Uncertainty Analysis of Dynamic PRA Using Nested Monte Carlo Simulations and Multi-Fidelity Models

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Abstract: Uncertainty gives rise to the risk. For nuclear power plants, probabilistic risk assessment (PRA) systematically concludes what people know to estimate the uncertainty in the form of, for example, risk triplet. Capable of developing a definite risk profile for decision-making under uncertainty, dynamic PRA widely applies explicit modeling techniques such as simulation to scenario generation as well as the estimation of likelihood/probability and consequences. When quantifying risk, however, epistemic uncertainties exist in both PRA and dynamic PRA, as a result of the lack of knowledge and model simplification. The paper aims to propose a practical approach for the treatment of uncertainty associated with dynamic PRA. The main idea is to perform the uncertainty analysis by using a two-stage nested Monte Carlo method, and to alleviate the computational burden of the nested Monte Carlo simulation, multi-fidelity models are introduced to the dynamic PRA. Multi-fidelity models include a mechanistic severe accident code MELCOR2.2 and machine learning models. A simplified station blackout (SBO) scenario was chosen as an example to show practicability of the proposed approach. As a result, while successfully quantifying risk triples, the analysis is also capable to provide uncertainty information in the form of probability distributions of risk metrics such as large early release frequency (LERF). In conclusion, the dynamic PRA approach can potentially provide more precise risk information by considering timing issues, and the uncertainty analysis can provide a complete probability density function for better decision making.

Keywords: Dynamic probabilistic risk assessment (PRA), Aleatory and epistemic uncertainties, Nested Monte Carlo, MELCOR2.2/RAPID, Multi-fidelity models, Machine learning, Large early release frequency (LERF)

1. INTRODUCTION

The safe operation of a nuclear power plant (NPP) is accomplished by implementing concepts such as defense-in-depth (DiD) and safety margin. Complementing the deterministic assessment of DiD, probabilistic risk assessment (PRA) is a comprehensive method being used to support both licensee and regulatory decision-makings under uncertainties. Characterizing aleatory uncertainties associated with the random nature of basic events such as initiating event and component failures, PRA is a probabilistic model that quantifies risks of NPPs [1][2]. However, PRA results inevitably contain epistemic uncertainties, which relate to the lack of knowledge and arise when making statistical inference from data. Uncertainty analysis measures the “goodness” of PRA results. Three types of epistemic uncertainties are parameter, model and completeness uncertainties. The completeness uncertainty relates to incomplete state of knowledge about potential failure mechanisms, and they are addressed by concepts such defense-in-depth and safety margin. For the other two types, the ASME/ANS standards on PRA require that both parametric and model uncertainties be addressed [3][4]. Better understanding the implications of PRA uncertainties ensures the confidence of decision-making under uncertainties.

As one of risk assessment approaches, dynamic PRA explicitly models system dynamics by employing system simulations. System dynamics and stochastic behaviors are taken into account to explore dependencies among failure events, such as the mutual influences between system dynamics and component failure probabilities [5]. Dynamic PRA can use simulations to alleviate part of epistemic uncertainties in PRA, however, the overall epistemic uncertainty is not possible to be eliminated completely. It is necessary to establish approaches for the quantification of epistemic uncertainties in dynamic PRA.

This paper aims to propose a practical approach for the uncertainty analysis associated with dynamic PRA. It is organized as follows. Section 2 reviews previous uncertainty analysis methods of PRA. Section 3 proposes an uncertainty analysis method for dynamic PRA, which consists of a nested Monte Carlo simulation using multi-fidelity models. Section 4 demonstrates the applicability of the method to estimate the probability-of-frequencies of large early release frequency (LERF) under the condition of station blackout (SBO) of a boiling water reactor (BWR) NPP.

2. UNCERTAINTY ANALYSIS IN PRA

Aleatory uncertainty is the uncertainty that deals with the inherent variability in the physical world. Aleatory uncertainty can arise because of natural, unpredictable variation in the performance of the plant dynamics. The characterization of aleatory uncertainty might change given additional information, for example, a larger database can provide better estimation of the standard deviation of a physical quantity. In principle, however, aleatory uncertainty is irreducible [6].

