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Correlation Sensitivity Analysis of Reliability of Passive System of small reactor

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The Emergency Heat Removal System (EHRS) is a critical passive safety system of the IRIS (International Reactor Innovative and Secure) reactor, and its reliability directly determines the decay heat removal capability following accidents. This paper employs the Active learning Metamodel-based Importance Sampling (AM-SIS) method to calculate and analyze the failure probability of the IRIS EHRS. To address the lack of information regarding correlations among input parameters, Gaussian Copula functions are introduced to impose artificially assumed correlation structures, systematically investigating the sensitivity of failure probability to pairwise correlations among eight key input parameters. The results indicate that among all parameter combinations, the negative correlation between in-containment refueling water storage tank (IRWST) water temperature and automatic depressurization system (ADS) discharge coefficient has the most significant impact on failure probability, with the maximum failure probability increasing by 163% compared to the baseline case. In contrast, the positive correlation between core power and decay heat power, which is of practical engineering concern, has a limited effect on failure probability, with an increase of only 18%. The study confirms that while certain parameter couplings may significantly amplify system risk, the correlation between core power and decay heat power does not pose a serious threat to the reliability of the IRIS EHRS. This work reveals the nonlinear impact of parameter correlations on the reliability assessment of passive safety systems and provides a theoretical basis for subsequent uncertainty analysis and model simplification.

Keywords: IRIS reactor, EHRS, AM-SIS method, Failure probability, Parameter correlation, Gaussian Copula.

1 Introduction

The failure probability of passive systems is extremely low. Using crude Monte Carlo methods for reliability assessment requires drawing a large number of sample points—theoretically, approximately 1/pf samples need to be evaluated to obtain a single failure sample. However, evaluating whether a sample point leads to failure using high-fidelity thermal-hydraulic codes demands substantial computational resources. For the IRIS case studied in this paper, evaluating a single sample point takes an average of one hour of computation time. This means that the computational cost of direct Monte Carlo simulation is completely unacceptable in engineering practice.

To address this computational bottleneck, this paper employs the AM-SIS (Pedroni and Zio 2015) method to assess the reliability of passive systems. The AM-SIS method first efficiently explores the failure region through subset simulation, obtaining sample points near the failure domain. It then constructs an appropriate importance sampling density function based on these near-failure samples. Finally, importance sampling is performed to obtain the failure probability of the passive system, with an Artificial Neural Network (ANN) (Cheng et al. 2008, Cardoso et al. 2008, Pedroni et al. 2010, Zio et al. 2010) metamodel accelerating the entire process.

The above analysis is based on the assumption of independence among input parameters. However, engineering experience indicates that certain thermal-hydraulic parameters exhibit significant positive correlations. For example, core power and decay heat typically show strong correlation, as both are related to the reactor operating history. Theoretically, these correlations should be estimated through experimental data or operating history. Unfortunately, for advanced passive systems such as the IRIS EHRS, sufficient operational data are lacking to accurately estimate the dependence structure between parameters. Given this data-scarce engineering context, this paper adopts a pragmatic research strategy: systematically investigating the impact of correlation strength on failure probability by artificially introducing correlations.

Copula theory (specifically Gaussian copula) is employed to introduce dependence structures while preserving the marginal distributions of input parameters. By varying the copula parameter (i.e., the correlation coefficient ρ), a series of input samples with different correlation levels are generated. The AM-SIS method is then applied to compute the system failure probability under each correlation level, ultimately yielding a sensitivity curve of failure probability as a function of the correlation coefficient. Although this approach cannot provide precise correlation values, it can reveal

the influence patterns of correlations on system reliability, identify the sensitivity of failure probability to parameter correlations, and provide conservative or optimistic bounds for engineering design.

2 Theoretical Foundations

This chapter presents the theoretical foundations of the methods employed in this study. Section 2.1 describes the AM-SIS method, which combines subset simulation, importance sampling, and artificial neural networks to efficiently estimate the failure probability of passive systems. Section 2.2 introduces the Copula theory for modeling correlations between input parameters, with a focus on the Gaussian copula used in this work.

