Integration of Physical Simulation with PRA for Nuclear Energy Systems: Literature Review and Conceptual Framework

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Abstract:

Physical simulations, such as thermal-hydraulic codes and finite element analysis, are increasingly utilized to support probabilistic risk assessment (PRA) of nuclear energy systems for constructing scenarios and quantifying their probabilities and consequences. This trend is driven, on the one hand, by advances in computational power. On the other hand, there is growing recognition of the value of integrating physical simulations with PRA. For novel reactor designs, physical simulations can compensate for limited operational data and provide a mechanistic understanding of system behaviors. For existing plants, integrating physical simulations into PRA can produce more detailed, in-depth risk insights grounded in first-principles engineering analysis.

Realizing these benefits requires that the interface between PRA and physical simulations (namely, the structural and methodological connection between PRA logic and simulation inputs/outputs) should be carefully designed, as the interface directly affects model accuracy, consistency, and computational feasibility. The goal of this research is to establish a generic technical basis, applicable across reactor types and simulation codes, for guiding the development and improvement of PRA-physical simulation interfaces.

This paper makes three contributions. First, a literature review is conducted to characterize the state of the art in PRA-physical simulation integration and to identify research gaps. Second, a conceptual framework is proposed to analyze PRA-physical simulation interfaces. The framework formalizes the multi-layer relationship between PRA model elements and the physical simulation scope, and provides a theoretical basis for evaluating the adequacy and feasibility of interface approaches. Third, building on the literature review and the conceptual framework, open research directions aimed at broadening the PRA-physical simulation integration to better support risk-informed decision-making are discussed.

1. INTRODUCTION

Physical simulations, such as thermal-hydraulic codes and finite element analysis, have been increasingly utilized to support probabilistic risk assessment (PRA) of nuclear energy systems for constructing risk scenarios and quantifying their probabilities and consequences. In this paper, physical simulations refer to physics-based computational models that numerically solve governing equations (e.g., conservation of mass, momentum, and energy) to predict the progression of physical phenomena and system behavior under specified conditions. Increased use of physical simulations in PRA is driven, on the one hand, by advances in computational power, which enable the execution of physical simulations within timeframes consistent with PRA implementation. On the other hand, there is growing recognition of the value of integrating physical simulations with PRA. For new reactor designs, physical simulations can compensate for limited operational data and provide a mechanistic understanding of system behavior. For existing plants, integrating physical simulations into PRA can produce more detailed risk insights that can facilitate risk-informed applications, such as lifetime extension, power uprate, and operational and maintenance efficiency.

Realizing these benefits requires a carefully designed computational interface between PRA and physical simulations to enable reliable and efficient information exchange between the two sides. Here, the 'interface' refers to the structural and methodological connection between PRA logic and physical simulations, specifically, how their input-output exchange is operationalized. However, in literature, there is no generalizable, systematic technical basis to inform the design of such interfaces, which has motivated this work.

The goal of this research is to establish a generic technical basis, applicable across reactor types and simulation codes, for guiding the development and improvement of PRA-physical simulation interfaces. This paper makes three contributions. First, a literature review is conducted to characterize the state of the art in PRA-physical simulation integration and to identify research gaps that require further investigation. Second, a conceptual framework is proposed to analyze the PRA-physical simulation interfaces, which serves as the theoretical basis for evaluating adequate and viable approaches. Third, building on the literature review and the conceptual framework, this paper discusses open research directions aimed at broadening the integration of physical simulations with PRA to better support risk-informed decision-making.

The remainder of this paper is organized as follows. Section 2 presents preliminary findings from the ongoing literature review. Section 3 proposes a conceptual framework for analyzing PRA-physical simulation interfaces. Section 4 uses the conceptual framework to identify open research directions. Section 5 provides concluding remarks.

2. PRELIMINARY LITERATURE REVIEW

This section reports preliminary insights from an ongoing literature review. Since this literature review is an ongoing effort, the findings should be regarded as tentative, grounded in the limited corpus reviewed to date.

Section 2.1 establishes a taxonomy used to structure the understanding of PRA-physical simulation integration. Section 2.2 presents preliminary insights from the literature review.

2.1. Hierarchical Viewpoint of PRA-Physical Simulation Integration

The PRA community broadly recognizes a high-level hierarchical structure of engineering systems, which typically encompasses five levels from top to bottom: systems, components, parts, physical failure modes, and physical failure mechanisms (Table 1) [1].

Table 1: Hierarchical Structure of PRA Modeling.

