Reliability Assessment of Passive Isolation Condenser System of AHWR Based on Artificial Neural Network

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Abstract: In evaluating the probability of functional failure in passive systems, Relap5/MOD 3.4 was utilized to model the isolated condenser system of the Advanced Heavy Water Reactor in India. Through the Sobol sensitivity analysis method, critical parameters were identified, and specific input parameters were established. For uncertainty propagation, RAVEN was used, and artificial neural network methods were employed to calculate the probability of functional failure within the natural circulation loop. Finally, probabilistic system failure criteria were applied to determine the failure probability and the confidence interval of the passive system, where the calculation result of the failure probability is 2.39E-5. The results demonstrate that the neural network method is effective in calculating the probability of functional failure in passive systems. Thus, the methodology presented in this study can be used to calculate the probability of functional failure in passive systems.

Keywords: Isolated condenser system, Reliability of passive system, Artificial neural network, Probabilistic failure criteria

1. INTRODUCTION

During the operation of a nuclear reactor, human factors and mechanical failures frequently occurring in active systems inevitably pose hazards to the reactor's safe operation. To enhance the safety and reliability of the reactor, the concept of passive safety has been gradually incorporated into nuclear reactor designs after years of development [1]. In contrast to hardware failures, functional failures in passive systems are easily influenced by various factors and require focused consideration.

The current method for estimating functional failure probability involves modeling passive systems using thermal-hydraulic programs such as RELAP5, followed by uncertainty propagation using Monte Carlo methods. Due to the inherent high reliability of passive systems, the probability of functional failure is extremely low. As a result, the computation of functional failure probability poses challenges in terms of the lengthy calculations and numerous iterations required by the thermal-hydraulic programs, which increase as the failure probability decreases [2, 3].

To minimize the computational time and number of runs required by thermal-hydraulic codes, alternative solutions, such as fast-running surrogate regression models (also known as response surface or metamodels) and advanced Monte Carlo simulation methods, can be considered. Currently, the commonly employed method for analyzing passive systems is the Reliability Methods for Passive Systems (RMPS) framework. This framework utilizes expert judgment or the Analytic Hierarchy Process (AHP) to identify key parameters within passive systems, enabling the calculation of system failure probability either directly using thermal-hydraulic codes or swiftly employing response surface methods. Building upon this framework, Burgazzi [4] applied it to analyze the reliability of the passive residual heat removal system in an air-cooled fast reactor. Bucknor et al. [5] utilized this approach to analyze the reliability of an advanced small modular reactor under external events. Huang et al. [6] conducted research on the reliability of the passive residual heat removal system in an AP1000 reactor. Xia et al. [7] performed a reliability analysis on the passive residual heat removal system in a Chinese lead-based research reactor. However, these studies have predominantly focused on specific failure criteria determined by fixed threshold values based on a single output parameter, with limited exploration of failure criteria characterized by certain distributions.

This study utilizes a probabilistic failure criterion to swiftly calculate the functional failure probability of the isolation condenser system in a reactor using response surface methodology. The Sobol sensitivity analysis method is employed to identify critical input parameters. Uncertainty propagation of input parameters is conducted using RAVEN, and an artificial neural network approach is applied to compute the functional failure probability in the natural circulation loop. Finally, passive failure probabilities with confidence intervals are presented. The methodology employed in this research can serve as a reference for the calculation of functional failure probabilities in other passive systems.

2. METHODS AND SOFTWARE

2.1. Artificial Neural Network

As a fundamental element within the realm of machine intelligence, neural networks are computational algorithms that mimic the intricate functioning of the human brain's neural network. Structured as an assembly of interconnected nodes (neurons), each node receives input signals and generates corresponding outputs. Organized in a hierarchical layout, each layer performs calculations on inputs and passes the results to subsequent layers, ultimately culminating in an output. These networks are widely deployed for tasks like classification, regression, image recognition, and language understanding. To facilitate their learning, extensive labeled data is typically necessary to guide the network in aligning inputs with accurate outputs, as depicted in Figure 1.

