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Dynamic Probabilistic Risk Assessment of Nuclear Power Plants Using Multi-Fidelity Simulations

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Abstract

Dynamic probabilistic risk assessment (PRA) more explicitly treats timing issues and stochastic elements of risk models. It extensively resorts to iterative simulations of accident progressions for the quantification of risk triplets including accident scenarios, probabilities and consequences. Dynamic PRA leverages the level of detail for risk modeling while intricately increases computational complexities, which result in heavy computational cost. This paper proposes to apply multi-fidelity simulations for a cost-effective dynamic PRA. It applies and improves the multi-fidelity importance sampling (MFIS) algorithm to generate cost-effective samples of nuclear reactor accident sequences. Sampled accident sequences are simulated in a parallel manner by using mechanistic codes, which is treated as a high-fidelity model. Adaptively trained by using the high-fidelity data, low-fidelity model is used to predicting simulation results. Interested predictions with reactor core damages are sorted out to build the density function of the biased distribution for importance sampling. After when collect enough number of high-fidelity data, risk triplets can be estimated. By solving a demonstration problem and a practical PRA problem by using MELCOR 2.2, the approach has been proven to be effective for risk assessment. Comparing with previous studies, the proposed multi-fidelity approach provides comparative estimation of risk triplets, while significantly reduces computational cost.

Keywords: Dynamic probabilistic risk assessment, Risk triplet, Multi-fidelity importance sampling, MELCOR 2.2, Surrogate model, Machine learning

1 Introduction

Nuclear power plants (NPPs) produce radioactive fission products in the reactor core in normal operations and may release them to the environment, also known as source terms, during core-melt accidents. The NPP's risk is, therefore, assessed from the viewpoints related with core-damage or source term, and its management is required by stringent regulations. The NPP's risk management is based on two concepts; defense-in-depth (DiD) and probabilistic risk assessment (PRA). The DiD assumes multiple levels of incidents corresponding to their frequency and consequence, and requires best-effort countermeasures for each level, which are independent to those for other levels. In contrast, the PRA overviews the plant vulnerabilities in all the levels of incidents as well as in the comprehensive plant systems. Results of the PRA can be used to improve the DiD and to determine the most effective resource distribution among the safety systems and components in the plant [1]. PRA is a complementary means of deterministic analysis to provide a comprehensive view of the overall safety of the plant for the entire frequency-consequence spectrum. A nuclear power plant PRA analyzes the risk associated with operating the plant, expressed in terms of various metrics related to the different levels of damage to the plant and its environment, for example, core damage frequency (CDF) as a surrogate for latent cancer risk and large early release frequency (LERF) as a surrogate for prompt fatality risk [2].

However, it is acknowledged that some residual risks will remain [3]. Low-frequency and high-consequence severe accidents still threaten the safety of the public and environment. Estimation of accident frequency and consequence inevitably includes uncertainties using present PRA approaches. By explicitly modeling system dynamics via simulations, dynamic PRA approaches can allow a comprehensive uncertainty analysis and take into account the impact of physics as well as time-dependent failures. However, the computational cost and simulation speed of dynamic PRA is still a challenging problem to prohibit its practicability [4].

This paper applied a multi-fidelity simulation method for the estimation of risk triplets in dynamic RPA of nuclear power plants. Specifically, the authors proposed an adaptive multi-fidelity importance sampling (AMFIS) algorithm for alleviating computational cost and applied the method to a practical PRA problem. In this section, backgrounds are provided for better readability, including brief introductions of PRA, dynamic PRA and multi-fidelity methods.

The paper is organized as following. Sections 1.1 ~ 1.3 introduce basics of PRA, dynamic PRA, multi-fidelity methods and importance sampling. Section 2 introduces a multi-fidelity DPRA approach and proposes the improved multi-fidelity importance sampling algorithm to balance the high-fidelity and low-fidelity simulations. Section 3 implements the proposed approaches to estimate the risk triplet of a boiling water reactor (BWR) station blackout (SBO) scenario, using MELCOR 2.2 [5], a severe accident code developed at Sandia National Laboratories (SNL). Section 4 summarizes the results and conclusions.

1.1 Probabilistic risk assessment (PRA)

PRA is a comprehensive, structured and logic-based methodology to identify and quantify risk of complex systems. In nuclear engineering, PRA can provide important information to support regulatory decision-making and prioritize risk-significant areas. The methodology is therefore particularly important for the optimization of safety work. PRA applications, related to nuclear safety regulation, risk-informed design and plant operation improvements, are more and more numerous worldwide. Nowadays PRA is a necessary part of safety assessment for nuclear power plants [6]. Many nuclear regulatory authorities consider that the current state of the art of PRA is sufficiently well developed that it can be used centrally in the regulatory decision process – referred to as "risk-informed regulation" [7]. In August 1995, the United States Nuclear Regulatory Commission (USNRC) issued a Commission Policy Statement on the use of PRA methods in nuclear regulatory activities. The statement adopted policies that the use of PRA technology in USNRC regulatory activities should be increased to the extent supported by the state-of-art in PRA methods and data [8], for example, PRA has been applied to evaluating risk-informed applications for a licensing basis change that considers engineering issues and applies risk insights [9]. In White Paper on Nuclear Energy 2020 published by Japan Atomic Energy Commission (JAEC), Japanese government introduced the risk-informed inspection program in April 2020 with reference to the Reactor Oversight Process (ROP) of the USNRC [10], and PRA is becoming more and more important in the nuclear regulation of Japan. Besides, risk-informed approaches and PRA have been widely applied by NASA (National Aeronautics and Space Administration) to improve design and operation [11].

Within the framework of PRA, as a widely used definition, risk can be represented by the following set of triplets [12][13]:

$$\boldsymbol{R} = \langle \boldsymbol{S_i}, \boldsymbol{P_i}, \boldsymbol{C_i} \rangle, \boldsymbol{i} = \mathbf{1}, \mathbf{2}, \cdots, \boldsymbol{N} \tag{1}$$

where S_i is a scenario of events that lead to hazard exposure, P_i is the probability/frequency/ likelihood of the corresponding scenario, C_i is the consequence of the scenario in terms of damage or loss. PRA's structured analytical process quantifies probabilities and consequences of system failures or other events that could lead to accidents. As shown in Figure 1 [14], by addressing three fundamental questions of risk analysis, PRA identifies potential scenarios, estimates associated frequencies and consequences. Scenario identification begins with the selection of initiating events (IEs), and proceeds by determining pivotal events that may mitigate or exacerbate accident influences. Meanwhile, the frequencies of potential scenarios are determined by branching probabilities, and the consequences can be estimated based on methods such as deterministic analyses. Finally, by collecting all scenarios, as shown in Figure 2 (a), it can estimate risk triplet that is crucial information to support risk management and decision making. Plotted on log scale of probabilities, a risk curve in Figure 2 (b) can be developed to help visualize the risk of a nuclear power plant.

