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COUPLING DEGRADATION AND MAINTENANCE TO MODEL SAFETY RISK AND FINANCIAL RISK UNDER AN INTEGRATED ENTERPRISE RISK MANAGEMENT FOR NUCLEAR POWER PLANTS

John Beal[1], Tatsuya Sakurahara[2*], Justin Pence[3], Pegah Farshadmanesh[2], Ernie Kee[4], Zahra Mohaghegh[5]

[1] Undergraduate Research Assistant, [2] Postdoctoral Research Associate, [3] Graduate Research Assistant, [4] Research Associate Professor, [5] Assistant Professor, Socio-Technical Risk Analysis (SoTeRiA) Research Laboratory, Department of Nuclear, Plasma, and Radiological Engineering, Grainger College of Engineering, University of Illinois at Urbana-Champaign, Urbana, IL, USA (*sakurah2@illinois.edu)

ABSTRACT

This research develops an Integrated Enterprise Risk Management (I-ERM) methodological framework for Nuclear Power Plants (NPPs). The value of I-ERM (compared to existing ERM approaches) is that more in-depth causality for physical degradation phenomena (e.g., Stress Corrosion Cracking; SCC) and social contributing factors (e.g., human, organizational, and regulatory performance), associated with the Operations and Maintenance (O&M) of the plant, is incorporated into an integrated assessment of safety risk and financial risk. The explicit incorporation of underlying causal mechanisms can help more realistically address the interrelationship between safety and financial risk induced by their shared physical and social factors; hence, it can enhance the accuracy of estimations of safety risk and financial outcome of O&M alternatives that are used as inputs to ERM of NPPs. In addition, the explicit incorporation of underlying causal factors allows for an in-depth importance measure analysis to identify the most critical safety and cost contributors, thus enhancing ERM by helping the decision makers generate more effective and efficient O&M strategies for the prevention and mitigation of undesirable events. This paper reports on the progress of the authors' research on creating a probabilistic coupling of a physics-based degradation model with human/social performance reflected in maintenance work processes and connecting this coupled physics-maintenance model with production loss modeling (Generation Risk Assessment; GRA) and Probabilistic Risk Assessment (PRA) to analyze the two interrelated performance measures of NPPs: safety and financial risks (as a function of plant unavailability and shutdown) within the I-ERM framework. For a case study, to show an implementation of the I-ERM framework, an elbow pipe of the Chemical & Volume Control System (CVCS) in Pressurized Water Reactors (PWRs) has been selected.

INTRODUCTION

Increased competition and fluctuations in the commercial electric sales market require a renewed focus on cost-saving initiatives to maintain the commercial viability of the Light Water Reactor energy sector. Utilities are seeking strategies to address the cost savings discussed in the "Cost & Benefit" lower tier in the NEI "Delivering the Nuclear Promise" initiative while continuing to maintain safety (Nuclear Energy Institute, 2016). Figure 1 depicts the author's proposed risk-informed framework (Bui, et al., 2019) for achieving the NEI Nuclear Promise. The two key goals – reducing cost and maintaining safety – are addressed through two paths: *addressing emergent safety concerns* (Node C in Figure 1) and *enhancing Enterprise Risk Management (ERM)* (Node E in Figure 1). To support these two paths, the authors have offered a two-step risk-informed strategy: (i) the *streamlined approach* (Node B in Figure 1), and (ii) the *advanced approach* (Node D in Figure 1).

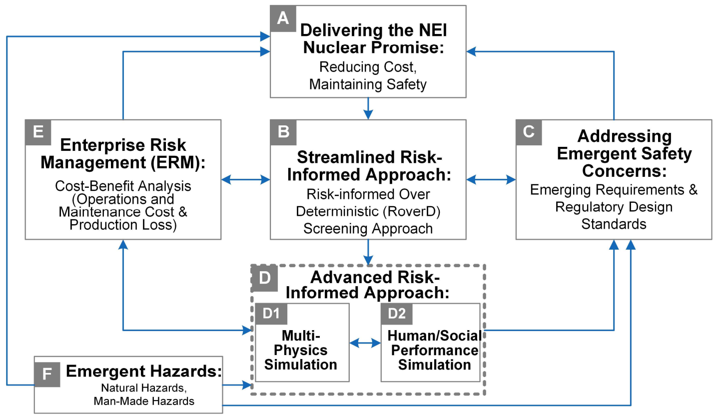

Figure 1. Proposed Risk-Informed Approaches to Reduce Cost while Maintaining Safety in Nuclear Power Plants.