2.1 *AM-SIS method*

The AM-SIS method is an advanced reliability analysis technique designed to efficiently estimate small failure probabilities in complex engineering systems. It integrates three key components: subset simulation (SS) for efficient exploration of the failure region, importance sampling (IS) for accurate probability estimation, and ANN as metamodels to accelerate computational evaluations.

The AM-SIS method integrates three components in a synergistic manner:

A feedforward neural network with multiple hidden layers is adopted in this study. The network structure consists of: An input layer with neurons corresponding to the number of input parameters, Multiple hidden layers with appropriate activation functions (typically ReLU or tanh), and an output layer with a single neuron representing the system response.

1) Initialization: Start with a small initial Design of Experiments (DoE). Train an initial ANN surrogate model $\hat{G}(\boldsymbol{x})$.

2) Exploration Sampling: Execute a standard subset simulation. Then, preserve the samples from the last levels. This collection of samples $\{\mathbf{x}_{SS}^{(j)}\}$, located in the high-probability failure region, serves as the ideal input for constructing an efficient ISD.

3) Active Learning for Model Update: From the exploration samples $\{\mathbf{x}_{SS}^{(j)}\}$, select the most informative points for refining the ANN. A common criterion focuses on failure samples x (i.e., $\hat{G}(\mathbf{x}) < 0$). Evaluate the true expensive model $G(\boldsymbol{x})$ at these selected points. Augment the training set and retrain the ANN model.

4) Iteration: Repeat steps 2 and 3. This process iteratively improves the ANN's accuracy in the failure region and pushes the exploration further towards the true failure domain, analogous to progressing through the levels of Subset Simulation but at a much lower cost.

5) Construct ISD and Perform Importance Sampling: Using the failure-region samples $\{\mathbf{x}_{SS}^{(j)}\}$ obtained from the surrogate-based SS, construct the Importance Sampling Distribution:

$$h(\boldsymbol{x}) = \frac{1}{M}\sum_{m=1}^{M} \kappa(\boldsymbol{x}|\mathbf{x}_{SS}^{\mathrm{m}}). \tag{8}$$

Following the suggestion of Botev, L'Ecuyer and Tuffin (2013), in this paper we use the transition density $\kappa(\boldsymbol{x}|\mathbf{x}_{SS}^{\mathrm{m}})$ adopted by the Gibbs Sampler (Neal 1993).

6) Importance Sampling: Draw N_{IS} independent samples $\mathbf{x}_{IS}^{(j)}$ from the constructed ISD $h(\boldsymbol{x})$, for each sample, compute its performance function value $G(\mathbf{x}_{IS}^{(j)})$ and its importance weight $w^{(j)} = f(\mathbf{x}_{IS}^{(j)})/h(\mathbf{x}_{IS}^{(j)})$. Then we can compute the IS estimator for the failure probability:

$$\hat{P}_f^{AM-SIS} = \frac{1}{N_{IS}}\sum_{j=1}^{N_{IS}} I(G(\mathbf{x}_{IS}^{(j)}) \le 0)\cdot w^{(j)}. \tag{9}$$

2.2 *Correlation modeling using copula theory*

Copula theory provides a rigorous framework for constructing joint distributions with specified marginal distributions and dependence structures. The fundamental insight of Sklar's theorem (Sklar, 1959) is that any joint distribution H with continuous marginal distributions F_1 and F_2 can be uniquely represented as:

$$H(x_1, x_2) = C(F_1(x_1), F_2(x_2)). \tag{10}$$

where C: [0,1]2 is a copula function that captures the dependence structure between the variables.

2.2.1 *Sampling from a gaussian copula*

Consider the problem of generating samples from a joint distribution with prescribed marginals F_1, F_2 and a Gaussian copula dependence structure parameterized by correlation coefficient ρ. The sampling procedure proceeds as follows:

1) Generate independent samples: Draw independent samples $X_1 \sim F_1$ and $X_2 \sim F_2$. By the probability integral transform, the transformed variables follow uniform distributions:

$$U_1 = F_1(X_1) \sim U(0,1), U_2 = F_2(X_2) \sim U(0,1). \tag{11}$$

where F_1 and F_2 are the cumulative distribution function (CDF) of marginal distributions, respectively.

