Reliability Analysis of Lead-Bismuth Cooled Passive Systems Based on Adaptive Collaborative Kriging Surrogate Model

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Abstract

Lead-bismuth cooled passive systems play a crucial role in the safe operation of reactors. However, due to various uncertainty factors present in reactors, including small driving forces, large fluctuations in design parameters, and high uncertainties in initial conditions, thermal-hydraulic processes may fail, thereby affecting the normal realization of system functions. Therefore, conducting reliability analysis of lead-bismuth cooled passive systems represents a critical step in ensuring their effectiveness and safety. This paper first presents an in-depth study of the adaptive importance sampling method and the collaborative Kriging model. Subsequently, verification for both single and multiple failure regions is performed on the constructed adaptive collaborative Kriging surrogate model. Finally, this paper systematically discusses the sensitivity analysis and reliability analysis of the TALL-3D passive system. The research results demonstrate that the combination of adaptive collaborative Kriging surrogate models yields more accurate failure probability estimation compared to traditional Monte Carlo analysis methods, significantly improving simulation efficiency. This method reduces computations in unnecessary regions by optimizing the sample selection strategy, enhances the exploration capability of limit state functions, and thereby substantially reduces the computational effort required for reliability analysis of complex systems. Furthermore, adaptive importance sampling demonstrates excellent performance in high-dimensional parameter spaces, can flexibly adapt to different sample requirements, and ensures more intensive sample collection in critical failure regions. This characteristic endows the proposed method with strong implementability and advantages, and can provide robust technical support for the application of lead-bismuth cooled passive systems.

Full Text

Reliability Analysis of Lead-Bismuth Cooled Passive System Based on Adaptive CoKriging Surrogate Model

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Abstract

Lead-bismuth cooled passive systems play a vital role in the safe operation of nuclear reactors. However, numerous uncertainty factors exist in reactor environments, including small driving forces, large fluctuations in design parameters, and high uncertainties in initial conditions, which may lead to thermal-hydraulic process failures and affect normal system function realization. Therefore, conducting reliability analysis of lead-bismuth cooled passive systems represents a critical step in ensuring their effectiveness and safety. This paper first presents an in-depth study of adaptive importance sampling methods and collaborative Kriging models. Subsequently, verification of the constructed adaptive CoKriging surrogate model is performed for both single and multiple failure regions. Finally, systematic discussions are presented on sensitivity analysis and reliability analysis of the TALL-3D passive system in a liquid lead-bismuth cooled thermal-hydraulic experimental platform. Research results demonstrate that the combination of adaptive CoKriging surrogate models provides more accurate failure probability estimation compared to traditional Monte Carlo analysis methods while significantly improving simulation efficiency. By optimizing sample selection strategies, this method reduces unnecessary computational regions, enhances exploration capability of limit state functions, and substantially decreases the computational requirements for reliability analysis of complex systems. Furthermore, adaptive importance sampling exhibits excellent performance in high-dimensional parameter spaces, flexibly adapting to different sample requirements and ensuring more intensive sample collection in critical failure regions. This characteristic endows the proposed method with strong feasibility and advantages, providing robust technical support for the application of lead-bismuth cooled passive systems.

Keywords: Adaptive collaborative Kriging; Surrogate model; Lead-bismuth cooled fast reactor; Passive cooling system; Reliability analysis

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As one of the six reactor types recommended by the Generation IV International Forum, lead-bismuth cooled fast reactors impose higher requirements on inherent reactor safety. To enhance reactor safety, lead-bismuth cooled fast reactors widely adopt passive systems. However, passive systems face numerous uncertainty factors that may cause thermal-hydraulic process failures and prevent the system from achieving its designed functions, such as small driving forces, large fluctuations in design parameters, and high uncertainties in initial conditions. Therefore, establishing surrogate models for lead-cooled fast reactor passive systems to conduct thermal-hydraulic reliability assessments and enhance understanding of uncertainties in system thermal-hydraulic processes holds significant importance [1-2].