To address emergent safety concerns (Node C in Figure 1), the Risk-informed Over Deterministic (RoverD) approach (Farshadmanesh, et al., 2018, Kee, et al., 2016), as an example of the streamlined approach, is developed. RoverD quantifies, using a conservative bounding approach, the extent of safety margin and defense-in-depth in the current design of protective systems to identify the modifications that can either be addressed at a lower cost or avoided. If plant risk metrics estimated by the streamlined approach do not satisfy the regulatory acceptance criteria, an advanced risk-informed approach (Node D in Figure 1) can be used to generate more resolution in plant risk estimates that can support compliance with regulatory acceptance criteria. As an example of the advanced approach, the Integrated Probabilistic Risk Assessment (I-PRA) methodological framework (Bui, et al., 2019, Mohaghegh, et al., 2013, Sakurahara, et al., 2018) has been developed and applied to two industry cases: (i) the risk-informed resolution of Generic Safety Issue 191 (GSI-191) in a full-scope NPP pilot project (Mohaghegh, et al., 2013); and (ii) Fire PRA for one critical fire-induced scenario of a plant, which has improved the realism of PRA, leading to a 50% reduction in core damage frequency (Sakurahara, et al., 2018). The I-PRA adds realism to plant risk estimations by explicitly incorporating the spatiotemporal evolution of physical failure mechanisms and human/social performance into the existing plant PRA structure while avoiding significant changes to the plant PRA structure.

This paper focuses on enhancing ERM for NPPs (Node E in Figure 1) and its connection with Node D by developing an Integrated ERM (I-ERM) framework. There have been many research studies on ERM in diverse industries; however, in the nuclear industry, publicly available academic research on ERM is limited (EnergyRisk, 2016). The nuclear industry uses ERM as an overarching process for gathering information to identify, assess, minimize or mitigate, and manage (INPO, 2013) near- and long-term organizational risks associated with safety, production, financial/commercial viability, reputation, strategy, regulatory and legal risks, and human capital (De Castro, et al., 2001, Zink, 1999). ERM research and development are moving towards a consideration of the "extended enterprise," which includes interfacing among a network of contractors, sub-contractors (with their own levels of transparency and quality) (Deloitte, 2016).

The value of I-ERM (compared to existing ERM approaches) is that more in-depth causality for physical degradation phenomena (e.g., Stress Corrosion Cracking; SCC) and social contributing factors (e.g., human, organizational, and regulatory performance), associated with the Operations and Maintenance (O&M) of a plant, is incorporated into an integrated assessment of safety risk and financial risk. In 2014, the authors published a conference paper on analyzing the causality between safety risk and financial risk (Abolhelm, et al., 2014). This research has led to a journal paper developing a systematic methodology to uncover the monetary benefit (in addition to safety benefits) that PRA can contribute by helping avoid plant shutdowns. The methodology was applied for one risk-informed application: Risk-Managed Technical Specifications (Pence, et al., 2018). Recently, other scholars in the risk analysis community have also appreciated the central idea of this line of research, for example: (a) (Dube, et al., 2017) developed an Economic Enterprise Risk (EER) approach, which considers aspects of public risk (i.e., PRA), and economic risk (i.e., asset losses and consequences), considering physical damage, lost generation, and regulatory impact (Dube, et al., 2017); (b) Mandelli, et al. (2018) are developing tools at the Idaho National Laboratory (INL) focusing on revenue risk analysis, considering energy demand and price forecasting, policy changes (Mandelli, et al., 2018).