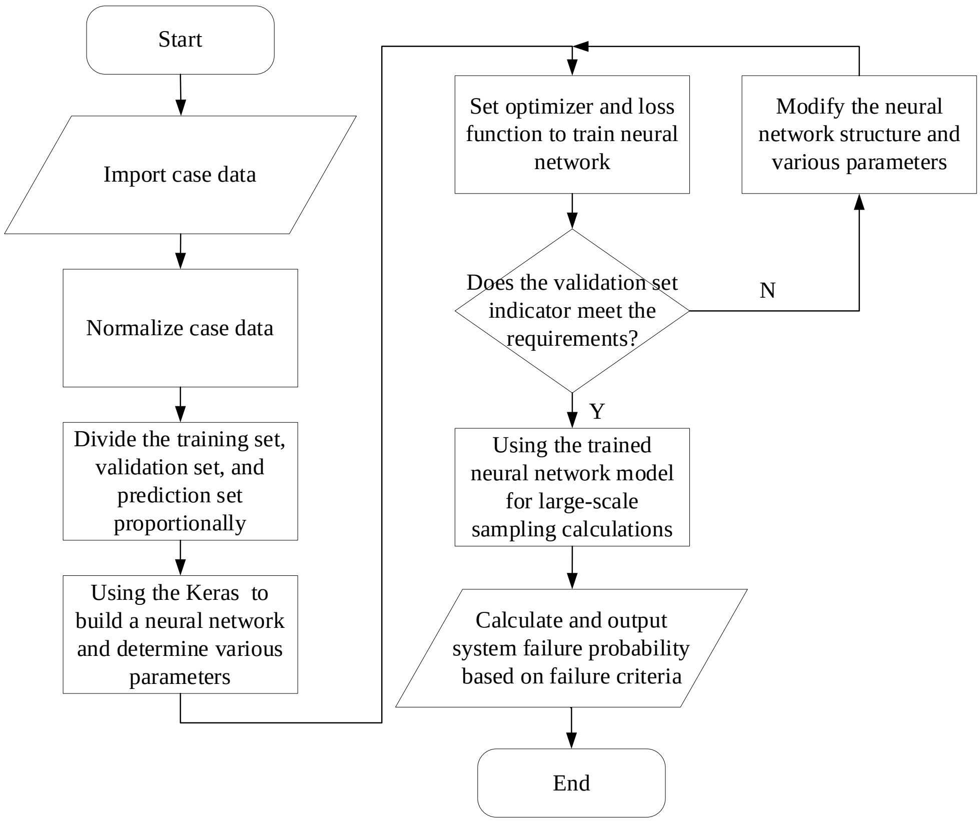

Figure 1. Neural Network Method Flowchart

2.2. RAVEN Software

The RAVEN (Risk Analysis Virtual Environment) is a versatile software framework designed for parameterized and probabilistic analysis based on complex system code responses. RAVEN interfaces seamlessly with the RELAP5 application through an Application Programming Interface (API), enabling analysts to leverage Monte Carlo, grid, or Latin hypercube sampling techniques for exploring the input space. One of its key features is its capability to operate on high-performance computing (HPC) platforms, enabling the execution of hundreds of parallel runs, thereby enhancing computational efficiency [8].

2.3. Sobol Sensitivity Analysis Method

The Sobol sensitivity analysis method is a statistical technique employed to quantify the sensitivity of model outputs (or objective functions) to input variables. This approach, introduced by Ilya Sobol [9], is commonly utilized in addressing parameter sensitivity issues in complex models, such as computer simulations, numerical models, and optimization domains.

Sobol sensitivity analysis is grounded on global sensitivity indices, which measure the individual contribution of each input variable to the output. In contrast to traditional methods that often focus on the effect of single variables, the Sobol method offers a more comprehensive perspective by considering the interdependencies among input variables.

