Available online at www.eccomasproceedia.org
Eccomas Proceedia UNCECOMP (2023) 585-598

ECCOMAS
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UNCECOMP 2023
5th ECCOMAS Thematic Conference on
Uncertainty Quantification in Computational Science and Engineering
M. Papadrakakis, V. Papadopoulos, G. Stefanou (eds.)
Athens, Greece, 12-14 June 2023

RISK-INFORMED DECISION-MAKING IN VERIFICATION AND VALIDATION UNDER UNCERTAINTY

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Abstract. *In recent years, the use of advanced simulation tools for modeling the behavior of flooding at a nuclear power plant has gained significant importance. The credibility of advanced simulation codes is assessed using formal approaches for verification and validation. This paper proposes a formal risk-informed validation approach that provides a basis to quantify the credibility of system-level risk assessments. The credibility of system-level validation is represented using a probabilistic metric and maturity levels. The applicability of the proposed framework is evaluated by application to a flooding scenario of a sunny day dam failure and is represented in terms of various maturity levels and helps in the process of decision-making.*

Keywords: Validation, Risk-informed, PRA, Uncertainty Quantification, External hazards, Bayesian Inference

doi: 10.7712/120223.10360.20354

1 Introduction

External hazards act as initiators of severe accidents in nuclear plants. As experienced in Fukushima-Daiichi nuclear disaster, it is necessary to improve our understanding of the accident sequence to assist decision-makers appropriately. In this context, studies have shown that significant uncertainties exist in the predictive capability of advanced simulation codes to evaluate the risk assessments [1, 2, 3, 4, 5]. The range of applicability of a simulation code is assessed by the physics and the models it contains. Verification, Validation, and Uncertainty Quantification (VVUQ) are ongoing active research areas that help to assess the adequacy of simulation models in predicting the risk over the range of an intended application and the uncertainties associated with those predictions. One of the major challenges in validation is related to the lack of relevant experimental data and lack of confidence in the applicability of simulation models [1, 6, 7]. This leads to excessive reliance on expert judgment and conservative assumptions in the nuclear plant safety assessment.

In recent years, many researchers have developed frameworks for nuclear plant safety applications. Boyack et al. [8] propose “Code Scaling, Applicability, and Uncertainty methodology (CSAU)” to identify and quantify all sources of uncertainties in a nuclear reactor. USNRC [9] introduces “Evaluation Model Development and Assessment Process (EMDAP)” to assess the adequacy of a simulation code for analyzing transient and accident behavior. Oberkampf et al. [10] develop “Predictive Capability Maturity Model (PCMM)” to assess the maturity of simulation code based on decision consequences. Athe and Dinh [3] propose “Predictive Capability Maturity Quantification (PCMQ)” to quantify the decision-making process for nuclear reactor engineering. However, these frameworks are quite powerful in certain aspects, yet they cannot be directly extended to a PRA-based approach for validation. The motivation of this study is to develop a robust risk-informed framework for the validation of advanced simulation codes with a probabilistic criterion for an adequate level of validation.

Some of the recent frameworks that are based on a PRA approach for validation, particularly in the context of external hazards, are proposed by Kwag et al. [1] and Bodda et al. [2, 11]. Kwag et al. [1] and Bodda et al. [2] illustrate the application of the risk-informed methodology for validation using a seismic and flooding case study, respectively. Bodda et al. [11] enhance the methodology by considering an additional validation index called consistency index that ensures that the system-level validation is complete and consistent.

In this study, the applicability of the proposed framework is evaluated by application to a relatively complex flooding scenario that corresponds to sunny day dam failure [12]. In the risk-informed framework, the validation for the system-level event is computed based on fragility estimates of structures, systems, and components (SSCs). However, in realistic flooding risk management, there are a few binary events (completely safe or fail), such as “random malfunction of pressurizer relief valve” and “random failure of boron system,” that are not sensitive to details of hydrodynamics and fragility modeling but are required for the probabilistic risk assessment (PRA). Therefore, in this paper, the risk-informed validation framework is updated by incorporating a new approach to handle the binary events that are not physics based. The solution for consideration of binary events can also be extended to events with cliff-edge effects. As the event tree resulting from the complex flooding scenario contains many SSCs, the importance rankings of SSCs are evaluated to determine the set of critical events from a system-level safety or system-level performance [13, 14, 15, 16].

2 Performance-Based Risk Informed Validation Framework

The proposed performance-based risk-informed validation framework shown in Figure 1 employs four key elements that are described below.