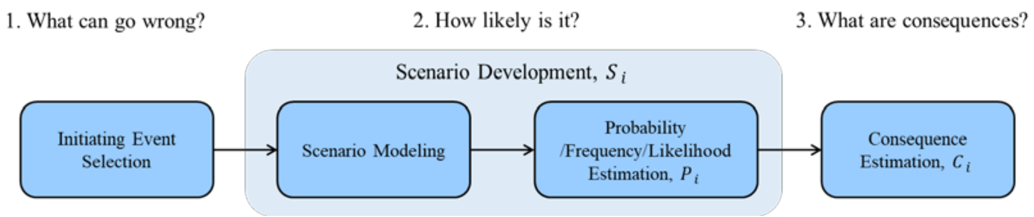
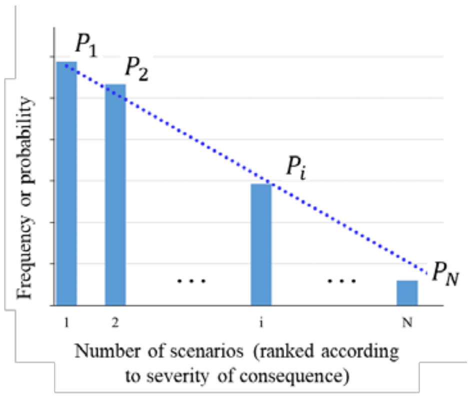


Figure 1 Implementation of risk triplet in PRA [11]

No.	Scenario	Probability	Consequence
1	S_1	P_1	C_1
2	S_2	P_2	C_2
…	…	…	…
i	S_i	P_i	C_i
…	…	…	…
N	S_N	P_N	C_N

(a) List of risk triplets



(b) Risk curve

Figure 2 An example of risk triplets and risk curve [12]

Basic elements of PRA include the development of logic structures such as fault tree (FT) and event tree (ET) to proceed accident progression, the estimation of basic event probabilities of the logic structure, as well as the assessment of accident frequencies. The process inevitably includes uncertainties that could have a significant impact on the results of PRA models. Most importantly, in PRA models, epistemic uncertainty may arise from reasons such as incomplete knowledge about how to represent plant behavior and when making statistical inferences from data [15]. Specific reasons may include, for example, wrongness in collection of operational failure data, estimation error of parameters in constant failure rate of reliability model, inappropriate failure models, and system's inability to perform its function under accidental conditions, etc.

1.2 Dynamic PRA

By explicitly considering time-dependent issues and stochastic behaviors of systems and components, dynamic PRA is one potential method to alleviate part of epistemic uncertainties in PRA. Dynamic PRA widely uses simulation approaches for generating risk scenarios. Stochastic and deterministic behaviors of plant elements are modeled as building blocks of the risk model [16]. Dynamic PRA uses a time-dependent phenomenological model of plant evolution along with is stochastic behavior to account for possible dependencies between failures [17].

Dynamic PRA can provide risk models which track changes, interdependences and interactions among plant elements as a function of time, so the overall methodology is more dynamic than FT/ET-based PRA. Over the past several decades, dynamic PRA methodologies have been developed and advanced, and numerous computational tools have emerged worldwide as well as associated applications to nuclear reactor PRAs. Figure 3 provides main tools, approaches and corresponding publications of dynamic PRA [18]-[36], and more detailed review of tools and methods can be found in publications [17][37]. The authors also added recent development statuses of Japan. Dynamic PRA tools are commonly coupled with deterministic system codes to quantify the risk triplet of Equation (1). The simulation-based scheme largely relies on Monte Carlo methods to estimate frequencies (P_i) and associated consequences (C_i). Dynamic PRA is an evolving research field. It has been applied to risk assessment of multi-unit nuclear power plant (NPP) [38][39], advanced fuel development [40], aging and degradation [41], and damage domain identification [42][43], to name a few.

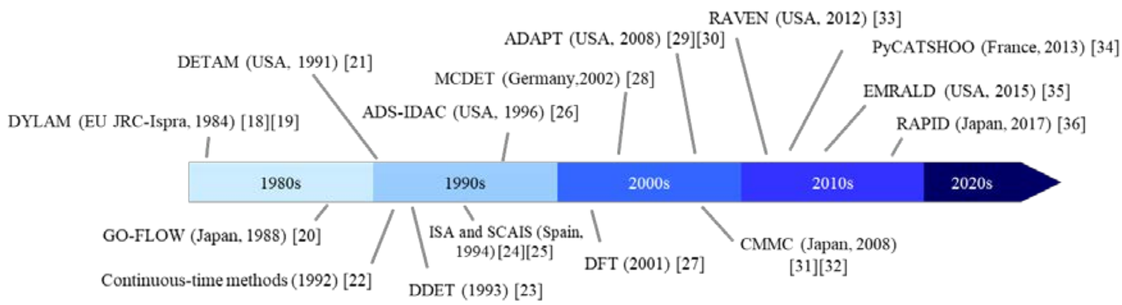


Figure 3 An incomplete list of dynamic PRA tools, approaches, and corresponding publications [4]

Monte Carlo methods are extremely widespread in numerous fields, especially in risk assessment [44]-[46]. By using randomly selected “what-if” scenarios, Monte Carlo simulation is a statistical technique by which a risk quantity can be calculated iteratively, with uncertainties visualized in the form of probability distribution. In the framework of dynamic PRA, models of accident evolution and human behaviors can be embedded within Monte Carlo simulation reproducing stochastic occurrences of system state transitions [47]. In practice, numerous trials of plant response are required to estimate the probability of rare critical scenarios and to identify associated hazardous conditions of the plant system. Data-mining-based methods are widely required to explore underlying risk information [48]-[51].

However, because the simulation of nuclear reactor accidents involves high-dimensional inputs/outputs, many of which evolves with time, and the simulation using black-box codes are usually computational demanding. These challenges make the Monte Carlo simulation of scenario identification and exploration difficult [52]. The computational cost problem of dynamic PRA has attracted wide interests and publications, for example, tradeoff between accuracy and cost [53], deterministic sampling [54] and machine learning algorithms [55][56] for scenario exploration, and guided simulation method [57], etc.

Compared with previous dynamic PRA approaches which couple Monte Carlo sampling with mechanistic simulations, the authors are proposing a multi-fidelity method which balances both high-fidelity simulation (mechanistic codes) for preciseness and low-fidelity simulation (machine learning surrogate models) for computational-cost-efficiency. Low-fidelity simulations can provide assistance by guiding the high-fidelity simulations with sampling candidates from important input domains or providing reliable predictions. Combing the following three potential strategies, the approach is capable to solve some limitations of present dynamic PRA methods.

(1) Generate and simulate numerous accident scenarios using high-performance computing including parallel and cloud computing.

(2) Use advanced sampling techniques including adaptive sampling and importance sampling etc. Importance sampling a Monte Carlo method with variance reduction [58], and it is widely applied in reliability engineering [59][60] and risk assessment [61] including rare event simulation [62].

(3) Apply multi-fidelity approaches by combining high-fidelity simulation based on severe accident codes and low-fidelity surrogate models.

Next section provides a brief introduction for multi-fidelity methods and importance sampling.

1.3 Multi-fidelity methods and multi-fidelity importance sampling (MFIS)

Overall introduction and review of multi-fidelity methods and applications can be found in a review paper [63]. Mathematically, a black-box accident simulation code can be written as a function $f: \mathcal{X} \rightarrow \mathcal{Y}$ that maps from an input $\mathbf{x} \in \mathcal{X}$ to an output $\mathbf{y} \in \mathcal{Y}$, where $\mathcal{X} \subseteq \mathbb{R}^d$ is the domain of d-dimensional model inputs and $\mathcal{Y} \subseteq \mathbb{R}^{d'}$ is the domain of d'-dimensional model outputs ($d, d' \in \mathbb{N}$). Representative inputs of nuclear reactor accident simulation codes include parameters related to thermal-hydraulic response of plant systems, core-degradation phenomena, hydrogen and fission product transport behaviors and setting of engineered safety features, etc. Representation outputs include fuel-cladding temperatures, core water level and source term released to the environment, etc. High-fidelity model $f_{hifi}: \mathcal{X} \rightarrow \mathcal{Y}$ is a model that can estimate outputs with the necessary accuracy for the task at hand, and low-fidelity model $f_{lofi}: \mathcal{X} \rightarrow \mathcal{Y}$ is a model that can estimate the same outputs with lower accuracy than high-fidelity models. Generally, the computational cost of high-fidelity models is larger than that of low-fidelity models. Low-fidelity models used in this paper are mainly statistical surrogate model using machine learning methods. Figure 4 conceptually illustrates the transition from high-fidelity dynamic RPA to multi-fidelity dynamic PRA. The left part is a typical dynamic PRA by using high-fidelity model iteratively to estimate the risk triplet of Equation (1), and the right part is the multi-fidelity dynamic PRA method, which introduces low-fidelity models to assist the risk triplet estimation with lower expected computational cost.

