Evaluation of Correlated Failure Effects on Seismic Fragility Analysis Using the Reed-McCann Approach

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Abstract: Seismic Probabilistic Safety Assessment (SPSA) has long relied on simplifying assumptions regarding component failure dependence, most notably, the use of bounding fragilities based on the weakest component or the adoption of fully independent/fully dependent models. While computationally convenient, these assumptions can introduce systematic bias, either masking critical risk contributors or overstating conservatism. This paper addresses a pressing gap in current practice: the rigorous, yet practical, treatment of partial correlation among non-redundant and spatially distributed components within fragility families. Building on regulatory drivers and recent methodological guidance, this work implements and extends the Reed–McCann framework to quantify joint seismic failure probabilities by explicitly decomposing epistemic and aleatory uncertainties into independent and common components. Computational workflow, supported by Latin Hypercube Sampling and numerical integration, is developed to generate system-level fragility curves that consistently capture partial dependency effects across multiple failure modes and components. The approach is benchmarked against established NUREG/CR-7237 [1] formulations and demonstrated through application to safety-significant systems in a full-scale nuclear plant SPSA. The results reveal that commonly used "weakest-link" representations can be non-conservative when component capacities are comparable, with deviations in High Confidence of Low Probability of Failure (HCLPF) values that are non-negligible for risk-informed decision-making. Sensitivity studies further show that correlation structure, not just median capacity, systematically shifts fragility curves, influencing both joint and union failure probabilities in ways that cannot be captured by traditional bounding assumptions. Importantly, the findings identify regimes where partial correlation meaningfully alters risk insights, particularly for complex, non-redundant systems with shared demand or capacity characteristics. This work is novel in that it converts an academically established, but not widely applied, methodology into a practical and scalable framework suitable for regulatory use. It effectively bridges the gap between theoretical formulation and SPSA implementation. By enabling the treatment of partial dependency, the approach goes beyond simplified correlation assumptions and provides a more rigorous and transparent representation of dependency in fragility modeling. For the international PSA community, these results are particularly relevant given increasing regulatory scrutiny, aging infrastructure, and the shift toward risk-informed licensing. The proposed methodology offers a defensible means to reduce epistemic bias, improve risk prioritization, and enhance the technical credibility and realism of Seismic Probabilistic Seismic Assessment (SPSA) evaluations.

Keywords: Seismic Probabilistic Safety Assessment (SPSA), Fragility Analysis, Reed–McCann, Correlation, High Confidence of Low Probability of Failure (HCLPF), and Partial Correlation

1. INTRODUCTION

Traditionally as part of the Seismic Probabilistic Safety Assessment (SPSA), the PSA components are first binned according to the same general safety function based on systems analysis. The resulting bins are evaluated to subgroup into fragility families accounting for the equipment type, location, potential differences in median capacities and the associated variabilities. The seismically weakest component in each family is evaluated for three (3) failure modes namely, function, structural integrity, and anchorage. Because these are due to independent effects the conditional probability of failure of the component is taken to be that of the controlling failure mode.

The fragility of the weakest component in the fragility family is taken as the representative fragility of the fragility family. All components in fragility family are assumed to fail after failure of the weakest component. This effectively assumes that failure of components in each family are fully dependent events. The Probabilistic Safety Assessment (PSA) quantification model assumes that failure of the fragility families are fully independent events in computing the combined failure probability of a sequence containing two (2) or more fragility families. If a specific fragility family includes items that are not co-located and are not clearly similar, then separate representative fragilities are developed. For example, four (4) valves at different floor elevations are evaluated and the governing fragility assigned to the fragility family. This was judged to be a reasonable simplification in the PSA model.

The current methodology is overly optimistic where full correlation cannot be justified. The recommended actions request that combined failure probabilities for all components in the fragility family be addressed. Additionally, for some mechanical components where structural integrity is determined by overstress at several locations the failure probability should be considered correlation between the events because these are at least partially dependent effects. EPRI 3002000709 [1] mentions that both assumption (independence or dependence) is extreme; but that it concludes that "…As a general rule, for identical, redundant equipment a correlation of 1 should be assumed. For all other equipment, a correlation of zero should be assumed…" Although most of the fragility families in the Seismic Equipment List (SEL) do not contain identical redundant equipment, the assumption of zero correlation is judged to be too conservative and could bias the risk insights.

Thus, a computational workflow, supported by Latin Hypercube Sampling and numerical integration, is developed using MATLAB scripts [2], to generate system-level fragility curves that consistently capture partial dependency effects across multiple failure modes and components. The approach is benchmarked against established NUREG/CR-7237 [1] formulations and demonstrated through application to safety-significant systems in a full-scale nuclear plant SPSA.

2. METHODOLOGY

Independence between failure modes implies that the probability of a second (or subsequent) failure isn't influenced by whether the first failure occurred or not. On the other hand, if there is dependency, the failures are connected in that the probability of the second failure is affected by the occurrence of the first, to some extent. In technical terms, if the conditional probability of a second failure increases given the first failure, it indicates dependency between the failures. Dependency and correlation are used interchangeably in this context of seismic fragilities.