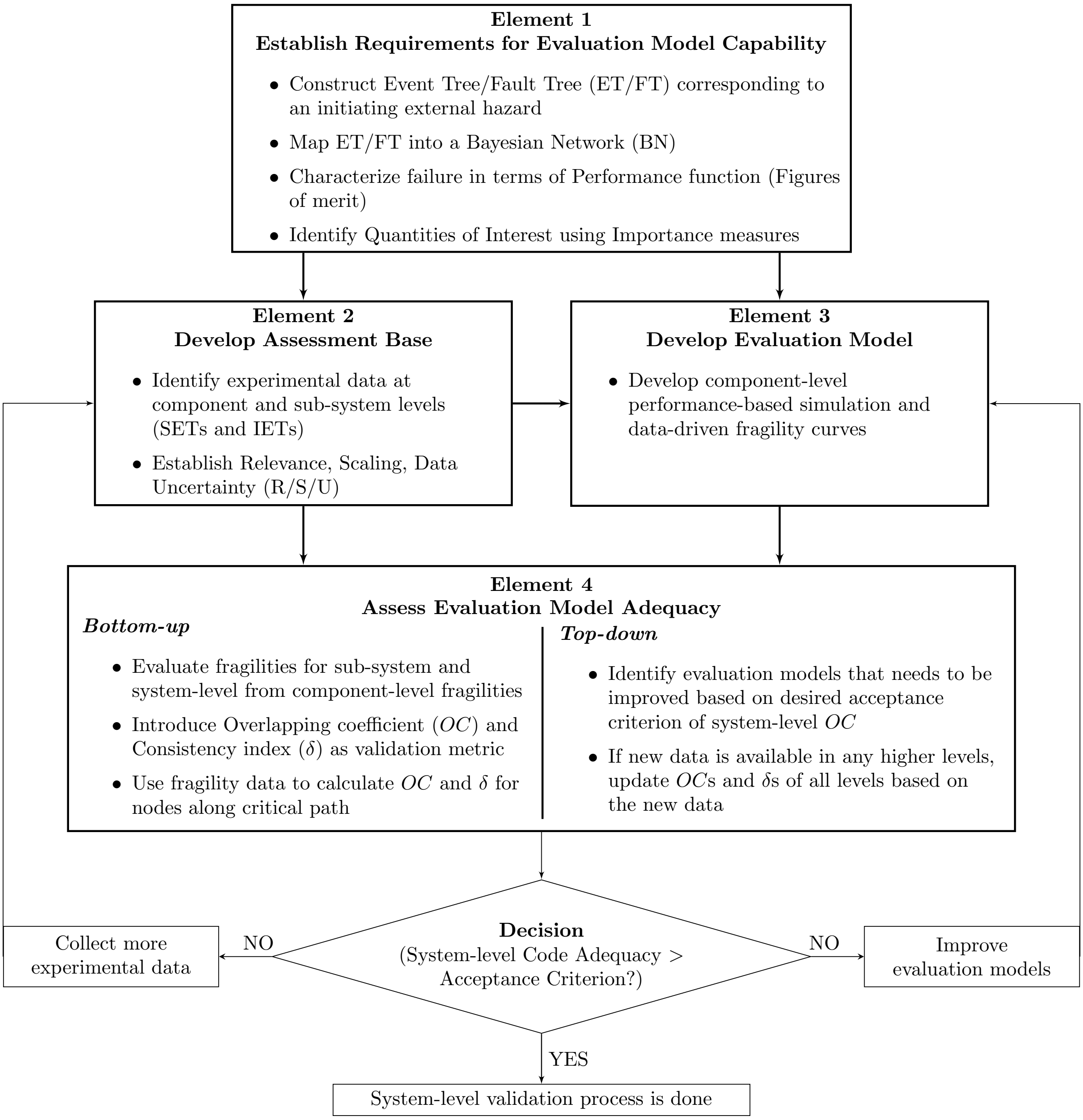


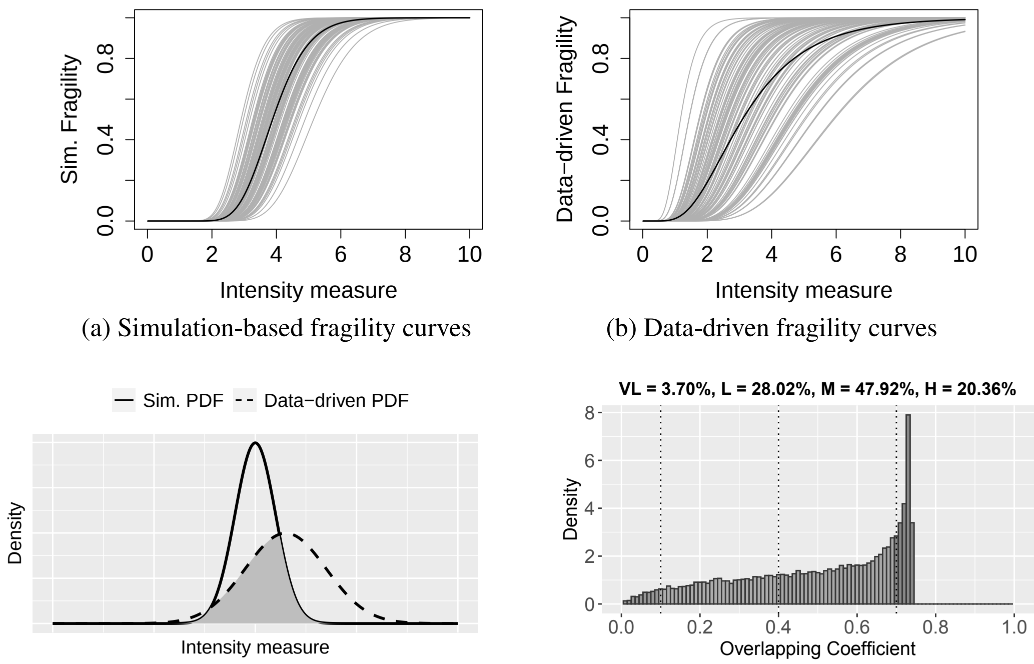
Figure 1: Performance-based risk-informed validation framework