In recent years, domestic research in reliability analysis has conducted a series of important studies on surrogate models. Li Yu [3] employed classical Monte Carlo sampling and Latin Hypercube Sampling (LHS) techniques. Traditional Monte Carlo sampling suffers from low efficiency in high-dimensional spaces due to its high computational complexity. Although LHS improves sample distribution, it may still face challenges where sample sizes are insufficient to adequately represent global characteristics when dealing with highly nonlinear problems. Additionally, Wang Xiaoye et al. [4] proposed a structural reliability analysis method based on active learning Kriging models, constructed a new learning function (Extended U, EU), and combined it with LHS and Monte Carlo Sampling (MCS) to significantly improve analysis accuracy and efficiency in numerical simulations and practical engineering applications. However, active learning Kriging models may exhibit bias in sample selection processes, and if initial samples fail to adequately cover the sample space, the reliability and accuracy of final results will be affected. Zhou Chengning et al. [5] proposed a series of structural reliability analysis methods based on Kriging models, including adaptive analysis with integrated learning functions under random uncertainty, improved sampling strategies, and small failure probability analysis with convergence criteria. These studies significantly improved the accuracy and efficiency of various reliability analyses. However, despite proposing multiple integrated learning methods for Kriging models, computational complexity and dependence on data sufficiency remain significant challenges when addressing high-dimensional random uncertainties, limiting their widespread application in practical engineering.

Overall, although traditional Kriging models and learning functions have achieved progressive results in practical applications, they still exhibit significant limitations such as high computational cost, strong data sensitivity, and insufficient adaptability to complex nonlinear problems [6-7]. These limitations suggest that future research must further explore efficient and flexible surrogate models to address the complexity and uncertainty in real-world engineering.

This paper takes the TALL-3D system as the research object and constructs an efficient and accurate reliability assessment framework for lead-bismuth cooled passive systems. First, the ATHLET software is used to simulate its thermal-hydraulic characteristics under station blackout conditions to reveal the system' s dynamic response characteristics. Next, the Extreme Gradient Boosting (XGBoost) model is employed for feature selection to identify key parameters with significant impact on system reliability, thereby reducing computational complexity. Subsequently, adaptive importance sampling methods are adopted to optimize sample extraction of key parameters, improving sample utilization efficiency and reducing computational cost. Finally, the CoKriging model is combined for efficient modeling, integrating information from primary and auxiliary models to improve failure probability prediction accuracy, and Bayesian updating is used to dynamically adjust the model and enhance its adaptability.

1.1 Cokriging

In spatial statistics and geographic information science, data interpolation and prediction are key components. Traditional Kriging methods primarily model spatial correlations for single variables, relying on high-fidelity data for predictions. However, practical applications often face the challenge of scarce high-fidelity data, which limits the effectiveness of Kriging models. To address this issue, the CoKriging method was developed. CoKriging can simultaneously integrate information from multiple correlated variables, thereby providing more accurate prediction results in scenarios where high-fidelity and low-fidelity data coexist [8-9].

CoKriging is an extended Kriging method applicable to situations considering multiple variables simultaneously. In CoKriging models, two variables are typically introduced: high-fidelity variable Y_H and low-fidelity variable Y_L. These two variables often exhibit certain spatial correlations, and utilizing observations from low-fidelity data can improve the prediction accuracy of high-fidelity variables. The CoKriging prediction formula is:

$$\hat{y}_H(s^*) = \mu_H + r^T R^{-1} y$$

where $\hat{y}_H(s^*)$ is the predicted value of the high-fidelity variable at location s^*, μ_H is the mean of the high-fidelity variable, y is the joint response vector including observations of both high-fidelity and low-fidelity variables, R is the joint covariance matrix constructed from covariances between high-fidelity and low-fidelity data, and r is the covariance vector between the high-fidelity variable and prediction points.

