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PHYSICS-BASED COMMON CAUSE FAILURE MODELING IN PROBABILISTIC RISK ANALYSIS: A MECHANISTIC PERSPECTIVE

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ABSTRACT

The modeling of dependent failures, specifically Common Cause Failures (CCFs), is one of the most important topics in Probabilistic Risk Analysis (PRA). Currently, CCFs are treated using parametric modeling, which is based on historical failure events. Instead of utilizing the existing data-driven approach, this paper proposes the concept of physics-based CCF modeling, which refers to the incorporation of underlying physical failure mechanisms into risk models so that the root causes of dependency can be "explicitly" included. This requires building a theoretical foundation for the integration of Probabilistic Physics-Of-Failure (PPOF) models into PRA in a way that can depict the interactions of failure mechanisms and, ultimately, the dependencies between the multiple component failures. To achieve this goal, this paper highlights the following methodological steps (1) modeling the individual failure mechanisms (e.g. fatigue and wear) of two dependent components, (2) applying a mechanistic approach to deterministically model the interactions of their failure mechanisms, (3) utilizing probabilistic sciences (e.g. uncertainty modeling, Bayesian analysis) in order to make the model of interactions probabilistic, and (4) developing appropriate modeling techniques to link the physics-based CCF models to the system-level PRA. The proposed approach is beneficial for (a) reducing CCF occurrence in currently operating plants and (b) modeling CCFs for plants in the design stage.

1. INTRODUCTION

This paper reports on a new line of research, which is related to the development of advanced methodologies and techniques for a physics-based CCF modeling in PRA of complex systems. PRA can provide input for risk-informed decision making [1, 2] for the design, operation and regulatory oversight of complex technological systems and processes (including Nuclear Power Plants; NPPs).

In 1975, the Atomic Energy Commission initiated the landmark Rasmussen study [3] that led to the advent of PRA in the nuclear industry. Over the years, PRA has grown into an accepted technical discipline with a wide range of applications. A growing number of government agencies in the U.S. have set a trend of using PRA to support their decisions and policymaking. Among these are the United States NRC, DOE, FAA, NASA, DOD, EPA, and FDA. There are also critical needs for utilizing and advancing PRA studies in other industries. For example, in the oil industry this could have been beneficial to BP to avert the oil spill in the Gulf of Mexico.

In PRA research and applications, the nuclear industry continues to be the leader. USNRC relies on PRA technology as one of the main pillars of its regulatory and oversight functions. Risk-informed activities include the licensing of new reactors, life extension and power upgrade decisions for the current generation of plants, operational decisions regarding maintenance, system upgrades, inspections, and assessments of operational events. These applications of PRA, despite significant methodological advancements over the past three decades, have pushed "classical" PRA methods to their limits of applicability. The need for new methods or a substantial upgrading of the existing PRA methods and tools is evident in all the above-mentioned areas.

One of the most important topics in PRA is the modeling of dependent failures. In general, dependent failures are defined as events in which the probability of each failure depends on the occurrence of other failures [4]. The major causes of dependence among a set of systems or components can be explicitly modeled using system reliability methods (e.g. fault trees). Other dependent failures, where root causes are not known or are difficult to model explicitly in the system or component reliability analysis, are grouped under CCFs [5, 6]. Currently, CCFs are treated using parametric modeling based on historical common cause events.

Better treatment of CCFs needs more advanced modeling of the underlying failure mechanisms of the elements of risk scenarios (i.e. hardware failure, human error and software fault). For this purpose, PRA requires roots and foundations in such diverse fields as engineering, materials science, cognitive psychology, organizational behavior, and computer science. There have been some studies on the incorporation of human and organizational failure mechanisms [7, 8], and others on the integration of software failure mechanisms [9] into PRA. This paper focuses on the incorporation of underlying physical failure mechanisms into risk models. Its purpose is to build a theoretical foundation for the integration of PPOF models [4] into PRA frameworks in a way that can depict the interactions of physical failure mechanisms and, ultimately, the dependencies between the component failures.

Section 2 summarizes the gaps in existing CCF and PPOF approaches. Section 3.1 explains the concept of physics-based CCF modeling and Section 3.2 highlights the methodological steps and the related challenges to operationalize the proposed concept.