Element 1: Establish Requirements for Evaluation Model Capability

- Construct the corresponding fault trees for the top events in the event tree.
- Map the fault trees and the event tree into a Bayesian network using a mapping algorithm.
- Characterize failure in terms of performance function and develop simulation-based fragility curves for the basic events.

- Identify critical events with respect to system vulnerability using importance measures.

In the current practice for the risk assessment of external hazards, the first step is to develop logic trees for representing the possible accident scenarios. Next, the fragility estimates are developed for basic events, where the fragility of an SSC is defined as the conditional probability of failure at a given measure of hazard intensity parameter. The simulation-based fragility curves for the basic events in a fault tree are developed using simulation software. For example, a flooding analysis may use a computation fluid dynamics (CFD) or a finite element (FE) model [4, 17, 18, 19]. Multiple simulation-based fragility curves can be generated by including epistemic uncertainty for the simulation median capacity (or median of the simulated lognormal fragility function) as shown in Figure 2 (a) [20, 21].



(a) Simulation-based fragility curves

(b) Data-driven fragility curves

(c) Overlapping coefficient (OC)

(d) Code Adequacy (histogram of OC)

Figure 2: Summary of existing risk-informed validation framework

In the performance-based risk-informed validation framework, binary trees (fault and event trees) are mapped into a Bayesian network using a mapping algorithm [22]. A Bayesian network is a probabilistic graphical model that provides a more general form of statistical relationships among the events compared to logic trees. Then, the probabilities of failure for system-level and intermediate-level events are obtained by propagating conditional probabilities of failure (fragilities for basic events or root nodes) through the Bayesian network. Next, critical events in the Bayesian network are identified using Fussell-Vesely (FV) importance measure at each intensity measure [11]. FV importance measures the relative contribution of each basic event to the system-level failure. In Bayesian networks, the FV importance is actually implemented by using a modified definition of FV importance which is termed as extended FV importance and is given by Eq. (1) [11].

$$FV(x_i) = P(x_i = 1|\phi = 1) \tag{1}$$

where, $FV(x_i)$ is the FV importance of node x_i in a Bayesian network, $P(x_i = 1|\phi = 1)$ represents the posterior failure probability of node x_i given that the system (ϕ) is failed.

Element 2: Develop Assessment Base

- Collect experimental data at the component and sub-system levels for the identified critical events.
- Establish the quality of experimental data based on Relevance, Scaling, and Data uncertainty (R/S/U) attributes.

In element 2, an assessment base is developed that is used to compare the accuracy of simulation models with respect to the experimental data. The quality of experimental data is graded by three attributes: Relevance, Scaling, and Data Uncertainty (R/S/U). Relevance attribute measures the degree to which the experimental data from existing studies is applicable to the current application. Scaling uncertainty incorporates both geometric and physics scaling uncertainties. Data uncertainty reflects the uncertainty in the measured data. If experimental data is not available for a critical event, then one could develop data-driven fragility curves based on experience data or even high-fidelity simulations that have been validated against some experiments [2]. The R/S/U attributes represent the epistemic uncertainty in the data-driven fragilities. They are quantified by assigning grades on a four-point scale (1-4, 1 being poor and 4 being excellent) based on the data quality.

Element 3: Develop Evaluation Model

- Develop performance-based data-driven fragility curves for the identified critical events. In general, fragility assessment requires the use of a Monte Carlo approach to include uncertainties from various sources. However, if a sufficient knowledge base has been developed, one can use the standard lognormal fragility parameters.

In element 3, data-driven fragilities are developed for the basic events identified as critical in Element 1 using the assessment database whenever possible. Then, multiple data-driven fragility curves can be generated by including the epistemic uncertainty due to data applicability as shown in Figure 2 (b) [2]. The data-driven fragilities of basic events are then propagated through the Bayesian network to obtain the fragilities of intermediate and system-level events.

Element 4: Assess Evaluation Model Adequacy

- For the bottom-up approach, propagate fragility information from basic events (root nodes) to intermediate-level and system-level through the Bayesian network. Then, calculate the overlapping coefficient (OC) and consistency index (δ) based on simulation and data-driven fragility curves for the events along the critical path. If $\delta = 1$ for all the events on the critical path, then calculate the system-level code adequacy.
- For the top-down approach, the evaluation models that need to be improved are identified by specifying the acceptance criterion of overall validation to be greater than 70%. This criterion corresponds to high maturity of code adequacy as shown in Table 1. Also, if additional data become available at higher levels, then update the fragility curves and the subsequent overlapping coefficient using Bayesian inference.