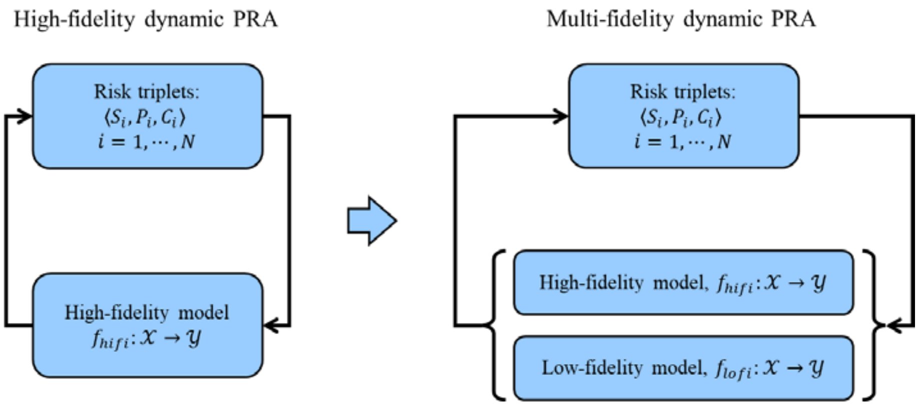


Figure 4 Expand the dynamic PRA from high-fidelity simulation to multi-fidelity simulation

Multi-fidelity methods have been successfully practiced in diverse fields such as (1) uncertainty quantification in which runtime is significantly reduced and unbiased estimators of statistics are provided [64]-[67], (2) optimization that uses low-fidelity models to accelerate the search of global optimum [68]-[71], and (3) statistical inference that leverages low-fidelity models to accelerate Markov chain Monte Carlo (MCMC) sampling for Bayesian inference [72]-[75].

Because multiple models are required in multi-fidelity simulation, model management is required. One specific model management strategy in multi-fidelity simulation is the "filtering" strategy represented by multi-fidelity importance sampling [76]-[78], by which the sampling of high-fidelity model is guided by a biased distribution that is constructed via a low-fidelity model. The method is originated from importance sampling, a useful variance-reduction method in Monte Carlo along with others such as control variates and stratification [79][80]. Importance sampling can significantly improve the simulation efficiency especially for rare events [81][82], which are of low-probability but high-consequence.

Importance sampling provided a foundation for simulation-based approaches for numerical integration, statistical physics, signal processing, reliability analysis and risk assessment, respectively [83]-[87].

Here provides the mathematical introduction of importance sampling [79]. The standard setting for the usage of importance sampling is the estimation of a quantity ℓ, which can be the statistics of uncertainty quantification or risk quantities.

$$\boldsymbol{\ell} = \int \boldsymbol{f}(\mathbf{x})\boldsymbol{\Pi}(\mathbf{x})\, \boldsymbol{dx} \tag{2}$$

where $f(\mathbf{x})$ is the objective function and $\Pi(\mathbf{x})$ is the probability density function of input vector $\mathbf{x}$.

To avoid the direct sampling from the density function Π, we can construct a biased distribution $g(\mathbf{x})$ as follows.

$$\boldsymbol{\ell} = \int \boldsymbol{f}(\mathbf{x})\boldsymbol{\Pi}(\mathbf{x})\, \boldsymbol{dx} = \int \boldsymbol{f}(\mathbf{x})\frac{\boldsymbol{\Pi}(\mathbf{x})}{\boldsymbol{g}(\mathbf{x})}\boldsymbol{g}(\mathbf{x})\, \boldsymbol{dx} \tag{3}$$

As a result, all random sample are independent and identically distributed (iid), and the sampling is transformed to that samples $(\mathbf{x}_1, \cdots, \mathbf{x}_M)$ are drawn from $g(\mathbf{x})$.

$$\mathbf{x}_1, \cdots, \mathbf{x}_M \sim_{iid} \boldsymbol{g}(\mathbf{x}) \tag{4}$$

The unbiased importance sampling estimator $\hat{\ell}$ of ℓ can be written as

$$\hat{\boldsymbol{\ell}} = \frac{\mathbf{1}}{\boldsymbol{M}} \sum_{\boldsymbol{m}=\mathbf{1}}^{\boldsymbol{M}} \boldsymbol{f}(\mathbf{x}_{\boldsymbol{m}}) \frac{\boldsymbol{\Pi}(\mathbf{x}_{\boldsymbol{m}})}{\boldsymbol{g}(\mathbf{x}_{\boldsymbol{m}})} \tag{5}$$

The weight function is the ratios of true density function and biased density function.

$$\boldsymbol{w}(\mathbf{x}) = \frac{\boldsymbol{\Pi}(\mathbf{x})}{\boldsymbol{g}(\mathbf{x})} \tag{6}$$

We can find that the most challenging part is the choice of the biased distribution $g(\mathbf{x})$, which largely affect the convergence speed of the statistical estimation. In practice, importance sampling method evolves with modifications, for example, adaptive importance sampling uses an adapting biased distribution [88][89] to improve the efficiency of importance sampling. In recent years, by using surrogate models, the MFIS algorithm has been developed to construct the biased distribution via surrogate model [76][90]. In Section 2, author improved the original MFIS algorithm by proposing an adaptive multi-fidelity algorithm to more quickly find the optimal biased distribution for importance sampling, and in Section 3, we apply it to dynamic PRA of nuclear power plants.

2 A multi-fidelity approach for dynamic PRA

Simulation-based scenario exploration and probability estimation need iterative execution of simulation codes. The number of iterations generally depends on the magnitude of the occurrence probability of the lowest-probability scenarios. In PRA of nuclear power plants, severe accidents are known as high-consequence and low-probability, and this property generally makes the number of Monte Carlo samples unaffordable. Multi-fidelity simulation is a powerful approach that can alleviate the unaffordable computational cost by appropriately using low-fidelity predictions to lead the sampling for high-fidelity simulations. It is expected that multi-fidelity approaches can make the simulation-based dynamic PRA more practical.

2.1 A multi-fidelity approach for dynamic PRA

Combining multi-fidelity modeling and importance sampling, we proposed JAEA's approach of dynamic PRA based on multi-fidelity simulations in Figure 5. The approach consists of steps including: (1) sample from a biased distribution, (2) execute high-fidelity simulation using deterministic accident simulation codes such as MELOR 2.2 and save results to high-fidelity database, (3) judge completeness based on the convergence of risk metrics, (4) train a low-fidelity surrogate model using high-fidelity data and machine learning methods, (5) perform low-fidelity simulation using the surrogate and save the data to low-fidelity database, (6) update the biased distribution for the importance sampling of next iteration, and (7) process all high-fidelity data to calculate the risk triplets including probabilities.