This paper reports on the progress of I-ERM that creates a probabilistic coupling of a physics-based degradation model with human/social performance reflected in maintenance work processes and connects this coupled physics-maintenance model with production loss modeling (Generation Risk Assessment; GRA) and Probabilistic Risk Assessment (PRA) to analyze the two interrelated performance measures of NPPs: safety and financial risks (as a function of plant unavailability and shutdown). The following sections include (i) an overview of the I-ERM framework, and (ii) the status of methodological and case study developments for a probabilistic coupling between physical degradation and maintenance work processes.

INTEGRATED ENTERPRISE RISK MANAGEMENT (I-ERM) FRAMEWORK FOR NPPS

The I-ERM framework (Figure 2) connects Nodes E and D (Figure 1) to integrate two interrelated outcomes of NPPs: safety and financial outcome, considering their underlying physical and social phenomena. In the scope of this research, safety is based on the systematic risk estimated from PRA and financial outcome is based on profitability defined as revenue minus cost (e.g., O&M costs). The Socio-Technical Risk Analysis (SoTeRiA) Computational Platform (dotted box in Figure 2) predicts systematic risk and profitability given diverse O&M alternatives.

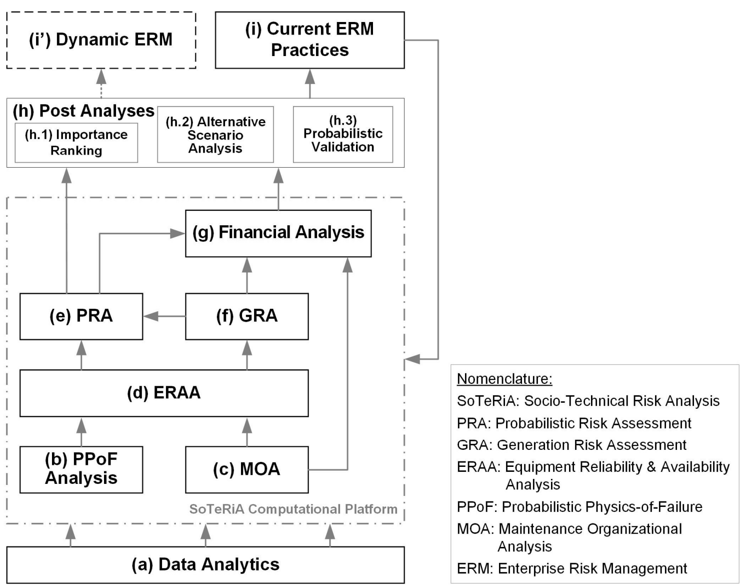

Figure 2. Integrated Enterprise Risk Management (I-ERM) Methodological Framework.

The PRA module ('e' in Figure 2) represents the plant PRA, consisting of Event Trees (ETs) and Fault Trees (FTs), and estimates systematic risk metrics associated with severe accident scenarios, such as Core Damage Frequency (CDF) and Large Early Release Frequency (LERF), using inputs from the other modules. In addition to CDF/LERF, ERM should evaluate safety risk throughout the lifecycle, considering scenarios that do not lead to severe accidents but can generate costs and loss of production. Economic risk management approaches (e.g., (Hunt and Modarres, 1987)) have been advanced, resulting in state-of-the-art approaches such as Generation Risk Assessment (GRA) (Blanchard, et al., 2004, Kee, et al., 2006). GRA estimates the frequency and duration of certain production loss events using techniques similar to PRA, such as fault tree analysis (Blanchard, et al., 2004). The PRA and GRA ('f' in Figure 2) modules require hardware equipment reliability and availability as inputs. The Equipment Reliability and Availability Analysis (ERAA) module ('d' in Figure 2), using a renewal process model, estimates the reliability and availability of hardware equipment subjected to physical degradation and maintenance. The physical inputs to ERAA are estimated based on outputs from the Probabilistic Physics of Failure (PPoF) Analysis module ('b' in Figure 2), while the maintenance inputs are estimated based on the Maintenance Organizational Analysis (MOA) module ('c' in Figure 2). The PPoF consists of physics-based degradation models and predicts physical Key Performance Measures (KPMs) associated with the failure events in PRA and GRA. The MOA includes a causal model for human and organizational factors that (i) influence maintenance performance leading to equipment reliability and availability; and (ii) directly influence cost through inefficiencies. MOA leverages the existing theoretical framework of organizational performance (Mohaghegh, 2007, Mohaghegh and Mosleh, 2009a) and the Data-Theoretic approach (Pence, et al., 2019a, Pence, et al., 2019b) to develop the causal models and quantify them. The Financial Analysis module ('g' in Figure 2) conducts a cost-benefit analysis of short-term costs (e.g., maintenance costs, production loss, regulatory costs) and long-term costs (e.g., severe accidents).