The concepts of overlapping coefficient (OC) and consistency index (δ) are used to quantify the degree of validation within the context of uncertainty. OC is defined as the fraction of common area between two probability density curves and is given by Eq. (2) and shown in Figure 2 (c). OC varies from 0 to 1, where $OC = 0$ represents complete disagreement between simulation and experimental models and $OC = 1$ represents perfect agreement between the models.

$$OC = \int_{-\infty}^{\infty} \min\Big(f_{sim}(y), f_{exp}(y)\Big)dy \tag{2}$$

where y is the intensity measure of external hazard, $f_{sim}(y)$ and $f_{exp}(y)$ represent the density of the simulation-based fragility curve and data-driven fragility curve, respectively. A point estimate of OC is obtained if only the mean/median fragility curve of simulation and data-driven models are considered. However, if the epistemic uncertainties for both simulation and data-driven fragility models are included, a histogram of OC is developed by considering various combinations of simulation-based and data-driven fragility curves as shown in Figure 2 (d).

The consistency index (δ) for an intermediate or system-level event ensures that the simulation and data-driven fragilities come from the same set of critical events. If the critical events are the same in both the simulation and data-driven models, then $\delta = 1$. If the critical events differ in both models, then $\delta = 0$. If $\delta = 0$ at a given intensity measure, then either the simulation model can be improved, or additional experimental data may be collected. It is also possible to improve both of these, and the true answer depends on the specific problem/scenario being considered. Subsequently, one would need to update the fragility curves until $\delta = 1$. The OC and δ are calculated for all the events in the Bayesian network. Next, the assessment of the decision regarding the adequacy of a simulation code is represented by four maturity levels (very low, low, medium, and high). Code applicability is evaluated by dividing the histogram of OC into four regions based on the maturity range given in Table 1. Then, the percentage of the area in each region is computed and assigned to its corresponding maturity level as shown in Figure 2 (d).

Decision

- If all the events on the critical path are consistent (i.e., $OC = 1$), then compare system-level code adequacy with a predefined acceptance criterion.
- If the adequacy of system-level validation is not satisfied, collect more data or improve evaluation (simulation or data-driven) models of the identified critical events. The data can be an either experimental, simulation, or both based on their degree of uncertainty.

Maturity Level	**% of Area in Histogram of Validation metric**
Very Low (VL)	$[0.0 \quad 0.1)$
Low (L)	$[0.1 \quad 0.4)$
Medium (M)	$[0.4 \quad 0.7)$
High (H)	$[0.7 \quad 1.0]$

Table 1: Maturity levels for Code Adequacy

3 Flooding Scenario – Sunny Day Dam Failure

The adequacy of the risk-informed validation framework is evaluated by application to a relatively complex flooding scenario. The flooding scenario is based on USNRC's study [12] on sunny day dam failure with advance warning of an external flood and severe site flooding. The scenario begins with a sunny day dam break upstream of a Pressurized water reactor (PWR) nuclear plant situated in a typical riverine environment (Initiating event, IE). The release of water due to a dam break acts as external flooding at the plant. The plant has a dike along the riverbank for basic flood protection (Event E1). If the plant has at least 8 hours of notification time before flood arrival, it is assumed that it will be successful in achieving a hot shutdown; otherwise, the plant must contend with external flooding (EF) site conditions of the plant during the shutdown (Event E2). During the flood event, all the key safety functions, such as maintaining onsite power (Event E3), reactivity control (Event E4), reactor cooling (Event E5), and reactor pressure (Event E6), should be in a safe, stable state. If the safety functions are working properly and there is sufficient warning time before the landscape flooding occurs, the operators will test and align the severe flood management system (SFMS) for external flooding (Event E7). Then, the atmospheric dump valves (ADVs) are opened to reject steam into the atmosphere (Event E8). If the ADVs are not able to be opened or prevented from reclosing, the main steam safety valves (MSSVs) will be opened to create an alternate path for steam rejection and secondary side heat removal (Event E9). The SFMS will be placed into service by providing power and water to the plant (Event E10). If the normal plant equipment is lost due to flooding, then the decay heat removal (DHR) will need to be transferred to the steam generator (SG) from the DHR system (Event E11). If the SFMS continues to remove decay heat (Event E12), the plant will be in a safe, stable state, and the post-flood procedures will be implemented. The event tree resulting from this example is shown in Figure 3, and the details of the fault trees of top events can be found at Bodda [6].