2.4. Failure Probability Model

Drawing upon the resistance-stress (R-S) interaction model from fracture mechanics, the probability of functional failure, such as the removal of decay heat, is defined in the context of ensuring a given safety function, as illustrated in Figure 2.

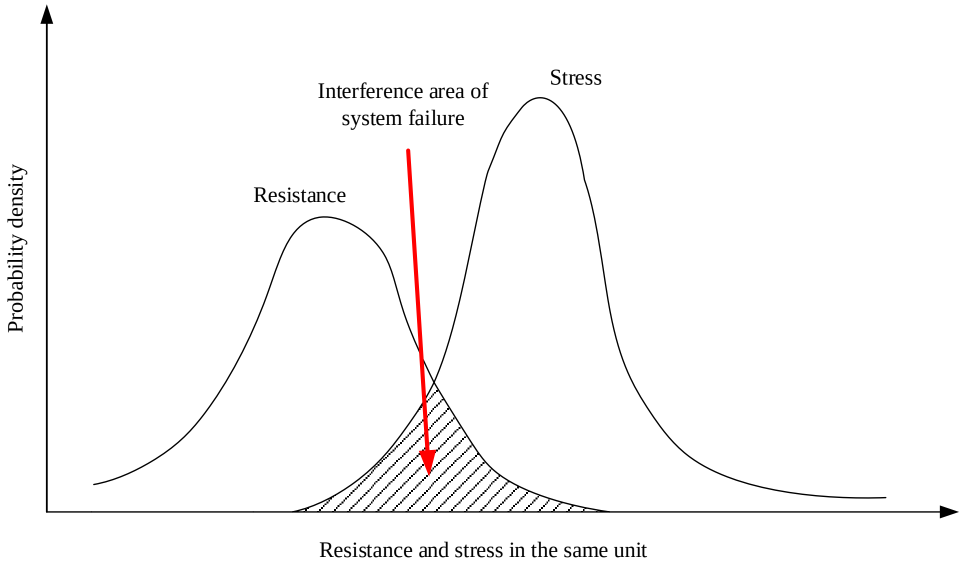

Figure 2. Resistance-Stress interference model

In the passive system reliability assessment framework, R and S denote the safety function requirements for physical parameters, such as the minimum flow rate threshold for a system to operate successfully (e.g., the number of cycles a system must complete), and system state, which refers to the actual flow rate in the cycle. Probability distributions are assigned to R and S to account for the uncertainty in safety margins and system conditions. The probability of system failure is calculated by comparing the state's probability density function with the probability density function representing the defined safety function requirements.

3. MODELING OF ISOLATED CONDENSER SYSTEM

3.1. Basic Information

The Indian Advanced Heavy Water Reactor (AHWR) is a 300 MWe (920 MWth) pressure tube-type reactor that employs heavy water moderation and boiling light water cooling in a natural circulation system [10]. The AHWR utilizes $(Th\text{-}^{233}U)O_2$ and $(Th\text{-}Pu)O_2$ as fuel. This fuel design is intended to maximize energy production from thorium, maintain self-sufficiency of ^{233}U, and achieve a small negative void coefficient to ensure safe and efficient operation.

The AHWR reactor core consists of 505 square grid points with a 245 mm pitch, forming a 505 × 505 arrangement. Among these, 53 positions are designated for reactivity control devices and shutdown systems. The core houses a total of 12 control rods, which are divided into regulating rods, absorbing rods, and spacer rods, with each category consisting of four rods.