The construction of the joint covariance matrix R is key to the CoKriging method. Setting the high-fidelity data covariance matrix as R_{11}, low-fidelity data covariance matrix as R_{22}, and the cross-covariance matrix between high- and low-fidelity data as R_{12}, the joint covariance matrix can be expressed as:

$$R = \begin{bmatrix} R_{11} & R_{12} \\ R_{12}^T & R_{22} \end{bmatrix}$$

The main advantage of CoKriging models lies in improving the prediction accuracy of high-fidelity variables. By introducing low-fidelity data, the model can effectively reduce uncertainty and achieve more accurate predictions. The spatial correlation between low- and high-fidelity variables enables low-fidelity data, even with lower precision, to provide valuable information and improve the prediction performance of high-fidelity variables. Selecting appropriate covariance functions (such as exponential or spherical) is crucial for capturing spatial correlations between high- and low-fidelity variables, typically involving precise parameter estimation through methods like maximum likelihood estimation and least squares. The prediction variance of CoKriging models can be expressed as:

$$\mathrm{Var}[\hat{y}_H(s^*)] = C(s^*, s^*) - r^T R^{-1} r$$

where $C(s^*, s^*)$ is the autocovariance at the prediction location, and $r^T R^{-1} r$ is the correction term calculated through the joint covariance matrix. This formula demonstrates that jointly considering low-fidelity data can effectively reduce prediction uncertainty and improve model accuracy. After model establishment, validating the model using methods like cross-validation is essential. By evaluating model performance across different regions and scenarios, the robustness of its predictive capability can be determined. If prediction errors are found to be large, model parameters can be adjusted or covariance functions modified to optimize prediction results.

In CoKriging models, parameter estimation is a critical step to ensure model effectiveness. Constructing the design matrix F containing the model' s basis functions can capture the basic trends in the data. Maximum likelihood estimation of model parameters can be achieved through the following formula:

$$\hat{\beta} = (F^T R^{-1} F)^{-1} F^T R^{-1} y$$

Optimization of covariance function parameters is equally important, as their form and parameters directly affect model prediction performance. Numerical optimization methods (such as Newton' s method) are required to estimate covariance function parameters, with the objective of maximizing the likelihood function:

$$\ln L(\theta) = -\frac{1}{2}\ln|R| - \frac{1}{2}(y - F\beta)^T R^{-1}(y - F\beta)$$

where $|R|$ is the determinant of the joint covariance matrix, reflecting model complexity and uncertainty. After completing parameter estimation and model establishment, evaluating model prediction performance through cross-validation and other methods is crucial. If model prediction results are unsatisfactory, the selection of covariance functions should be re-examined or model parameters adjusted to ensure model validity and accuracy. CoKriging provides a powerful tool for prediction problems in complex scenarios, significantly improving spatial interpolation accuracy by integrating multi-source data.

1.2 Adaptive Importance Sampling

Importance sampling is a statistical method for estimating expectations under a distribution [10-12]. Its basic idea is to sample from an easily-sampled proposal distribution and use these samples to weight the target distribution, thereby estimating the target distribution' s expectation. Given target distribution $p(x)$ and proposal distribution $q(x)$, the basic importance sampling formula is:

$$E[f(x)] = \int f(x)\frac{p(x)}{q(x)}q(x)dx \approx \frac{1}{N}\sum_{i=1}^{N} f(x_i)\frac{p(x_i)}{q(x_i)}$$

where x_i are samples drawn from proposal distribution $q(x)$, and $f(x)$ is the function to be estimated. In practical engineering problems, failure probabilities are typically small, causing most sample points from conventional Monte Carlo simulation to fall within the safe domain. To increase sample points in the failure domain, sample sizes often need to be expanded, which greatly reduces computational efficiency. To address this issue, adaptive importance sampling methods are introduced. These methods obtain information by training importance sampling models to determine sample point locations for the next iteration, gradually introducing more sample points to increase the occurrence probability of small-probability events. This process helps reduce the coefficient of variation of failure probability and improve sampling efficiency. To intuitively demonstrate the sampling efficiency of adaptive importance sampling, a schematic diagram is shown in [Figure 2: see original paper].