Seismic dependency or correlation is typically defined by the joint probability of multiple seismic-induced failures occurring together, given an earthquake event. If there's no dependency, the probability of multiple components failing simultaneously is merely the product of their individual failure probabilities. Seismic dependency is influenced by two (2) main factors: similarity in seismic capacity and similarity in seismic demand. Similarity in capacity considers dynamic characteristics and seismic failure modes of components, while similarity in demand considers the dynamic response at component anchor points.

Aside from joint probability, the union of probabilities (i.e., at least one [1] failure occurring) is important for defining fragility parameters for groups of components with multiple failures, especially with similar capacities.

EPRI 3002012994 [3] highlights that when a fragility group consists of multiple Systems, Structures, or Components (SSCs) with several similar failure modes, it may be challenging to determine which mode is dominant. In such cases, multiple fragility curves can be developed for the group, each representing a different failure mode. These fragilities can be incorporated into the systems model by providing them to the systems analyst. Alternatively, the fragilities can be combined into a single fragility curve representing the overall probability of failure for the group. This approach can be applied to a single SSC which has multiple failure modes with similar fragilities as well.

For instance, let's consider a fragility group with two (2) components, A and B. P(A) represent the probability of failure for component A, P(B) is the probability of failure for component B, and $P(A \cap B)$ is the probability of both components failing simultaneously. The probability of at least one (1) failure occurring, denoted as $P(A \cup B)$, can be calculated using the following equation:

$$P(A \cup B) = P(A) + P(B) - P(A \cap B) \tag{1}$$

where $P(A \cup B)$ is also referred to as union probability, $P(A \cap B)$ is referred to as the joint probability.

For independent events:

$$P(A \cap B) = P(A) \times P(B) \tag{2}$$

For fully dependent events:

$$P(A \cap B) = P(A) \text{ or } P(B) \text{ (whichever is governing)} \tag{3}$$

In the case of partially dependent or correlated events, NUREG/CR-7237 [4] recommends a methodology to obtain the joint probability as part of seismic Probabilistic Risk Assessment (PRA) for nuclear power plants (NPPs). NUREG/CR-7237 [4] outlines a method called the "Reed-McCann Procedure" for estimating dependency between component failures and obtaining correlated joint probabilities in a seismic probabilistic risk assessment (SPRA). It is designed to handle partial dependency between component fragilities. The analyst needs to identify similarities and differences between components that contribute to partial dependence.

2.1. Reed-McCann Procedure

The Reed-McCann Procedure first identifies common sources of the variability in response calculations and the variability in strength calculations. The dependencies are quantified by examining how individual factors of safety are developed in a fragility assessment. According to NUREG/CR-7237 [4] this procedure is the most promising. The subsequent step of constructing system fragilities involves two (2) stages.

1st Stage of Reed-McCann Procedure:

First, a Latin Hypercube Sampling (LHS) technique is employed to sample the median capacities of all components within the system. Each component's median capacity is independently sampled using a log standard deviation β_U' which accounts for correlation between these median capacities and is determined using the following expression:

$$\beta_U' = (\beta_U^2 - \Sigma\, \beta_U{*}^2)^{1/2} \tag{4}$$

In Equation [4], the common logarithmic standard deviation, β_U* represents the correlation between a component under consideration and other components. Multiple β_U* values are typically needed to account for different groups of correlation. For instance, if components 1, 2, and 3 share a common building response (i.e., they are in the same building) and components 1 and 4 share a common β_U* value due to capacity (e.g., they are the same type of pumps), then the calculation of β_U' for component 1 would involve subtracting two (2) β_U* values from β_U.

Second, the sampled median capacity is adjusted by multiplying it with correction factors, which are also sampled from probability distributions with a median value of 1.0 and log standard deviation equal to β_U*.

2nd Stage of Reed-McCann Procedure:

The second stage develops a single system fragility curve for each group of dependent median capacity values. This curve reflects the dependency among capacity values based on known interdependencies. Component's capacities can be dependent due to common variables. To determine the fragility of a system, first, the fragility is calculated based on the known value of the common dependent variable. Then, this fragility is integrated across the probability distribution of the common variable.

Consider the probability of failure for components 1 and 2.