2. GAPS IN EXISTING COMMON CAUSE FAILURE AND PROBABILISTIC PHYSICS-OF-FAILURE MODELS

2.1 Existing Common Cause Failure Models

As mentioned above, the major causes of dependence among a set of systems or components can be explicitly modeled using system reliability methods (e.g. fault trees). Other dependent failures, where root causes are not known or are difficult to model explicitly in the system or component reliability analysis, are grouped under CCFs [5, 6]. There have been several definitions for CCFs over the past 30 years. One prevalent definition is given by Mosleh et al. [5] as: "…a subset of dependent events in which two or more component fault states exist at the same time, or in a short-time interval, and are direct results of a shared cause."

The initial approach for treating CCFs was the one used in the WASH-1400 [3]. Based on this simple method, the overall system failure probability was calculated as a geometric mean value of system failure probability assuming independence (P_I) and system failure probability assuming maximum dependence (P_D). Due to the inadequacy of this method, treatment of CCFs moved to parametric approaches. Parametric approaches can be classified based on their number of parameters into (1) single parameter model (β- factor model [10]) and (2) multi-parameter models (Multiple Greek Letter (MGL) [11], α-factor [12], Binomial Failure Rate (BFR) [13] methods). Multi-parameter models give more accurate assessments of CCFs in systems with higher levels of redundancy. The multi-parameter models are further classified into subcategories called shock and non-shock models. Among the multi-parameter methods , BFR is the only shock-dependent model and it considers two types of common cause shocks (lethal and nonlethal), so that it is too complex to be widely used . Currently, MGL and α-factor methods are the most common parametric approaches for CCF modeling. [14]

An important requirement in the quantification of CCFs, based on the parametric approaches, is the collection and proper usage of data for the estimation of model parameters. The common approach for implementing data for CCF models is presented in [15] by using Impact Vectors. This methodology helps interpret data involving CCF with respect to taxonomy of causes and coupling factors. It also helps adjust for differences between generic raw data and plant specific data.

The current parametric approaches for CCF modeling are very dependent on the availability and quality of historical failure data. They are also inadequate in providing quantitative causal relations for CCFs. Therefore, they are not sufficient in (a) reducing CCF events in current operating plants, and (b) making design and licensing decisions for new reactors. In order to improve the treatment of CCFs, the following three aspects need to be considered:

1. Developing "theoretical" foundations for depicting the underlying failure mechanisms of the elements of risk scenarios (i.e. hardware failures, human errors, and organizational behavior) to identify the root causes and phenomenology of dependencies.
2. Applying appropriate "modeling techniques" (e.g., causal modeling) in order to explicitly and quantitatively relate the root causes in the failure mechanisms to the top events and, consequently, to the accident sequence models.
3. Applying more advanced data-driven approaches, consistent with the nature and availability of the data, in order to "empirically" deal with dependencies (in situations where it is difficult to model the root failure mechanisms any further).

There have been studies on the development of theories and techniques for the incorporation of human and organizational failure mechanisms [e.g. 7 and 8] and others on the integration of software failure mechanisms [e.g. 9] into PRA. Also, there are studies on using causal modeling techniques (e.g. Bayesian approach) for CCF modeling [16].

The focus of this paper is to model CCFs based on the incorporation of the underlying physical failure mechanisms (and their interactions as important sources of CCFs) or the PPOF approach into PRA, covering both the required theoretical perspectives (referring to item #1 above) and modeling techniques (referring to item #2 above).

2.2. Existing Probabilistic Physics-Of-Failure Models

The first attempt to consider physical characteristics in reliability models was in the electronic industry in the early 60's. This was because of unsatisfactory results when using exponential distributions for time-to-failure of specific products under degradation process. This led to the use of other distributions (e.g. Weibull) for time-to-failures in order to partially include physical aspects by considering variable hazard rates. The next step (in the 80's) was the rise of accelerated life testing methods to incorporate the aggregate effects of operational conditions (i.e. stress) to life models. The development of accelerated life testing, which required understanding the underlying failure mechanisms, gradually led to the creation of POF models. The concept of POF had been used for many years in the area of structural engineering, but in the early 90's, reliability engineers adopted it for reliability assessment of electrical, electronic, and even mechanical systems and components in order to reduce the need to rely solely on historical failure data. POF models had a deterministic nature and they needed a separate stochastic process such as Monte Carlo-based simulations to make them probabilistic. [17]