The Post Analysis module ('h' in Figure 2) prepares information for the Current ERM Practices ('i' in Figure 2) by running the SoTeRiA Computational Platform for diverse O&M alternatives and analyzing the outputs related to systematic risk and profitability. The Importance Ranking submodule ('h.1' in Figure 2) performs an in-depth IM analysis (Sakurahara, et al., 2017) to rank the underlying physical and human/social contributing factors (e.g., physical design, maintenance characteristics) based on their impact to systematic risk and profitability. The Alternative Scenario Analysis submodule ('h.2' in Figure 2) generates alternative scenarios with respect to plant O&M, considering safety margins and regulatory constraints. The simulation models and techniques in the SoTeRiA Computational Platform require verification and validation. The most common approach for validation of a simulation model is "empirical validation" where the model prediction is compared against empirical data, e.g., experimental or observational data. For the I-ERM framework, the empirical validation is challenging since the outputs of interest (systematic risk and profitability) can involve rare events. As an alternative method, the Probabilistic Validation submodule ('h.3' in Figure 2) (Sakurahara, et al., 2019b) characterizes and propagates epistemic uncertainties associated with the models and simulation techniques (used in the SoTeRiA Computational Platform) to construct the uncertainty bounds (representing the "degree of confidence/validity") for simulation-based estimations of risk and profitability.

The following section reports on the status of three modules of I-ERM including ERAA, PPoF Analysis, and MOA as well as their connections. As a case study, an elbow pipe of the Chemical & Volume Control System (CVCS) in PWRs is selected. Operating experience demonstrates that the failure of the CVCS piping can result in an unexpected plant shutdown or an entry to the Limiting Condition for Operation (LCOs). The failure of the CVCS pipe can have strong impacts on plant safety and availability; thus, this is a reasonable choice for the case study in this research. Although the I-ERM methodology is applicable to various types of systems and components, the remainder of this paper focuses on Reactor Coolant Pressure Boundary (RCPB) piping.

COUPLING OF DEGRADATION AND MAINTENANCE IN THE I-ERM FRAMEWORK

In the I-ERM framework, the coupling between physical degradation and maintenance organizational performance is generated through the ERAA module that consists of a renewal process model. In the authors' previous study (Sakurahara, et al., 2019a), the physics-based degradation models have been integrated with a renewal process model through a probabilistic interface, while maintenance performance was quantified by a data-driven method that relies on historical service data. In this paper, maintenance performance analysis is advanced by developing a model-based approach in the MOA module and is coupled with PPoF Analysis through ERAA, as follows:

