Next-Generation Probabilistic Risk Assessment via Advanced Simulation-Informed, Socio-Technical, and AI-Driven Approaches

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Abstract: The Socio-Technical Risk Analysis (SoTeRiA) Research Laboratory at the University of Illinois at Urbana-Champaign (UIUC) supports the development of next-generation Probabilistic Risk Assessment (PRA) through advanced simulation-informed dependency modeling, uncertainty-based validation, and the treatment of socio-technical interactions among humans, physical systems, AI-driven automation, and organizational factors. This paper reports recent progress from two sponsored research efforts. The first is a U.S. Department of Energy (DOE) sponsored and industry-cost-shared project on simulation-informed dependency treatment to enhance operational flexibility, avoid production loss, and maintain safety of operating plants and advanced reactors. This project develops the Simulation-Informed Probabilistic Dependency Analysis (SIP-DA) framework for treating dependencies in nuclear plant PRA, using hardware common cause failures (CCFs) as the primary example. SIP-DA addresses a central limitation of conventional CCF treatment, which relies on sparse and sometimes outdated historical event data and therefore cannot adequately capture plant-specific conditions, updated maintenance strategies, or newer reactor designs. The framework extends the conventional PRA hierarchy downward, from PRA events to functional and physical failure modes, key performance measures, and coupled physics of failure (POF) and maintenance work process (MWP) simulations, and then propagates results upward through uncertainty treatment, probabilistic validation, and integration with empirical CCF parameters. An emergency diesel generator case study illustrates the workflow and its quantitative outcomes. The second project is a U.S. National Science Foundation (NSF) sponsored project that advances the theoretical and methodological bases for incorporating interactions among human performance, physical failure mechanisms, organizational factors, and AI-based automation into PRA and Generation Risk Assessment (GRA), with emphasis on AI-driven predictive maintenance systems in nuclear power plants. A central challenge is limited trust in AI-based automation by regulators, operators, and managers, which can delay licensing, constrain adoption, and reduce potential safety and economic benefits. Recent progress on this NSF project highlights approaches for characterizing how these interactions influence safety and financial risks and for identifying the most risk-significant socio-technical contributors. Taken together, these efforts advance PRA beyond static, data-limited formulations toward more mechanistic, uncertainty-aware, and socio-technical representations of risk, thereby strengthening risk-informed decision making while preserving safety and reducing operational, financial, and regulatory burdens.

Keywords: probabilistic risk assessment; common cause failure; simulation-informed dependency analysis; probabilistic physics of failure; socio-technical risk analysis; AI-driven predictive maintenance; trust in automation.

1. INTRODUCTION

Probabilistic Risk Assessment (PRA) is a cornerstone of risk-informed decision making across the nuclear power plant (NPP) lifecycle, supporting design, licensing, operation, and maintenance. Conventional PRA formulations, however, remain largely static and data-limited: they depend on historical operating experience and generic parameter databases that may not represent plant-specific configurations, modernized equipment, updated maintenance strategies, or newer reactor designs. For operating fleets undergoing digital upgrades and/or experiencing equipment aging, and for advanced

reactors with little or no operating history, these limitations constrain the realism, traceability, and defensibility of risk estimates. Next-generation PRA therefore requires more mechanistic, uncertainty-aware, and socio-technical representations of risk that can be updated as plants and technologies evolve.

The SoTeRiA Research Laboratory develops the theoretical foundations, methodologies, and computational platforms needed to advance PRA in this direction, building on prior work that incorporates organizational factors and underlying physical failure mechanisms into integrated risk models [1-5]. This paper reports recent progress from two complementary, sponsored research efforts. The first is a U.S. DOE-sponsored project, cost-shared by Constellation, to develop the Simulation-Informed Probabilistic Dependency Analysis (SIP-DA) framework for treating dependencies in nuclear plant PRA, focusing on hardware common cause failures (CCFs). The second, sponsored by the U.S. NSF, advances the socio-technical modeling of interactions among human performance, physical degradation, organizational factors, and AI-based automation. Both efforts extend the predecessor results presented in [6, 7].

The remainder of this paper is organized as follows. Section 2 presents the SIP-DA framework and the limitations of conventional CCF treatment that it addresses. Section 3 describes the coupled simulation platform and an emergency diesel generator (EDG) case study, including representative quantitative results, for demonstrating the SIP-DA framework. Section 4 reports progress on the NSF-sponsored socio-technical and AI-driven research, emphasizing AI-driven predictive maintenance and the role of trust in AI-based automation. Section 5 discusses the combined implications for next-generation PRA, and Section 6 provides some concluding remarks.