Levels	Descriptions
Systems	Critical functions and the systems required to fulfill them (e.g., emergency core cooling, reactor protection)
Components	Individual hardware elements constituting each system, such as pumps, valves, and pipes (e.g., pumps, valves, pipes)
Parts	Sub-elements of each component necessary to perform its designed function (e.g., a pump shaft or motor)
Physical failure modes	Observable manifestations of component/part failure (e.g., leak, rupture, or excessive vibration)
Physical failure mechanisms	Underlying physical processes that can result in each physical failure mode (e.g., fatigue crack growth, corrosion, or creep)

Systematic risk models, such as event trees and fault trees, typically capture the higher levels of this hierarchy, most often the system and component levels. Physical simulations, such as finite element analyses and fracture mechanics models, are typically used at the lower levels of this hierarchy, where the underlying physical processes are explicitly solved. Of particular interest in this study is the interface between PRA logic models and physical simulations, where these two modeling paradigms exchange information. The location of this interface within the hierarchy is a modeling choice that can substantially influence the scope, fidelity, and feasibility of the PRA-physical simulation interface.

2.2. Preliminary Insights

This section summarizes preliminary insights from a selective literature review, which covers two groups of literature: (i) two representative references from the authors' prior research on an integrated PRA (I-PRA) methodology [2, 3] and (ii) research and development by Idaho National Laboratory (INL) on a suite of simulation-based risk analysis tools under the Risk-Informed Systems Analysis (RISA) pathway [4-15]. A more systematic literature review is ongoing to generate comprehensive results.

In most of these studies, the computational interface is located at the part or component level [2-14]. In these studies, physical simulations are used to analyze the progression of failure mechanisms that initiate and accumulate damage in parts and components. In dynamic PRA studies (e.g., Ref. [15]), by contrast, physical simulation is used to analyze system-level response to risk scenarios. Thermal-hydraulic simulation (e.g., RELAP5-3D) is used to model reactor system behavior under risk scenarios, while the status and recovery times of individual components are sampled from probabilistic distributions. This type of simulation is not used to analyze physical failure mechanisms at the component or part level, but it captures system-level responses and consequences.

Table 2 summarizes the key features and functionalities of the PRA-physical simulation interface identified in the preliminary literature review.

Table 2: Key Features and Functionalities of the PRA-Physical Simulation Interface (Preliminary List)

Key Feature and Functionality	References
Uncertainty quantification	[2-15]
Stochastic process models	[3, 14]
Component dependency	[2]
Reduced order models (ROM) or surrogate models	[4-13, 16]
Verification and validation (V&V)	[2, 3]

The most common functionality is sampling-based uncertainty propagation, which makes deterministic physical simulations probabilistic. Some studies [3, 14] also incorporated stochastic process models into the interface, specifically, a multi-phase Markov process [3] and a semi-Markov process [14], to model time-dependent transitions among component or part damage states, accounting for degradation and maintenance.

All the reviewed studies that used physical simulations to model component degradation and damage mechanisms connected the computational interface to a single component [3-14], with the exception of Ref. [2]. When two or more components are connected, the interface must account for component dependencies. For that purpose, Sakurahara et al. [2] developed an interface that explicitly analyzes dependencies arising from shared causal factors and failure mechanisms through physical simulations.

Another recurring feature is the use of reduced-order models (ROM) or surrogate models. Most often, full physics simulations are computationally expensive, and sampling-based uncertainty propagation compounds this burden by requiring a large number of repeated simulation runs. Rather than interfacing directly with full physics simulations, several studies developed ROMs or surrogate models for physical simulations and integrated them with a PRA model. One common approach uses interpolation from a pre-computed table of simulation outputs [5-14]; another approach trains a surrogate model, such as a regression or machine learning model, on precomputed data [16]. It should be noted that the accuracy of such models warrants careful evaluation, particularly when extrapolation beyond the training range is needed [16].

Verification and validation (V&V) of the computational interface is a consideration that has received less attention than V&V of physical simulations themselves. The interface introduces its own potential uncertainty sources, including specific models (e.g., stochastic processes), numerical methods (e.g., sampling methods), and associated parameters (e.g., state transition rates, sample sizes). One possible approach is to conduct a comprehensive uncertainty analysis to characterize the overall uncertainty induced by the computational interface, covering both aleatory and epistemic sources [17, 18]. However, the scope and quantitative approaches of V&V must be balanced with additional computational burden.

3. CONCEPTUAL FRAMEWORK

One lesson from the authors' research experience is that no generic conceptual framework currently exists for the PRA-physics simulation interface. Such a framework could offer scientific and practical benefits to PRA research by informing the design of the computational interface and guiding efforts to address practical challenges and needs.