The POF models connect intra- (e.g. environmental temperature and pressure) and inter-environmental conditions (e.g. load, viscosity, and design specs) to "time-to-failure" using the scientific knowledge of degradation processes (e.g. fatigue generated crack initiation and propagation) and regression-based curve fitting to estimate the exponents in equations. PPOF [4] combines the scientific knowledge of degradation processes with the uncertainties (e.g. load profile applied to the item, its architecture, material properties and environmental conditions) to predict the time-to-failure of the item. Modarres [18, 19] developed a number of these probabilistic relationships for most common failure mechanisms at the material-level and used Bayesian updating (with test data or field data as evidence) to find the distributions of the parameters of time-to-failure, including probabilistic assessment of model errors. With this, the epistemic uncertainties associated with the deterministic POF models are accounted for and models are turned into probabilistic forms and ready to be used in current PRA frameworks.

Although the Bayesian approach facilitates (a) more efficient considerations of uncertainties and (b) integration and updating with diverse sources of data (accelerated testing, field data, and expert judgment), dealing with the related multidimensional joint distributions has been quite challenging. With the advancement in computational tools in the 2000s, Bayesian statistical methods, such as the Markov Chain Monte Carlo (MCMC) Simulation and other sampling-based methodologies, have improved numerically and computationally, so that the Bayesian inference is becoming a common practice in PPOF. [20]

Gaps to be considered in the PPOF analysis are:

1. The methodology is developed for each individual failure mechanism and the interactions of failure mechanisms have not been considered.
2. The methodology is developed at the material-level and has not yet been expanded to the component- or system-level. An agent-based approach [17] is proposed but has not yet been validated.
3. Since the parameters are the result of curve fitting in a specific condition (i.e. geometry and stress), the equations are not generic.

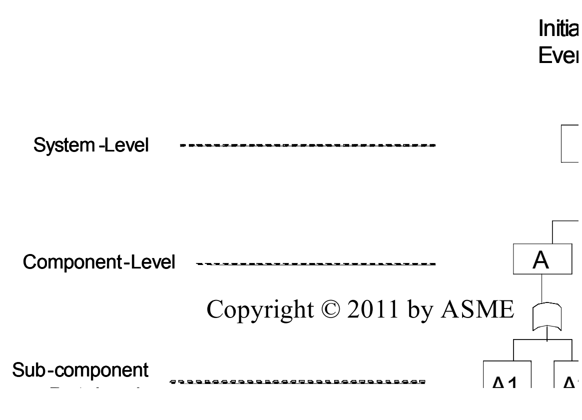
3. PHYSICS-BASED CCF MODELING

3.1. The concept of using probabilistic POF analysis to model CCFs

Figure 1 shows a simple PRA framework where Event Tree (ET) delineates the possible risk or hazard scenarios. The events, conditions, and causes of the scenarios are incorporated through the Fault Tree (FT). In many cases, direct causes of accidents are those system failures or human operational errors that appear as the top events of FTs. The top events of FTs (e.g., System 1 in Figure 1) are plugged into the ETs. ETs represent a set of possible risk scenarios where, given the occurrence of the initiating event, the state of System 1 (a Pivotal Event), if it works, determines whether the sequence leads to success (End State S). If System 1 fails, then an operator action is required, and given the success of the operator action, the final outcome would be success (state S). Conversely, the failure of the operator action leads to failure (state F). The failure of System 1 relates to the failures of two components (i.e. A and B) which have two sub-components or parts (i.e. A1, A2, B1, and B2).

Instead of dealing with dependencies using existing data-driven CCF approaches (which use part- or sub-component level data), this paper proposes bringing the POFs into the risk model so that the sources of dependencies can be "explicitly" included. The simplest form would be in a case where each part has one failure mechanism. For example, consider two parts, A2 and B2, in a PRA model (as shown in Figure 1) where part A2 fails due to fatigue and part B2 fails due to wear. Because these two failure mechanisms share common intra- (e.g. environmental temperature and pressure) and inter-environmental conditions (e.g. load, viscosity, and design specifications), parts A2 and B2 have dependent failures. Since the POF approaches explicitly include the intra- and inter-environmental factors in the failure equations, the dependencies will be covered via the equations. The only challenge in dealing with the dependencies between A2 and B2 would be the expansion of the probabilistic POF models from material-level to component-level, and from component-level to system-level. Section 3.2 will explain the modeling challenges.