2) Transform to standard normal space: Apply the inverse standard normal CDF Φ^{-1} to obtain independent standard normal variables:

$$Z_1 = \Phi^{-1}(U_1) \sim N(0,1), Z_2 = \Phi^{-1}(U_2) \sim N(0,1). \tag{12}$$

3) Introduce correlation: Linearly combine the independent normal variables to obtain correlated normal variables:

$$Y_1 = Z_1, Y_2 = \rho Z_1 + \sqrt{1-\rho^2} Z_2. \tag{13}$$

The pair (Y_1, Y_2) follows a bivariate standard normal distribution with correlation coefficient ρ, i.e., $(Y_1, Y_2) \sim N(\mathbf{0}, \Sigma)$ with $\Sigma = \begin{bmatrix} 1 & \rho \\ \rho & 1 \end{bmatrix}$.

4) Transform back to original space: Apply the standard normal CDF followed by the inverse marginal CDFs to obtain correlated samples in the original space:

$$X_1^{corr} = F_1^{-1}(\Phi(Y_1)),\ X_2^{corr} = F_2^{-1}(\Phi(Y_2)). \tag{14}$$

The resulting samples (X_1^{corr}, X_2^{corr}) follow the desired joint distribution with marginals F_1, F_2 and Gaussian copula dependence parameter ρ.

2.2.2 *Parameter estimation via maximum Likelihood*

In practical applications where observational data are available, the copula parameter ρ can be estimated using maximum likelihood estimation. Given a set of n observed data pairs $\{(x_{1,i}, x_{2,i})\}_{i=1}^{n}$, the likelihood function is:

$$L(\rho) = \prod_{i=1}^{n} C_\rho(F_1(x_{1,i}), F_2(x_{2,i})) \cdot f_1(x_{1,i}) \cdot f_2(x_{2,i}). \tag{15}$$

where C_ρ is the Gaussian copula density function:

$$C_\rho(u,v) = \frac{1}{\sqrt{1-\rho^2}} exp\left(-\frac{\rho^2(z_1^2+z_2^2)-2\rho z_1 z_2}{2(1-\rho^2)} + \frac{z_1^2+z_2^2}{2}\right). \tag{16}$$

with $z_1 = \Phi^{-1}(u)$ and $z_2 = \Phi^{-1}(v)$. For computational convenience, the log-likelihood function is typically maximized:

$$\ell(\rho) = \sum_{i=1}^{n} log C_\rho(F_1(x_{1,i}), F_2(x_{2,i})) + \sum_{i=1}^{n} log f_1(x_{1,i}) + \sum_{i=1}^{n} log f_2(x_{2,i}). \tag{17}$$

Since the terms involving only the marginal densities do not depend on ρ, maximization of $\ell(\rho)$ is equivalent to maximization of the copula log-likelihood:

$$\ell_c(\rho) = \sum_{i=1}^{n} log C_\rho(F_1(x_{1,i}), F_2(x_{2,i})). \tag{18}$$

The maximum likelihood estimate $\hat{\rho}$ is then obtained by solving:

$$\hat{\rho} = \underset{\rho \in [-1,1]}{argmax} \ell_c(\rho). \tag{19}$$

3 Case study: IRIS EHRS

This section presents the IRIS EHRS case study and shows the failure probability results calculated using the AK-MCS and AM-SIS methods.

3.1 *Introduction to IRIS reactor*

The International Reactor Innovative and Secure (IRIS) is an advanced integral pressurized water reactor led by Westinghouse Electric Corporation of the United States, with joint research and development by more than ten countries and over twenty research institutions worldwide. The conceptual design of the reactor was initiated in 2001,

and the pre-licensing application process with the U.S. Nuclear Regulatory Commission (NRC) was launched in 2002. Starting from 2006, to meet the requirements of design certification, Westinghouse carried out a series of experimental verification works. After 2010, Westinghouse withdrew from the project leadership, and the subsequent R&D efforts have been mainly continued by relevant institutions in Italy, Croatia and Japan (Ricotte 2011).