Developing a Renewal Process Model (ERAA module): at this stage of the research, a time-homogeneous Markov process model (Figure 3) that has the same structure as the one developed by Fleming (Fleming, 2004) is selected, while ongoing research by the authors is advancing ERAA to relax the assumptions made in the Markov process model. A set of discrete states (New, Flaw, Leak, and Rupture) is defined based on the physical degradation mechanism (e.g., Stress-Corrosion Cracking [SCC]) and the practical information about maintenance (e.g., whether a specific state can be detected). For each state, the associated physical criteria (e.g., a threshold value with respect to a defect size) are defined. The fundamental processes of SCC include: pit initiation, pit growth, pit transition to crack, and crack growth. This research adopts a criterion proposed by Kondo (1989), which states that a pit transitions to crack once the SCC growth rate exceeds the pit growth rate (Kondo, 1989). The transition from New to Flaw occurs when the SCC growth rate becomes larger than the pit growth rate. A component is defined as being in the Leak state when it has any defects with a depth equal to the wall thickness of the component, i.e., a 100% through-wall crack. A component enters the Rupture state if the internal pressure is beyond the burst pressure. The state probabilities (New, Flaw, Leak, and Rupture) are computed by solving a set of differential equations representing the Markov process model. For further details on this Markov process model, the readers are referred to (Sakurahara, et al., 2019a)

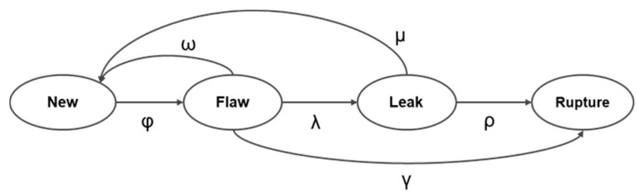

Figure 3: A Markov process model for RCPB components.

Estimating Degradation Parameters of the Renewal Process Model based on Physics of Failure and with Consideration of Uncertainties: In most of the existing studies using a Markov process model, the transition rates are estimated from statistical data. In this research, to estimate the transition rates of the Markov process model, the physics-based degradation models (corresponding to the PPoF Analysis module in Figure 2) are developed for the dominant degradation mechanisms (e.g., pit growth and SCC growth). The PoF model for SCC of 316 stainless steel is formulated as follows:

$$CPR_{SS} = C_{SS}\exp\left[\frac{Q}{R}\left(\frac{1}{T}-\frac{1}{T_{ref}}\right)\right](\sigma_{ys})^{m_{SS}}(K-K_{thSS})^{n_{SS}}, \tag{1}$$

where CPR_{SS}: crack propagation rate; C_{SS}, m_{SS}, and n_{SS}: empirical parameters; T: operating temperature [K]; T_{ref}: reference temperature; R: universal gas constant; Q: activation energy [kJ/mol]; σ_{ys}: yield strength [MPa], K: stress intensity factor (SIF) [MPa·m$^{1/2}$]; and K_{thSS}: threshold SIF value [MPa·m$^{1/2}$]. A similar PoF model is also developed for pit growth. The empirical parameters (C_{SS}, m_{SS} and n_{SS}) are estimated by fitting the PoF model to experimental data using Bayesian regression analysis. The PoF models are then made probabilistic, i.e. the Probabilistic Physics of Failure (PPoF), by Uncertainty Quantification (UQ) using Monte Carlo simulation. The input parameters (including the initial pit size and empirical parameters) are randomly sampled from probability distributions using Latin Hypercube Sampling (LHS). The PoF models are then run with each set of randomly-sampled input parameters (referred to as a 'crack sample') to generate random samples of the time profiles of defect size. To estimate degradation transition rates, for example, λ (Flaw to Leak), the Time-from-Flaw-to-Leak (TFL) is recorded for each crack sample, and the Mean Time-from-Flaw-to-Leak (MTFL) is estimated. The point estimate of λ is then computed by Equation (2):

$$\lambda = \left(\frac{\#Transitions(Flaw \rightarrow Leak)}{Total\ \#\ Crack\ Samples}\right)\times\left(\frac{1}{MTFL}\right). \tag{2}$$

φ, γ, and ρ are estimated based on the PPoF outputs using the similar method. For further details on PPoF models and the estimation of transition rates, the readers are referred to (Sakurahara, et al., 2019a)