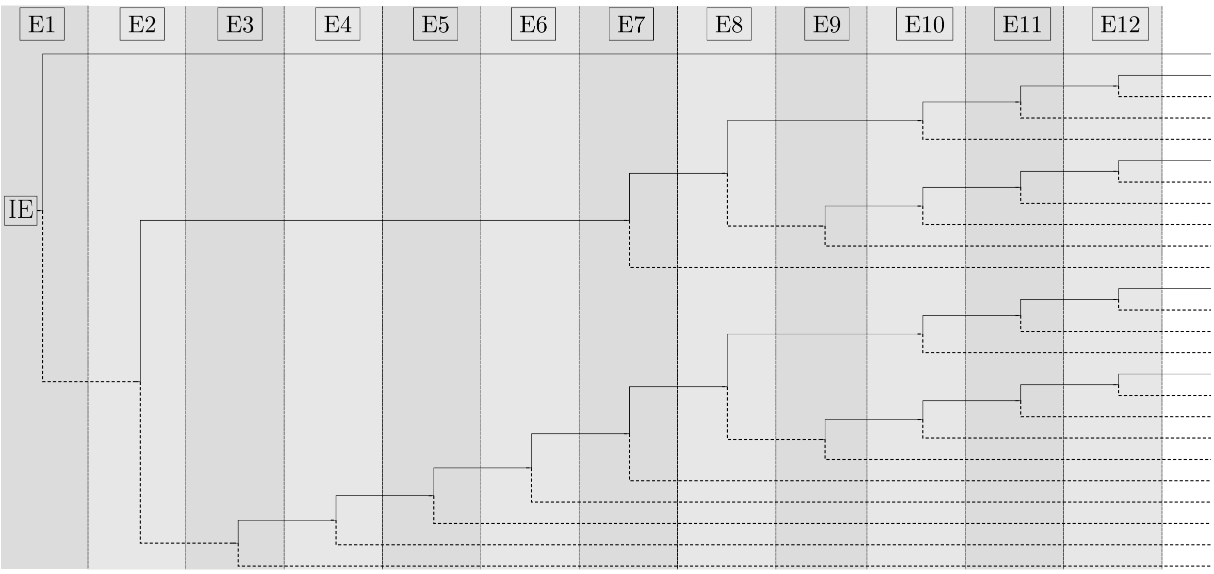


Figure 3: Event Tree logic for the Sunny Day Dam failure

4 Application of Risk-Informed Framework

In this section, the application of the risk-informed framework is illustrated for the flooding scenario by establishing the four elements of the framework presented in section 2.

4.1 Element 1: Establish Requirements for Evaluation Model Capability

The flooding scenario consists of a total of 12 top events in the event tree and 26 unique basic events in the fault trees. The event tree and the corresponding fault trees are mapped into a Bayesian network as shown in Figure 4.

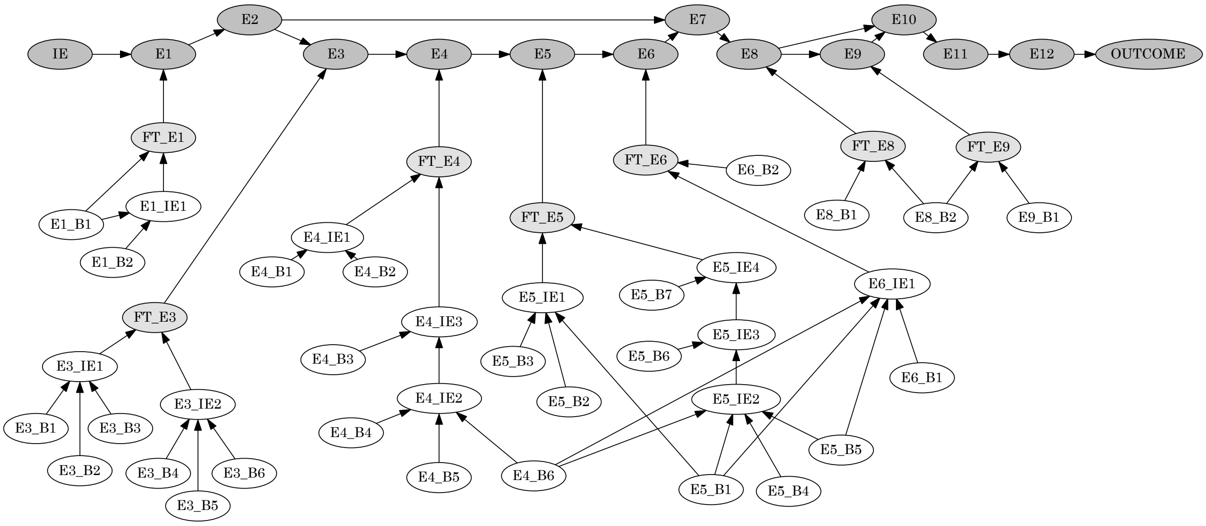


Figure 4: Mapped Bayesian network corresponding to the event tree shown in Figure 3

In this scenario, there are a total of five top events and seven basic events that are due to random or operational failures, as shown below:

- **Top events:** *Event 2, Event 7, Event 10, Event 11, Event 12*.
- **Basic events:** *E4–B1, E4–B3, E5–B6, E5–B7, E6–B2, E8–B1, E9–B1*