$$Pf_1 = P\ (c_1 < a_g) \tag{5}$$

$$Pf_2 = P\ (c_2 < a_g) \tag{6}$$

The failure probabilities can be expressed as a function of component capacities (c_1 and c_2) and peak ground acceleration due to earthquakes (a_g). However, c_1 and c_2 can be decomposed into their independent parts (c_1x and c_2x) and a common dependent part (x). This allows us to express the failure probabilities as follows:

$$Pf_1 = P\ (c_1' < ag/x) \tag{7}$$
$$Pf_2 = P\ (c_2' < ag/x) \tag{8}$$

The failure of both components, Pf (1 ∩ 2), is given by the following equation:

$$Pf\ (1 \cap 2) = \int P\ (c_1' < ag/x)\ P\ (c_2' < ag/x)\ p(x)\ dx \tag{9}$$

The parameters for components 1 and 2 in the lognormal capacity model are LN(Am_1/x, β_{R1}') and LN(Am_2/x, β_{R2}'), respectively. The distribution for the common dependent part x is LN(1, β_R*), where Am_1 and Am_2 are the median capacities from the selected set of median values in Stage 1. The values of β_{R1}' and β_{R2}' are derived from the following equation:

$$\beta_{Ri}' = (\beta_{Ri}2 - \Sigma\ \beta_R{*}^2)^{1/2} \tag{10}$$

It is anticipated that the $\Sigma\ \beta_R{*}^2$ is less than β_{Ri}^2. This underscores the need for the analyst to assess both similarities and differences in component randomness, even when components are nominally identical. Variations in mounting and the stochastic nature of earthquake inputs can result in diverse dynamic responses among components within a group.

Once the joint probability [Pf (1 ∩ 2)] is obtained, union of fragilities [Pf (1 ∪ 2)] can be obtained by using the formulation in the beginning of this Section.

Extending from the two-component case to multiple dependencies is straightforward. Each group of dependencies corresponds to one (1) level of integration. To obtain the reduced logarithmic standard deviation for each component, we subtract the common group β*s using the Equation [10]. The median values for each component are derived by dividing the component's median values by the product of the dummy variables x1, x2, …, xN, representing common dependencies. Only the xi terms relevant to a component's dependencies are included in its expression.

2.2. Implementation of the Reed-McCann Approach using MATLAB Scripts

The Reed-McCann procedure as described in NUREG/CR-7237 [4] is incorporated into MATLAB scripts for pair-wise dependencies between two (2) components. A problem from Section 7.4 of NUREG/CR-7237 [4] is presented below in detail as an example, to present the detailed steps involved in the methodology implementation.

System Description: There are two (2) identical and redundant yard tanks, A and B. The system fails only if both tanks fail during an earthquake.

Median Ground Acceleration Capacity: The median ground acceleration capacity of both tanks is 0.7 g. The logarithmic standard deviations are $\beta_R = 0.20$ and $\beta_U = 0.30$. Tanks A and B have response dependencies due to being ground-mounted and near each other. They also have high degree of capacity dependence because they are identical and installed in the same manner.

Common Uncertainty: The common part of the epistemic uncertainty (β_U*) arises from similarity in material, failure mode, and capacity calculation procedures. Assume $\beta_U^* = 0.15$, results in the independent part of epistemic uncertainty (β_U') of 0.26.

1st Stage of Reed-McCann Procedure:

In Stage 1, LHS is performed to obtain a given number of sample sets. At least ten (or preferably more) samples will be required. This example uses ten (10) samples.

Sampling Procedure: Using LHS, ten (10) samples of median capacity (Am values) are obtained for each of the tank's A and B based on the log-normal distribution defined by LN(0.7 g, 0.26), representing the independent uncertainties. These samples are randomly ordered to pair median values of A and B. Additionally, ten (10) samples are generated for the correction factors using the distribution defined by LN(1.0, 0.15), representing the correlated uncertainties. These samples are also randomly ordered.

Combined Median Values: The correlated samples of Am values for tanks A and B are obtained by multiplying the respective independent Am samples by the dependency correction samples.

2nd Stage of Reed-McCann Procedure:

In Stage 2, fragility curves are developed. For each set of the correlated Am values, a single system fragility curve is generated, reflecting the dependency in capacity values based on known dependent median values. The reduced randomness logarithmic standard deviation, obtained using $\beta_R^* = 0.15$, is calculated as follows:

$$\beta_{Ri}' = (\beta_{Ri}^2 - \Sigma\, \beta_R^{*2})^{1/2} = (0.20^2 - 0.15^2)^{1/2} = 0.13 \tag{11}$$

For sample set 1, the median values of A and B are $c_A' = 1.08$ g and $c_B' = 0.83$ g.

$$Pf\,(A \cap B) = \int P\,(c_A' < ag/x)\, P\,(c_B' < ag/x)\, p(x)\, dx \tag{12}$$

where $P\,(c_A' < ag/x) = \Phi\,[(\ln\,(1.08/(ag/x))/0.13]$, $P\,(c_B' < ag/x) = \Phi\,[(\ln\,(0.83/(ag/x))/0.13]$ and x is LN(1.0, 0.15)

To obtain the family of fragility curves, the following steps are performed:

Integral Calculation: Using the input parameters and specific ag values, the integral is computed to determine the conditional failure probability for the system.

Varying ag Values: The ag value is systematically varied to cover a range of seismic intensities. For each ag value, the conditional failure probability for the system is calculated. This results in the system fragility curve for one (1) sample of input parameters.

Repetition for Sample Sets: The process is repeated for other sample sets (based on LHS) of median values. Each sample set represents a different scenario or condition that affects the system's fragility.