2. SIMULATION-INFORMED PROBABILISTIC DEPENDENCY ANALYSIS

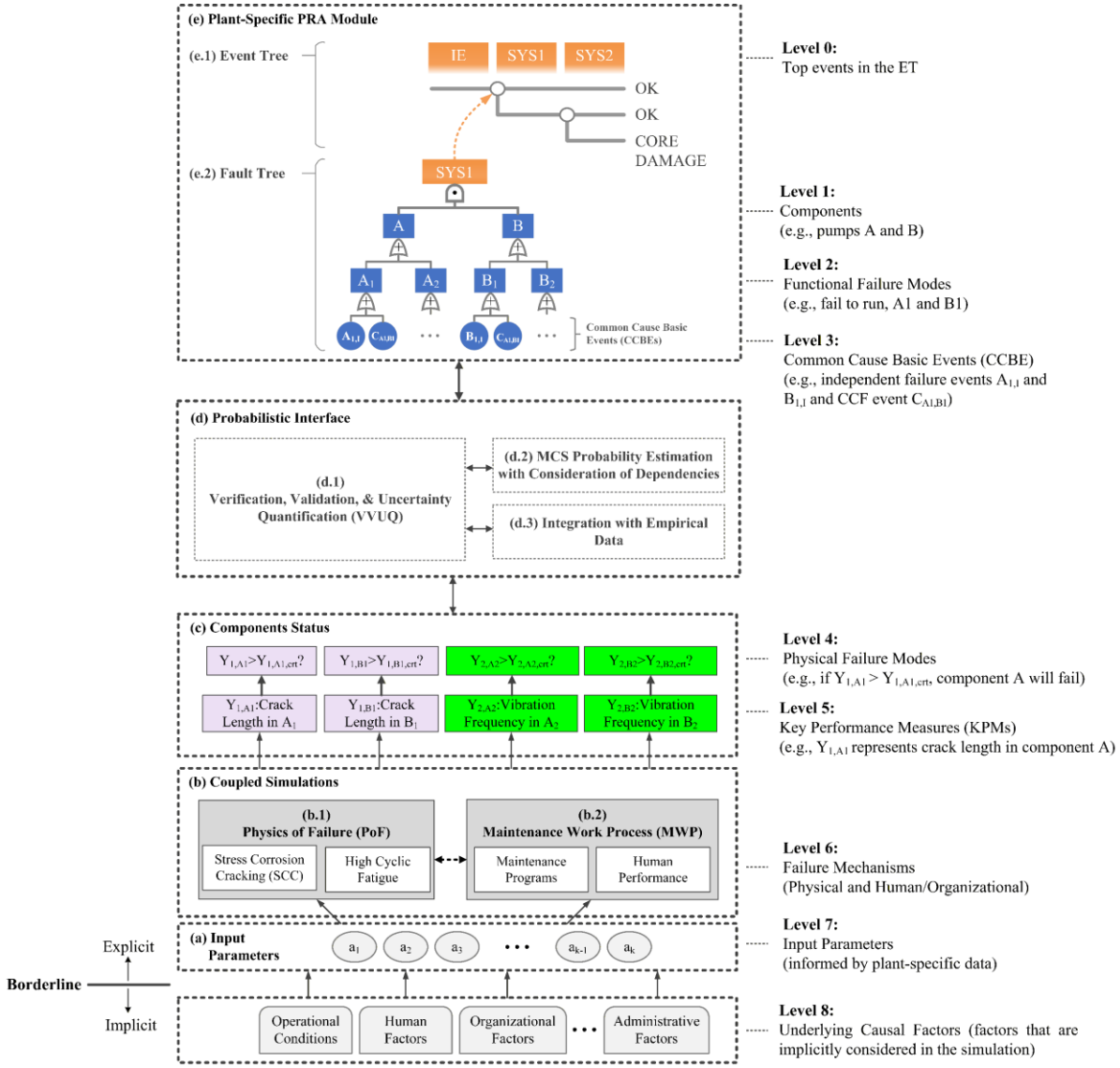
2.1. Limitations of Conventional CCF Treatment

Dependency in NPPs arises when the performance or failure of one protective system, structure, or component is correlated with that of others. Because NPP defense-in-depth relies on redundancy within and across layers of protection, dependent failures can undermine the effectiveness of these layers, and CCFs are among the most risk-significant dependency contributors. Conventional CCF treatment quantifies these contributions using parametric models, such as the Beta-Factor, Multiple Greek Letter (MGL), and Alpha-Factor models, whose parameters are estimated from historical CCF event databases [8, 9]. While these models are well established and embedded in current PRA practice, they exhibit several limitations. The underlying event data are sparse, are subject to interpretation and classification ambiguity, and provide limited causal resolution, so the resulting parameters cannot readily distinguish among the physical, maintenance, operational, and organizational mechanisms that drive dependent failures [10, 11]. The estimates are generic rather than plant-specific, are slow to reflect equipment replacements, digital upgrades, or improved maintenance practices, and become especially problematic for advanced reactors and first-of-a-kind designs where little or no operating experience exists. This zero-data problem weakens the technical basis for risk-informed reviews precisely where realistic dependency characterization is most needed.

