figure 6, the GRU model achieved over 94% diagnostic accuracy for most periods. Relatively lower accuracy (75%-94%) occurred during time slices 34-51, 281-300, and 334-350, primarily because S2, S7, and S8 scenarios were introduced at seconds 170 of time slices 34, 281, and 334, respectively. These scenarios exhibited subtle parameter changes in short timeframes, leading to misdiagnosis as previous scenarios.

The average diagnostic accuracy of the GRU model during these three periods was calculated and compared with BPNN, SVM, and XGBoost, as shown in Table 5 .

Even in these high-misdiagnosis periods, the GRU model maintained higher average accuracy than the other three models. This comparative analysis confirms the accuracy of the developed fault diagnosis GRU model.

(2) Robustness Comparison

To validate robustness, Gaussian noise of varying intensities was added to normal and fault parameters using Equation (16):

$$f(x) = \frac{1}{\sqrt{2\pi\mu}} \exp\left(-\frac{x^2}{2\mu}\right) \tag{16}$$

where $f(x)$ is the Gaussian noise probability density function, x is the random variable, and μ is the variance.

The developed GRU model and conventional BPNN, SVM, and XGBoost models were applied to diagnose the eight scenarios in Table 1. Diagnostic accuracies under different noise levels were calculated using Equation (15), with results shown in Figure 7 [Figure 7: see original paper].

When Gaussian noise with standard deviation 0.05 was added, all four models showed accuracy degradation: GRU decreased from 99.04% to 97.23%, BPNN from 97.33% to 96.61%, SVM from 96.66% to 64.40%, and XGBoost from 98.84% to 94.51%. With noise standard deviation of 0.1-0.15, GRU, BPNN, and XGBoost accuracies continued declining while SVM first decreased then increased. As noise standard deviation increased to 0.2-0.45, all four models showed decreasing accuracy, with XGBoost dropping most severely (42.96%), followed by BPNN (38.95%), while SVM showed the smallest decline (28.81%). At noise standard deviation 0.5, BPNN, SVM, XGBoost, and GRU accuracies dropped to 40.97%, 41.64%, 42.23%, and 59.84%, respectively.

These results demonstrate that across all noise levels, the developed GRU model maintained higher diagnostic accuracy than BPNN, SVM, and XGBoost models, confirming its robustness.

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5 Conclusion

This study constructed a nuclear power plant RCS fault diagnosis GRU model with the following findings:

1. The GRU method enables determination of model structure and initialization parameters, establishing an initial RCS fault diagnosis GRU model.
2. Backpropagation through time and adaptive moment estimation optimization algorithm effectively correct initialization parameters (including reset gate, update gate, candidate hidden state weights, and hidden-to-output connection weights), yielding the final RCS fault diagnosis GRU model.
3. The developed model can calculate diagnostic accuracy for RCS faults across different time slices (results shown in Figure 6).
4. Comparative analysis of diagnostic accuracy and robustness against BPNN, SVM, and XGBoost models (results in Tables 4-5 and Figure 7) validates the effectiveness of the developed GRU model.
5. Current research demonstrates that the developed GRU model can accurately diagnose RCS faults in noisy environments.

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