PRA models explicitly address aleatory uncertainty. In PRA, the aleatory uncertainty is represented by the randomness associated with the events in the model logic structures. The aleatory uncertainty is generally characterized in the form of frequencies such as core damage frequency (CDF) or LERF. However, the quantification of aleatory uncertainty inevitably contains epistemic uncertainties.

Arising from incomplete theory or incomplete understanding of a system or phenomena, epistemic uncertainty is the uncertainty attributed to a lack of knowledge. It is reducible, in principle, although it might be difficult or expensive to do. Epistemic uncertainties arise when making statistical inferences from data and from incomplete knowledge about how to represent plant behavior in the PRA model. For example, simplification of complex component failure mechanism to a random probabilistic distribution will introduce epistemic uncertainty to PRA results. This paper focuses on the quantification of epistemic uncertainty in dynamic PRA.

In all facets of PRA (e.g. frequencies of initiating events, probability of failure of components, human error probabilities, etc.), the sources of uncertainties need to be addressed. Categorizing into three types of parameter, model and completeness uncertainties, epistemic uncertainties in PRA and dynamic PRA arise for different reasons [1][7].

a. The choice of logic structure and the mathematical form of failure models.
   - In PRA, for example, uncertainty exists as to how to construct event tree and fault model according to specified scope and level-of-detail. Uncertainty also exits as to how to model failures of hardware, software and human actions, as a result of reasons that it is unclear if the simplified probabilistic model can replace the latent physics-of-failure model.
   - In dynamic PRA, for example, different choices of probability distributions for the occurrence timing of events may result in uncertainties, and plant modeling using system codes may result in uncertainties in the accident consequence estimation.

b. The estimation of PRA model parameters.
   - In PRA models, uncertainty exists in the estimation of frequencies of initiating events, branching probabilities in event trees and failure probabilities of components. As a specific example, uncertainty exists in the parameter setting of Poisson model which assumes that

failures of components in a standby state occur at a constant rate. Failure data are required to assess the constant rate, so the uncertainty may be caused by the fact that initiating events and basic events are relatively rare. The method of failure data collection also introduces uncertainties because failure data from maintenance records do not ensure that the failure would have prevented the component from performing the desired function.

- In dynamic PRA, for example, the subjective setting of parameters for probability distributions may result in uncertainties.

c. Uncertainty in characterizing the success criteria.
   - In PRA, changing environmental conditions result in uncertainty in the functionality of systems, for example, the functionality of systems in a room where a loss-of-cooling occurs.
   - In dynamic PRA, overlooking potential correlation in the sampling of parameters may result in uncertainties.

A typical approach of uncertainty analysis for PRA is shown in Fig.1, uncertainties of PRA parameters can be treated in the form of probability distributions. After when sources of uncertainties are identified and defined using probability distributions, uncertainty propagation can be performed by using methods such as Monte Carlo simulations. Because PRA models quantify risk metrics such as CDFs and LERFs, the epistemic uncertainty in PRA can be visualized as probability distributions of the frequencies. Therefore, the main steps can be summarized as follows.

a. Uncertainty source identification
b. Probability distribution modeling
c. Uncertainty propagation
d. Results visualization