2.2. The Simulation-Informed Probabilistic Dependency Analysis (SIP-DA) Framework

To address these limitations, this research develops the Simulation-Informed Probabilistic Dependency Analysis (SIP-DA) framework, which grounds dependency estimates in the mechanistic causes of dependent failures rather than relying primarily on aggregated historical data [6]. SIP-DA extends the conventional PRA decomposition downward, from PRA events to the physical and human mechanisms that produce the events, then propagates simulation-derived evidence upward into PRA-compatible dependency parameters. Fig. 1 presents the SIP-DA methodological framework as a multi-level hierarchy bounded by an explicit-implicit causal boundary.

Fig. 1: The SIP-DA methodological framework.



The downward extension proceeds through successive levels of resolution (Fig. 1). At the top, the plant-specific PRA module represents top events in the event tree (Level 0), components (Level 1), functional failure modes (Level 2), and common cause basic events (CCBE) (Level 3). The decomposition then continues below the conventional PRA boundary to physical failure modes (Level 4), key performance measures (KPMs) that quantify the proximity of a component to failure (Level 5, for example crack length or vibration frequency), and the coupled failure mechanisms that govern KPM evolution (Level 6). These mechanisms are represented by two interacting modules: a Physics of Failure (POF) module capturing degradation phenomena such as stress corrosion cracking and high-cycle fatigue, and a Maintenance Work Process (MWP) module capturing maintenance programs and the associated human and organizational performance. The lowest levels represent the input parameters (Level 7) and the underlying causal factors, namely operational conditions, human factors, organizational factors, and administrative factors (Level 8), that are implicitly embedded in the simulation.

Results generated at the mechanistic levels are propagated upward through a probabilistic interface (module (d) in Fig. 1) that performs verification, validation, and uncertainty quantification (VVUQ), estimates failure and joint-failure probabilities with explicit consideration of dependencies, and integrates the simulation-derived estimates with empirical CCF data. Operationally, SIP-DA is implemented as a structured workflow: (i) screen and prioritize the common cause component groups (CCCGs) and define the simulation units; (ii) down-select the dominant sub-components and physical

failure modes; (iii) define the KPMs and their failure thresholds; (iv) identify the governing degradation and maintenance mechanisms and the required model fidelity; (v) build and bidirectionally couple the POF and MWP modules; (vi) simulate failure multiplicity, distinguishing no failure, single failure, and joint failure; and (vii) convert the simulated multiplicities into PRA dependency metrics, quantify aleatory and epistemic uncertainty, perform probabilistic validation, and aggregate the results with empirical parameters. This workflow preserves traceability from PRA dependency parameters down to the physical and organizational mechanisms that produce them.

2.3. Prioritizing Where Simulation Adds the Most Value

Because high-fidelity coupled POF-MWP simulation is computationally and analytically demanding, SIP-DA includes a screening methodology to focus effort where simulation is expected to provide the greatest benefit. Building on the predecessor screening approach [6], an Analytic Hierarchy Process (AHP) is used to rank candidate CCCGs against multiple criteria applicable to both operating and advanced reactors, combining expert judgments through structured aggregation of priority vectors. The screening identifies the components and failure mechanisms whose mechanistic modeling would most improve dependency characterization and risk-informed decisions, providing a practical basis for incremental deployment within large and complex systems.

3. SIP-DA CASE STUDY: EMERGENCY DIESEL GENERATORS

3.1. Coupled Physics of Failure and Maintenance Work Process Simulation

At the core of SIP-DA is the bidirectional coupling of physical degradation and maintenance performance. The POF module simulates the spatiotemporal progression of degradation, while the MWP module simulates inspection, repair, and replacement activities and the human and organizational performance that govern their effectiveness. The two modules exchange information through a master logic structure that passes degradation indices to the maintenance process and returns maintenance outcomes, such as imperfect or deferred repair, to the degradation model. This coupling captures mechanisms by which shared maintenance practices and common operating conditions can synchronize degradation across redundant components and thereby generate insights on dependent failures that historical data alone may not explain.

The coupled platform is implemented within the Multiphysics Object-Oriented Simulation Environment (MOOSE), an open-source finite-element and multiphysics framework [12, 13], using its stochastic-simulation capabilities for parallel, memory-efficient uncertainty propagation [14]. The coupled MOOSE-based platform incorporates a Probabilistic Physics of Failure (PPOF) treatment that represents degradation as a stochastic process and, in this work, adopts a damage-endurance formulation suitable for fatigue-driven failure. Custom samplers, state managers, and probabilistic aggregation modules convert simulated component states into PRA-comparable dependency metrics.