This section presents an initial attempt to develop such a framework, with particular focus on mapping across layers of the hierarchical structure of PRA modeling (Table 1). Understanding this cross-layer mapping has direct implications for several features and functionalities identified in Section 2.2 (Table 2), including the treatment of component dependencies, reduction of computational burden, and the use of ROMs and surrogate models.

3.1. Mathematical Notations for Problem Formalization

To analyze the PRA-physical simulation interface systematically, a set of mathematical notations that formalize the hierarchical structure defined in Section 2.1 is introduced. A key insight emerging from this formalization is that the size of the explicit modeling scope grows multiplicatively as deeper levels of the hierarchy are explicitly modeled.

Let $\mathcal{S} = \{s_1, s_2, \cdots, s_H\}$ denote the set of systems in the PRA logic model. Each system s_h comprises a set of components $\mathcal{C}_h = \{c_{h,1}, c_{h,2}, \cdots\}$. Each component $c_{h,i}$ is composed of a set of parts $\mathcal{P}_{h,i} = \{p_{h,i,1}, p_{h,i,2}, \cdots\}$. Each part $p_{h,i,j}$ has a set of physical failure modes $\mathcal{F}_{h,i,j} = \{f_{h,i,j,1}, f_{h,i,j,2}, \cdots\}$, and each failure mode $f_{h,i,j,k} \in \mathcal{F}_{h,i,j}$ is caused by a set of physical failure mechanisms $\mathcal{M}_{h,i,j,k}$. For simplicity, the sets at each level are assumed to be disjoint: no component is shared across systems, no part is shared across components, no failure mode is shared across parts, and no failure mechanism is shared across failure modes. This assumption is not realistic and will be relaxed in Section 3.2.

A simulation instance (i.e., each instance of physical simulation) can be defined as a tuple (p_j, f_k, m_l) representing a specific part failure mode-mechanism combination that requires physical simulation. The set of all simulation instances under the disjointness assumption is:

$$\mathcal{T}^{\text{disjoint}} = \{(p_j, f_k, m_l) : p_j \in \mathcal{P}_{h,i}, f_k \in \mathcal{F}_{h,i,j}, m_l \in \mathcal{M}_{h,i,j,k}\} \quad (1)$$

Define β_c, β_p, β_f, and β_m as the average branching factors at the system-to-component, component-to-part, part-to-failure-mode, and failure-mode-to-failure-mechanism transitions, respectively. As the depth of explicit modeling moves to lower levels in the hierarchy, each additional level introduces a new branching factor that multiplies the size of the modeling space:

$$
\begin{gathered}
|\mathcal{C}| = |\mathcal{S}| \cdot \beta_c, \\
|\mathcal{P}| = |\mathcal{S}| \cdot \beta_c \cdot \beta_p, \\
|\mathcal{F}| = |\mathcal{S}| \cdot \beta_c \cdot \beta_p \cdot \beta_f, \\
\left|\mathcal{T}^{\text{disjoint}}\right| = |\mathcal{S}| \cdot \beta_c \cdot \beta_p \cdot \beta_f \cdot \beta_m
\end{gathered} \tag{2}
$$

Since each β can be much greater than one in nuclear systems, $\left|\mathcal{T}^{\text{disjoint}}\right|$ can be orders of magnitude larger than $|\mathcal{S}|$ or $|\mathcal{C}|$.

3.2. Dependency Can be Used to Reduce the Number of Distinct Physical Simulations

The multiplicative growth of $\left|\mathcal{T}^{\text{disjoint}}\right|$ poses a fundamental challenge: exhaustive physical simulation across all elements of $\mathcal{T}^{\text{disjoint}}$ is computationally and practically infeasible for realistic systems. Even if individual simulations are tractable, the number of (p_j, f_k, m_l) combinations makes full coverage impossible within the typical timeframes of PRA development and update workflow. This is the central bottleneck in integrating a PRA model with physical simulations.

In practice, the disjointness assumption introduced in Section 3.1 is unrealistic. The same failure mode or mechanism can affect multiple parts and components sharing common materials and operating environments. This type of shared influence can occur at any transition level: a component may be connected to multiple systems (i.e., functional dependency), a failure mode connected to multiple parts, and a failure mechanism connected to multiple failure modes. As shown below, such shared influences (or dependencies) can be used to reduce the structural size of the full modeling space; hence, provided that dependent failures are modeled and quantified properly, accounting for shared influences can be leveraged to facilitate the PRA-physics simulation integration.