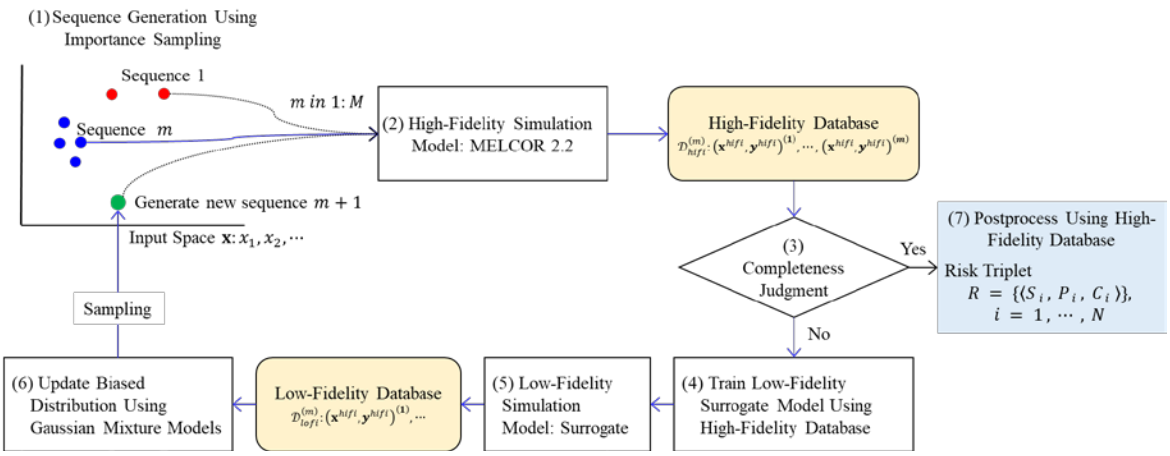


Figure 5 The dynamic PRA approach using multi-fidelity importance sampling

Estimating statistics of model output with the Monte Carlo method often requires many model evaluations. The problem of computational cost gets worse when high-consequence accident sequences are of low-frequency, so it requires much more samples to re-generate those sequences. Furthermore, severe accident codes of nuclear power plants are expensive to evaluate. Importance sampling can reduce the number of samples, but it is difficult to find an appropriate biased distribution. Multi-fidelity importance sampling is such a method that it uses surrogate model to obtain interested predictions, and then use the predictions to fit a usable biased distribution. Therefore, only a small number of high-fidelity model executions are required to get a biased distribution, which guide the random sampling so that unbiased estimation of the statistics of model output can be obtained at a low computational cost. The original MFIS algorithm is shown in Table 1. It consists of three main steps: (1) Surrogate model construction, (2) biased distribution fitting, and (3) importance sampling. The efficiency of cost-saving depends on the usability of biased distributions which are determined by the predictability of trained surrogate models. The number of high-fidelity model evaluations (M') is therefore required to be optimized. Too large M' results in the unnecessary computational cost, but too small M' will slow the convergence of importance sampling. However, it relies subjective judgements to determine the optimal value of M'.

Table 1 The original MFIS algorithm [76]

- Initialization

  Set the initial biased density distribution as the original probability density distribution $g_0(\mathbf{x}) = \Pi(\mathbf{x})$.
- Surrogate model construction

  Evaluate the objective function for M' times and save the high-fidelity database as $\mathcal{D}_0$.

  Use database to train a surrogate model S_0.
- Biased distribution fitting

  Initialize low-fidelity dataset $\mathcal{D}' = \{\}$.

  for $k \; in \; 1, \cdots, K$

      Sample $\mathbf{x}_k$ from $g_0(\mathbf{x})$.

      Evaluate surrogate S_0 at $\mathbf{x}_k$ and obtain the output $S_0(\mathbf{x}_k)$.

      if $S_0(\mathbf{x}_k)$ is a desired value

          add $\mathbf{x}_k$ to dataset $\mathcal{D}'$.

  Using dataset $\mathcal{D}'$, fit a mixture of normal distribution $g_{bias}(\mathbf{x})$, which is a biased distribution fitted by using low-fidelity predictions.
- Importance sampling

  Draw M samples $\mathbf{x}'_1, \mathbf{x}'_2, \cdots, \mathbf{x}'_M$ from $g_{bias}(\mathbf{x})$.

  Compute importance weights $w(\mathbf{x}'_1), w(\mathbf{x}'_2), \cdots, w(\mathbf{x}'_M)$ based on Equation (6).

  Evaluate high-fidelity model.
- Outputs

  Calculate the unbiased importance estimator based on Equation (5).

To improve the predictability of surrogate model and usability of biased distribution, as shown in Table 2, the authors have added an adapting step and release the computational requirements of the burn-in step. This approach can continuously optimize the surrogate model when more high-fidelity simulations are performed. Other applications of adaptive multi-fidelity surrogates can be found in recent publications for efficiency improvement [91]. When the number of adapting steps J becomes large, the predictability of surrogate model will improve, so low-frequency and high-consequence accident sequence will be sampled in a more frequent manner. Weights of samples will be normalized using the equation at the final step of the algorithm.

Table 2 The proposed AMFIS algorithm

- Initialization

  Select the total number of adapting steps J.

  Set the initial biased density distribution as the original probability density distribution $g_0(\mathbf{x}) = \Pi(\mathbf{x})$.

  Evaluate the objective function for M' times ($M' \geq 1$) and save the high-fidelity database as $\mathcal{D}_0$.
- Model evaluation, surrogate model construction and biased distribution generation

  for $j\ in\ 1, \cdots, J$

  Use the database $\mathcal{D}_{j-1}$ to train a low-fidelity surrogate model, S_j.

  Initialize low-fidelity dataset $\mathcal{D}' = \{\}$.

  for $k\ in\ 1, \cdots, K$

  Sample $\mathbf{x}_{jk}$ from $g_{j-1}(\mathbf{x})$.

  Evaluate surrogate S_j at $\mathbf{x}_{jk}$ and obtain the output $S_j(\mathbf{x}_{jk})$.

  if $S_j(\mathbf{x}_{jk})$ is a desired value

  add $\mathbf{x}_{jk}$ to dataset $\mathcal{D}'$.

  Using dataset $\mathcal{D}'$, fit a mixture of normal distribution $g_j(\mathbf{x})$, which is an updated biased distribution.

  Check if $g_j(\mathbf{x})$ converges to an optimal biased distribution $g_{opt}(\mathbf{x})$. If converged, stop adapting.

  Draw M samples $\mathbf{x}'_{j1}, \mathbf{x}'_{j2}, \cdots, \mathbf{x}'_{jM}$ from $g_j(\mathbf{x})$ or $g_{opt}(\mathbf{x})$, compute importance weights $w(\mathbf{x}'_{j1}), w(\mathbf{x}'_{j1}), \cdots w(\mathbf{x}'_{jM})$, evaluate high-fidelity model, and update the high-fidelity database $\mathcal{D}_{j-1}$ to $\mathcal{D}_j$.
- Outputs

  Normalize importance weights $\overline{w}(\mathbf{x}'_{jm}) = \frac{w(\mathbf{x}'_{jm})}{\sum_{j=1}^{J}\sum_{m=1}^{M} w(\mathbf{x}'_{jm})}$ [84], and calculate the unbiased importance estimator.