From a validation point of view, these non-physical events are not sensitive to hydrodynamic and fragility modeling details. These events can be treated as cliff-edge events, and therefore, in the integrated framework, the non-physical events are categorized into the following two cases:

- ***Safe-Binary/Cliff-Edge Condition:*** Treating non-physical binary events or cliff-edge events as completely safe
- ***Fail-Binary/Cliff-Edge Condition:*** Treating non-physical binary events or cliff-edge events as completely fail

The failure probability of the non-physical events remains the same for all the intensity measures of flood height. The fragility estimates needed for basic events in this study are mostly adopted from different simulation-based studies [23, 24], and a few are based on the author's experience in conducting such studies for nuclear power plant facilities. The values of fragility curves used in this application are considered only for illustrative purposes. The proposed framework and its salient features would not change if different values are adopted for the fragilities of SSCs. Like seismic PRA, flooding fragilities of many SSCs can follow (or be fitted into) a lognormal distribution [17, 19]. Then, the fragility values at a specified intensity measure are mapped into the failure probability of root nodes of the corresponding

Bayesian network. Subsequently, the critical path is obtained for different values of intensity measures as the failure probability of an event depends on the intensity measure used. In this study, the critical events for both cases are evaluated by calculating the FV importance measure for all the basic events using Eq. (1).

4.2 Element 2 & 3: Develop Assessment Base and Evaluation Model

Next, the data-driven fragility parameters are assumed only for the identified critical events shown in Table 2. For all the non-critical events, the data-driven fragility parameters are considered to be the same as the simulation-based fragility parameters. Table 2 gives the lognormal data-driven fragility parameters for all the critical events. In addition to the data-driven fragility parameters, the grade quality of experimental data for the critical events is assumed to be directly available.

Basic Event	$\hat{\lambda}\,(m)$	β_{AU}	**Data Applicability**	**Simulation Uncertainty**
E1–B1	2.795	0.30	High Maturity	Medium Maturity
E1–B2	2.225	0.40	High Maturity	Medium Maturity
E8–B2	2.591	0.30	Medium Maturity	High Maturity

Table 2: Data-driven Lognormal fragility parameters and Epistemic uncertainty (maturity) of critical events

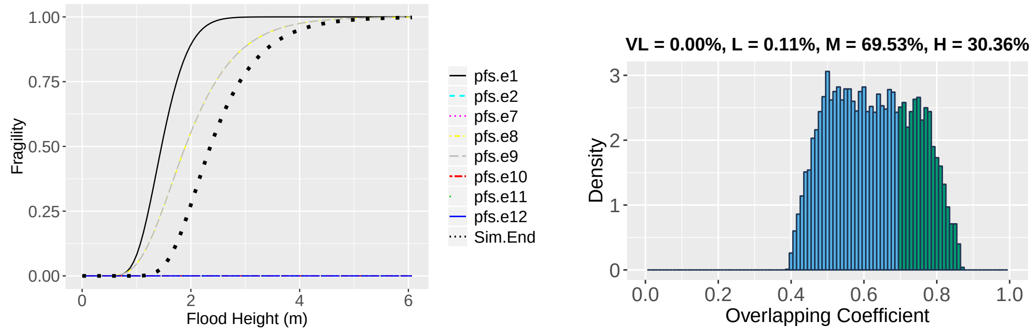
4.3 Element 4: Assess Evaluation Model Adequacy

In element 4, the system-level code adequacy is evaluated for the two cases of non-physical events.

4.3.1 *Safe-Binary/Cliff-Edge Condition:*

The failure probability of all the non-physical events equals 0 for all the intensity measures of flood height. The identified critical event, in this case, is “E8–B2: partial or complete failure of turbine building due to potential adverse flood effects” that corresponds to the basic event in the fault trees of *Event 8: EF-ADVS* and *Event 9: EF-MSSVS*. The simulation and data-driven fragility curves for the system-level or end-state event are obtained by propagating the fragilities from basic events and top events through the mapped Bayesian network. The simulation-based fragility curves for the system-level and top events are shown in Figure 5 (a). As seen in Figure 5 (a), the three events for which fragility curves propagate through the event tree are top events $E1, E8$, and $E9$. The fragility curves for other top events are non-existent or have zero probability of failure because they correspond to the safe binary cliff-edge condition of non-physical events. Multiple simulation fragility curves are generated by assuming a coefficient of variation of 0.1 for the simulation median capacity. Similarly, multiple data-driven fragility curves are generated by including data applicability [2, 20, 21].

In the next step, the overlapping coefficient (OC) for the system-level event is computed (Eq. 2) by taking multiple combinations of simulation and data-driven fragility curves. The histogram of obtained OCs is shown in Figure 5 (b), and it is divided into four regions based on the maturity quantification given in Table 1. Then, the percentage of overlapping areas for each maturity level is computed. The OC for the system-level event has a high maturity of 30.36% and medium maturity of 69.53%, as shown in Figure 5 (b).