3.2. EDG Case Study Setup

The framework is demonstrated on the dependency relationship associated with two EDG failure-to-run basic events, denoted as A_1 and B_1; the two EDGs (EDG-A and EDG-B) were identified as a high-priority CCCG and then selected for the case study based on insights from an AHP screening [6]. A review of licensee event reports from 2013 to 2025 localized a representative degradation mechanism to a Swagelok coupling on the turbocharger assembly of the EDG lubricating oil system (Fig. 2), where high-cycle fatigue is driven by service vibration in combination with maintenance-induced misalignment on the coupling. The corresponding KPM is the fatigue-induced crack state of the coupling, with a failure threshold defined by fracture of the pressure boundary. Crack initiation is modeled using a stress-life formulation calibrated to the relevant brass alloy [15], and crack propagation is modeled using linear-elastic fracture mechanics (LEFM) consistent with ASME Boiler and Pressure Vessel Code (BPVC) Section XI methods [16]. Maintenance-related human actions, including the

likelihood of imperfect repair, are modeled using maintenance event tree (Fig. 3) and quantified using the IDHEAS-ECA human reliability analysis (HRA) framework [17] together with Bayesian parameter estimation. The coupled POF-MWP model for the Swagelok coupling is simulated over a forty-year horizon at twelve-hour timesteps, with a nested aleatory-epistemic sampling scheme executed on high performance computing resources. Table 1 summarizes the case-study configuration.

Fig. 2: Model of the Swagelok coupling of interest on the EDG-lubricating-oil-system turbocharger assembly subject to high-cycle fatigue.

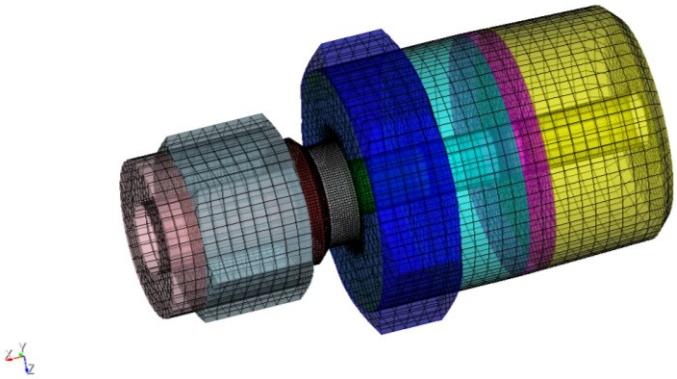


Fig. 3: Event tree of the maintenance activities modeled in the EDG case study

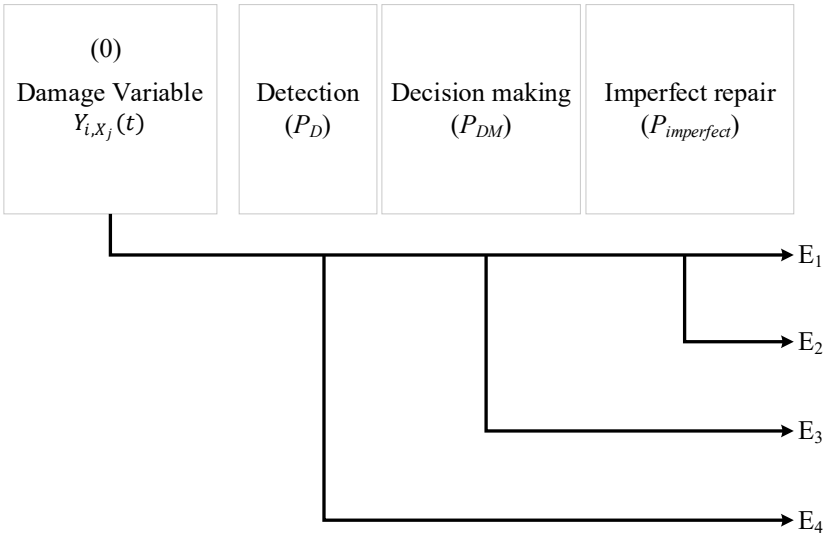


Table 1: Configuration of the emergency diesel generator case study.

Attribute	Case study configuration
System / CCCG	A CCCG consisting of two emergency diesel generators (EDG-A and EDG-B)
Simulated sub-component	Turbocharger lubricating-oil-system Swagelok coupling (brass)
Dominant mechanism	High-cycle fatigue from service vibration and maintenance-induced misalignment (introduced through imperfect repair)
Key performance measure	Fatigue-induced crack state of the coupling
Failure threshold	Crack reaching fracture (loss of pressure boundary)
Physics of failure models	Stress-life crack initiation (brass) and LEFM crack propagation (ASME BPVC Section XI)
Maintenance / human reliability	Including inspection (periodic walkdowns, surveillance tests), decision-making, and repair activities; modeled with event tree and quantified with IDHEAS-ECA and Bayesian parameter estimation.