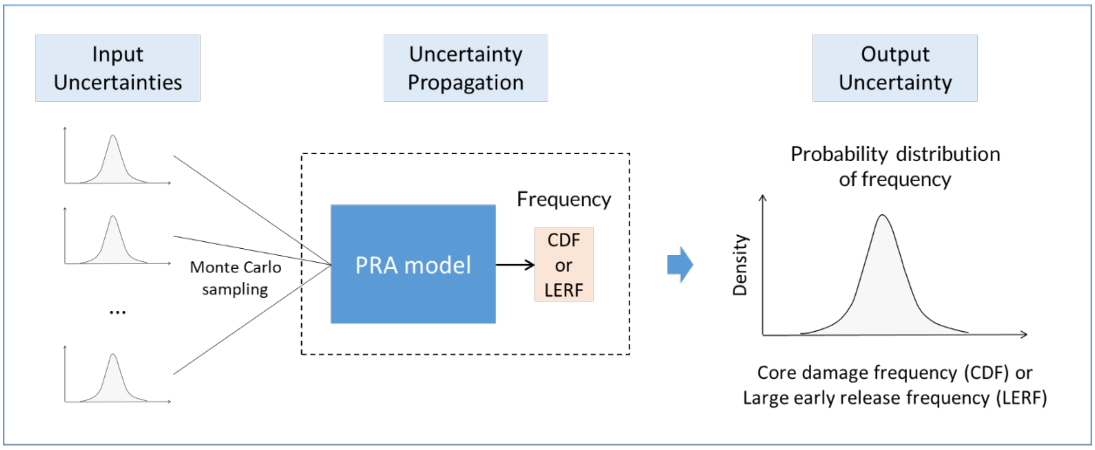

Fig. 1 Treatment of uncertainties in PRA [8]

3. THE PROPOSED APPROACH FOR UNCERTAINTY ANALYSIS OF DYNAMIC PRA

3.1. Review of Related Methods

This section provides a review on previous studies on which the present paper is based.

The MCDET method for dynamic PRA is a combination of Monte Carlo (MC) simulation and the discrete dynamic event tree (DDET) approach. It is capable of treating both aleatory and epistemic uncertainties, by using a two-stage nested Monte Carlo method [9][10]. The inner Monte Carlo loop treats aleatory uncertainty, and it corresponds to the dashed rectangle in Fig.1, by which the risk metrics are assessed. The outer Monte Carlo loop corresponds to the overall procedure of epistemic uncertainty analysis in Fig.1, so it provides the probability distribution of frequencies.

The QMU method of quantification of margins and uncertainties (QMU) provides a systematic process for the treatment of aleatory and epistemic uncertainties in risk assessment and safety analysis [11][12]. The method is also referred to as the "probability-of-frequency approach" [13]. From the categorization of aleatory and epistemic uncertainties to the approach of quantification, consistency can be found among the QMU method, the PRA uncertainty analysis procedure of Fig.1 and the MCDET method. The nested Monte Carlo method well fits the separated treatment of aleatory and epistemic uncertainties for dynamic PRA.

Other publications also show the advantages of dynamic PRA in simultaneous consideration of both aleatory and epistemic uncertainties. It was found that the shape of cumulative density functions is influenced by aleatory uncertainty, and the variations in the magnitudes of cumulative density functions are determined by epistemic uncertainty [14].

3.2. The Proposed Approach Combining Two-Stage Nested Monte Carlo and Multi-Fidelity Models

Fig.2 shows the improved uncertainty analysis approach combining two-stage nested Monte Carlo simulation and multi-fidelity models. Epistemic parameters are categorized as epistemic hyper-parameters such as parameters of probability distributions and other epistemic parameters such as state-of-knowledge correlation (SKOC) and parameters related to plant dynamics. After when sampling from the outer Monte Carlo loop, the inner Monte Carlo loop samples stochastic parameters for frequency simulations. To save computational cost, we use both mechanistic system code and statistical surrogate model combining with a model selection scheme [15]. When enough simulation data are collected, frequency estimation of CDF or LERF can be performed. With varying the epistemic parameters, the variation of CDF and LERF can be summarized as a probability distribution, which is also known as the probability distribution of frequency. On the other hand, results can also be visualized as risk curves characterized by risk triplets of scenarios/sequences, frequencies and consequences.