A more realistic situation would be the case where two (or more) failure mechanisms interact. An example would be the dependencies between parts A1 and B2 in Figure 1, where the failure of A1 comes under both fatigue and wear and the failure of B2 comes under wear. In this case, there are two important challenges (1) modeling the interactions of fatigue and wear in A1 and (2) expanding POF models from the material-level to the system-level (as in the previous example).



In this paper, it is proposed that such problems are solvable using a mechanistic perspective (i.e. using semi-empirical models of failure mechanisms). This theoretical perspective would need appropriate "modeling techniques" to operationalize and quantify the interactions of failure mechanisms. The next section describes the challenges and methodological steps related to the proposed mechanistic perspective.

3.2 Methodological steps for physics-based CCF modeling

This section summarizes the proposed methodological steps of a mechanistic approach for CCF modeling. For clarification, consider parts A1 and B2 in Figure 1. As discussed in the previous section, these two parts have dependent failures since they share common inter- and intra-environmental factors as root causes of their failure mechanisms (i.e. fatigue and wear). If we develop models for their failure mechanisms (as functions of the inter- and intra-environmental factors) and, integrate them with the risk scenarios, we can accomplish a physics-based CCF failure modeling as the root causes of their dependency are explicitly included in the PRA. The following covers the methodological steps to achieve this goal. It also highlights the associated ongoing research by the authors:

I. Developing a probabilistic wear model at the material-level for B2: we use the test data at the material-level for wear and find the parameters of this failure mechanism (by combining the deterministic science of mechanics of failure and regression- and/or Bayesian-based [20] curve fitting). This gives us "time-to- failure" as a function of stress and other inter- and intra-environmental factors. Using uncertainty propagation techniques and Bayesian updating, we estimate the probabilistic distribution of time-to-failure (this converts the deterministic POF models to probabilistic forms and makes them ready to be linked with PRA frameworks).

In order to explain the methodology, we start with the development of a simplified probabilistic wear model for part B2 (e.g. a journal bearing) having vibration as its failure mode. Failure (i.e. vibration) happens when total damage (i.e. total wear; W_{total} [m]) reaches critical damage (i.e. wear critical; $W_{critical}$ [m]). Therefore, the number of cycles-to-failure ($N_{f\text{-}B2}$) can be estimated based on Equation 1.

$$N_{f-B2} = \left(\frac{W_{critical}}{\dot{W}_{B2}} \right) \qquad (1)$$

$\dot{W}_{B2}$ stands for wear rate [m/cycle] of part B2 .

It is assumed that the wear rate is a function of both "maximum shear stress in the vicinity of the contacting surface" ($\tau_{1\max}$) and "shear strength of the coating material at the test condition (τ_{1yp}). Therefore, the ratio of these two variables is the independent variable for the wear rate model that is expressed as a power law function in Equation 2. [17, 21]

$$\dot{W}_{B2} = C_1 \left[\frac{\tau_{1\max}}{\tau_{1yp}} \right]^{n_1} \quad (2)$$

C_1 and n_1 respectively stand for proportionality constant [m/cycle] and constant power parameter.

Using Equation 1 and 2, the wear life of B2 can be related to the shear stress using the inverse power law relationship as described in Equation 3.

$$N_{f-B2} = K_1 \left[\frac{\tau_{1yp}}{\tau_{1\max}} \right]^{n_2} \quad (3)$$

K_1 stands for a proportionality constant. In addition, τ_{1yp} and τ_{1max} can be estimated as functions of inter- and intra-environmental factors using Equations 4 to 8 .