The IRIS reactor is equipped with eight built-in once-through steam generators with helical tube bundles, which serve as the core components of the passive EHRS. Compared with the traditional straight tube design, the helical tube structure can better absorb thermal expansion stress and suppress flow-induced vibration, improving the reliability under transient accident conditions (Cinotti, Bruzzone, Meda, et al 2002).

IRIS features a unique integral design that integrates all major primary loop equipment, including the reactor core, control rod drive mechanisms, steam generators, main coolant pumps and pressurizer, into a single pressure vessel. This design eliminates the possibility of large break loss of coolant accidents (LBLOCA) and significantly reduces the risk of small break loss of coolant accidents (SBLOCA). Its safety systems inherit the passive safety philosophy of the AP1000, primarily relying on physical principles such as natural circulation, gravity and condensation to achieve long-term core cooling without external power supply or active intervention, thus greatly reducing the accident probability. According to the preliminary Probabilistic Risk Assessment (PRA) (Ricotte 2011), the Core Damage Frequency (CDF) of the IRIS reactor can be reduced to 1.21E-8.

3.2 *Analysis tools and models*

This study adopted the internationally recognized reactor system safety analysis code RELAP5, developed by the Idaho National Laboratory of the United States, as the high-fidelity thermal-hydraulic simulation tool. RELAP5 is capable of simulating a wide range of thermal-hydraulic transients and accidents in light water reactor systems, including various break accidents and loss of off-site power, and its models and algorithms have been extensively verified and recognized by regulatory and research institutions at home and abroad.

The RELAP5 nodalization diagram includes automatic depressurization system (ADS), EHRS, pressurizer, emergency boration tank (EBT), steam generator (SG), reactor core and so on, as shown in Figure 1.

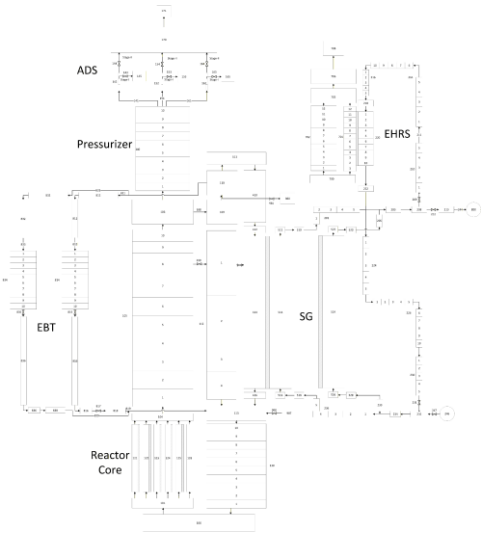

Figure 1. RELAP5 nodalization diagram of the IRIS reactor.

In the analysis, the simulation model of the IRIS reactor under SBLOCA was constructed by writing and modifying specific input cards of RELAP5 (such as pipe cards, thermal structure cards, valve cards and control system cards). During the probabilistic sampling process, random assignment of each key uncertainty parameter was realized through programmatic modification of the input card text, thus automatically generating a large number of calculation conditions reflecting parameter uncertainties, which provides a foundation for subsequent reliability analysis based on the Monte Carlo method and advanced sampling methods.

3.3 *EHRS accident analysis*

According to the preliminary probabilistic safety assessment (PSA) of IRIS (Mizuno, Ninokata and Finnicum 2005), among numerous design basis accidents, SBLOCA contributes the highest proportion to the Core Damage Frequency (CDF). In this accident sequence, the EHRS undertakes the critical safety functions of removing decay heat from the pressure vessel and depressurizing the system, and its reliability directly determines the severity of accident consequences. Therefore, it is reasonable and necessary to select SBLOCA as the reference accident for evaluating the reliability of the EHRS.