Attribute	Case study configuration
Simulation horizon	40 years at 12-hour timesteps
Sampling scheme	Nested aleatory-epistemic sampling on high-performance computing
Relevant PRA basic events	EDGs fail to run

3.3. CCF Quantification, Uncertainty, and Probabilistic Validation

At each simulation timestep, the system state manager collects the status of the two PRA basic events (EDG-A and EDG-B failure-to-run events, respectively A_1 and B_1). This is based on continuously evaluating whether the associated Swagelok coupling remains functional or has failed due to through-wall cracking and leakage. The component status indicators therefore correspond to:

$$S_{A_1}(t) = \begin{cases} 1, & \text{EDG-A failure-to-run event has occurred} \\ 0, & \text{EDG-A remains functional} \end{cases} \quad (1)$$

and

$$S_{B_1}(t) = \begin{cases} 1, & \text{EDG-B failure-to-run event has occurred} \\ 0, & \text{EDG-B remains functional} \end{cases} \quad (2)$$

where the failure condition is reached when the crack length predicted by the coupled POF-MWP simulation reaches the wall thickness, producing through-wall leakage. Using the evolving component-status information, the system state manager generates the multiplicity indicator associated with the joint event $(A_1.B_1)$ according to:

$$I_{(A_1,B_1)}(t) = \begin{cases} 0, & S_{A_1}(t) = 0,\ S_{B_1}(t) = 0 \\ 1, & S_{A_1}(t) \neq S_{B_1}(t) \\ 2, & S_{A_1}(t) = 1,\ S_{B_1}(t) = 1 \end{cases} \quad (3)$$

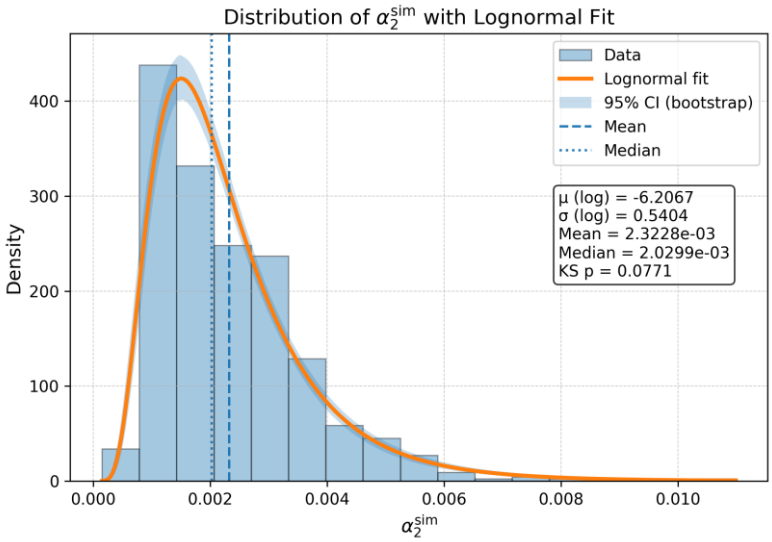
where:

- $I_{(A_1,B_1)}(t) = 0$ corresponds to no EDG failure,
- $I_{(A_1,B_1)}(t) = 1$ corresponds to a single EDG failure, and
- $I_{(A_1,B_1)}(t) = 2$ corresponds to simultaneous failures of both EDGs.

The multiplicity indicator therefore represents a time-dependent system-state trajectory indicator that continuously tracks the evolution of independent and joint failure conditions throughout the stochastic simulation.

The simulated failure multiplicity indicator is then converted into PRA dependency parameters through the basic-parameter representation of CCF, yielding simulation-informed estimates of the alpha factor for the modeled sub-component. Because the simulation propagates both aleatory and epistemic uncertainties, the output is a distribution rather than a point estimate. For the EDG case study, the simulation-based two-component alpha factor is well represented by a lognormal distribution (Fig. 4). A Kolmogorov-Smirnov goodness-of-fit test produced a p-value of approximately 0.077, indicating no strong evidence against the lognormal representation at conventional significance levels; the fitted log-mean and log-standard-deviation are approximately -6.21 and 0.54, with a distribution mean of about 2.32×10^{-3} and a median of about 2.03×10^{-3}.

Fig. 4: Simulation-informed distribution of the EDG two-component alpha factor with fitted lognormal distribution and bootstrap confidence interval.



A global Sobol sensitivity analysis identified the imperfect repair probability as the dominant contributor to uncertainty in the simulation-informed alpha factor, with contributions from the POF degradation parameters being substantially smaller. This result indicates that maintenance process uncertainty and maintenance effectiveness, rather than the physical degradation parameters alone, are the principal drivers of degradation-induced dependency formation in the modeled EDG system, a causal insight that conventional data-driven CCF analysis cannot provide.