(a) Simulation fragility curves for TOP events

(b) Code adequacy

Figure 5: Safe-Binary/Cliff-Edge Condition

Decision:

Next, a decision maker would need to decide on an acceptance criterion for validation. If an acceptance criterion that the overall validation (OC) needs to be greater than 70% is adopted, then it means all the OC area (100% of it) must lie in the high maturity region. For such an acceptance criterion, the adequacy of the code when the overall validation lies only 30.36% in the high maturity region would be unacceptable. Therefore, the system-level validation needs to be improved by enhancing either the simulation models or collecting additional experimental data for the identified critical events.

4.3.2 *Fail-Binary/Cliff-Edge Condition:*

In this case, the failure probability of all the non-physical events is equal to 1 for all the intensity measures of flood height. In this case, the identified multiple critical events are "E1–B2: dike collapses due to structural failure" and "E1–B1: Overtopping of dike". These critical events correspond to the basic events in the fault tree of *Event 1: EF-Protect*. The simulation-based fragility curves for the system-level and critical events $(E1 - B1, E1 - B2)$ are shown in Figure 6. As seen in Figure 6, the event $E1 - B2$ governs until a flood height of $2.438\ m$, and the event $E1 - B1$ governs after the flood height of $2.438\ m$. This is because *Event 1: EF-Protect* is connected to basic events $E1 - B1$ and $E1 - B2$ by OR logic. Therefore, the fragility of *Event 1: EF-Protect* is governed by the event with the highest failure probability.

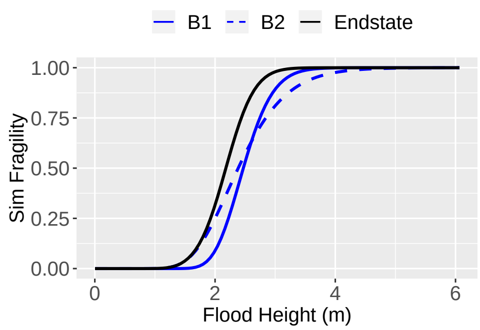
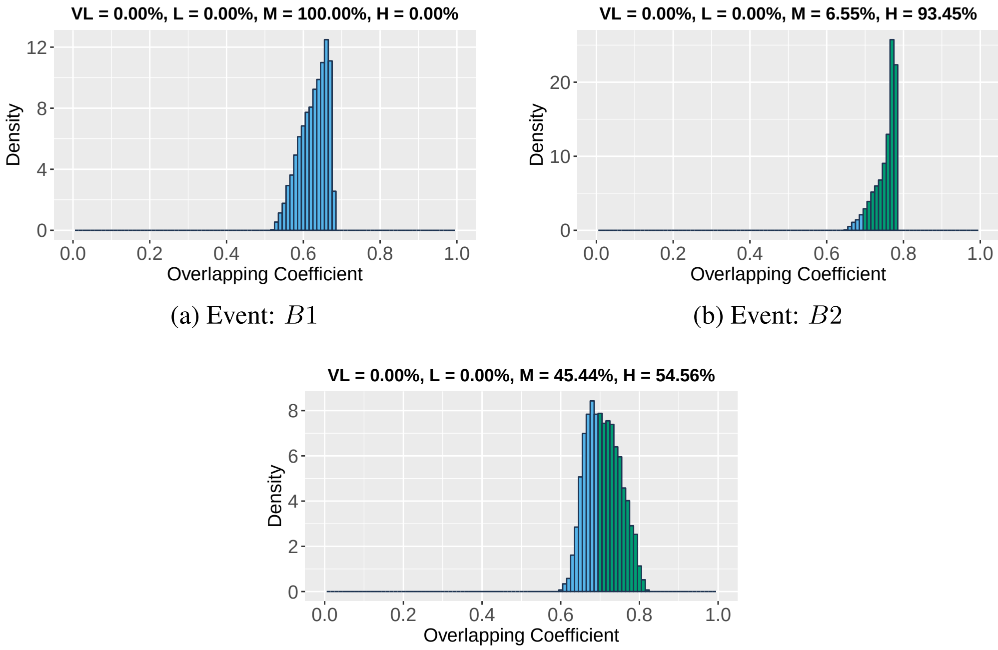


Figure 6: Simulation fragility curves for system-level and critical events (Fail-Binary/Cliff-Edge Condition)

In the next step, the overlapping coefficient (OC) for the system-level event and the critical events is computed (Eq. 2) by taking multiple combinations of simulation and data-driven fragility curves. The histogram of obtained OCs is shown in Figure 7, and it is divided into four regions based on the maturity table given in Table 1. Then, the percentage of overlapping areas for each maturity level is computed. The code adequacy for the system-level and critical events are shown in Figure 7. The mean value of OC for system-level, $E1 - B1$, and $E1 - B2$ events are 0.71, 0.63, and 0.75, respectively. As the system-level fragility depends on multiple critical events, the OC for the system-level event lies between the OC for the critical events.