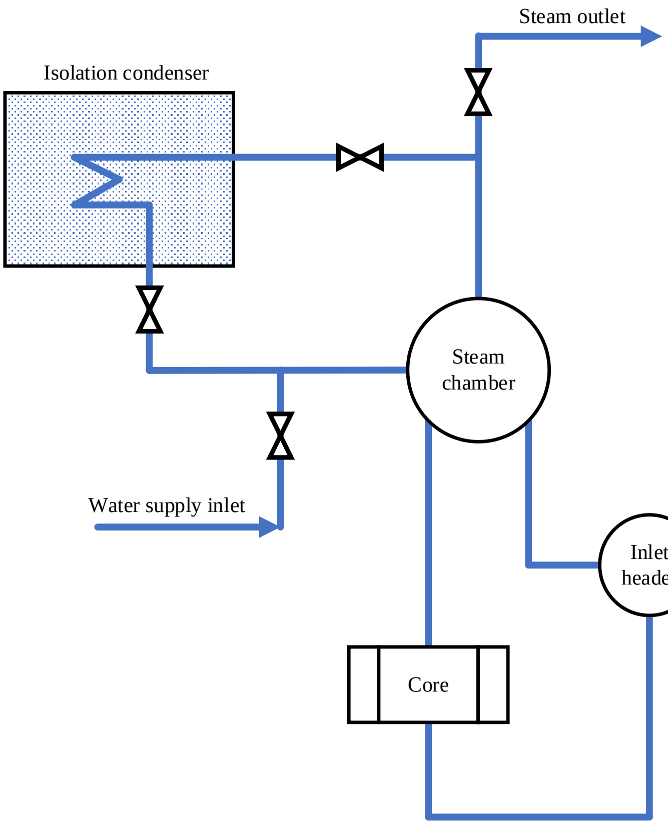

Figure 3. Schematic diagram of the isolation condenser system

The Isolation Condenser System (ICS) is a characteristic passive system in advanced nuclear power plants. Its purpose is to transfer the decay heat generated in the reactor core non-actively to a heat sink by condensing primary fluid (steam) in the heat exchanger (IC) tubes [11]. Depending on the plant design, there may be two or more redundant ICS circuits. Each ICS circuit typically consists of a steam chamber, an isolation condenser submerged in a high-level water pool, steam supply valves, condensate return valves, and associated piping. The steam supply valve is always open, while the condensate return valve is kept closed. Figure 3 illustrates a schematic diagram of a typical ICS circuit deployed in advanced nuclear power plants.

In normal operation, steam generated in the steam chamber is conveyed to the turbine via steam lines. The main condenser dissipates heat to the atmosphere through the condenser cooling system and circulates the condensed water back to the steam chamber via a series of feedwater heaters and pumps. In the event of an accident, the valves connecting the main steam line to the ICS loop switch from open to closed. The steam rises to the isolation condenser, which is typically located at a higher elevation and gravity-driven water pool (GDWP), where a density difference is created within the loop, driving the ICS operation. The steam condenses in the immersed isolation condenser, and the condensed liquid, due to gravity, flows back to the steam chamber through the reflux valve. The reflux valve opens when ICS activation is needed. The entire loop stands at a height of 39 meters.

3.2. System Modeling

In this section, a RELAP5 model for the isolation condenser system was developed using Relap5/MOD 3.4, which encompasses the reactor core, riser, steam chamber, primary loop of the isolation condenser, and the secondary water tank. The node diagram is depicted in Figure 4.

Before embarking on accident analysis, reactor stability must be ensured. Therefore, the correctness of the computational results derived from the RELAP5 model established in this study was validated using the design basis accident scenario, as per Nayak [12]. Figure 5 and Figure 6 illustrate the time variations of steam chamber pressure, core power, and heat transfer rate through the IC pipe. The calculations confirm that the model developed in this paper meets the requirements.