Shared structure can be used to reduce the set of simulation instances from $\mathcal{T}^{\text{disjoint}}$ to an effective set $\mathcal{T}^{\text{eff}}$, under the condition that a single physical simulation of a unique (f_k, m_l) pair can be used to analyze multiple parts sharing that pair. This condition is referred to as "transferability condition." Formally,

$$\mathcal{T}^{\text{eff}} \subseteq \mathcal{T}^{\text{disjoint}}, \text{ retaining one tuple per unique } (f_k, m_l) \text{ pair}$$

$$\left|\mathcal{T}^{\text{eff}}\right| = \text{number of unique } (f_k, m_l) \text{ pairs in } \left|\mathcal{T}^{\text{disjoint}}\right|$$

The overall scope reduction is summarized by the physical simulation reduction ratio:

$$\rho = 1 - \frac{\left|\mathcal{T}^{\text{eff}}\right|}{\left|\mathcal{T}^{\text{disjoint}}\right|}, \quad \rho \in [0, 1) \tag{3}$$

where $\rho \to 0$ indicates no shared influences across the hierarchy, while $\rho \to 1$ indicates a substantial reduction in the number of physical simulation runs.

In practice, the transferability condition may not hold because parts sharing the same (f_k, m_l) pair may differ in geometry, material properties, or operating conditions. Systematically determining which shared pairs satisfy the transferability condition is a prerequisite for practical PRA-physical simulation integration. Another potential solution is to develop generalizable physics-based models for each (f_k, m_l) pair that possesses a high degree of transferability. This idea is further discussed in Section 4.

3.3. Illustrative Example

To demonstrate the application of the conceptual framework, consider a system (s_1) consisting of two pumps (c_1 and c_2) in a parallel configuration. The hierarchical structure of this example is summarized in Table 3. Each pump consists of two parts, including a mechanical seal and an impeller, resulting in four parts at L3. Two generic failure modes are defined at L4: seal failure (f_1) and impeller failure (f_2), each of which is shared across both pumps. At L5, two failure mechanisms are identified: corrosion (m_1) that underlies both failure modes (f_1 and f_2); and fatigue (m_2) that underlies seal failure (f_1) only. The corresponding directed acyclic graph (DAG) is shown in Figure 1.

Table 3: Hierarchical Structure of the Illustrative Example.

Level	Entity	Notation
L_1: System	Pump system	s_1
L_2: Components	Pump 1, Pump 2	c_1, c_2
L_3: Parts	Mechanical seal (x2), Impeller (x2)	$p_{1,1}$, $p_{2,1}$, $p_{1,2}$, $p_{2,2}$
L_4: Physical failure modes	Seal failure, Impeller failure	f_1 f_2
L_5: Physical failure mechanisms	Corrosion, Fatigue	m_1 m_2

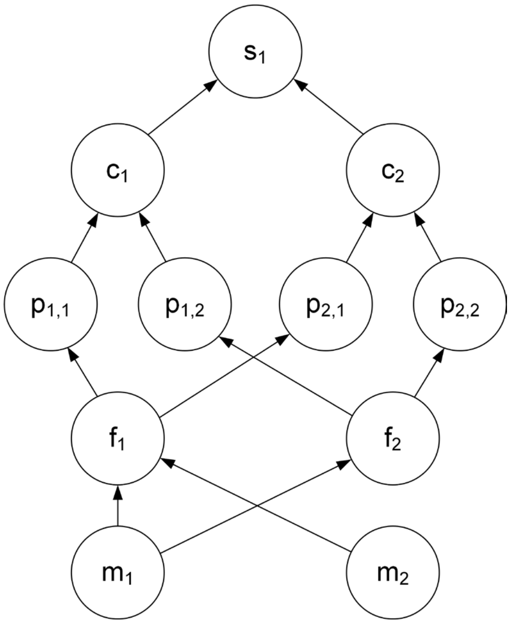

Figure 1: Directed Acyclic Graph (DAG) for an Illustrative Case Study.

This system consists of two components ($\beta_c = 2$), and each component has two primary parts ($\beta_p = 2$). Each part is associated with one failure mode ($\beta_f = 1$), and each failure mode is attributed to, on average, $\beta_m = (2+1)/2 = 1.5$ failure mechanisms. Under the disjointness assumption (Section 3.1), this situation results in $|\mathcal{T}^{\text{disjoint}}| = (2)(2)(1)(1.5) = 6$ physical simulation instances.