(a) Event: $B1$

(b) Event: $B2$

(c) System-level

Figure 7: Code Adequacy of system-level and critical events (Fail-Binary/Cliff-Edge Condition)

Decision:

Similar to case 1, the acceptance criterion for the overall validation is adopted to be greater than 70%, i.e., corresponding to 100% of the high maturity region. In this case, the adequacy of the code for the overall validation is unacceptable for the desired acceptance criterion. Therefore, Bayesian inference is used to identify the evaluation models that need to be improved. The updated simulation and data-driven fragility curves of the critical events are shown in Figure 8. In this case, the simulation-based evaluation models for both critical events must be improved. Once additional data is collected from experiments or high-fidelity simulations for the identified critical events, Bayesian inference can be used to update the fragility curves, and the subsequent overlapping coefficients [2]. The process is repeated until the code adequacy meets the desired acceptance criterion.

The code adequacy obtained for the binary case studies does not reflect the actual degree of validation. However, the main objective of this study is to use risk-informed decisions to identify critical events for which collecting additional data would reduce the uncertainty and improve the validation of overall risk estimates. The code adequacy can be re-calculated by collecting additional data for the identified critical events and using exact failure probabilities for non-physical events.

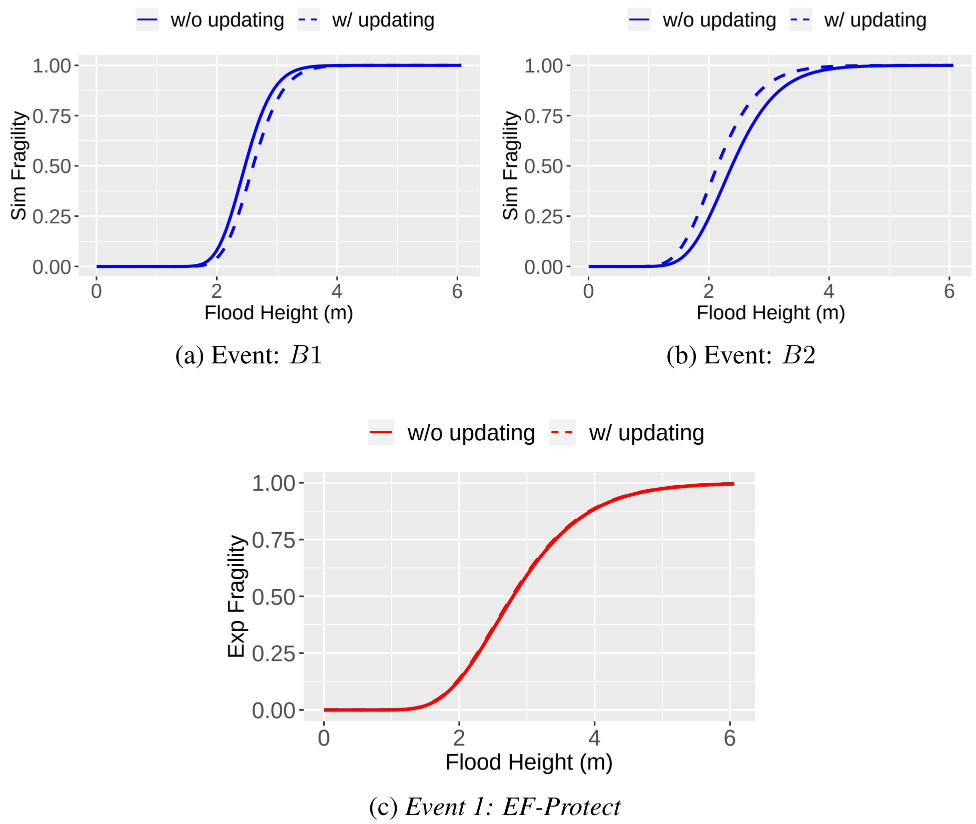


Figure 8: Simulation and Data-driven fragility curves of critical events (Fail-Binary/Cliff-Edge Condition)

5 Summary and Conclusions

The proposed framework formalizes the validation process for an external hazard scenario and serves as a basis for validation data planning by identifying the critical events that require experimental data in the context of system-level failure. In this study, an external flooding scenario is considered to evaluate the applicability of the proposed risk-informed . The data-driven fragilities are generated only for critical events. For non-critical events, the data-driven fragilities are assumed to be same as simulation-based fragilities. This assumption for the non-critical events is employed due to the computational challenges posed by the generation of multiple fragility curves for many non-critical events in the Bayesian network. However, this limitation can be addressed through the Bayesian framework by updating the fragility curves for the non-critical events whenever new data becomes available for the non-critical events in the future. The key conclusions of this study are summarized as follows:

- The proposed risk-informed framework enables us to quantify the validation for a flooding scenario.
- It is also illustrated that the proposed framework allows the implementation of Bayesian inference to identify the critical events for which collecting additional data would reduce the uncertainty and improve the validation of overall risk estimates.
- The framework formalizes the validation process by quantifying the expert knowledge and making it less heuristic.

- The non-physical events in the PRA model are identified and treated as either completely safe or fail in the validation process.

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