Because direct validation data for the coupled simulation are generally unavailable, SIP-DA incorporates and advances the Probabilistic Validation (PV) methodology previously developed by some of the authors [18, 19]. Candidate model forms of the POF-MWP coupled model are combined through a Bayesian belief network structure to handle model-form uncertainty, while uncertainties in the simulation model input parameters are treated with Monte Carlo-based uncertainty propagation (through the candidate model forms). Together, this extended PV methodology produces a probability box (p-box) that bounds the simulation-informed estimate of the CCF parameter α_2, which is then evaluated against predefined acceptability criteria. This method provides a structured process for establishing credibility for simulation-informed dependency estimates under data scarcity, which is essential for advanced reactor applications and aging NPPs. The detailed development of this extended PV methodology is subject to a journal manuscript under review.

3.4. Aggregation with Empirical CCF Parameters

To integrate the simulation-derived estimates into current PRA practice, SIP-DA aggregates the mechanistically derived, sub-component-specific alpha factor with the empirical, data-driven alpha factor used for the remaining EDG failure contributors. In the case study, only one EDG sub-component failure mechanism was simulated, while the remaining contributors retained the currently utilized industry data-driven alpha factors. Accordingly, the simulation-informed EDG common cause alpha factor was estimated using Eq. (4):

$$\alpha_2^{(\text{sim-informed})} = \frac{N^{(x)}\alpha_2^{(x)} + \sum_{d \neq x} N^{(d)}\,\alpha_2^{(d)}}{\sum_d N^{(d)}} \tag{4}$$

where $\sum_d N^{(d)}$ is the total number of EDG failure events from all sub-components, $N^{(x)}$ is the number of EDG failure events attributed to the simulated sub-component, $\alpha_2^{(x)}$is the simulation-based alpha factor obtained from the coupled simulation framework, and $\alpha_2^{(d)}$represents the currently utilized data-driven alpha factor for the remaining non-simulated sub-components. For this case study, the currently

utilized industry value $\alpha_2^{(\mathrm{d})}$ was taken as 0.0138 based on currently available INL/NRC industry data. The simulation framework produced a significantly lower dependency estimate for the simulated mechanism ($\alpha_2^{(x)} \approx 0.0023$). The total number of EDG failure events identified in the historical database was 52 events. Initially, the simulated sub-component was associated with only one historical EDG failure event ($N^{(x)} = 1$), while the remaining 51 events were associated with other sub-components. Substituting these values into Eq. (4) yielded $\alpha_2^{\text{sim-informed}} \approx 0.0136$ corresponding to approximately a 1.6% reduction relative to the currently utilized industry value. This relatively small reduction is expected because the simulated sub-component represents only a small fraction of the total EDG failure population contained in the empirical database.

To evaluate the influence of sub-component representativeness, a second aggregation scenario was considered in which the simulated sub-component was assumed to represent a broader failure category contributing to three EDG failure events ($N^{(x)} = 3$). Under this assumption, the updated aggregation yielded $\alpha_2^{\text{sim-informed}} = 0.0131$ which corresponds to approximately a 4.8% reduction relative to the currently utilized industry alpha factor. This result demonstrates that the influence of mechanistic simulation results on the final PRA dependency parameter increases as the simulated mechanism accounts for a larger fraction of the observed failure experience. This incremental aggregation strategy preserves compatibility with current PRA practice while enabling dependency characterization to transition gradually from predominantly empirical toward more mechanistically informed estimates as additional mechanisms are modeled, and it provides a prioritization basis, since sub-components associated with larger values of $N^{(d)}$ contribute more strongly to the final aggregated alpha factor and therefore offer greater potential impact on reducing dependency uncertainty. All methodological developments and case study demonstration of the SIP-DA project are completed and subject to a three-part series of journal papers under review.