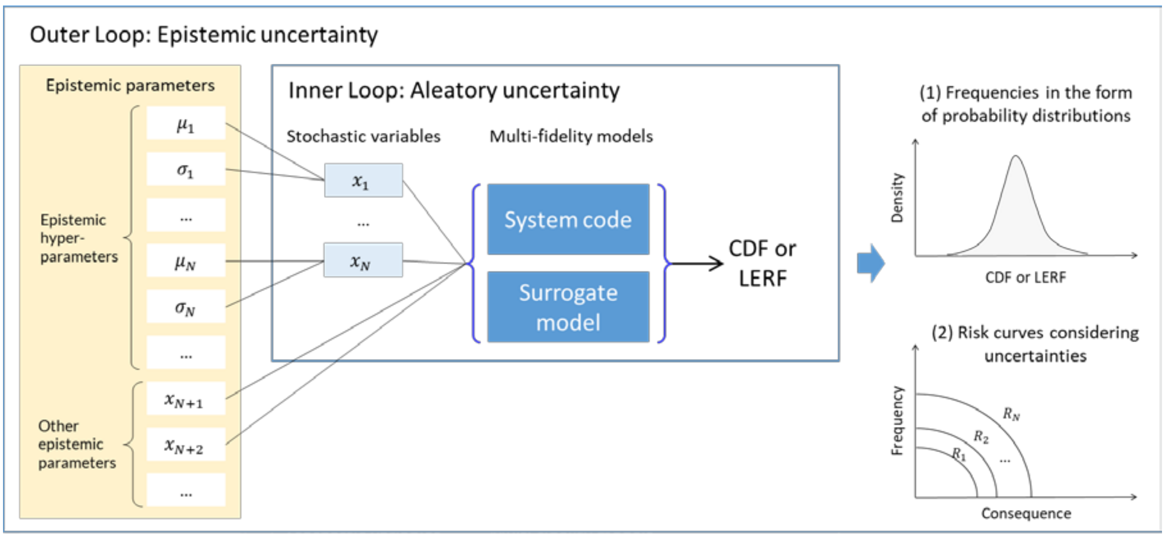

Fig. 2 Two-stage nested Monte Carlo simulation for uncertainty quantification using multi-fidelity models

4. TEST APPLICATIONS FOR A BWR SBO SCENARIO

The CDF of BWR SBO scenario with a SRV stuck-open is relatively low, but the steam-driven RCIC pumps are not functional from early period of accident, so accident countermeasures such as early coolant injection via portable equipment are required. Dynamic PRA can be useful to verify if the time margin of emergency injection is adequate for the SBO scenario.

Mechanistic BWR SBO simulation is performed using MELCOR, Version 2.2 [16]. Fig.3 depicts the MELCOR nodalization scheme. The input deck has been built based on BWR test case input of Sandia National Laboratories (SNL). 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 (RCS) is modeled 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.