The basic steps of adaptive importance sampling are as follows:

Step 1. Initialization: Select an initial proposal distribution $q(x)$, typically set as a distribution similar to the target distribution.

Step 2. Sampling: Draw N samples from proposal distribution $q(x)$.

Step 3. Weight Calculation: Calculate the weight for each sample: $w_i = \frac{p(x_i)}{q(x_i)}$.

Step 4. Update Proposal Distribution: Update the parameters (mean and variance) of the proposal distribution based on sample weights, making the proposal distribution better fit the target distribution.

Step 5. Convergence Check: Determine whether the current proposal distribution has converged. If not, repeat Steps 2 through 4.

Through the above process, this integrated CoKriging model and data acquisition reliability analysis method not only improves analysis efficiency but also significantly enhances the accuracy of failure probability assessment, providing strong technical support for safety evaluation of nuclear power plants and other complex systems.

1.3 Reliability Calculation Process

In modern engineering fields, particularly reliability analysis of nuclear safety systems, accurately assessing system failure probability is crucial [13]. To this end, this paper proposes a reliability analysis method based on establishing an adaptive CoKriging surrogate model. This method improves the efficiency and accuracy of failure probability calculation by optimizing sample selection and model construction processes. The specific procedure is as follows:

(1) **LHS Sampling to Construct Candidate Sample Pool:** Latin Hypercube Sampling (LHS) method is used to generate a candidate sample pool $(X_1, X_2, ..., X_{N_{mc}})$, where each sample point x_i contains values of D random variables, ensuring representativeness in high-dimensional space through uniform distribution.

(2) **Importance Sampling to Construct Initial Design of Experiments (DOE) and Calculate True Response Values:** Importance sampling technique is used to construct the initial DOE with n sample points, and the true response value $G(x_i)$ (where $i = 1, 2, ..., n$, and n is the number of initial sample points) is calculated for each sample. True response values are obtained through physical models or numerical simulations.

(3) **Construct CoKriging Model:** Using sample data $(X_{DOE}, G(X_{DOE}))$ obtained from Step 2, a CoKriging model is established. The predicted mean $\hat{G}(x)$ and standard deviation $\sigma(x)$ for all points in the candidate sample pool are calculated by selecting appropriate covariance functions to describe spatial correlations between variables.

(4) **Define Prior Distribution and Calculate Likelihood Function:** Define prior distribution $P(\theta)$ and calculate likelihood function $L(y|\theta)$, describing the probability of observing data y given parameters θ.

(5) **Update Parameter Distribution Using Bayes' Theorem:** Bayes' theorem is used to combine prior distribution with observed data to obtain posterior distribution $P(\theta|y)$.

(6) **Monte Carlo Simulation to Calculate Failure Probability:** Monte Carlo simulation method is applied to calculate system failure probability P_f. Using a large number of random samples $(X_1, X_2, ..., X_{sim})$, system performance under different conditions is evaluated. The failure probability calculation formula is:

$$\hat{P}_f = \frac{1}{N_{sim}} \sum_{i=1}^{N_{sim}} I[G(x_i)]$$

where $I[G(x)]$ is the failure indicator function, with $I[G(x)] = 1$ when $G(x) \leq 0$ (failure domain) and $I[G(x)] = 0$ when $G(x) > 0$ (safe domain).

(7) **Check if Failure Probability is Below 0.001:** By comparing the calculated failure probability $\hat{P}_f$ with the threshold $\varepsilon = 0.001$, if $\hat{P}_f < \varepsilon$, the system design is considered reliable.

(8) **Output Failure Probability:** Based on calculation results, output the failure probability $\hat{P}_f$.

Through the above process, this integrated CoKriging model and data acquisition reliability analysis method not only improves analysis efficiency but also significantly enhances the accuracy of failure probability assessment, providing strong technical support for safety evaluation of nuclear power plants and other complex systems.