Meanwhile, under the transferability condition (Section 3.2), there are three distinct (f_k, m_l) pairs at the failure mode and mechanism levels in Figure 1: (f_1, m_1), (f_1, m_2), and (f_2, m_1). Therefore, $|\mathcal{T}^{\text{eff}}| = 3$, yielding a simulation reduction ratio of:

$$\rho = 1 - \frac{|\mathcal{T}^{\text{eff}}|}{|\mathcal{T}^{\text{disjoint}}|} = 1 - \frac{3}{6} = 0.50 \tag{4}$$

In this example, shared influences across two consecutive levels of the hierarchy (namely, the failure mode and mechanism levels) reduce the number of physical simulation instances by 50%. If this concept can be fully implemented, the number of physical simulations becomes less dependent on β_p, β_f, and

β_m in Eq. (2), contributing to a major reduction in computational time and resources for PRA-physical simulations integration.

4. OPEN RESEARCH DIRECTIONS

From the preliminary findings of the literature review, one critical question about PRA-physical simulation integration is how to more widely adopt it in the nuclear applications without exceeding the limits of modern computational capabilities or the timeline constraints of practical PRA implementation workflows.

Using the conceptual framework developed in Section 3, the actual time required to execute physical simulations across all elements of $\mathcal{T}^{\text{eff}}$ in PRA can be expressed as:

$$T^{\text{eff}} = \frac{|\mathcal{S}| \cdot \beta_c \cdot \beta_p \cdot \beta_f \cdot \beta_m \cdot (1-\rho) \cdot N_S \cdot \bar{t}}{\pi}, \tag{5}$$

where $|\mathcal{S}|, \beta_c, \beta_p, \beta_f, \beta_m$, and ρ are as defined in Sections 3.1 and 3.2, N_S is the average sample size for uncertainty propagation, $\bar{t}$ is the average computational time per physical simulation run, and π is the average degree of parallelization of simulation runs (i.e., the number of runs that can be executed simultaneously).

Equation (4) reveals that there are five distinct levers for reducing T^{eff}:

- Reducing $|\mathcal{S}|$ or the branching factors $\beta_c, \beta_p, \beta_f, \beta_m$ by narrowing the scope of explicit physical modeling. This can be achieved by performing sensitivity or importance measure analysis at the physical failure mode and/or mechanism level [19]. To perform this, it is beneficial to develop a fast-running reduced-order model (ROM) or surrogate model that can conservatively evaluate the relative importance among a large number of failure modes and mechanisms.

- Increasing the physical simulation reduction ratio, ρ, by exploiting shared failure modes and mechanisms across parts and components. For instance, developing a fast-running surrogate model applicable to a wide range of materials and operating conditions, e.g., a Bayesian network-based surrogate model trained for broad conditions [20], can help increase ρ.

- Reducing N_S by, for instance, executing an adaptive sampling method to concentrate samples in the most critical region in the input space. The process of discovering the critical region can be facilitated by AI and machine learning methods.

- Reducing $\bar{t}$ through the use of ROMs or surrogate models in place of full physical simulations.

- Increasing π through parallelization of simulation runs. As an example, some commercial finite element software (e.g., ABAQUS) imposes a constraint that parallel computation can be performed only on a single node, even when the analyst has access to a large number of computing nodes. While the analyst may purchase multiple licenses to resolve this issue, alternatively, an open-source finite element analysis code, such as Multiphysics Object-Oriented Simulation Environment (MOOSE), can be utilized, where there is no limit to the license, and the user can fully use available computational resources without software license constraints.

5. CONCLUSION

Physical simulations are increasingly integrated with PRA of nuclear facilities, driven by advances in computational power and growing recognition of the value of additional data and detailed insights generated by physics-based simulations. Carefully designed PRA-physical simulation interfaces are essential, as the interface can directly impact PRA model accuracy, consistency, and computational feasibility.

The goal of this research is to establish a generic technical basis for integrating PRA with physical simulations, applicable to a wide range of PRA implementations for nuclear energy systems. A literature review is being conducted to characterize the state of the art in PRA-physical simulation integration and identify research gaps. A conceptual framework is then proposed to analyze these interfaces, formalizing the multi-layer relationship between PRA model elements and physical simulation scope. Building on them, open research directions have been identified to guide broader efforts to integrate PRA with physical simulation.

Ongoing work by the authors focuses on expanding the literature review through a systematic search and review to achieve comprehensive coverage of relevant existing studies. Additionally, the conceptual framework is being refined based on new findings from the updated literature review to create a more complete and versatile technical basis for designing and improving PRA-physical simulation interfaces.

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