2.2 Comparison of sampling methods including MC, IS, MFIS, AMFIS

Modifying Equation (2), failure probability of a system can be defined as [92]

$$\boldsymbol{P_f} = \int_{\Omega_f} \boldsymbol{\Pi}(\mathrm{x})\boldsymbol{dx} = \int \boldsymbol{I}(\mathrm{x})\boldsymbol{\Pi}(\mathrm{x})\,\boldsymbol{dx} \tag{7}$$

$$\boldsymbol{I}(\mathrm{x}) = \begin{cases} \mathbf{1}, & \boldsymbol{h}(\mathrm{x}) \leq \boldsymbol{C} \\ \mathbf{0}, & \boldsymbol{h}(\mathrm{x}) > \boldsymbol{C} \end{cases} \tag{8}$$

Where P_f is the failure probability, Ω_f is the area of failure domain, Π is the probability density function of input vector $\mathbf{x}$. $I(\mathbf{x})$ is an indicator function whose value is determined by the state function $h(\mathbf{x})$ and the critical value C. The failure probability can be acquired by concluding the limit state function and the area of failure domain, as shown in Figure 6, so the calculation of failure probability can be reached by sampling from the whole input space

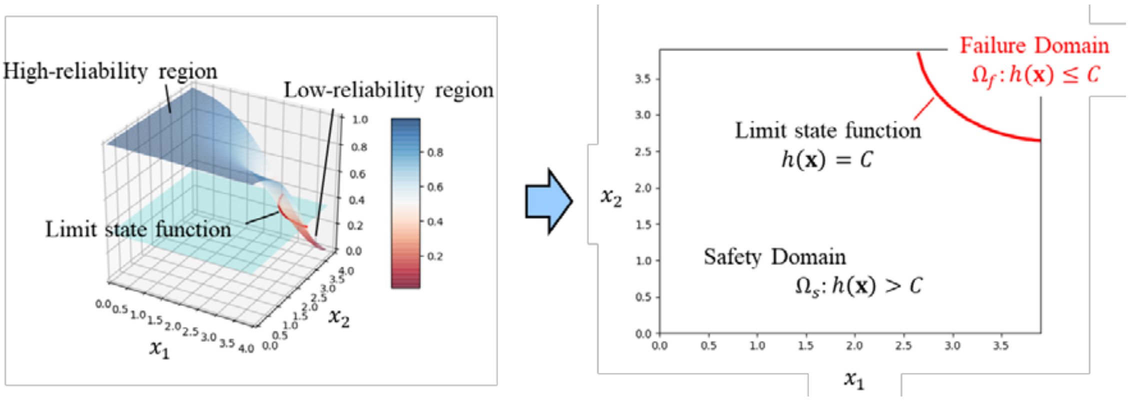


Figure 6 Limit state function of the basic reliability

Using the sampling-based simulation, the failure probability can be written as

$$\boldsymbol{P_f \approx \frac{\sum_{m=0}^{M} I(\mathbf{x}_m)}{M}} \tag{9}$$

To efficiently obtain a credible failure probability, we compare the computational cost of different sampling methods with a simple problem, of which x_1 and x_2 are of truncated exponential distributions and critical value C of reliability state function equals 0.35. We selected exponential distribution as an example because the relative low failure probability can reflect the practical occurrence frequency of severe accidents of nuclear power plants.

$$\boldsymbol{x_1 \sim Truncated\ Exponential(\lambda = 1)} \tag{10}$$

$$\boldsymbol{x_2 \sim Truncated\ Exponential(\lambda = 1)} \tag{11}$$

$$\boldsymbol{0 < x_1, x_2 \leq 4} \tag{12}$$

Figure 7 provides a qualitative comparison according to the convergence rate of Monte Carlo, importance sampling with an appropriate biased distribution, original multi-fidelity importance sampling, and multi-fidelity importance sampling with adaptive surrogates. It can be observed that importance sampling provides faster generation of rare failure events compared with Monte Carlo sampling. For small failure probabilities, the number of samples in the failure domain of the surrogate model typically decreases significantly such that fitting a mixture model fails [76]. Comparing with MFIS, AMFIS does not need to train a precise surrogate model beforehand, while the predictability of surrogate used by AMFIS will improve as more high-fidelity data accumulate. Besides, the exploration of input domain in AMFIS also taking into account the prediction uncertainty so that the low-probability area tends to be more frequently visited.

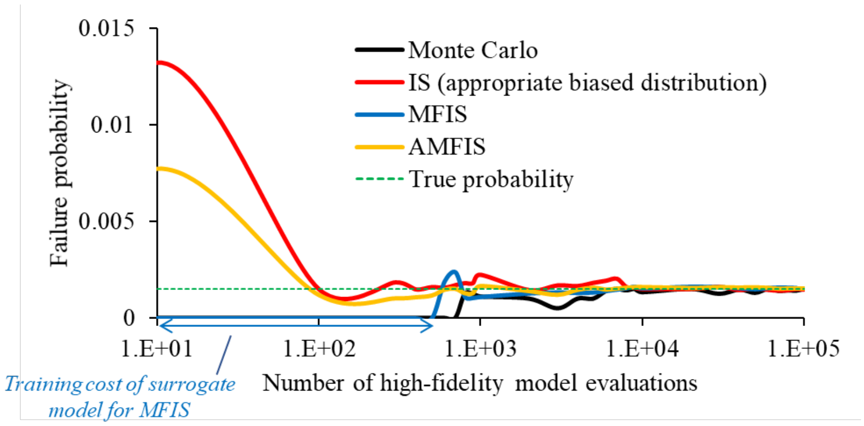


Figure 7 Calculation of failure probability by using different methods

Figure 8 depicts the adjustment of biased distribution with the prediction from low-fidelity simulations, which provide data for fitting a biased distribution. A probably appropriate biased distribution can be obtained by the converging statistics of the finite Gaussian Mixture model. Figure 9 shows the 1000 samples generated from Monte Carlo, importance sampling and AMFIS. The areas of sample points represent the weights that are necessary for estimating the final probability results. Samples of AMFIS shows a more averaged distribution on the input space with limited number of samples.

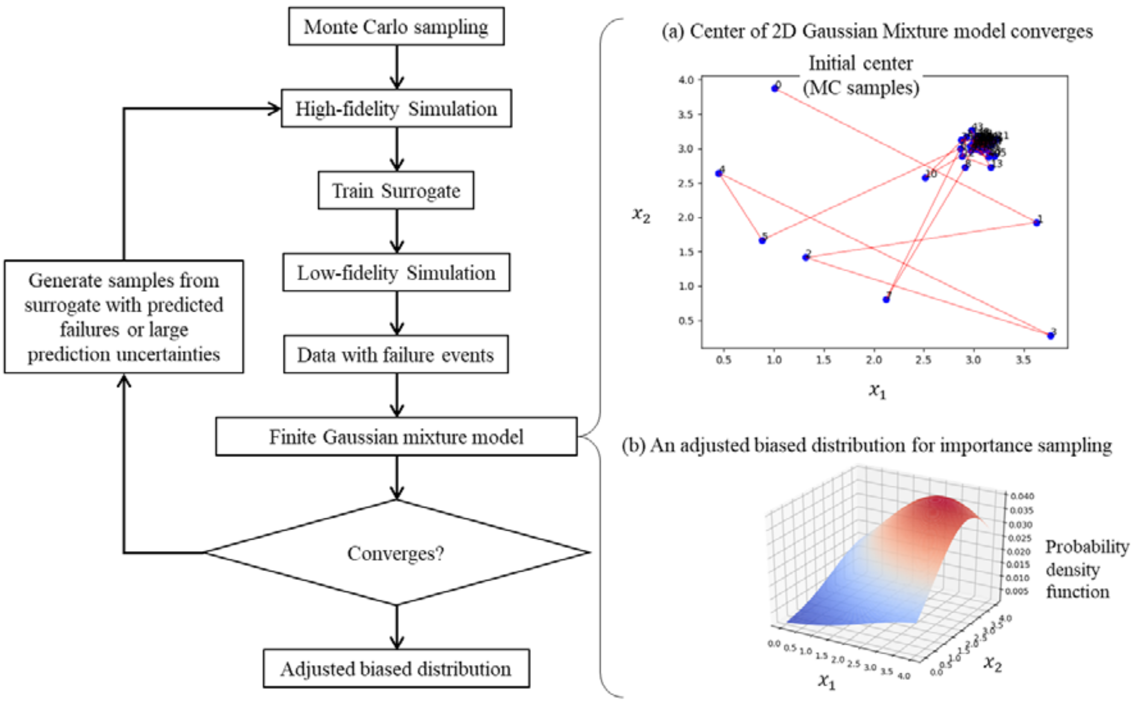
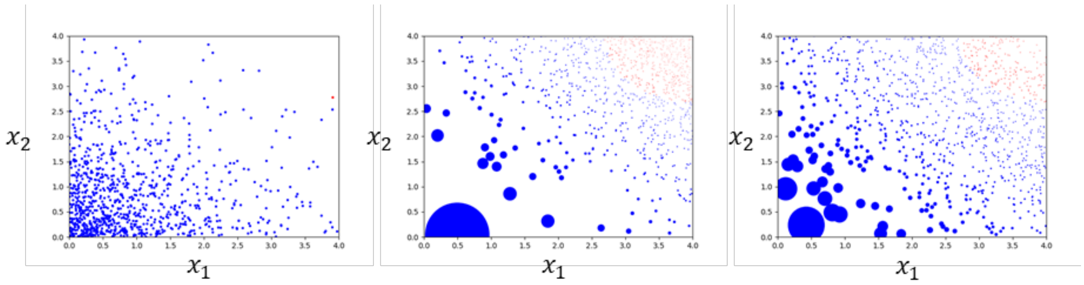