The SBLOCA scenario can be summarized as follows (Kujawski, Kitch and Conway 2002). Three main phases can be identified:

1) Discharge Phase (Phase 1): Following the initiation of LOCA, the RV depressurizes, while the Containment Vessel (CV) pressure begins to rise due to mass and energy release from the Reactor Vessel (RV). After the delay time, reactor scram and pump trip occur, and the EBT is activated to inject borated water. The EHRS is started, depressurizing the primary side by condensing steam on the secondary side of the steam generators (depressurization without mass loss), and finally the ADS is actuated to assist the EHRS in depressurizing the RV. Containment pressure is limited by the Pressure Suppression System (PSS), and the break flow is reduced due to heat removal by the EHRS (via condensation) and depressurization of the RV by ADS discharge. At the end of the discharge phase, the RV and CV pressures equalize (pressure equilibrium), with the CV pressure peak at approximately 8 barg.

2) RV/CV Depressurization Phase (Phase 2): After pressure equalization, the EHRS depressurizes the coupled RV/CV system by condensing steam within the RV. During this phase, the break flow reverses because heat is being removed from inside the vessel (via the EHRS) rather than from the containment atmosphere. The water level in the RV rises due to condensation of containment steam inside the reactor vessel and makeup water provided by the PSS. As the CV pressure decreases, a portion of the suppression pool water is expelled through the vents, helping to flood the cavity. Eventually, both RV and CV pressures are reduced to below 2 barg in less than 12 hours.

3) Long-Term Cooling Phase (Phase 3): As the core decay heat decreases, the RV and CV pressures decrease slowly. During this recovery phase of the accident, gravity makeup of borated water from the suppression pool and the reactor cavity is available as needed. Since the decay heat is removed directly from inside the vessel (via the EHRS), and the vessel and containment are thermodynamically coupled, the long-term break flow is not dependent on the core decay heat, but is in practice limited primarily by heat losses from the containment to the environment.

3.4 *Failure criteria and key uncertainty parameters*

To quantitatively evaluate the reliability of the EHRS, the system's failure criteria must be clearly defined. Based on the principle of conservatism and to ensure the computability of the analysis, the failure criterion in this study is defined as follows: the minimum hot leg collapsed liquid level in the core falls below the height of the core active region (6.08 m) during the accident progression (Ye 2019). This criterion is directly related to the functional integrity of the core fuel assemblies and is a key indicator for measuring whether the EHRS can effectively prevent core uncovering and overheating.

To ensure the quality of the reliability analysis, this study systematically identified and quantified the key uncertainty parameters affecting the SBLOCA progression and EHRS performance based on the Phenomena Identification and Ranking Table (PIRT) methodology. The PIRT analysis was completed by a diverse expert committee independent of the project, covering key fields such as nuclear safety, thermal-hydraulics and engineering design (US Nuclear Regulatory Commission (NRC) 1997). Through expert judgment, key phenomena with high importance to the accident progression but with existing uncertainties in current understanding were screened out and mapped to specific input parameters.

Based on the test data and analysis results from relevant literatures (Sallehhudin and Diab 2021), this study finally determined the key input parameters for probabilistic analysis and their probability distributions. The input uncertain parameters include core power (P_{core}), decay heat (Q_d), fuel thermal conductivity (k_f), in-containment refueling water storage tank (IRWST) water temperature (T_{IRWST}), EHRS fouling factor (ff), pressurizer pressure (P_{pzr}), ADS discharge coefficient (C_d), and ADS friction coefficient (C_f). The statistical properties of each input parameter include the mean (μ), standard deviation (σ), lower bound (LB), and the upper bound (UB). The distributional characteristics of the different input parameters are provided in Table 1.

Table 1. distributional characteristics of key input parameters.

parameters	Distribution	μ	σ	LB / μ	UB / μ
P_{core} / W	Truncated normal	1E9	1E7	0.98	1.02
Q_d / W	Truncated normal	8207426	270845	0.934	1.066
k_f / ($W \cdot m^{-1} \cdot K^{-1}$)	Uniform	5.988342		0.847	1.153
T_{IRWST} / K	Truncated normal	322	10.304	0.98	1.02
ff	Truncated normal	1	0.1965	0.936	1.064
P_{pzr} / Pa	Uniform	1.5512E7		0.607	1.393
C_d	Uniform	1		0.84	1.16
C_f	Uniform	6.3E-6		0.8	1.2