Estimating Maintenance Parameters of the Renewal Process Model: the authors' previous study (Sakurahara, et al., 2019a) estimated the repair transition rates (ω and μ) by a data-driven maintenance model (Fleming, 2004):

$$\omega = P_{FI}P_{FD}/(T_{FI} + T_{FR}), \tag{3}$$

$$\mu = P_{LI}P_{LD}/(T_{LI} + T_{LR}), \tag{4}$$

where P_{FI} is a probability that a component is inspected to detect flaws within an inspection interval; P_{FD} is a conditional probability that a component flaw is detected, given that the component is inspected; T_{FI} is an inspection interval for flaws; T_{FR} and T_{LR} are times-to-repair once a component is identified as being in Flaw and Leak states, respectively (estimated from the service data); P_{LI} is a probability that the component is inspected for leak detection; P_{LD} is a conditional probability that the component is detected as being in the Leak state, given that the respective component is inspected for leak detection; and T_{LI} is an inspection interval for leaks.

This methodology has been applied to two RCPB components: (i) the expansion-transition region of steam generator tubes fabricated from Alloy 690 and (ii) the high-strain hardened region of pressurizer heater sleeves made of stainless steel (Sakurahara, et al., 2019a). Global sensitivity analysis (SA) (Liu and Homma, 2010) is conducted to rank the input parameters of the PoF models (temperature, yield strength, and hydrogen concentration) based on their influence on the rupture probability and has identifies that temperature is the most influential factor. The global SA is selected since it can account for uncertainties associated with input parameters and model outputs, non-linearity of the model, and interactions among input parameters (Sakurahara, et al., 2017).

The global SA results can help improve the maintenance programs, e.g., concentrating the maintenance resources on those RCPB components that are exposed to high temperature. The data-driven maintenance model, however, has key limitations: (i) it cannot explicitly capture the dependency between physical degradation and maintenance performance, particularly if common causal factors contribute to both; (ii) its accuracy could be questioned if the system design, operational conditions, and maintenance programs are significantly changed; and (iii) it does not allow an in-depth IM analysis to be conducted to identify the critical physical and maintenance causal factors. Therefore, the authors propose a model-based method for maintenance analysis to depict maintenance work processes and their contributing factors. This paper covers the first step for developing a model-based approach.

As a first step to develop the model-based approach, global SA is conducted to rank the maintenance characteristics used in Equations (3) and (4). This SA aims to identify which maintenance characteristics are the most critical contributors to rupture frequency and, hence, need to be prioritized in the development of a model-based maintenance analysis as part of the MOA module. One key assumption in the Markov model (Figure 3) is that, if a flaw or leak is found in inspections, the component is immediately and perfectly repaired. In reality, there is a certain probability that the repair is not carried out perfectly; hence, this assumption may skew the SA results. In order to relax this assumption, the possibility of a repair error is considered as follows, either (i) a component in the Flaw state will not return to the New state after repair; or (ii) a component in the Leak state will return only to the Flaw state after repair. In other words, this study assumes that the repair outcome is between as-good-as-new and as-bad-as-old conditions. In addition, when a component is in the Leak state, it is assumed that there is no possibility for the post-repair component to remain in the Leak state. These two assumptions are justified by considering that, in ASME B&PV Code Section XI, a pressure test is typically required after the repair/replacement, which can detect a leak with relatively high reliability. To account for imperfect repair, the Markov model (Figure 3) is modified by adding a new repair transition path from Leak to Flaw with the associated rate τ. The equations for the repair transition rates (ω, μ, and τ) are then generated by constructing an event tree representing the inspection and repair process. Figure 4 shows an event tree developed for leak inspection and repair.

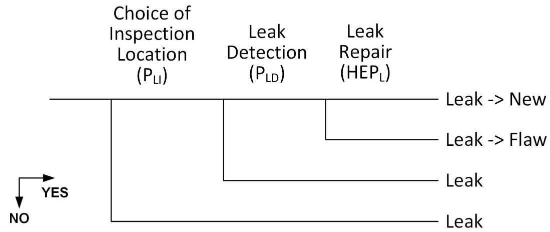

Figure 4: An event tree model for inspection and repair of a leak.