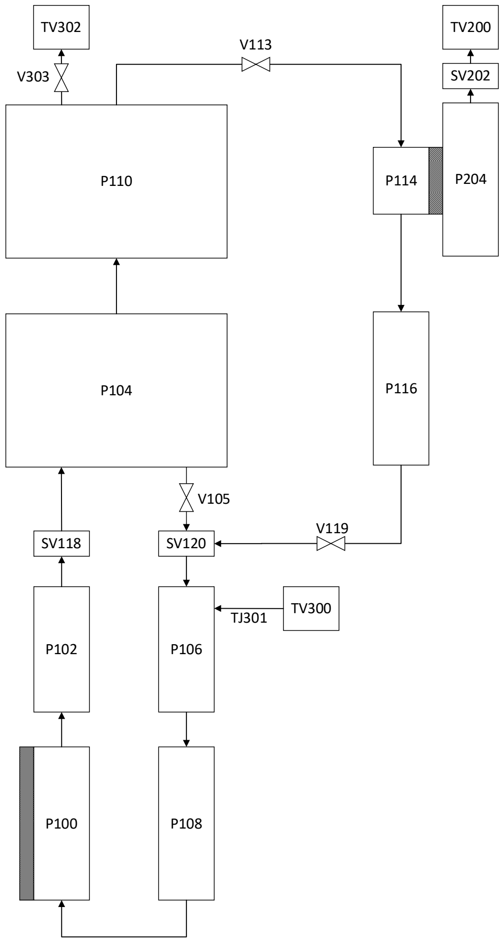

Figure 4. Nodalization of the ICS in the RELAP5 model

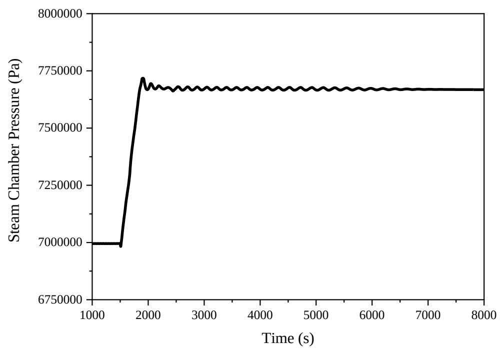

Figure 5. Changes in steam drum pressure over time

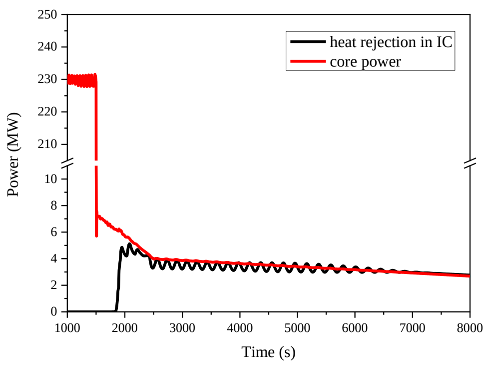

Figure 6. Changes in core power and heat rejection in IC over time

4. CALCULATION OF THE FUNCTIONAL FAILURE PROBABILITY OF ICS

This study employs the RMPS framework methodology to calculate the probability of ICS functional failure, which can be broken down into the following steps:

1. Identify the accident scenarios for analysis;
2. Apply the Sobol sensitivity analysis method to identify key parameters;
3. Perform uncertainty propagation using RAVEN and train a neural network model;
4. Utilize the neural network to compute the probability of system functional failure.

4.1. Description of Accident Conditions

Considering the system undergoing transient decay heat at 1500 seconds, with both feedwater inlet and steam outlet valves simultaneously closed, the ICS valves transition from closed to open, creating a natural circulation loop between the core and the ICS at this point.

4.2. Identify Key Parameters

Based on the uncertainty parameters that may affect passive systems, as listed in references [13-16], a total of 12 input parameters are considered in this study, with their distributions and ranges presented in Table 1.