The maximum shear stress can be estimated based on the maximum shear stress theory in the vicinity of contact surface. As it is expressed in Equation 4, the maximum shear stress is a function of "normal stress on the surface resulting from pressure" (σ_{1n}) and the "friction generated shear stress" (τ_{1f}). The "stress concentration factor" (K_{e1}) may be significant when misalignment or other manufacturing errors are in place, and can be found in machine design handbooks for different geometry and materials. [21]

$$\tau_{1\max} = K_{e1} \sqrt{\left(\frac{\sigma_{1n}}{2} \right)^2 + \tau_{1f}^{\ 2}} \quad (4)$$

As Equation 5 shows, the "friction generated shear stress" (τ_{1f}) is the multiplication of "normal load" (L_{B2}) and the "friction factor" (COF_1).

$$\tau_{1f} = COF_1 * L_{B2} \quad (5)$$

The friction factor depends on the lubrication regime and is usually plotted versus the Sommerfeld number, as shown in the Equation 6 as a function of "lubricant viscosity" μ_1, "lubricant velocity" V, and normal load for B2

$$COF_1 = f_1 \left\{ \frac{\mu_1 * V}{L_{B2}} \right\} \quad (6)$$

Also, the shear strength of the coating material relates the temperature as shown in Equation 7 where A and B are constants and T_1 stands for temperature of B2.

$$\tau_{1yp} = B * \exp\left(\frac{A}{T_2} \right) \quad (7)$$

The "normal stress on the surface resulting from pressure" (σ_{1n}) is a function of the load and the geometry or design specification (DE_{B2}) in part B2.

$$\sigma_{1n} = f_2 \{ L_{B2}, DE_{B2} \} \quad (8)$$

By substituting τ_{1yp} and τ_{1mx} from the Equations 4 to 8 into the Equation 3, we can have a semi-empirical model of the cycles-to-failure ($N_{f\text{-}B2}$) as a function of intra- and inter-environmental factors and the two parameters of wear model (i.e. n_1 and K_1) . These two parameters would be the results of regression- and Bayesian-based curve fitting [20] using data (field data and accelerated life testing). Utilizing Bayesian updating, we can incorporate the uncertainly of the model parameters (n_1 and K_1) as shown in Equation 9.

$$\pi\left(N_{f-B2}; n_1, K_1, \sigma \mid Data\right) \propto \mathrm{L}\left(Data \mid N_{f-B2}; n_1, K_1, \sigma\right) * \pi\left(n_1, K_1, \sigma\right) \quad (9)$$

The term on the left side of Equation 9 stands for the "posterior joint distribution of the parameters (n_1 and K_1)", and the first and second terms on the right are the "likelihood function of a set of data" and "the prior joint distribution of the wear model parameters" respectively. Having the posterior distribution of the model parameters (n_1 and K_1) from the Equation 9, we can develop a distribution of cycles-to-failure for part B2, which is π ($N_{f\text{-}B2}$). Therefore, the aforementioned equations link π ($N_{f\text{-}B2}$) to the intra- and inter- environmental factors.

II. <u>Applying a mechanistic approach to deterministically model the interactions of wear and fatigue mechanisms at the material-level for A1:</u> at this step, we need to understand and model the deterministic phenomena of the interactions of wear and fatigue mechanisms leading to the failure mode (i.e. breakage due to crack) in part A1. There have been very few studies [e.g. 22] in fields other than risk analysis (e.g. Mechanical and Materials Engineering) to formally model the interactions of failure mechanisms. These studies applied the Finite Element (FE) method to depict the interactions (e.g. fatigue and wear). In short, the interaction phenomenon has been depicted using two approaches [22] :

a. Damage-based interaction model: In this approach, the FE wear model is initially run (for a number of cycles; ΔN) to estimate the effects of wear on geometry (and stress). Then, fatigue damage related to ΔN cycles is calculated using the stress-cycle fatigue relationship (the so-called S-N curve or more advanced relationships such as Smith-Watson-Topper parameter [23] and the damage accumulation rule [24]. In other words, in every time step of the model, the number of cycles-to-failure (N_f) associated to the level of stress (due to wear) is calculated using the stress-cycle fatigue relationship. Then, the fatigue damage related to this time step would be (ΔN / N_f). The cycles would repeat until the accumulation of damage reaches a specific failure criterion (associated with crucial crack). The total number of cycles (Σ ΔN) at that point would be the deterministic number of cycles-to-failure for a wear-fatigue mechanism.