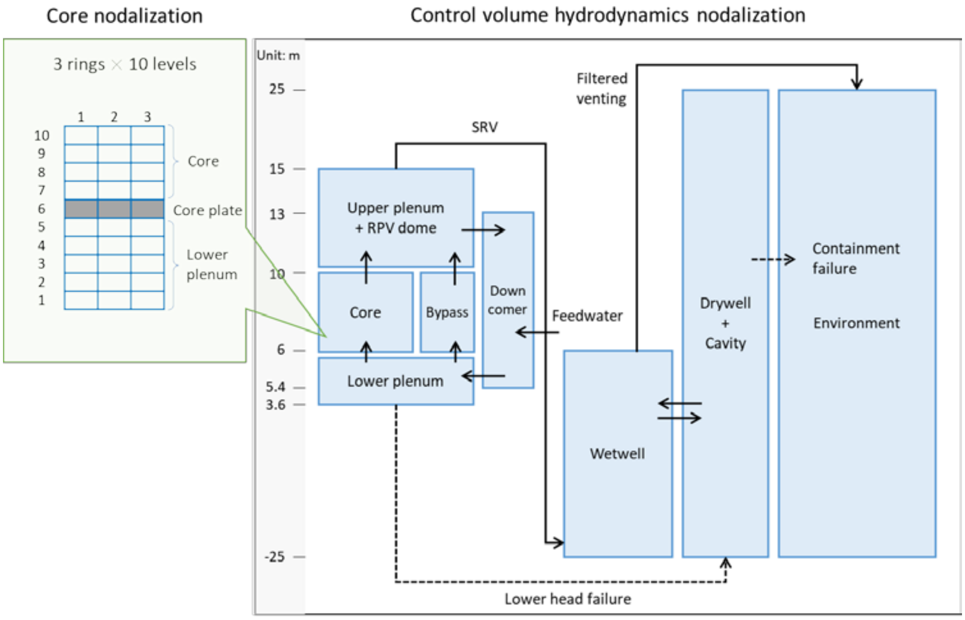

Fig. 3 MELCOR modeling of the BWR NPP

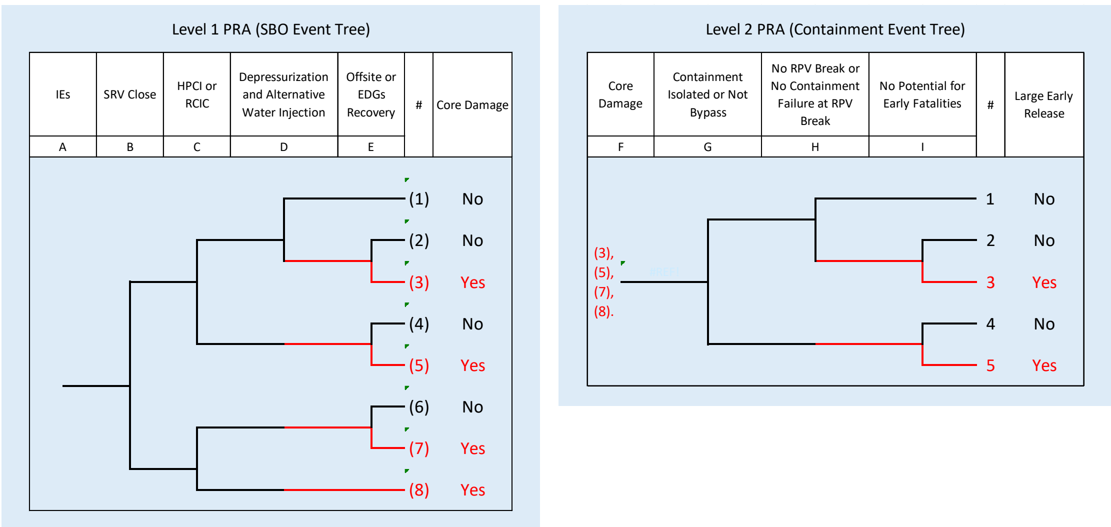

Fig. 4 SBO event tree [17] and containment event tree [18] of a BWR4 Mark-I NPP

Fig.4 depicts simplified SBO event tree and containment event trees for the analysis of large early release. Stochastic variables that affect the occurrence of pivotal events in SBO event tree of Fig.4 are shown in Table 1. The selection and parameter setting of probability distributions refers to previous researches on BWR SBO dynamic PRA [17], and sampled values have been reflected to MELCOR inputs via control functions. Listed in Table 2, epistemic parameters include parameters that affect probability distributions of stochastic variables and parameters that affect the branching of containment event tree in Fig.4.
The uncertainty analysis process has been implemented by using the dynamic PRA tool, RAPID [19]. RAPID is being developed at Japan Atomic Energy Agency (JAEA), and it is programmed using Python. It consists of modules such as random sampling, code execution, data processing and surrogate model building, etc. Recently, it enhanced by implementing functions such as parallel processing and multi-fidelity simulations.

Table 1 List of stochastic variables

	Stochastic variables	Distributions	Parameters of distribution
1	EDGs recovery time (h)	Lognormal	μ_1, σ_1
2	Power grid recovery time (h)		
3	Battery life (h)	Triangular	a, b, c
4	Number of cycles before SRV stuck open happens	Geometric	Stuck-open probability of an individual trial: p
5	RCIC failure time (h)	Exponential	λ
6	HPIC failure time (h)		
7	RCIC extended time (h)	Lognormal	μ_2, σ_2
8	Alternative water available time (h)	Lognormal	μ_3, σ_3
9	Manual automatic depressurization activation (h)		

Table 2 List of epistemic parameters

	Epistemic parameters		Distributions
1	Parameters of distributions shown in Table 1	$\mu_1, \sigma_1, a, b, c, p, \lambda, \mu_2, \sigma_2, \mu_3, \sigma_3$	Uniform
2	Containment bypass time (h)		Uniform
3	Containment early failure pressure (Pa)		Lognormal
4	Criteria for early and large [20]		Early: 4 hours after EAL-GE (declaration: 5 mins after the loss of AC and DC powers), Large: 3% of initial radionuclide inventory including Cs, I and Te)

5. RESULTS

After 6723 times of the inner loop multi-fidelity simulation, Fig.5 quantifies aleatory uncertainties in the form of probabilities of large early release. To obtain stable uncertainty information, 200 times of outer loop simulation are performed, and Fig.6 illustrates the epistemic uncertainties of the conditional large early release probability estimation. A portion of simulations is simulated by applying machine learning models when results can be predicted according to previous results, and this implementation saves computational efforts.