[Figure 1: see original paper] Flow chart of adaptive agent model

2.1 Single Failure Region Verification

Functional failure of passive systems belongs to small-probability events, with failure regions typically far from design targets, leading to low efficiency of traditional reliability analysis methods [14]. To evaluate the performance of the new algorithm, this paper selects a two-dimensional example function with similar characteristics. This function sets a single failure region with a small failure probability. The example function expression is:

$$G(x) = \text{[function expression not fully provided in original]}$$

In this expression, x_1 and x_2 are independent random variables following standard normal distribution. This function can effectively test the new algorithm' s performance in handling small failure probability events.

As shown in the example diagram [Figure 2: see original paper], adaptive importance sampling method is introduced as an advanced sampling technique to improve simulation efficiency for small-probability events. This method obtains valuable information from existing sample data by training importance sampling models to determine sample point locations for the next iteration. This process aims to gradually introduce more sample points, thereby significantly increasing the occurrence probability of small-probability events and enhancing the model's ability to capture failure regions. The core advantage of adaptive importance sampling lies in its ability to effectively reduce the coefficient of variation of failure probability, thereby improving overall sampling efficiency. By precisely locating sample points near failure regions, this method can better reflect the true system behavior and reduce uncertainty.

[Figure 2: see original paper] Adaptive importance sampling schematic diagram

2.2 Multi-Failure Region Verification

The Rastrigin function is a highly nonlinear function with multiple discontinuous failure regions [15]. This paper uses this function for testing to evaluate performance in handling multi-failure region problems. Its mathematical expression is:

$$G(x) = \sum_{i=1}^{d} \left[x_i^2 - 10\cos(2\pi x_i) + 10 \right]$$

where variables x follow standard normal distribution. [Figure 3: see original paper] shows the results of adaptive importance sampling method in solving complex optimization problems compared with the true distribution of the Rastrigin function. In traditional Monte Carlo simulation, sample points uniformly cover the entire sample space through random methods. Although this method has the advantage of simplicity and easy implementation, when facing complex functions, it often leads to excessive concentration of sample points in non-failure regions. This phenomenon makes failure risk estimation less accurate because important failure regions may not be adequately explored, affecting the reliability of analysis results. Additionally, Monte Carlo methods typically require large sample sizes, and computational costs increase accordingly, which may become an important limiting factor in practical applications.

In contrast, adaptive importance sampling methods intelligently adjust sampling strategies by incorporating feedback information from current samples. This approach not only focuses more effectively on regions near limit state functions but also performs more sampling where prediction variance is large. This strategy makes sample selection more targeted, thereby improving the effectiveness and representativeness of sample points.

(a) True distribution of Rastrigin function

(b) Adaptive model sampling results
[Figure 3: see original paper] True distribution of Rastrigin function and adaptive importance sampling results

3.1 Thermal-Hydraulic Model

Taking the TALL-3D passive system as the analysis object and using the ATHLET program as the model, this study investigates the functional failure probability of the system under station blackout accident conditions. The TALL-3D node diagram is shown below. After a station blackout accident, the TALL-3D system will be automatically activated by natural circulation and gravity to effectively remove residual heat from the reactor without requiring external power. The system transfers residual heat through heat exchangers to the cooling medium, reducing reactor temperature. When the accident occurs, the cooling medium flows naturally due to temperature increases, removing generated residual heat and ensuring safe reactor cooling. This passive characteristic provides additional safety assurance for nuclear power plants to maintain safe states under extreme conditions [16].

[Figure 4: see original paper] TALL-3D node chart

During operation of this model system, the main heater power is set to 2 kW, while the 3D test section heater power is set to 5 kW. Since pressure loss information for certain key components (such as rotary mass flow meters and ball valves) is not yet clear in experiments, the main pump pressure has been adjusted accordingly. This adjustment ensures that the main pump can effectively control forced circulation in the main pipeline of the heat exchanger, maintaining the working fluid mass flow rate at the set value of 4.8 kg/s. details the operating condition time sequence for this example case to provide clear operational information.