Family of Fragility Curves: A family of fragility curves is generated representing the selected sample sets. This family of curves illustrates how the system's failure probability changes across different seismic intensities and under various conditions represented by the sample sets. The mean fragility curve of the sample set can be taken as the joint probability. Similarly, union of fragilities can be obtained.

2.3. MATLAB Scripts Benchmark

The MATLAB scripts implementing the Reed-McCann approach are applied to the same example problem described in Section 2.2 and the results compared with the results provided in Section 7.4 of NUREG/CR-7237 [4]. Figure 1 presents the ten (10) sets (pairs) of median values obtained from Stage 1 of the procedure as documented in NUREG/CR-7237 [4]. These same sample sets are used in MATLAB scripts for benchmarking the scripts.

Sample	Independent Step A	Independent Step B	Dependent Step	Combined Median A (g)	Combined Median B (g)
1	0.83	0.64	1.30	1.08	0.83
2	0.79	0.58	0.91	0.72	0.53
3	0.66	0.30	0.99	0.65	0.30
4	0.52	0.71	1.12	0.58	0.80
5	0.73	0.93	0.94	0.69	0.87
6	0.95	0.85	1.03	0.98	0.88
7	0.59	0.56	1.18	0.70	0.66
8	1.05	1.17	0.80	0.84	0.94
9	0.35	0.69	0.82	0.29	0.57
10	0.64	0.78	1.07	0.68	0.83

Figure 1: Sample of Median Capacity Values Presented in Table 7-3 of NUREG/CR-7237 [4]

Figure 2 shows the family of fragility curves reported in NUREG/CR-7237 [5] using the ten (10) sample sets in Figure 1. Figure 2 also shows the mean curve (black) as the representative joint probability accounting for partial dependency.

Figure 3 shows the family of fragility curves obtained from the MATLAB scripts developed here using the same ten (10) sample sets in Figure 1. The mean curves represent the average behavior across multiple samples, while individual probability curves show the specific outcomes for each sample set. Following are the observations from Figure 2 and Figure 3:

1. Both mean curves exhibit similar key values, such as the Am (50% probability of failure) and HCLPF (1% probability of failure), indicating consistency across the samples.
2. The smoothness of the curves in Figure 3 compared to Figure 2 suggests differences in numerical integration techniques or computational methods used in the solutions. It is believed that the numerical methods with finer sampling would be superior in MATLAB.

The good match between the mean curves and individual probability curves from each sample set effectively benchmarks the scripts. This consistency between the mean and individual curves is crucial in verifying the reliability and accuracy of the analysis results. The fact that they align well with key values like Am and HCLPF further reinforces the robustness of the implementation.

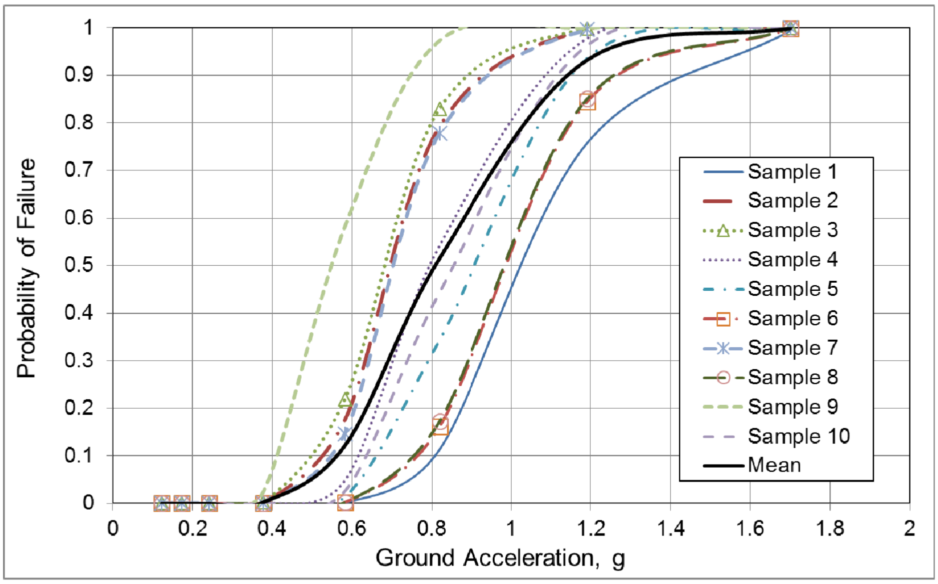

Figure 2: P (A ∩ B) for the Example Problem as Presented in Figure 7-3 of NUREG/CR-7237 [4]