3.5 *Correlation sensitivity of reliability of IRIS EHRS case*

First, based on the AM-SIS method, the failure probability of the IRIS EHRS case was calculated to be $\hat{P}_f$=0.02955. To investigate the sensitivity of this failure probability to the correlation among input parameters, this paper introduces the Gaussian Copula function to impose a correlation structure on all dimensional combinations of the eight input

parameters. By varying the magnitude of the correlation coefficients, input samples with different correlation strengths can be generated, and Monte Carlo simulations are performed based on these samples to calculate the corresponding failure probabilities. It is worth noting that, to avoid repeating the complete adaptive sampling process of AM-SIS, the already trained surrogate model is directly used for prediction here. To simplify the analysis, this paper only considers the correlation combinations between pairs of parameters. The resulting sensitivity curve of the failure probability to changes in correlation is shown in Figure 1.

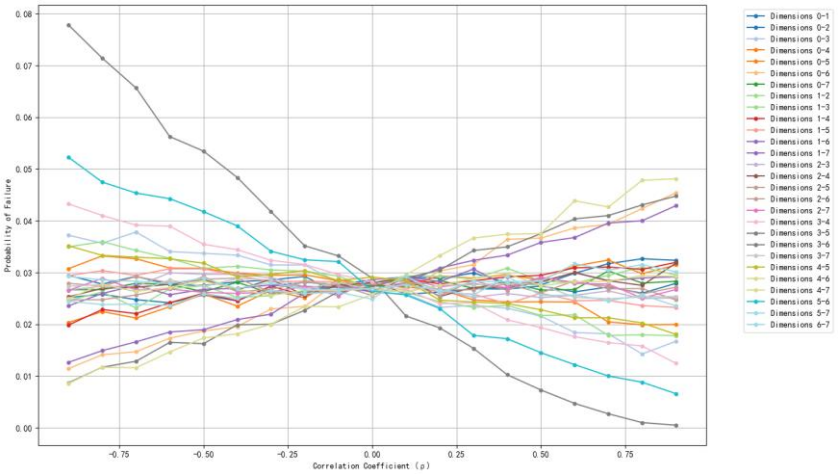

Figure 1. Variation of failure probability with correlation coefficient under different input parameter combinations.

Based on the failure probability sensitivity curves with respect to correlation shown in Figure 1, the maximum failure probability $\hat{P}_f^{max}$ for each parameter combination can be identified. The results indicate that among all considered parameter combinations, the combination of IRWST water temperature and ADS discharge coefficient (T_{IRWST} and C_d) exhibits the most significant maximum failure probability. Compared to the baseline failure probability $\hat{P}_f$=0.02955, which is calculated without considering correlations, the $\hat{P}_f^{max}$ for this combination increases by 186%. Table 2 lists the top ten input parameter combinations with the largest $\hat{P}_f^{max}$ values.

Notably, this maximum failure probability occurs under the condition of a negative correlation between T_{IRWST} and Cd. From a physical mechanism perspective, a higher IRWST water temperature increases the saturation vapor pressure within the tank, thereby suppressing the discharge capacity of the ADS line (i.e., reducing the discharge differential pressure). Meanwhile, C_d, as a coefficient representing the actual flow efficiency of the ADS valve, has a smaller value indicating lower valve discharge performance. When the two parameters are negatively correlated, the scenario where "higher IRWST temperature coincides with lower ADS discharge efficiency" is simultaneously amplified. This coupled effect significantly weakens the primary system depressurization capability during an accident, subsequently leading to degraded core cooling and a substantial increase in failure probability.

Regarding the physical plausibility of such a negative correlation, it is important to clarify that T_{IRWST} and C_d are governed by fundamentally distinct physical processes. T_{IRWST} is primarily determined by the thermal-hydraulic transients within the containment and the operational status of the IRWST cooling system, while C_d is an inherent design characteristic of the ADS valves, typically fixed by valve geometry and manufacturing tolerances. Under normal operating conditions, these two parameters are generally independent, as there is no direct physical mechanism that would cause higher IRWST temperatures to systematically coincide with lower valve discharge coefficients. However, if long-term degradation mechanisms—such as fouling, corrosion, or common-cause aging effects—were to simultaneously impair both the IRWST cooling performance and the ADS valve flow characteristics, a weak coupling could theoretically emerge. Nevertheless, for the purposes of this sensitivity analysis, the negative correlation considered here represents a hypothetical scenario constructed to investigate the impact of parameter dependence on failure probability, rather than a claim of an empirically observed or physically inherent correlation.