Figure 8 Adjustment of biased distribution using adaptive surrogate for multi-fidelity importance sampling



(a) Monte Carlo:1/1000 (b) Appropriate biased distribution: 502/1000 (c) AMFIS: 176/1000

Figure 9 Comparison of three samplers at 1000 times of sampling (area of each sample represents the associated weight, and the numbers show fractions of failure data)

2.3 Risk triplet estimation

Low-fidelity data accelerate the analysis by providing appropriate biased distributions for importance sampling, and when enough number of high-fidelity simulations has been performed, risk triplets are able to be calculated, as Step (7) of Figure 4. Step (3) of completeness judgement is based on the convergence of risk triplets such as probability distributions of accident sequences, with unavoidable subjectivities. Section 3 implements the multi-fidelity approach to PRA of a BWR NPP.

3 Multi-fidelity dynamic PRA of a BWR nuclear power plant

This section demonstrates the application of multi-fidelity importance sampling to practical BWR dynamic PRA of the scenario of SBO considering the stuck-open of a safety relieve valve (SRV).

3.1 Traditional PRA model

To well illustrate the proposed importance sampling method, a simplified BWR SBO scenario is chosen, as shown as an event tree in Figure 10 [93][94]. Starting from initiating events (IEs), the even tree consisting pivotal events including SRVs' success to close, operability of high-pressure coolant injection (HPCI) and reactor core isolation cooling (RCIC) systems, availability of depressurization and alternative water injection and recovery of offsite and emergency diesel generators (EDGs). The model presents eight accident sequences, associated end states and probabilities. The risk triplet can be calculated by using tools such as SAPHIRE [95], based on Boolean algebra and branch probabilities.

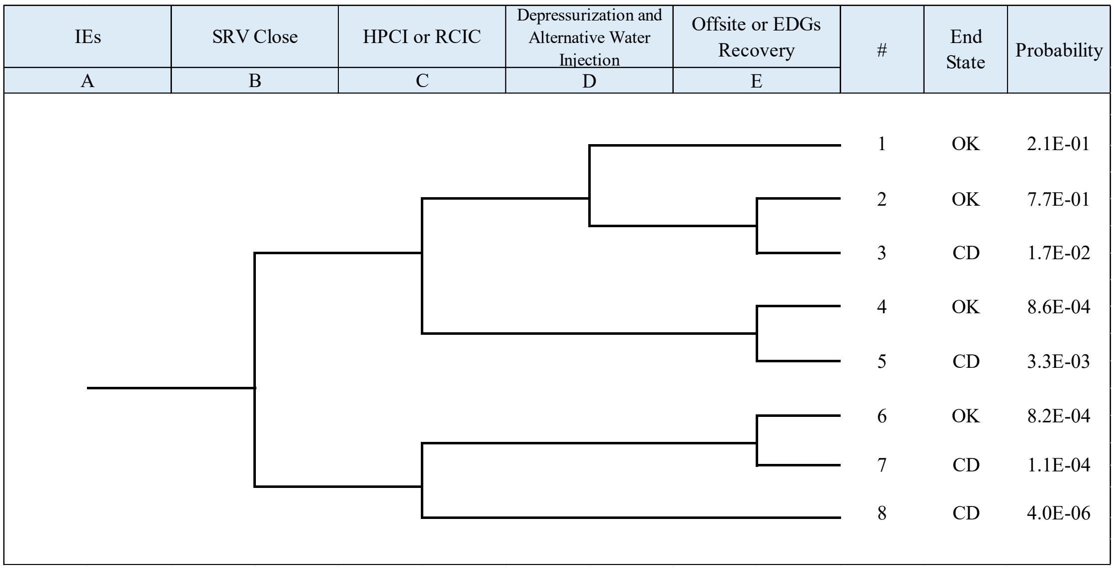


Figure 10 Simplified event tree model for BWR SBO with an SRV stuck open

3.2 High-fidelity model for accident simulation using MELCOR

Mechanistic BWR SBO simulation is performed using MELCOR, Version 2.2. Figure 11 depicts the MELCOR nodalization scheme. The creation of a simplified BWR model is for saving time in dynamic PRA. The input deck has been built based on BWR test case input of Sandia National Laboratories and the modeling of Fukushima Daiichi NPP Unit 1 [96]. The plant model includes two main parts of hydrodynamics and core. Core channel has been divided in two control volumes of core and bypass. The reactor coolant system (RCSodeled as a lower plenum, downcomer, upper plenum with reactor pressurized dome (RPV). Control volumes are connected with flow paths, which allow mass and energy exchange. Containment system consists of wetwell and drywell. Drywell is equipped with a filtered vent to the environment. Drywell is accepting mass from lower plenum leak and releasing mass to the environment after when the containment fails. Stochastic variables that affect the occurrence of pivotal events of Figure 10 are shown in Table 3. The selection and parameter setting of probability distributions refers to previous researches on BWR SBO dynamic PRA [94], and sampled values have been reflected to MELCOR inputs via control functions.