Table 1. Distribution and range of input parameters

Symbol	Input Parameters	Distribution Form	Distribution Range
heatpower	Core Power/W	Normal	[1.932e+8,2.668e+8]
SD_P	Steam Chamber Pressure/Pa	Discrete	[7.0e+6,8.6e+6]
SD_L	Steam chamber Liquid Level/m	Discrete	[0.8,3.0]
GDWP_L	GDWP Liquid Level /m	Discrete	[1.75,5]
GDWP_temp	GDWP Water Temperature /K	Discrete	[308.15,368.15]
core_d	Inner Diameter of Heating Section Heat Exchange Tube /m	Normal	[0.01008,0.01232]
core_rough	Heating Section Wall Roughness /m	Uniform	[5.1e-6,6.9e-6]
cond_d	Inner Diameter of Condensation Section Heat Exchange Tube /m	Normal	[0.039392,0.059088]
cond_tc	Thermal Conductivity of Condensation Section Material /(W/(m· K))	Uniform	[320.8,481.2]
core_h	Heating Section Convective Heat Transfer Coefficient Factor	Uniform	[0.8,1.2]
cond_hin	Convective Heat Transfer Coefficient Factor on The Inner Surface of The Condensation Section	Uniform	[0.8,1.2]
cond_hout	Convective Heat Transfer Coefficient Factor on The Outer Surface of The Condensation Section	Uniform	[0.8,1.2]

Considering the peak cladding temperature as the output parameter, this paper employs the Sobol method to analyze the sensitivity between inputs and outputs. A total of 7168 samples were taken for the 12 input parameters, forming an input matrix of 7168*12, which was then inserted into RELAP5 for calculation, yielding corresponding output values. The analysis results are presented in Table 2 and Figure 7.

Based on the Sobol method's analysis, five input parameters (GDWP_L, SD_P, heatpower, core_d, and cond_d) with ST indices greater than 0.05 were selected as key parameters for further uncertainty propagation [17].

Table 2. Sensitivity analysis results of Sobol method

Symbol	**ST**	**ST_conf**	**S1**	**S1_conf**
GDWP_L	0.253104	0.017611	0.150917	0.017934
SD_P	0.610814	0.019497	0.601257	0.021936
SD_L	0.011438	0.00057	-0.00132	0.002376
GDWP_temp	0.013052	0.000467	0.001959	0.002474
heatpower	0.095829	0.007809	0.034088	0.006241
core_d	0.07366	0.002927	0.047299	0.00575
cond_d	0.052435	0.005537	0.000916	0.005239
core_rough	0.01071	0.000536	-0.00023	0.002117
cond_tc	0.001711	8.67E-05	-1.45E-05	0.000947
core_h	0.025171	0.001048	0.019602	0.003114
cond_hin	0.022961	0.002091	-0.00022	0.003518
cond_hout	0.007753	0.000371	6.95E-05	0.001941

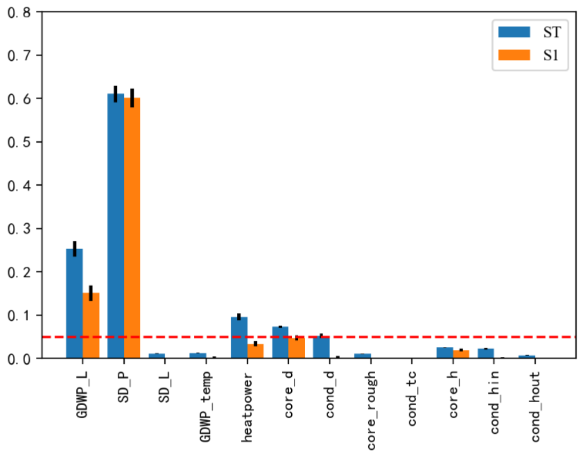

Figure 7. Sensitivity analysis results of Sobol method

4.3. Uncertainty Propagation

This study employed RAVEN to generate and modify samples of the critical input parameters and their related parameters in the input deck, which were then inserted into RELAP5 for multiple calculations. A total of 1000 samples were taken, resulting in an input matrix of 1000*5, representing all combinations of the five key parameters; the output vector consisted of 1000 peak clad temperatures corresponding to each input parameter combination.