After model establishment, qualitative validation was performed to confirm program correctness and reliability. In this phase, by comparing model output results with experimental data, the basic functionality and structural rationality of the model were demonstrated, laying a solid foundation for subsequent research. Based on this model, more complex reactor thermal-hydraulic models with variable control systems can be further constructed to explore and analyze system performance under different operating conditions. Parameters obtained through steady-state calculations will provide deeper verification and support for program accuracy.

Model Condition Time Series

[Figure 5: see original paper] shows mass flow rate variations in three pipe sections: heat exchanger pipe section, main heater pipe section, and 3D test section. Calculation results indicate mass flow rates of 2.64 kg/s and 2.16 kg/s in the main heater and 3D test section legs, respectively, which are very close to the expected experimental values of 2.6 kg/s and 2.1 kg/s.

[Figure 5: see original paper] Experimental results of flow rate variations in three pipe sections of TALL-3D

[Figure 6: see original paper] shows flow rate variations in the heat exchanger pipe section, main heater pipe section, and 3D test section from the ATHLET model. The steady-state values calculated in the ATHLET model are 2.65 kg/s and 2.13 kg/s, respectively, with a total flow rate of 4.79 kg/s.

[Figure 6: see original paper] ATHLET simulation results for flow rate variations in three pipe sections of the TALL-3D model

The flow stability comparison shown in the above figures is detailed in . Through data analysis, flow errors are found to be below 3%, indicating the correctness of benchmark problem construction and model reliability. The error range of less than 3% demonstrates high consistency between model design and calculations, effectively reflecting actual system operating characteristics and dynamic behavior.

Flow Comparison

3.2 Failure Criterion

Many nuclear power plant operation and accident analyses have shown that when coolant flow rate decreases to a certain critical value, system cooling efficiency significantly declines. This phenomenon has been confirmed in multiple historical accident cases, particularly when cooling systems fail or have insufficient flow, reactor safety is severely threatened. Through in-depth analysis of extensive related research and historical accident data, researchers have found that when coolant flow rate drops below 90% of its rated flow, cooling capacity insufficiency often occurs, posing potential risks to reactor operational safety. Therefore, based on these historical lessons and research results, this paper adopts flow rate below 90% of rated flow as the failure state criterion [14]. This setting aims to ensure that the reactor can maintain certain cooling capacity under extreme conditions, thereby effectively reducing potential safety risks. Specifically, when coolant flow rate drops to this critical level, operators can take timely measures such as adjusting the cooling system or increasing flow rate to prevent further decline in cooling capacity. Additionally, this standard provides a clear reference basis for nuclear power plant operation monitoring and safety assessment, helping operators enhance monitoring of cooling system status in daily management and improve overall safety.

3.3 Key Parameter Selection

In reliability analysis of the TALL-3D natural circulation system, selection of key uncertainty parameters and application of effective analysis methods are fundamental to ensuring research result reliability and accuracy. This paper comprehensively elaborates this process by combining uncertainty parameter selection, XGBoost model feature importance evaluation, and subsequent reliability analysis.

In this study, ten key uncertainty parameters X_1 to X_{10} were selected for the TALL-3D natural circulation system. These parameters cover the system's main operating characteristics and design performance, having significant impacts on natural circulation process stability and safety. Specific parameter information is as follows:

Uncertainty parameter distribution

After analyzing the above ten parameters, the XGBoost model was applied for feature importance evaluation. The influence degree of each uncertainty parameter on main flow rate is shown in the figure below. Ultimately, five key parameters with significant impact on system performance were selected: expansion pressure, secondary side inlet flow rate, heat exchanger secondary side temperature, secondary side exchanger inlet/outlet boundary, and primary loop width.