b. Crack-based interaction model: A more complete approach is based on explicit modeling of crack fracture mechanics. For this, the total cycles-to-failure is the summation of the "number of cycles-to-nucleation of crack" (Nnu) and the "number of cycles-to-propagation of the crack" (Np). The nucleation time can be simulated in the same manner as the approach explained in (a), with the damage accumulation threshold associated with the crack initiation size. The updated geometry and stress at the end of the nucleation cycles (from the FE nucleation module) are considered as inputs for the FE propagation module. In the FE propagation model, in each cycle, the damage due to failure mechanism #1 (i.e. wear) is calculated and the finite element model is updated due to the change in geometry (due to wear) and the new distribution of stress and strength is found. This is then input into the equations of the failure mechanism #2 (i.e. the well-known Paris law for the crack growth rate in fatigue [25]) to calculate the crack growth and, consequently, the change of geometry due to crack growth. The FE model would be updated again due to the change of geometry (due to crack growth). This loop continues through the cycles until total crack size reaches the critical stage, and, at that point, failure occurs. Again, the total number of cycles (Σ ΔN) at that point would be the deterministic number of cycles-to-failure for a wear-fatigue mechanism.

In existing FE models, the interactions between failure mechanisms are primarily through the change in stress as the geometry (in the FE models) is updated in each cycle due to wear accumulation and crack growth. However, interactions stem from many sources. For example, due to damage in each cycle, temperature and viscosity will change, leading to an additional variation in stress and temperature. In order to fully complete step II of this methodology, it requires adding a module (including energy equations) to these models to update temperature (in addition to geometry) in each cycle.

III. <u>Developing the probabilistic model of the interactions of wear and fatigue mechanisms at the material-level for A1</u>: In order to accomplish step III of the proposed methodology, the following stages are essential:

- Currently, there are very few deterministic models (FE models) and no probabilistic models that consider the interactions of failure mechanisms. It is required to apply advanced uncertainty propagation methods (separating aleatory and epistemic uncertainty propagation and considering the uncertainties due to dynamic interactions of diverse equations and the variability of multiple parameters) and Bayesian updating approaches with the existing FE models to provide distributions of "cycle-to-failure". This changes the existing deterministic POF models (of the interacting failure mechanisms) to PPOF models.

- The existing FE models of the interactions of failure mechanisms have been developed assuming constant parameters in the failure equations (e.g. constants in Paris law equation) even though geometry and stress changes with each cycle. This can be improved by (1) using a large number of test data to find a proper "distribution" of the parameters. Using the distribution and utilizing uncertainty propagation methods, we can then reduce the effects of "approximation" on the parameters and establish a more realistic PPOF model for each individual failure mechanism and/or (2) at least considering different parameters for different ranges of geometry and stress.

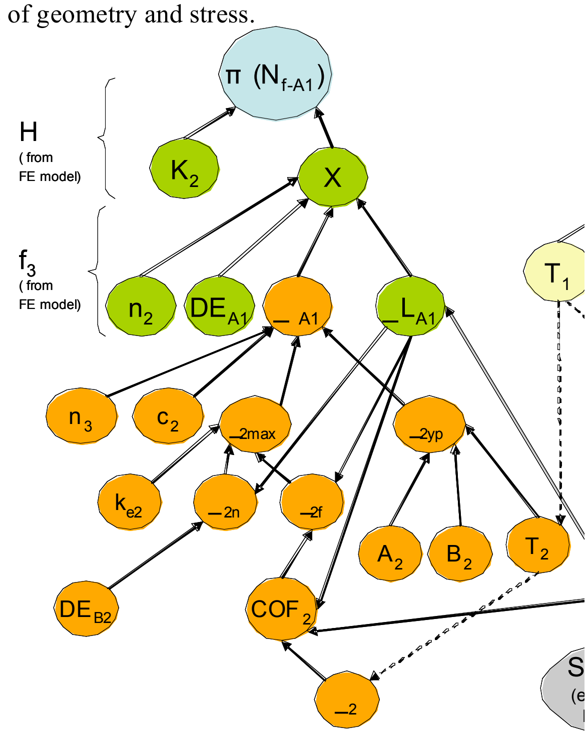


Figure 2 Causal modeling approach f

- Another stage, related to Step III of the methodology, is the exploration of possibilities and benefits of using other "modeling techniques" (other than FE or a hybrid integration of FE with other modeling techniques) in order to operationalize the mechanistic perspective of the interactions of failure mechanisms. Casual modeling techniques (e.g. Bayesian Belief Network (BBN) [23] or a combination of FE with BBN) are proposed as potential candidates since (1) they have been easily linked to FT/ET in PRA (as it will be explained in step IV) and (2) they are useful in tracking the sources of dependencies in CCFs, and (3) they can be built and expanded as probabilistic nets.