To enhance the efficiency of estimating the failure probability of the computational system, a neural network approach was employed to model the relationship between the input matrix and the output vector. First, the 1000 case data were normalized to fall within the range of [-1, 1]. Then, the data were split into training, validation, and prediction sets with a ratio of 7:2:1, resulting in a training set size of 700 cases.

Next, a neural network model was constructed, where the Keras module was utilized to generate the network's structural parameters. A hidden layer with 10 nodes and a single layer were set. The optimizer (Adam) and loss function (Mean Squared Error, MSE) were then configured. The model was initially trained using the validation set's metrics, such as MSE, to assess its adequacy. If the requirements were not met, the network structure or parameters were adjusted, and the training process was repeated until the model's metrics met the desired criteria. Common metrics for evaluating the model's fit include the coefficient of determination (R^2) and the Root Mean Squared Error (RMSE), which are expressed as follows:

$$R^2 = 1 - \frac{MSE(\hat{y} - y)}{Var(y)} \tag{1}$$

$$RMSE = \sqrt{\frac{1}{m}\sum_{i=1}^{m}(y_i - \hat{y}_i)^2} \tag{2}$$

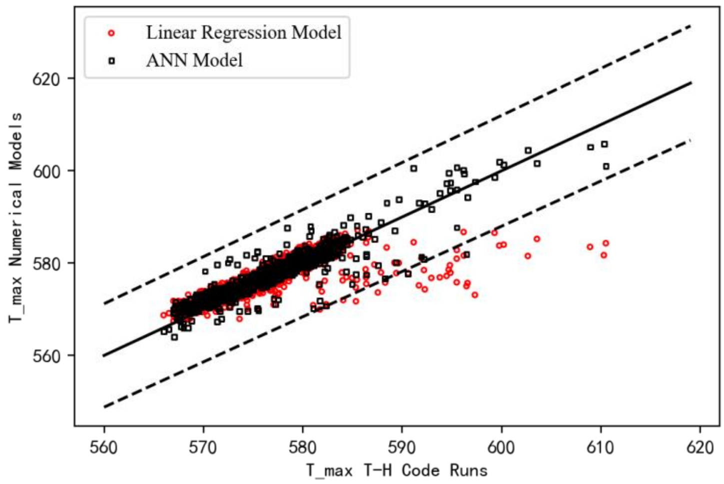

Figure 8. Comparison of neural network and multidimensional linear fitting effects

The neural network model trained in this study achieved an R^2 of 0.879 and an RMSE of 1.99. For comparison, a direct multivariate linear fit of the input-output relationship resulted in an R^2 of 0.565 and an RMSE of 3.78. As shown in Figure 8, where the x-axis represents the output values directly calculated by RELAP5 and the y-axis displays the predicted outputs from both models, the dashed line represents a 2% error margin.

As evident from Figure 8, the neural network's fitting performance is superior to that of the multivariate linear fit, particularly in regions where peak clad temperatures are higher.

4.4. Calculate Failure Probability

As a fast computational alternative to RELAP5, the trained neural network model was employed for extensive sampling calculations. A Latin Hypercube Sampling was applied to the five key parameters for 1,000,000 samples, resulting in a new input matrix. This matrix was then fed into the neural network model to predict the output results. The distribution of the output values is depicted in Figure 9.