Sequences in Fig.5 are constructed and simulated using dynamic Level 2 PRA. We can see that it simulates accident sequences by seamlessly connecting two event trees in Fig.4. Monte Carlo sampling generate stochastic variables and accident sequences for MELCOR simulation. RAPID controls the overall process including the final step of probability estimation. Green sequences are newly generated sequences after when occurrence timings are more treated in a more detailed manner. Blue sequences are merged because time margin of emergency evacuation is too small for sequences with containment bypass. Dynamic PRA provides a practical way for treating complicated combinations of events. The point estimate of conditional probability of large early release is 1.38E-3.

Fig.6 shows the goodness of the point estimate after when uncertainty analysis is performed. Uncertainty distribution quantifies the probability range between 8.62E-4 to 3.62E-3, and it reveals how reliable the dynamic PRA results are. As a result, the nested Monte Carlo method shows the practicability in quantifying both aleatory and epistemic uncertainties.

To validate the results of risk triplet and uncertainty distribution, traditional PRA must be performed. Authors provides a validation analysis from the perspective of CDF by comparing PRA, high-fidelity dynamic PRA and multi-fidelity dynamic PRA, and results show agreements [19].

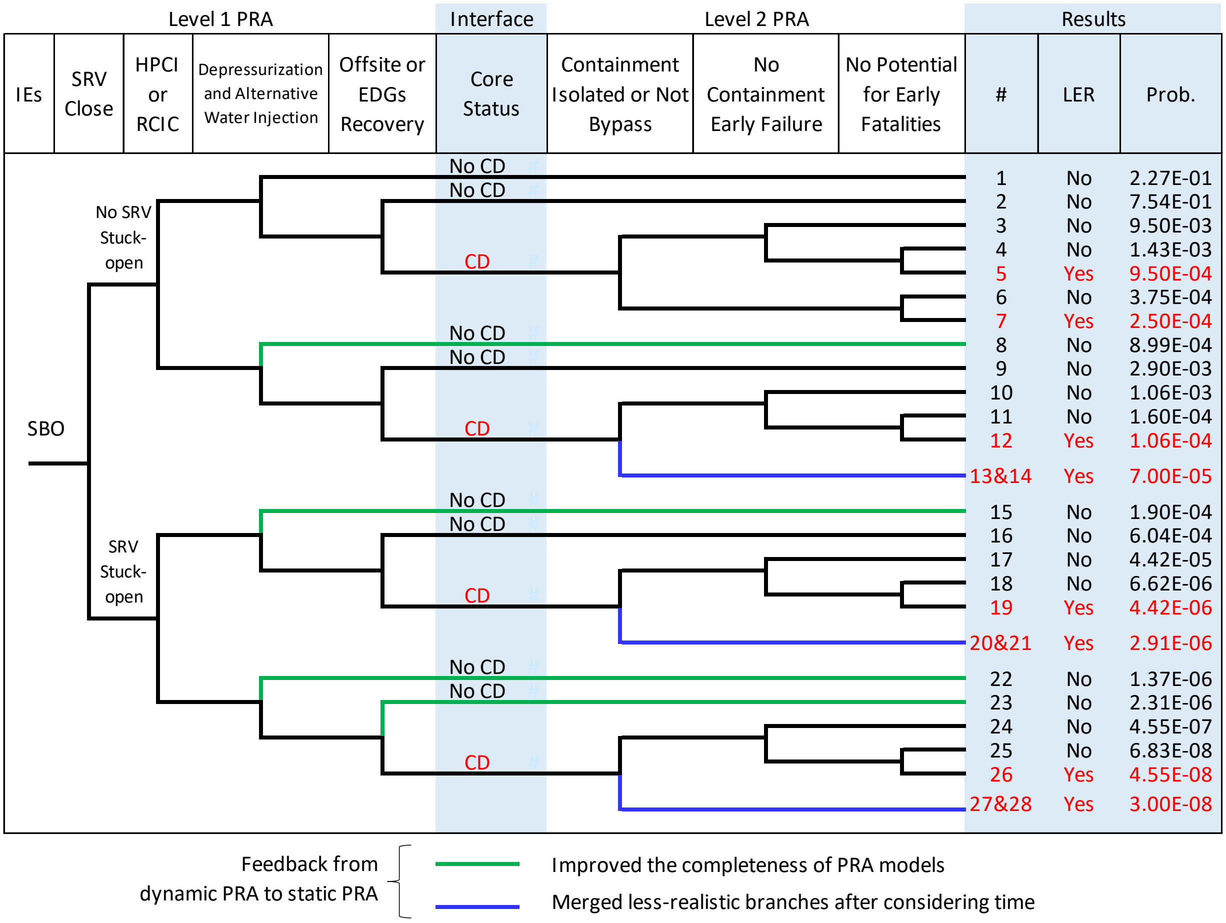

Fig. 5 Point estimates of large early release probabilities of sequences

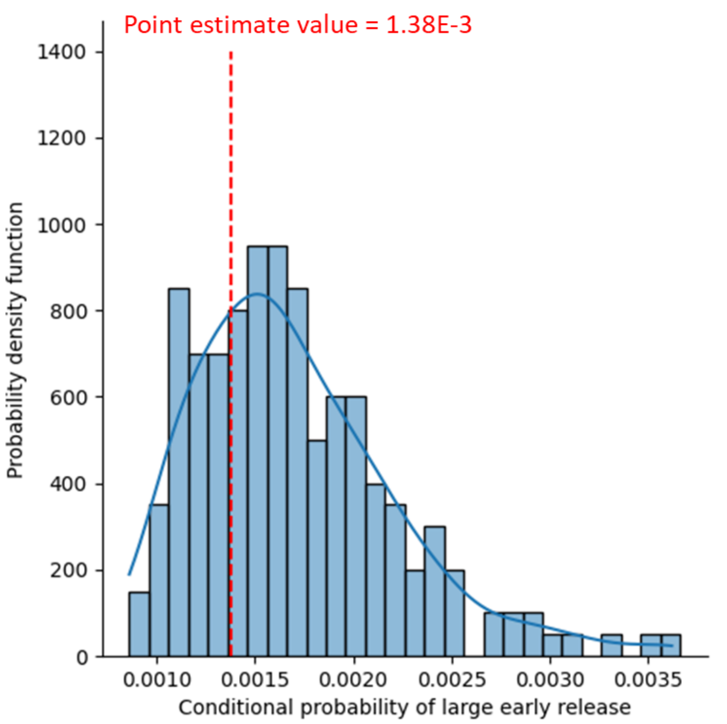

Fig. 6 Probability distribution characterizing uncertainties in conditional LERF estimation

6. CONCLUSIONS