Three pivotal events (or phases) of the inspection and repair process are considered: (i) choice of inspection location (associated with P_{LI}); (ii) leak detection (associated with P_{LD}); and (iii) leak repair. The end state of each scenario indicates the transition path in the Markov processmodel (Figure 3) after the inspection and repair are performed. The transition from Leak to New occurs only if all pivotal phases are success; hence, the equation for μ (i.e., Equation (4)) is modified as follows:

$$\mu = P_{LI}P_{LD}(1 - HEP_L)/(T_{LI} + T_{LR}), \tag{5}$$

where HEP_L is a Human Error Probability (HEP) for leak repair. The transition from Leak to Flaw occurs when an RCPB location is covered in the leak inspection program and a leak is detected, but a repair error occurs; hence, the equation for τ is obtained as follows:

$$\tau = P_{LI}P_{LD}HEP_L/(T_{LI} + T_{LR}), \tag{6}$$

By developing a similar event tree for flaw detection and repair, the equation for ω (i.e., Equation (3)) is modified as follows:

$$\omega = P_{FI}P_{FD}(1 - HEP_F)/(T_{FI} + T_{FR}), \tag{7}$$

where HEP_F is a human error probability for flaw repair. For the purpose of SA aimed at screening the maintenance parameters, the conservative bounds for HEP_F and HEP_L are obtained by the Standardized Plant Analysis Risk Human Reliability Analysis (SPAR-H) method (Gertman, et al., 2005). SPAR-H considers eight Performance Shaping Factors (PSFs): available time, stress and stressors, complexity, procedures, experience and training, ergonomics and human-machine interface, fitness for duty, and work processes. For the RCPB component repair, the possible range of each PSF is assessed based on the plant expert's opinion. In SPAR-H, the human error probability is computed as a multiplication of a base probability (0.01 for diagnosis tasks, and 0.001 for action tasks) and the composite PSF calculated by multiplying eight PSFs. The ranges of HEP_F and HEP_L are obtained by propagating the ranges of eight PSFs by Monte Carlo simulation. The upper and lower bounds (95th and 5th percentiles) for the HEP_F are [0.0034, 0.9213], while those bounds for the HEP_L are [0.0044, 0.9400]. At this stage of research, for the other maintenance characteristics in Equations (5) to (7), the point estimates from (Fleming, 2004) are used as nominal values, and the upper and lower bounds are selected as 90% above and below the nominal value (constrained between 0 to 1 for probabilities). To avoid the "false negative" results (i.e., mistakenly screen out the parameters) in the SA, these upper and lower bounds are selected based on the principle that uncertainty of each parameter is overestimated rather than being underestimated.

The sensitivity of rupture frequencies (at 10 and 40 years) to maintenance parameters is computed using the first-order sensitivity index (Homma and Saltelli, 1996). The first-order sensitivity index for input parameter X_i, denoted as S_i, is defined as follows:

$$S_i = V[E(Y|X_i)]/V(Y), \tag{8}$$

where $E(Y|X_i)$ is the conditional expected value of a model output Y, given a specific fixed value of X_i. A uniform distribution is assumed for each maintenance parameter with the upper and lower bounds described above. To estimate S_i, the computational algorithm proposed by (Homma and Saltelli, 1996) is used. The sample size (N = 500,000) is selected by conducting a convergence study, where the sample size is gradually increased until the standard error of S_i becomes smaller than or equal to 0.010. Table 1 shows the results of global SA.

Table 1: Global SA results. The parenthesized values show the standard errors of S_i.

Parameter	S_i at t = 10 yr	S_i at t = 40 yr	Parameter	S_i at t = 10 yr	S_i at t = 40 yr
P_{FI}	0.012 (0.009)	0.024 (0.004)	P_{LD}	0.286 (0.010)	0.289 (0.005)
P_{FD}	0.011 (0.009)	0.020 (0.004)	T_{LI}	0.329 (0.010)	0.214 (0.005)
T_{FI}	0.032 (0.009)	0.051 (0.004)	T_{LR}	0.000 (0.009)	0.000 (0.004)
T_{FR}	0.000 (0.009)	0.000 (0.004)	HEP_F	0.008 (0.009)	0.019 (0.004)
P_{LI}	0.278 (0.010)	0.285 (0.005)	HEP_L	0.000 (0.009)	0.000 (0.004)