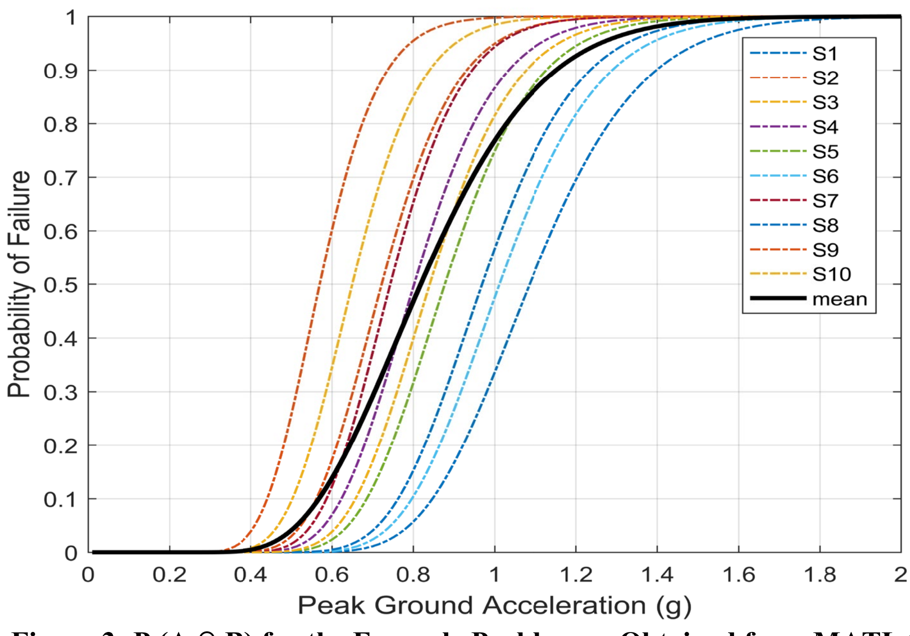

Figure 3: P (A ∩ B) for the Example Problem as Obtained from MATLAB

2.4. Sensitivity Studies

Multiple sensitivity analyses were performed using the MATLAB scripts to assess how different input parameters affect joint fragilities or the union of fragilities. The sensitivity analyses performed are outlined below:

1. The initial sensitivity study aimed to assess how varying the number of Latin Hypercube sample sets (N) impacts results. Using the same example problem as in Section 2.2, P(A ∩ B) was computed for N values of 10, 30, 60, 100, and 200. The resulting joint fragility curves, depicted in Figure 4, illustrate that increasing the sample size improves accuracy, with noticeable convergence in results after utilizing at least 30 samples.
2. The second sensitivity study focused on how changes in common epistemic and randomness uncertainties (β_U* and β_R*) affect outcomes in the calculation of union of fragilities. Using the same example problem from Section 2.2 and assuming $\beta_R = \beta_U = 0.30$, P (A ∪ B) were calculated using β_U* and βR* values ranging from 0.05 to 0.29. The resulting union of fragility curves, depicted in Figure 5 alongside individual component fragilities (black curve) and the fully independent fragility curve (red curve), highlight how the correlation level among components influences where the union of fragility curve falls relative to the limiting curves.
3. In the third sensitivity study, the focus was on how changes in common epistemic uncertainty (β_U*) affect outcomes in the calculation of union of fragilities for fully correlated randomness uncertainty β_R*=0.3. This is a probable case for two (2) similar components in terms of dynamic characteristics and failure modes located on the same floor. Using the same example problem in the second sensitivity study, calculations were made for P (A ∪ B) with β_U* values ranging from 0.05 to 0.29. Figure 6 shows the resulting fragility curves relative to the limiting red and black curves.
4. In the fourth sensitivity study, the focus was on how distinct median capacities (Am) affect the calculation of the union of fragilities for a given common uncertainty (β_R*= 0.25, β_U* = 0.15). This study scenario reflects a likely case involving two (2) failure modes of the same equipment. Using the example problem from the second sensitivity study, calculations were conducted for P (A ∪ B) with Am_B values ranging from 1.15 times Am_A to 2.0 times Am_A. The resulting fragility curves, shown in Figure 7, move closer to the black curve (fragility of component A) with increased separation between Am_A and Am_B values.

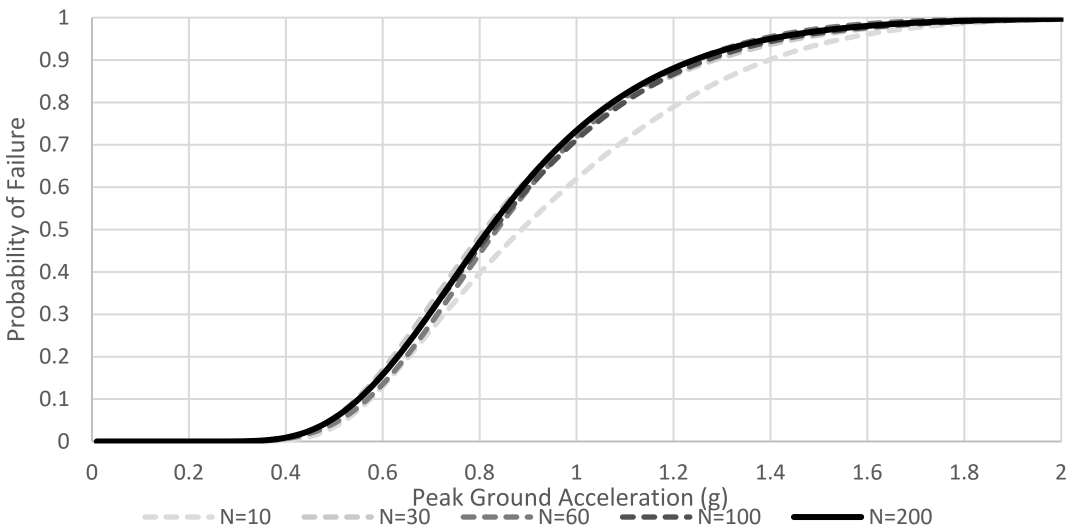

Figure 4: P (A ∩ B) for the Example Problem Using Different Sample Sets (N)