From an engineering perspective, the parameter combination of greater practical concern is core power and decay heat power, as operating experience indicates a positive correlation between these two parameters. According to the results shown in Figure 1, the maximum failure probability $\hat{P}_f^{max}$ for the combination of core power and decay heat power increases by 18% compared to the baseline case without correlation.

Physically, this positive correlation is inherently reasonable: core power determines the fuel burnup and fission product inventory accumulated during operation, which directly governs the decay heat power following reactor shutdown. A higher core power level leads to greater energy stored in the fuel and a larger inventory of radioactive isotopes, resulting in higher decay heat levels after scram. When these two parameters are positively correlated—meaning that a high-power operating condition is simultaneously accompanied by high decay heat—the thermal load

on the emergency core cooling system during an accident is intensified. This increased decay heat imposes a greater challenge for long-term heat removal, potentially prolongating the reflooding phase and elevating the risk of core overheating. Although the 18% increase in failure probability is relatively modest compared to other parameter combinations, it underscores the importance of accurately capturing the physical coupling between core power and decay heat in realistic risk assessments.

Table 2 Top ten input parameter combinations ranked by maximum failure probability $\hat{P}_f^{max}$

Parameters one	Parameters two	$\hat{P}_f^{max}$	$\hat{P}_f^{max}/\hat{P}_f$
T_{IRWST}	C_d	0.0778	186%
P_{pzr}	C_d	0.05225	92%
ff	C_d	0.0481	77%
P_{core}	C_d	0.0454	67%
T_{IRWST}	P_{pzr}	0.04475	64%
T_{IRWST}	ff	0.04325	59%
Q_d	C_d	0.0429	58%
P_{core}	T_{IRWST}	0.0372	37%
Q_d	T_{IRWST}	0.03595	32%
ff	P_{pzr}	0.03515	29%

4 Conclusion

This paper employs the AM-SIS method to calculate the failure probability of the IRIS EHRS. Given the absence of sufficient empirical data to characterize the correlations among input parameters, this study introduces artificially assumed correlation structures using Gaussian Copula functions. By varying the correlation coefficients across all pairwise combinations of eight key input parameters, the sensitivity of the system failure probability to parameter dependencies is systematically investigated.

The results reveal that the impact of parameter correlations on failure probability varies significantly depending on the specific parameter pair and the direction of correlation. Among all combinations, the negative correlation between IRWST water temperature and the ADS discharge coefficient exhibits the most pronounced effect, with the maximum failure probability increasing by 163% compared to the baseline case where no correlation is considered. This significant increase is attributed to the coupled degradation of both the driving force for depressurization and the discharge capacity, which collectively impair the primary system depressurization capability and subsequent core cooling.

In contrast, the positive correlation between core power and decay heat power—a parameter combination of particular practical concern due to engineering experience—results in a relatively modest increase of only 18% in the maximum failure probability. From a physical perspective, this positive correlation is inherently reasonable, as higher core power leads to greater fuel burnup and fission product inventory, which directly governs the decay heat level after reactor scram. However, the results indicate that even when this positive correlation is considered, its effect on the overall reliability of the IRIS EHRS remains limited. This suggests that, within the range of correlations examined, the coupling between core power and decay heat power does not pose a significant threat to system performance.

The findings of this study have important implications for reliability assessment and model simplification. First, they highlight the necessity of accurately capturing certain critical parameter correlations—such as that between IRWST water temperature and ADS discharge coefficient—where the risk amplification effect is substantial. Second, they provide justification for potentially neglecting the correlation between core power and decay heat power in future analyses, thereby reducing the complexity of input parameter modeling without compromising the accuracy of reliability predictions. Overall, this work demonstrates that the influence of parameter correlations on passive system reliability is highly nonlinear and pair-specific, underscoring the value of sensitivity analysis in identifying dominant risk contributors.

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