[Figure 7: see original paper] Influence degree chart of each parameter

Using the above five parameters, an XGBoost model was constructed, trained on the training set, and optimized through cross-validation. The feature importance function of XGBoost was utilized to evaluate the influence degree of each parameter on system performance, ensuring selected parameters have significant impact on system reliability analysis. Model output results will be used to analyze the effects of different parameter variations on natural circulation system performance, providing support for subsequent reliability analysis. Through these steps, key parameters affecting TALL-3D natural circulation system performance can be effectively identified, forming the basis for in-depth reliability analysis. This process will combine simulation and experimental data to further validate model effectiveness.

3.4 Results Analysis

In nuclear power plant safety assessment, accurately calculating system failure probability is a critical safety component. For the TALL-3D natural circulation system, the target is to control system failure probability at the order of 10^{-4} to ensure reliable cooling capacity under various extreme conditions. Traditional failure probability calculation methods, particularly Monte Carlo methods, although widely used in complex system analysis, require 10^5 to 10^6 simulations, which are time-consuming and demanding on computational resources. The method used in this paper achieves the same failure probability estimation accuracy with only 1,078 simulations through effective application and optimization of surrogate models. Surrogate models can capture system nonlinear characteristics on smaller sample sets, and combining them with CoKriging methods significantly improves prediction accuracy, enabling rapid convergence of failure probability calculations to true values and avoiding redundant computations.

This paper focuses on reliability analysis of the TALL-3D passive system. First, adaptive importance sampling methods and CoKriging models were systematically investigated, and an adaptive CoKriging surrogate model was established by combining Bayesian updating techniques. During model validation, single and multiple failure region tests were conducted to ensure model reliability. Additionally, the XGBoost algorithm was used to screen key parameters, identify factors with significant impact on system performance, and conduct sensitivity analysis of the passive system to quantify these parameters' effects on overall performance. Finally, comprehensive evaluation of system failure probability under multiple uncertainty factors demonstrated that the model significantly improves both accuracy of failure probability assessment and computational efficiency.

1) This paper obtained detailed system response data by using ATHLET software to simulate dynamic responses of the TALL-3D passive system. Based on this data, the XGBoost algorithm was applied to screen key parameters and identify factors with significant impact on system performance. Subsequently, an efficient adaptive CoKriging surrogate model was established by combining adaptive importance sampling and Bayesian updating techniques based on the CoKriging model. This model design enables more accurate failure probability assessment with significantly improved computational efficiency. Compared with traditional Monte Carlo methods, the proposed method requires only 1,078 simulations to achieve the same accuracy, greatly reducing computational resource consumption.

2) The adaptive importance sampling technique used in this paper optimizes the sample selection process, enabling the model to more effectively concentrate on regions with greater impact on failure probability and improving computational efficiency. Meanwhile, the CoKriging model enhances prediction capability and interpolation accuracy, enabling effective output in high-dimensional parameter spaces. Additionally, the introduction of Bayesian updating mechanisms allows the model to be dynamically adjusted based on newly obtained data, further improving its adaptability and reliability. These advantages collectively ensure the accuracy of failure probability estimation, providing strong support for safety evaluation of the TALL-3D system.

The adaptive CoKriging surrogate model proposed in this paper demonstrates superior adaptability and flexibility, particularly in high-dimensional parameter spaces, where it can effectively identify key parameters affecting system performance. This provides a basis for dynamic model adjustment, enabling continuous optimization under constantly updated data and thereby improving prediction capability for system failure mechanisms. The method of this study can be further extended to other complex engineering systems, especially large facilities requiring real-time monitoring and safety evaluation. Furthermore, by combining with the latest machine learning technologies, future research will focus on enhancing model intelligence and automation levels to better address increasingly complex safety challenges.

Author Contributions

ZENG Youwei: Drafted the manuscript and collected data. LI Feiyang: Assisted in program development. ZHAO Pengcheng: Responsible for overall research design, guidance, funding acquisition, and administrative support. LIU Zijing: Analyzed data. LI Wei: Proofread the manuscript.

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