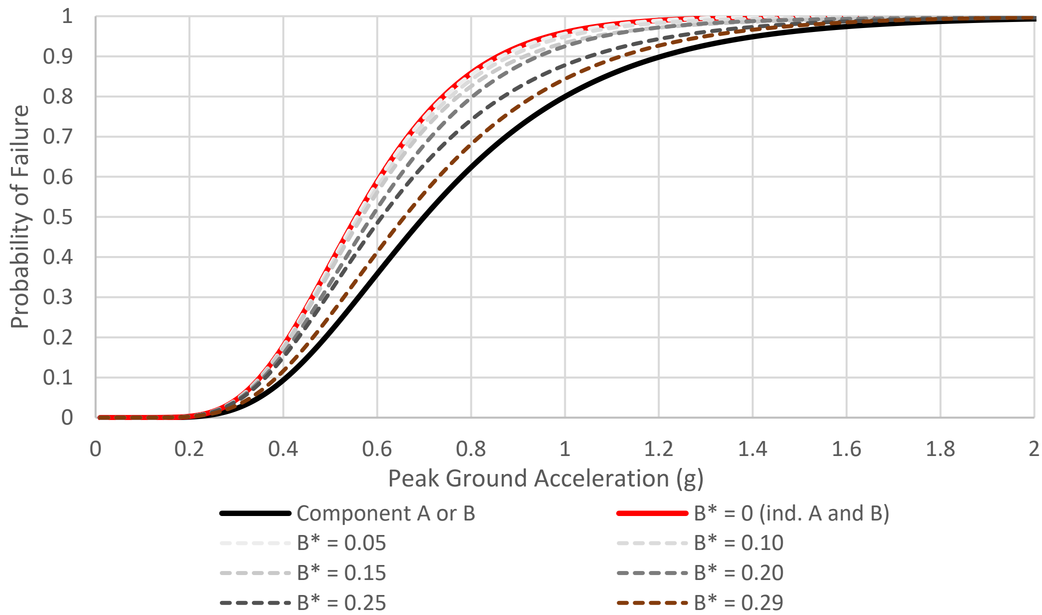

Figure 5: P (A ∪ B) for Different Common Epistemic and Randomness Uncertainty (B*) Between A AND B

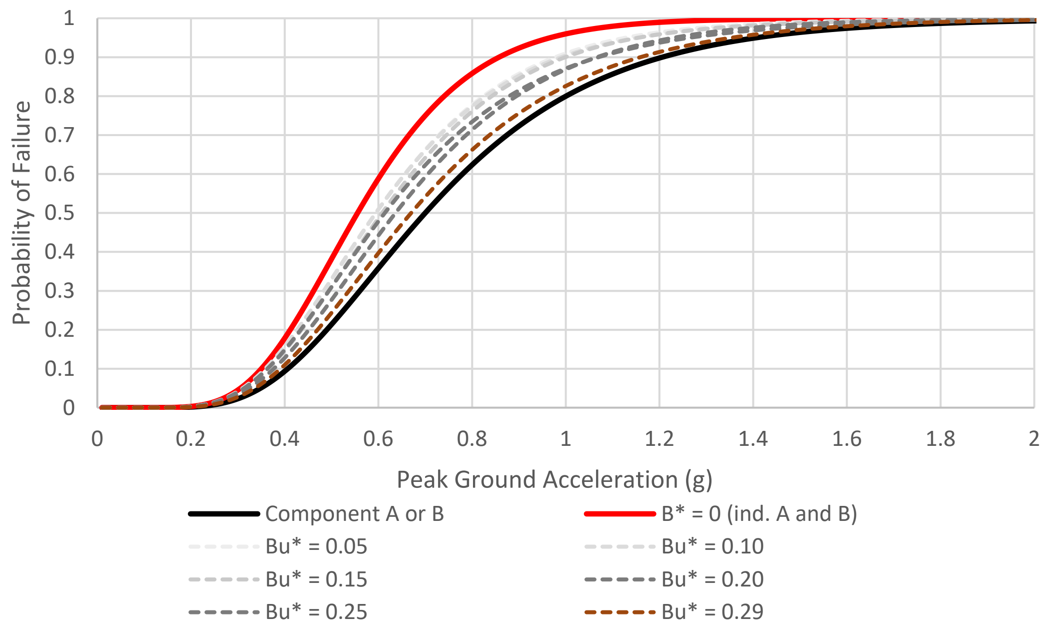

Figure 6: P (A ∪ B) for Different Common Epistemic Uncertainty (B_U*) and Given Common Randomness (B_R*=0.3) Between A and B