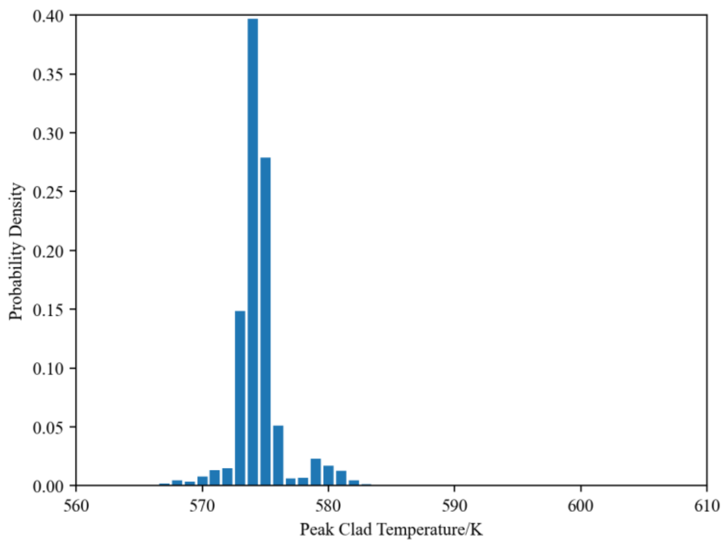

Figure 9. Distribution of peak cladding temperature

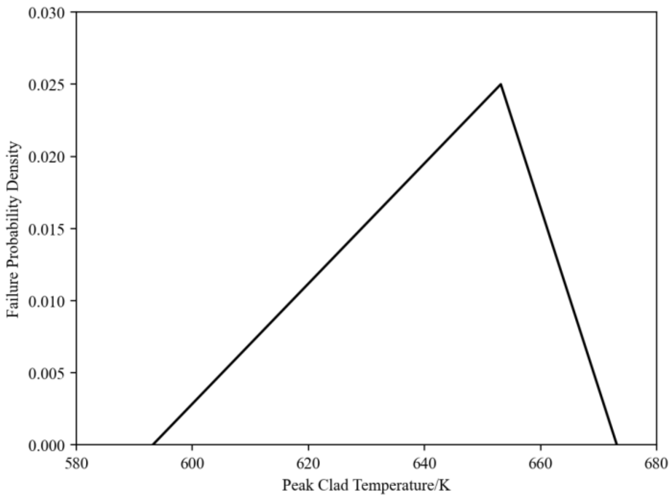

Figure 10. Distribution of failure probability density

In contrast to Nayak's deterministic failure criterion [12], which considers a system failure when the peak clad temperature exceeds 400°C, this study employs a probabilistic failure criterion. It assumes that the failure probability density of ICS is related to the peak clad temperature in a triangular distribution, with three transition points at 593.15K, 653.15K, and 673.15K, as shown in Figure 10.

Based on the probabilistic failure criterion, the convolutional calculation of ICS's failure probability resulted in a value of 2.39E-5. For the 1000 samples directly computed by RELAP5, the statistical failure probability was 2.62E-5. The magnitudes are similar, and the values are close, indicating the validity of using a neural network approach to predict the functional failure probability of a passive system.

4.5. Confidence Interval of Failure Probability

Considering the confidence interval for failure probability, a Latin Hypercube Sampling of 1,000,000 samples was repeated for the input parameters, and the system failure probability was calculated using the neural network model. The uncertainty distribution of the failure probability was statistically analyzed, as shown in Table 3. Therefore, the 95% confidence interval for the system's functional failure probability is [2.31E-5, 2.57E-5].

Table 3. Uncertainty distribution of failure probability

Mean	**Variance**	**2.5% Percentile**	**50% Percentile**	**97.5% Percentile**
2.43E-5	4.28E-13	2.31E-5	2.43E-5	2.57E-5

4. CONCLUSION

This study, grounded in probabilistic failure criteria, employed the Relap5/MOD 3.4 model to simulate the isolation condenser system in an Indian heavy water reactor. It utilized the Sobol sensitivity analysis to identify crucial input parameters and RAVEN for uncertainty propagation. By adopting a neural network approach, the functional failure probability in the passive system was calculated to be 2.39E-5, which was found to be of similar order of magnitude and numerical proximity to the results obtained through direct statistical analysis. The confidence interval for the failure probability was reported as [2.31E-5, 2.57E-5].

The methodology employed in this study has the potential to be applied to the calculation of functional failure probabilities in other passive systems, though its wider applicability necessitates further validation.

Acknowledgements

This research did not receive any specific grant from funding agencies in the public, commercial, or not-for-profit sectors.

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