4. SOCIO-TECHNICAL RISK ANALYSIS METHODOLOGICAL FRAMEWORK FOR MODERN COMPLEX TECHNOLOGICAL SYSTEMS

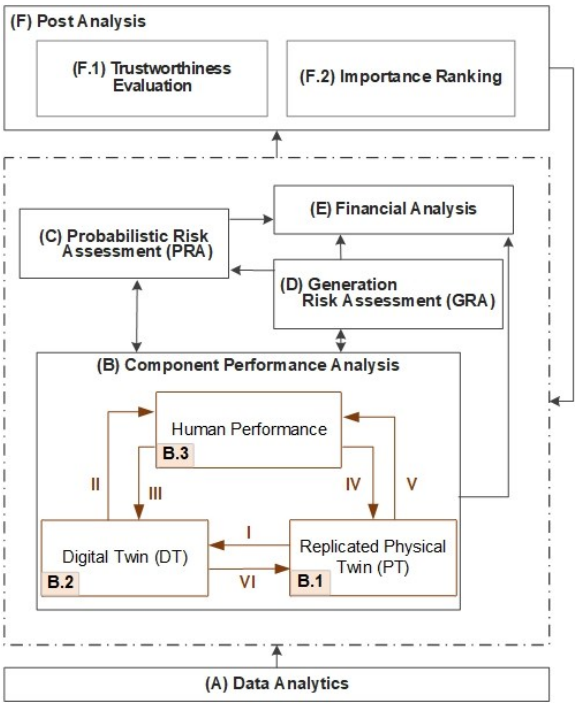
4.1. Motivation and Scope

Major technological accidents, including Fukushima Daiichi, the Boeing 737 MAX accidents, and the Deepwater Horizon spill, demonstrate that human performance, physical failure mechanisms, and organizational factors jointly drive risk, yet conventional PRA and HRA tend to treat these contributors in isolation and do not fully capture their dynamic interplay [7]. The ongoing NSF-sponsored research reported here advances the theoretical and methodological bases for explicitly incorporating interactions among these factors into PRA and, in parallel, into Generation Risk Assessment (GRA), so that the same socio-technical mechanisms can be evaluated for their influence on both safety and financial performance [5]. The application focus is AI-driven predictive maintenance in NPP modernization, where AI-based automation increasingly mediates the relationships among operators, equipment degradation, and management decisions.

4.2. Ongoing Methodological Framework Development and Case Study Demonstration

A methodological framework (Fig. 5) and an associated computational platform are being developed to quantify interactions among human performance, AI-driven automation responses, and physical phenomena, and their combined effects on safety (through PRA) and profitability (through generation risk assessment or GRA). In the selected context of AI-driven predictive maintenance in NPP modernization, the Component Performance Analysis, as shown in Module B in Fig. 5, captures the interactions among human performance, physical failure mechanisms, organizational factors, and AI-based automation. The numbered interactions in Fig. 5, labeled I through VI, represent the bidirectional couplings among the physical twin, the digital twin, and human performance, while the surrounding modules propagate component-level behavior into PRA (safety) and GRA (financial) metrics and into a post-analysis stage comprising trustworthiness evaluation and importance ranking.

Fig. 5: Socio-technical risk analysis framework for modern complex technological systems.



In the proposed methodological framework (Fig. 5), the Component Performance Analysis Module consists of three sub-modules:

- The Human Performance Sub-module (B.3 in Fig. 5) models maintenance tasks performed by the NPP maintenance unit, quantifying human error probabilities and completion times using the IDHEAS-ECA methodology developed by the U.S. NRC [17]. Event Trees (ETs) for relevant maintenance strategies (e.g., normal in-service inspections) are developed and quantified within this sub-module. This sub-module also explicitly incorporates AI transparency and operator trust in AI as Performance Influencing Factors (PIFs), a gap in the existing IDHEAS framework (and other HRA methods). To address this, controlled experiments using the G-PWR simulator integrated with an AI-driven Digital Twin (DT) are being conducted to measure human error rates under varying trust and transparency conditions and estimate corresponding IDHEAS weighting factors.
- The Replicated Physical Twin Sub-module (B.1 in Fig. 5) models long-term physical degradation mechanisms relevant to maintenance programs (e.g., stress corrosion cracking) using physics-based simulations. This sub-module is developed using the Extremely Low Probability of Rupture (xLPR) code, a probabilistic fracture mechanics code developed by the U.S. NRC [20].
- The Digital Twin Sub-module (B.2 in Fig. 5) comprises: (i) an AI-driven component-level predictive model built using Random Forest Classifier and Regression, trained and validated against governing probabilistic fracture mechanics equations [21, 22]; and (ii) a Multiphase Markov Process Model for real-time monitoring and performance prediction. The AI-driven model receives real-time component performance data from the Physical Twin and predicts failure transition rates for the remaining component lifetime, which are then used by the Markov model to compute component state probabilities at each time step. Maintenance strategies recommended by the DT sub-module are fed to the Human Performance sub-module to guide maintenance performance. In addition to leveraging recommendations from the DT sub-module, real-time performance data for plant equipment (provided by the Replicated Physical Twin sub-module) guides maintenance performance.

The Component Performance Analysis (Module B of Fig. 5) is connected to (i) the PRA (Module C in Fig. 5) to conduct a safety risk assessment, (ii) GRA (Module D in Fig. 5) to quantify production loss associated with system unavailability due to maintenance or unexpected equipment failure, and (iii) Financial Analysis (Module E in Fig. 5) to estimate the impact of various maintenance strategies on the financial outcome.

A distinguishing feature of the framework is the explicit treatment of AI transparency and operator trust in AI as PIFs, which are not represented in existing HRA methods. By introducing these factors, the framework links the design characteristics of AI-based automation, such as transparency and explainability, to human performance and, ultimately, to safety and financial risk.