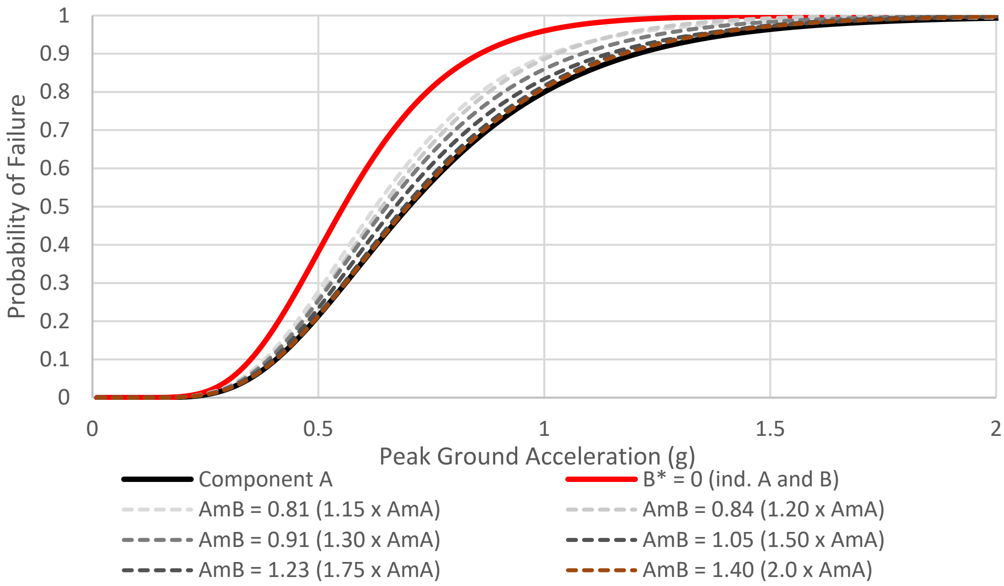

Figure 7: P (A ∪ B) for Distinct Median Capacities (Am) and Given Common Uncertainty (B_R*=0.25, B_U*=0.15) Between A AND B

3. ASSESSMENT OF PARTIAL CORRELATION

3.1 Decomposition of Epistemic and Aleatory Uncertainties

The fundamental mechanism for assessing partial correlations within the framework involves decomposing the total logarithmic standard deviations for randomness (β_R) and modeling uncertainty (β_U) into common (dependent) and independent sources.

For electrical components, the fragility parameters are primarily influenced by variables associated with the Equipment Capacity Factor (F_C) and the Structure Response Factor (F_{RS}). Common sources of uncertainty, such as floor response spectra (F_{RS}) clipping and peak valley mismatches, were isolated to assign the dependent parts of the log standard deviations. Where the sub-group items exhibited different β values, the minimum value was conservatively assigned as the common value.

For mechanical components, the Equipment Response Factor (F_{RE}) introduces additional variables. Variabilities in material properties, calculation methods, spectral shape, equipment damping, and mode combinations were scrutinized. For example, mechanical sub-components whose responses are dominated by a specific mode (such as snubbers) are inherently less affected by mode combination uncertainties compared to complex support frames evaluated against strict code allowable.

Furthermore, common standard deviations for structural response (F_{RS}) were assigned based on probabilistic soil-structure interaction (SSI) variables. Site-dependent factors such as horizontal peak responses, time-history phasing, and ground motion incoherency were treated as common variables applying equally across identical elevations and buildings.

3.2 Application Case Studies

To demonstrate the methodology, two (2) specific fragility families were isolated for detailed evaluation: one (1) electrical and one (1) mechanical.

Electrical Equipment (0.4kV Motor Control Center [MCC]): This family consists of two (2) MCC. Because the equipment (MCC 1 and MCC 2) considered are located on different floor elevations and have different individual capacities, they cannot be assumed to be fully correlated. Common uncertainties were extracted from shared structural response randomness (common $\beta_R^* = 0.20$) and modeling uncertainty (common $\beta_U^* = 0.44$).