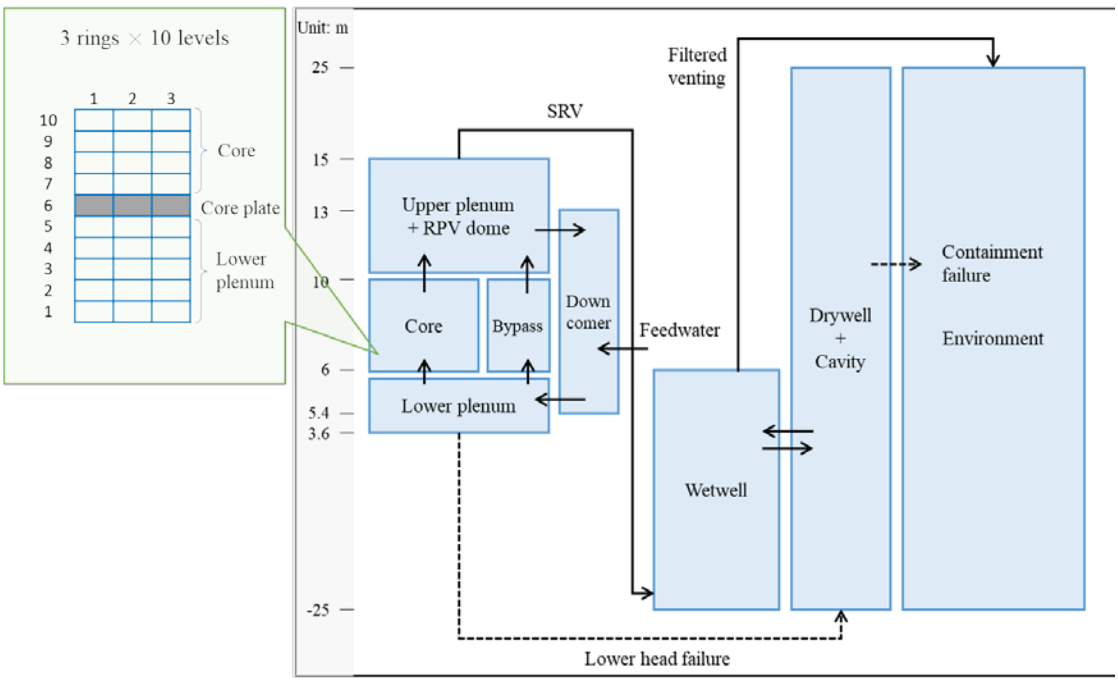


Figure 11 Nodalization of a simplified BWR model using MELCOR 2.2

Table 3 List of stochastic input variables and associated distributions

	Stochastic variables	Distributions	Parameters
1	EDGs recovery time	Lognormal	μ=0.793, σ=1.982
2	Power grid recovery time		
3	Battery life	Triangular	(left, mode, right): (4,5,6)
4	Number of cycles before SRV stuck open happens	Geometric	Stuck-open probability of an individual trial: 8.56E-4
5	RCIC failure time	Exponential	λ=1.0E-1
6	HPIC failure time		
7	RCIC extended time	Lognormal	μ=0.75, σ=0.5
8	Alternative water available time	Lognormal	μ=0.75, σ=0.5
9	Manual automatic depressurization activation		

3.3 Adaptive multi-fidelity importance sampling with parallel computation

To saving the computation cost, the multi-fidelity importance sampling has been executed in parallel on JAEA's supercomputer system, which applies HPE SGI8600 that comprises a CPU calculational unit and a GPGPU calculational unit. The CPU unit in HPE SGI8600 is a blade-type large-scale cluster system with a total theoretical peak performance of 2.801 PFLOPS. It contains 706 nodes, each of which owns two Intel Xeon Gold 6242R Processors of 3.1 GHz and 20 cores.

Figure 12 depicts the iterative process that consist of the initial sampling, 40 parallel processing of high-fidelity simulation, low-fidelity simulation and the obtaining of final risk results. Surrogate model has been trained by using support vector machine (SVM), and introductions of SVM can be found in references [97]-[99].

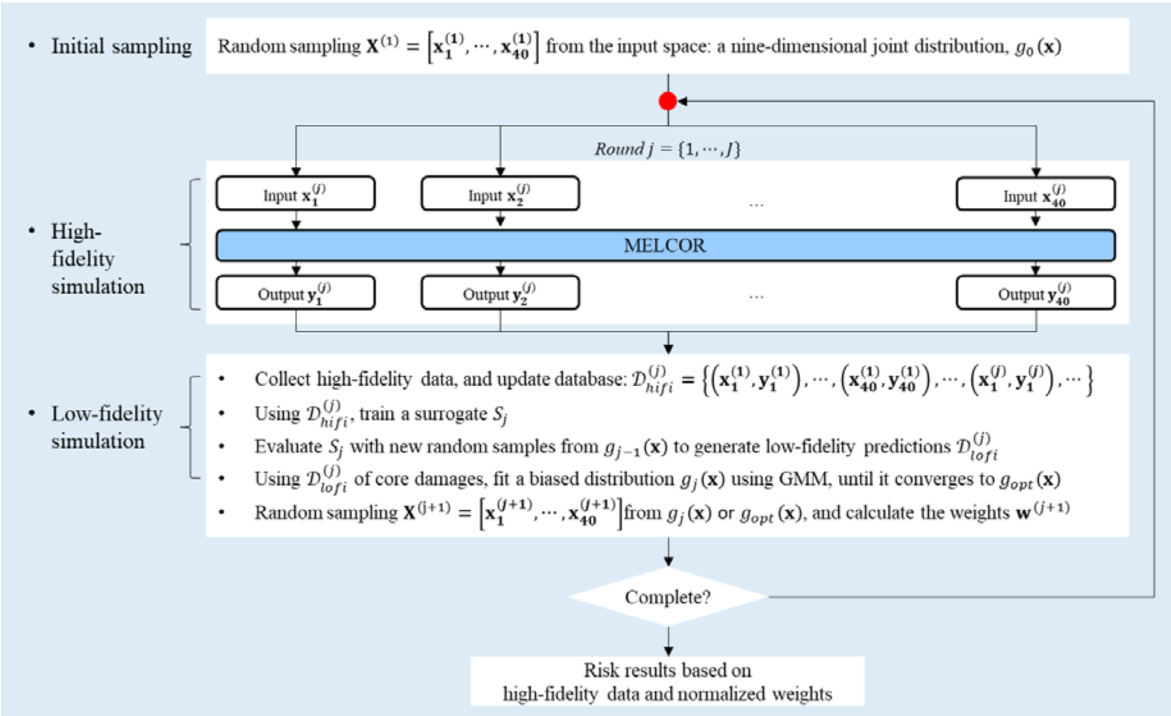
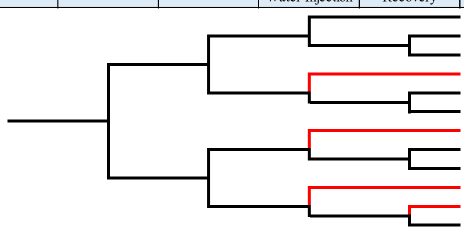


Figure 12 Implementation of multi-fidelity DPRA with AMFIS applying parallel processing (40 processes) of high-fidelity MELCOR simulations

3.4 Results of multi-fidelity dynamic PRA

Figure 13 summarize the results of BWR SBO accident, comparing with traditional PRA and previous dynamic PRA results. In general, dynamic PRA is capable of providing a more complete risk provide by covering more trivial accident sequences, which are neglected for the convenience of modeling or for their insignificant risk influence. For example, as a complement of the conservativeness of traditional PRA, Sequences 4, 7, 10 and 11 are generated by the dynamic PRA simulations. In accordance with previous studies [93][94], consisting of heading events of no SRV stuck open, HPIC and RCIC failures, successful alternative water injection, Sequence 4 was not modeled in traditional PRA, because it was assumed that there is no adequate time for operators to depressurize reactor coolant system (RCS) and align alternative water injection system. Sequences 7, 10 and 11 are neglected because RCS depressurization are not modeled for simplification in the original event tree model when an SRV is stuck open. However, in the present study, SRV stuck-open failure is modeled as geometric distribution, which means that the failure doesn't have to occur at the initial timing of the accident. Dynamic PRA softens the conservative assumption, so Sequences 7, 10 and 11 appears in the current risk triplet.

Compared with previous PRA and dynamic PRA results, JAEA's dynamic PRA also shows agreements on the estimation of probabilities and consequences, as shown in Figure 14. Most results of multi-fidelity dynamic PRA agree with that of high-fidelity analysis, as the direct comparison in Figure 15 illustrates. However, for low-frequency sequences, there are variations which are most likely resulted from the weight calculation process. Gaussian mixture model is used to estimate high-dimensional probability density functions of biased distributions, so the estimation process unavoidably brings noises to the weight calculation of Equation (6), but the variation is trivial as the final point estimate of conditional core damage probability (CCDP) does not differentiate. Comparing with the four practical exercises of risk assessment, Table 4 shows that estimates of CCDP show good agreements between high-fidelity and multi-fidelity dynamic PRA results. Dynamic PRA generally applies a simulation-based method, which is based on random sampling. The proposed multi-fidelity method additionally combines both high- and low-fidelity simulators. The multi-fidelity dynamic PRA also provides comparative results, while the computational cost is largely reduced, especially the execution of high-fidelity simulations. For each importance sampling, five thousand low-fidelity simulations are performed to obtain the biased distribution, so totally low-fidelity simulations have been executed for millions of times. However, because the cheap computational cost of low-fidelity models, the overall CPU time is reduced form 2.39E+04 hours to 3.11E+03 hours, reduced by 87.0%. Because the multi-fidelity simulation is performed in parallel following the process of Figure 12, the actual wall-time is even shorter.