  To articulate the causal modeling approach for a physics-based CCF modeling, Figure 2 shows a preliminary causal model for failure mechanisms of two parts, A1 and B2, from Figure 1. The target nodes of these causal models are the distributions of cycles-to-failures for B2 (π ($N_{f\text{-}B2}$)) and A1 π ($N_{f\text{-}A1}$)). As Figure 2 shows, the causal model for B2 connects the target node π (N_{B2}) to its immediate inflecting factors (i.e. c_1,τ_{1max}, τ_{1yp}, n_1) used in the Equation 2. The next layers of causal factors are also built based on Euations 4 to 8. The only causal relation that is not included in these equations, but is added to the model (Figure 2), is the physical relation of T_1 on μ_1 .

  In order to build the causal model for the failure of component A1, the symbolic functional relationships are developed based on the deterministic phenomenon of the interactions of fatigue and wear in the aforementioned FE approach. For example, based on approach (a) in Step II, the number of cycles-to-failure for A1 can be expressed using the so-called S-N curve model as follows:

$$N_{f-A1} = K_2\left(\frac{1}{S}\right)^{n2} \tag{10}$$

Where K_2 , S, n_2 stand for the proportionality constant, the stress amplitude, the power parameter respectively.

Since stress in this interaction approach is due to the accumulation of wear over time and the cyclic load, it can be shown as:

$$S = f_3\left(\Delta L_{A1}, \dot{W}_{A1}, DE_{A1}\right) * g\left(N_{f-A1}\right) \tag{11}$$

Where $\Delta L_{A1}, \dot{W}_{A1}, DE_{A1}$ stand for load amplitude, wear rate, and design specification in Part A1.

g and f_3 are functions based on the FE model of the interactions of fatigue and wear (considering approach (a) in Step II). By combining Equations 11 and 10, we would have the following relationships for $N_{f\text{-}A1}$:

$$N_{f-A1} * \left[g\left(N_{f-A1}\right)\right]^{n_2} = K_2 * \left[f_3\left(\Delta L_{A1}, \dot{W}_{A1}, DE_{A1}\right)\right]^{-n_2} \tag{12}$$

$$N_{f-A1} = H\left\{K_2, f_3\left(\Delta L_{A1}, \dot{W}_{A1}, DE_{A1}, n_2\right)\right\} \tag{13}$$

The left side of Figure 2 shows the causal model of the distribution of number of cycles-to-failure for A1 (i.e. π ($N_{f\text{-}A1}$)), which is built based on the Equations 10 to 13.

H and f_3 are functions based on the FE model of the interactions of fatigue and wear (considering approach (a) in Step II). Also, the causal model for $\dot{W}_{A1}$ is developed using the Equations similar to 2 to 8.

As the figure shows, there are three types of factors in the causal models of A1 and B2: (1) the independent factors (e.g. K_{e1} and K_{e2}), (2) the common factors (e.g. Source Load and V), and (3) different factors but dependent (e.g. T_1 and T_2) . The CCFs can happen due to the existence of root causes of type 2 and/or type 3 in the causal model.

Figure 2 is based on approach (a) of the interaction, but it is also possible to develop the symbolic functional relationships for approach (b) in Step II, which is a crack-based FE model of the interactions, and develop the causal model based on it.

IV. Expanding material-level models to component-level (using the FE method) and also finding an appropriate modeling technique to link the FE component-level models to the system-level: There is a need for a technique that can store and update the resulting data from FE models in the component-level POF and transfer them to system-level. The system-level modeling would be challenging due to the diversity of components and the interactions of their failure mechanisms. Azarkhail [17] has suggested an agent-based computing approach as a promising technique for this. We propose using a hybrid modeling approach for this step of the methodology. This means keeping Fault Tree (FT) and Event Tree (ET) methods at the higher level of system analysis, and linking the probabilistic models of physical failure mechanisms (e.g. probabilistic FE and/or other potential causal models as explained in step III) of the lower-level parts, as modules, to the system-level FTs/ETs in PRA. This approach would be similar to the hybrid method that Mohaghegh et al. [8] utilized for incorporating human and organizational factors to PRA. They used the System Dynamics (SD) [24] and the Bayesian Belief Network (BBN) approaches for modeling the underlying human and organizational failure mechanisms, and integrated them with FT /ET scenarios of the risk model.