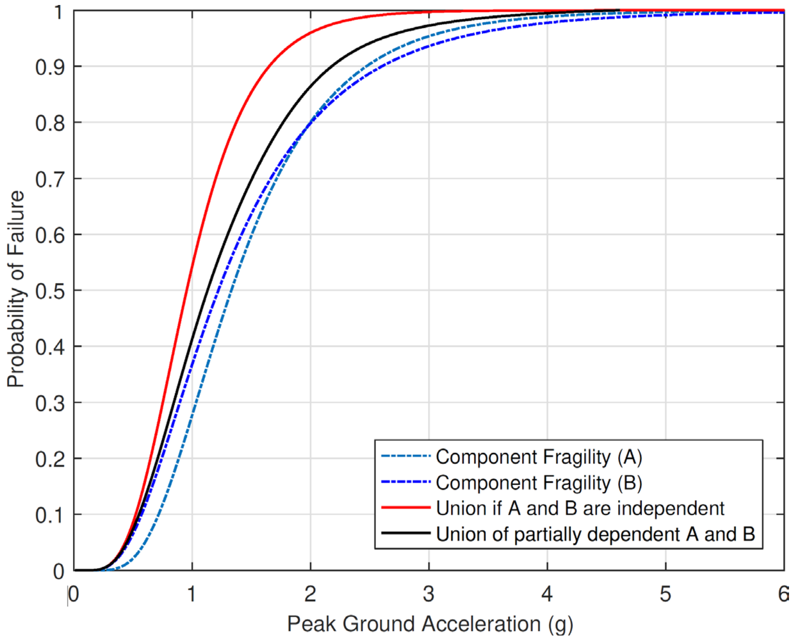

Figure 8: Combined Fragilities Along With Individual Fragilities For MCC Function During

In a traditional "weakest-link" (fully correlated) assumption, the system capacity would be bound by the weakest component (Train 2 at 1.22g). However, the partial correlation approach calculates a combined median capacity of 1.13g. As illustrated in Figure 8, the combined fragility curve shifts distinctly to the left of the weakest component's curve. This visually depicts that the conditional probability of failure for the system is higher than what is assumed under full correlation.

Mechanical Equipment (Steam Generator (SG) Support System): This family is subdivided into sub-groups: 1) Support frame structures and anchorage, 2) Accident ring anchor plate, and 3) Snubbers. While they share dominant modes and code allowables, their individual capacities differ. Common variances in spectral shape and material properties were used to develop joint probabilities. The joint fragility calculation for this family is performed in two (2) steps – the first obtains joint fragilities for sub-groups 1 and 2 and then the second step combine the joint fragility of 1 and 2 with and the fragility of subgroup 3.

Here, the two (2) controlling components have nearly identical median capacities (1.36g and 1.35g). Bounding by the weakest link would assume a system capacity of 1.35g. The partial dependency model, however, drops the combined capacity to 1.23g. As shown in Figure 9, because the component capacities are so comparable, the "union of partially dependent" curve separates significantly from the individual component curves, demonstrating a non-negligible increase in calculated risk.

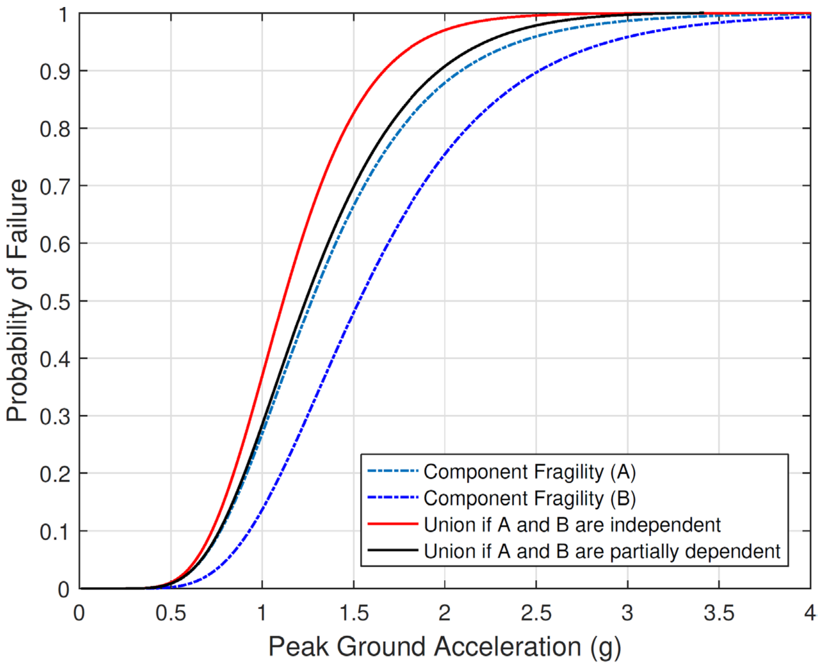

Figure 9: Combined Fragilities Along with Individual Fragilities For SG Support System

4. CONCLUSION

The results demonstrate that traditional simplifying assumptions specifically, the "weakest-link" representation or full correlation models can obscure critical risk insights. The results reveal that the combined fragility curves incorporating partial correlations fall systematically above those generated under the assumption of full correlation. Consequently, the conditional failure probabilities for the evaluated equipment groups, when considering partial dependency, are greater than initially calculated under fully correlated bounding assumptions. This finding confirms that the "weakest-link" approach is non-conservative when component capacities within a system are comparable. By extending the Reed-McCann framework to explicitly decompose and recombine independent and common uncertainties, this evaluation provides a defensible, scalable methodology that reduces epistemic bias. Ultimately, transitioning from simplified correlation bounds to a rigorous partial dependency model significantly enhances the technical credibility and realism of Seismic Probabilistic Safety Assessment (SPSA) evaluations, directly supporting robust, risk-informed regulatory decision-making.

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