SBO	SRV Close	HPCI or RCIC	Alternative Water Injection	Offsite or EDG Recovery	#	End State	Traditional PRA (INL PRA)	High-Fidelity DPRA (INL RELAP5-3D)	High-Fidelity DPRA (MELCOR+Monte Carlo)	Multi-Fidelity DPRA (MELCOR+AMFIS)
					1	OK	2.10E-01	1.00E-01	2.27E-01	2.02E-01
					2	OK	7.70E-01	8.60E-01	7.54E-01	7.83E-01
					3	CD	1.70E-02	1.00E-02	1.25E-02	1.36E-02
					4	OK	N/A	2.10E-02	8.99E-04	1.10E-04
					5	OK	8.60E-04	5.60E-03	2.90E-03	1.69E-04
					6	CD	3.30E-03	5.00E-03	1.40E-03	2.29E-04
					7	OK	N/A	9.90E-06	1.90E-04	1.88E-04
					8	OK	8.20E-04	1.70E-06	6.04E-04	6.11E-04
					9	CD	1.10E-04	2.10E-07	5.81E-05	5.01E-05
					10	OK	N/A	6.70E-07	1.37E-06	2.03E-06
					11	OK	N/A	9.70E-07	2.31E-06	3.57E-06
					12	CD	4.00E-06	5.00E-07	5.99E-07	1.50E-06

Figure 13 Results comparison among traditional PRA, high-fidelity DPRA (RELAP5-3D), high-fidelity DPRA (MELCOR + Monte Carlo), multi-fidelity DPRA (MELCOR + AMFIS)

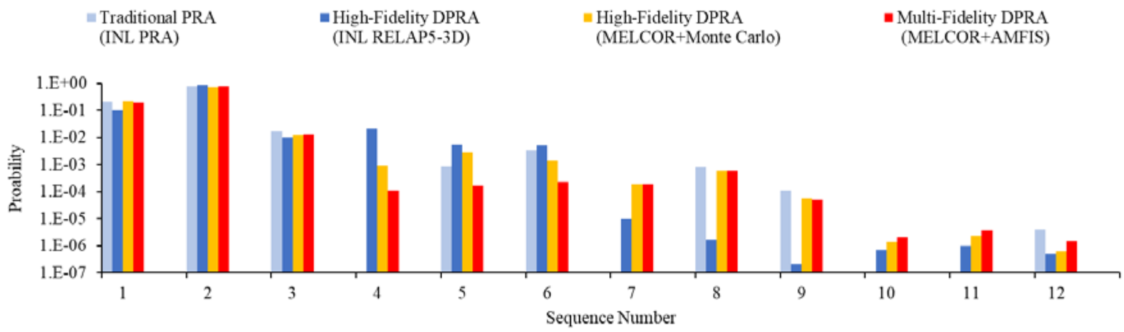


Figure 14 Comparison of sequence probabilities

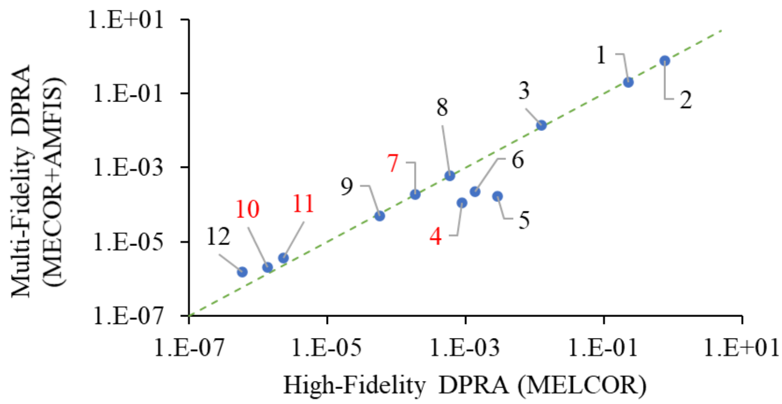


Figure 15 Validation of multi-fidelity simulation results

Table 4 Comparison of methods

		Traditional PRA (INL)	High-Fidelity DPRA (INL)	High-Fidelity DPRA (JAEA)	Multi-Fidelity DPRA (JAEA)
Methodology		Logic-based	Simulation-based	Simulation-based	Simulation-based
Sampling methods		-	Monte Carlo	Monte Carlo	Multi-fidelity importance sampling
Simulators		-	RELAP5-3D	MELCOR 2.2	MELCOR2.2 and Machine learning model
Cost	High-Fidelity (number of runs)	-	2.00E+04	2.00E+04	2.06E+03
	Low-Fidelity (number of runs)	-	-	-	9.92E+06
	Total CPU time (hours)	-	-	2.39E+04	3.11E+03
Estimated CCDP		2.04E-02	1.50E-02	1.40E-02	1.39E-02

4 Conclusions

As an evolving research field, dynamic PRA approaches explicitly treat stochastic elements including timing issues in PRA of nuclear power plants. It can provide a more elaborate risk assessment by detailed modeling, but on the other hand, dynamic PRA faces practicability obstacles for its computational complexity and overwhelming cost. Because dynamic PRA extensively applies Monte Carlo simulations to assess uncertainties and risk, many samples are required to quantify accident scenarios, frequencies/probabilities and consequences, that is, the risk triplet. The number of samples increases significantly especially when low-frequency scenarios need to be generated.

To improve the practicability of dynamic PRA regarding computational cost, the authors have proposed to apply multi-fidelity importance sampling (MFIS) to accelerate the assessment. Importance sampling has been an effective method for rare event simulation. The main idea is to use low-cost low-fidelity surrogate model to build an appropriate biased distribution for importance sampling, from which random samples are extracted and sent to high-fidelity simulation. The overall method structure of MFIS is kept unchanged for the application, but to optimize the biased distribution, the authors slightly improved MFIS by adding an adapting step in which the biased distribution keeps being updated with forthcoming high-fidelity simulation data. To distinguish from the previous study, the improved method is called adaptive multi-fidelity importance sampling (AMFIS). As an example, we provide a demonstration of estimating failure probability of a two-dimensional problem to show advantages of importance sampling and multi-fidelity importance sampling. Results confirm the effectiveness of AMFIS in rare event simulation and most importantly, with it avoids the predetermination of a biased distribution when using an adaptive surrogate model.

The proposed method is applied to a practical PRA example that requires to evaluate the core damage frequency of a BWR SBO scenario with the possibilities of safety-relief valve stuck-open, loss of coolant injection and recovery of power. To treat the time-dependency of event tree headings, we selected stochastic variables and determined their distributions based on previous researches. The accident is simulated using MELCOR2.2, as a high-fidelity model. Low-fidelity surrogate models are constructed in the analysis by using MELCOR2.2 simulation data and a machine learning algorithm of support vector machine. The surrogate model keeps being updated during the analysis when high-fidelity data accumulates. Therefore, the biased distribution is adaptive. According to the previous publications, because only high-fidelity data are used for probability estimation, the estimate of risk triplet is theoretically unbiased. A parallel version of AMFIS is also provided to further accelerated the analysis. The authors have implemented the multi-fidelity simulation and importance sampling methods in the JAEA’s dynamic PRA tool of RAPID, which controls the computational procedure of sampling, code execution, surrogate model training/updating, probability density estimation of biased distribution, weight calculation and data processing. As the results, JAEA’s dynamic PRA results show agreements with previous PRA and dynamic PRA results of Idaho National Laboratory in United States. It proves that the multi-fidelity approach can provide reliable risk results while being cost-effective versus plain Monte Carlo simulation.

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