4. SUMMARY AND CONCLUSION

One of the most important topics in Probabilistic Risk Assessment (PRA) is modeling dependent failures. In general, dependent failures are defined as events in which the probability of each failure depends on the occurrence of other failures. The major causes of dependence among a set of systems or components (or parts) can be explicitly modeled using system reliability methods (e.g. Fault Trees). Other dependent failures, where root causes are not known or are difficult to model explicitly in the system or component reliability analysis, are grouped under Common Cause Failures (CCFs).

This research leads to a shift of paradigm in the assessment of CCFs. Instead of utilizing existing data-driven approaches, this paper proposes the concept of physics-based CCF modeling which refers to incorporating underlying physical failure mechanisms into risk models so that the root causes of dependency can be "explicitly" included. This requires building a theoretical foundation for the integration of PPOF models into PRA in a way that can depict the interactions of failure mechanisms and, ultimately, the dependencies between the component failures. To achieve this goal, the following methodological steps are highlighted:

1. Probabilistic modeling of the individual failure mechanisms (e.g. fatigue and wear) of two dependent components at the material-level.
2. Modeling the deterministic phenomena of failures (at the material-level) due to the interactions of two failure mechanisms (e.g. fatigue and wear). It is proposed that this theoretical foundation can be developed based on a mechanistic perspective (i.e. using semi-empirical models of failure mechanisms).
3. Utilizing advanced uncertainty characterization and propagation methods (probabilistic assessment of model errors, aleatory and epistemic uncertainty modeling considering the dynamic interactions of diverse equations and a large number of parameters) and Bayesian approach to make the deterministic models of interactions (developed in step 2) probabilistic and ready to be linked with the PRA frameworks.
4. Expanding material-level PPOF models to the component-level in order to create physics-based CCF models and developing appropriate modeling techniques to link the physics-based CCF models (at the component-level) to the system-level PRA.

In general, some of the applications and advantages of this research include the abilities to:

- Incorporate operational and environmental conditions in hardware failure models
- Model aging and degradation processes
- Model CCFs in PRAs of operating plants
- Model CCFs in PRAs of plants in design stages
- Use retrospective assessments intended to estimate the risk significance of single or multiple equipment failures (degradation) accompanied by a deficiency in design, operating conditions, and/or a process such as scheduling maintenance (the so-called Significant Determination Process by the U.S. Nuclear Regulatory Commission Inspectors)
- Schedule optimum maintenance intervals based on more realistic estimates of time to failure (and, ultimately, reduce maintenance costs)
- Facilitate the connection between POF models and CCF models and the harsh, post-accident environment in a nuclear power plant (using common physical variables)
- Facilitate the connection between CCF models and the thermo-hydraulic and other mechanistic codes (e.g. reactor vessel and other reactor structure neutron embrittlement) using common physical variables, which would facilitate the development of accident simulators

- Track the condition of individual component and structures to assess their reliability, given their design characteristics, history and operational experience
- Extend the notion of dependence beyond identical and redundant components into diverse components and applications. This research also forms a formal basis for the assessment of passive system reliability for advanced reactor concepts, and the inclusion of structure (piping, steam generator tubes, etc.) failures in advanced nuclear installation PRAs.
- Model common causes among group of components such as all motor operated valves in a power plant

In addition to contribution to PRA, this line of research will also make a scientific contribution to other engineering domains, as it will build a foundation on which to model the interactions of two different failure mechanisms. There are limited studies that have tried to consider the interactions of two failure mechanisms but they have been based on significant simplifications. Researchers have not adequately considered the interactions of failure mechanisms since the consequences can be ignored in designs with large safety margins. However, as system design becomes more energy efficient and time-to-obsolescence is shortening, the need for this type of research will be critical.

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