This paper discussed approaches for the uncertainty analysis of dynamic PRA. By using two-stage nested Monte Carlo, the simultaneous treatment of aleatory and epistemic uncertainties is practical according to the test analysis and previous studies such as the MCDET method. However, the nested Monte Carlo method requires a large number of simulations, $N \times M$, where N is the minimal number of samples (inner loop) for frequency estimation and M is the minimal number of frequency estimates (outer loop) for a stable probability distribution. The authors proposed to use low-fidelity machine learning models as surrogate for the high-computational system code. It can be expected that the surrogate model can accelerate the uncertainty quantification while maintain the preciseness. Table 3 provides a preliminary comparison of uncertainty analysis between PRA and dynamic PRA.

Table 3 Comparison of uncertainty analysis for PRA and dynamic PRA

		PRA	**Dynamic PRA**
Method of frequency estimation (Aleatory uncertainty)		Boolean-Logic-based	Simulation-based
Epistemic uncertainty types	Examples of parameter uncertainty	Frequencies of initiating events, branching probabilities, etc.	Parameters of probability distributions
	Examples of model uncertainty	ET/FT structure, failure model of sub-systems, etc.	Mathematical form of probability distributions, reliability modeling, etc.
	Completeness	Treated by Defense-in-Depth and maintenance of safety margin	
Method for uncertainty propagation		Monte Carlo	Two-stage nested Monte Carlo
Result visualization		Probability distribution of frequencies, risk curves	

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