Technical feasibility of the proposed methodological framework is being demonstrated through an AI-driven digital twin predictive maintenance case study in NPPs. The case study involves a simplified NPP comprising a production system that generates electricity outputs, and a protection system required for preventing catastrophic failure (i.e., core damage) when a transient occurs (e.g., failure of production system). The components of interest in this case study are the pumps and their connected pipes in the production system. These pipes are exposed to stress corrosion cracking, impacting the performance of the pumps, and consequently the production system. The degradation of the pipes is modeled by the PT submodule, which simulates lifetime progression of NPP piping components subject to physical degradation. The impact of pipe degradation on the status of the pumps is modeled using a Generic Pressurized Water Reactor (G-PWR) simulator at UIUC.

4.3. Trust in AI-Based Automation

A central challenge for AI-driven automation in safety-critical nuclear applications is limited trust by the principal stakeholders, namely operators, managers, and regulators. Insufficient or miscalibrated trust can delay licensing, constrain adoption, and reduce the potential safety and economic benefits of automation, whereas excessive trust can introduce new failure modes through over-reliance. This research characterizes trust as a modeled, physically grounded factor rather than a qualitative attribute, drawing on an ongoing structured systematic literature review spanning operator, management, and regulatory perspectives and synthesized around a set of guiding research questions. This treatment connects trust and transparency to observable human actions and, through them, to PRA and GRA outcomes, providing a basis for evaluating how automation design choices influence risk.

4.4. Characterizing Risk Influence and Identifying Significant Contributors

To quantify how socio-technical interactions influence safety and financial risk, the framework maps trust- and transparency-related factors to PRA and GRA metrics using Bayesian belief network structures grounded in physically realizable component behavior, and ranks the most risk-significant socio-technical contributors. The AI-driven digital twin has progressed from a planned physics-informed neural-network formulation to an implemented machine-learning predictive model trained against physics-based degradation behavior, complemented by a multi-state Markov representation of component condition; a simulator-based human-subject study of trust, transparency, and human performance has been designed to provide empirical grounding. As an in-progress effort, the work to date emphasizes theoretical and methodological development and construction of the integrated platform, with quantitative risk results to follow as the case study matures.

5. DISCUSSION: TOWARD MECHANISTIC, UNCERTAINTY-AWARE, SOCIO-TECHNICAL PRA

The two efforts/projects reported in this paper are complementary expressions of a single objective: moving PRA beyond static, data-limited formulations toward mechanistic, uncertainty-aware, and socio-technical representations of risk. SIP-DA grounds hardware dependency parameters in physical and maintenance mechanisms and propagates uncertainty and validation evidence upward into PRA.

The NSF-sponsored research extends the same mechanistic and uncertainty-aware philosophy to the interactions among humans, AI-based automation, and organizations, and connects them to both safety and financial risk. Both rely on a common methodological spine of coupled simulation, probabilistic physics of failure, uncertainty quantification, and probabilistic validation.

By producing cause-specific, plant-specific estimates even where few or no failure events have been recorded, these approaches strengthen the technical basis for risk-informed applications, including the significance determination of inspection findings, risk-informed technical specifications, the categorization of structures, systems, and components under 10 CFR 50.69, risk-informed in-service inspection, and the licensing of advanced reactors under risk-informed, performance-based frameworks such as NEI 18-04. They are particularly relevant to advanced reactors, small modular reactors, multi-unit facilities, and modernized plants, where increasingly integrated designs and limited operating experience make purely data-driven approaches difficult to apply.

Several limitations bound the present results. The SIP-DA case study addresses a single sub-component mechanism, so the aggregated effect on plant-level risk metrics remains modest and is expected to grow as additional mechanisms are modeled; the computational cost of high-fidelity coupled simulation motivates the screening methodology and continued efficiency improvements. The NSF-sponsored framework is at an earlier stage, and its quantitative safety and financial results await maturation of the case study and the planned human-subject experiments. Future work will extend SIP-DA to additional dependency classes and reactor types, and integrate the socio-technical and AI-trust modeling with plant-level risk and economic metrics.

6. CONCLUDING REMARKS

This paper presented recent progress from two sponsored SoTeRiA research efforts that together advance next-generation PRA. The Simulation-Informed Probabilistic Dependency Analysis (SIP-DA) framework extends the PRA hierarchy downward to coupled physics of failure and maintenance work process simulations, and propagates simulation-derived evidence upward through uncertainty treatment, probabilistic validation, and integration with empirical CCF parameters. An emergency diesel generator case study demonstrated the workflow, produced an uncertainty-informed and mechanistically traceable alpha factor distribution, identified imperfect maintenance as the dominant dependency driver, and showed how simulation-informed estimates can be aggregated incrementally with industry data. The NSF-sponsored socio-technical and AI-driven research advances the modeling of human, physical degradation, and organizational interactions, as well as the modeling of trust in AI-based automation, linking them to both safety and financial risk through PRA and GRA. Taken together, these efforts move PRA from static, data-limited formulations toward more mechanistic, uncertainty-aware, and socio-technical representations of risk, thereby strengthening risk-informed decision making while preserving safety and reducing operational, financial, and regulatory burdens.

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