P_{LI}, P_{LD}, and T_{LI} are identified as the three parameters with the largest impacts on the rupture frequencies. P_{LI} and T_{LI} are determined by maintenance strategies; therefore, in the I-ERM framework, their possible values associated with maintenance alternatives should be addressed in the Alternative Scenario Analysis submodule. P_{LD} is determined by the inspection performance and should be assessed in the MOA module. Table 1 indicates that T_{FR}, T_{LR}, and HEP_L are not influential for the rupture frequencies; hence, these three parameters could be screened out from the scope of the maintenance causal model in the MOA module. Ongoing research by the authors analyzes the RCPB piping maintenance practices based on the ASME B&PV Code Section XI and historical records (e.g., NRC Licensee Event Reports [LERs]) to generate more realistic ranges of the maintenance characteristics. This may further reduce the number of influential maintenance parameters, and more conclusive insights on prioritization of the maintenance characteristics in the MOA development can be derived. For the most influential maintenance characteristics identified by the SA, a causal model for the maintenance organizational performance will be developed using the organizational performance theoretical framework (Mohaghegh, et al., 2009, Mohaghegh and Mosleh, 2009b) and the associated Data-Theoretic measurement techniques (Pence, et al., 2019b).

CONCLUSION

To promote the sustainability of the U.S. nuclear fleet, this research develops an Integrated ERM (I-ERM) framework (Figure 2) that supports plant decision-making to improve safety and cost savings and to avoid production loss while satisfying short- and long-term regulatory standards and requirements. The I-ERM framework identifies alternative scenarios associated with the plant O&M and evaluates the two interrelated outcomes of a nuclear power operating organization, namely safety and financial outcome. This research advances ERM of NPPs by explicitly incorporating the underlying causality, both physical (e.g., degradation) and human/social (e.g., maintenance work processes), into the assessments of safety risk and financial outcome. By explicitly incorporating the underlying causality, the dependency between safety risk and financial outcome induced by the shared causal factors is captured more realistically; hence, this research can help improve the accuracy of risk and cost assessments as inputs to ERM of NPPs. In addition, the explicit incorporation of underlying causality allows for an in-depth ranking of underlying causal factors to identify the most critical risk and cost contributors; therefore, it can help improve risk management by providing the decision makers with more in-depth risk and cost insights.

This paper reports on the progress of the authors' research on creating a probabilistic coupling of a physics-based degradation model with human/social performance reflected in maintenance work processes and connecting this coupled physics-maintenance model with production loss modeling (Generation Risk Assessment; GRA) and Probabilistic Risk Assessment (PRA) to analyze safety and financial risks (as a function of plant unavailability and shutdown) within the I-ERM framework. The coupling between physical degradation and maintenance is created by a renewal process model in the ERAA module ('d' in Figure 2). The ERAA require two types of input parameters: the physical parameters are generated by the PPoF Analysis, while the maintenance parameters are generated by the MOA. Using the RCPB components of NPPs as a case study, this paper explains how an interface between the ERAA and the PPoF Analysis is created. This paper also reports on the global SA performed to identify the maintenance characteristics that should be prioritized in the development of a model-based approach for maintenance analysis in the MOA module. To generate more realistic results from the global SA, event tree models for inspection and repair of flaws and leaks are developed, and the repair transition rates in the Markov process model are quantified.

Ongoing research by the authors focuses on several modules in the I-ERM framework, including: (a) developing the Financial Analysis module; (b) advancing the ERAA module to relax the assumptions in the Markov process model; (c) advancing the PPoF Analysis by developing a mechanistic physical model using the finite element analysis; and (d) constructing more realistic ranges of maintenance parameters to update the global SA for inspection and repair processes. For the most critical maintenance characteristics identified by the global SA, future research will develop a causal model of maintenance work processes as part of the MOA module.

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