An Overview of Dependency Modeling for Nuclear Plant Seismic Probabilistic Risk Assessment with Open-Source Codes

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Abstract: A significant factor contributing to the seismic risk in a nuclear power plant is seismic-induced dependencies. However, no universally accepted method for seismic dependency modeling exists yet. This paper aims to summarize the dependency modeling methods with open-source codes for seismic probabilistic risk assessment in nuclear power plants. Specifically, we demonstrate the application of four state-of-the-art methods for dependency modeling using a numerical example of a three-component system, including the Monte Carlo simulation (MCS), Reed-McCann, COREX, and Bayesian network methods. All source codes are developed with the R programming language and are publicly accessible on GitHub: https://github.com/tzhou4/PSAM_seismic. Finally, this paper seeks to improve the understanding of seismic dependency modeling and promote transparency, collaboration, and innovation in probabilistic risk assessment research.

Keywords: Dependency Modeling; Seismic Probabilistic Risk Assessment; Nuclear Power Plant; Open-Source Codes.

1. INTRODUCTION

Seismic events are paramount to the safe operation of nuclear power plants [1]. These events can trigger ground displacement and rupture, which poses severe risks to the plant's critical structures, systems, and components (SSCs). Strong spatial dependencies are imposed on SSCs in reactor units that are either the same or separate from one another when an earthquake occurs. As such, some SSCs fail concurrently due to the dependencies arising from similarities in ground motion, seismic demand, and seismic capacity [2]. Therefore, it is crucial to properly assess the risk profile associated with the plant's location to design robust safety measures and infrastructures to withstand seismic events.

The seismic risk in nuclear power plants is typically quantified using the methodology of seismic probabilistic risk assessment (SPRA) [3]. SPRA involves a systematic analysis that integrates data on seismic hazards, structural engineering, and system vulnerabilities. By considering uncertainties in seismic hazard characterization and the response of SSCs to seismic forces, SPRA provides insights into the likelihood and consequences of different levels of seismic-induced accidents. Notably, SPRA often relies on simplifying assumptions to represent inter-dependency behavior, which is that seismic failures are either entirely independent or fully dependent. While these simplifications may be necessary for computational tractability, they can introduce uncertainties and limitations in the accuracy of risk estimates since the actual dependencies should be partial [4].

A considerable effort has been dedicated to studying the impact of seismic dependencies on nuclear power plant operations. For instance, a study of the correlation of seismic performance in Similar SSCs was reported by the U.S. Nuclear Regulatory Commission (NRC) [5]. Particularly, there are two main tasks to accomplish seismic dependency modeling [6]: (a) specify the degree of dependencies between the SSCs of interest, which mainly relies on the separation-of-variable-approach by grouping the similar attributes in the fragility development; (b) assess the system risk by incorporating the dependent effects into the system-level model. This can be achieved by a fully simulation-based approach or a hybrid approach by combining the simulation-

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based approach and the conventional CCF modeling. Interested readers can refer to a comprehensive review of seismic dependency modeling [6].

This paper aims to present an overview of state-of-the-art methods for seismic dependency modeling in nuclear power plants, with open-source codes publicly available. Section 2 briefly summarizes the current practice of seismic PRA. Section 3 demonstrates the application of four methods for seismic dependency modeling using a numerical example and the source codes are made publicly accessible. Section 4 provides conclusions and recommendations. Note that we develop this paper fully based on one of our previous papers [7] published in the *Journal of Reliability Engineering & System Safety*, but provide additional details specifically in the source codes used to generate the findings and conclusions.

2. BACKGROUND ON SEISMIC PROBABILISTIC RISK ASSESSMENT

Seismic risk is estimated in terms of conditional failure probability by the systematic integration of seismic hazard analysis and seismic fragility evaluation in SPRA. For the completeness of the discussion, the subsequent section presents a brief background of seismic hazard analysis and seismic fragility evaluation.

The goal of seismic hazard analysis is to produce a seismic hazard curve, which describes the annual exceedance frequency of earthquakes at a certain intensity of ground motion (i.e., peak ground acceleration, PGA) [8]. Generally, the power-law relationship can represent the seismic hazard curve in Equation (1), where PGA denotes the ground motion intensity in units of the gravitational acceleration, g, $f(PGA)$ is the annual exceedance frequency of a ground motion intensity PGA, $k_0$and k are empirical constants.

$$f\big((PGA)\big) = k_0 \cdot (PGA)^{-k} \tag{1}$$

Upon a seismic event with a specific ground motion intensity, seismic fragility evaluation aims to determine the conditional failure probability of an SSC by estimating its seismic capacity, known as seismic fragility [9]. Typically, the seismic capacity of an SSC is defined in terms of a ground motion intensity measure, referred to as ground acceleration capability. As shown in Equation (2), the seismic capacity, A, is modeled as a product of the median ground acceleration capacity A_m, the randomness and uncertainty components of the median estimates, which are ϵ_R and ϵ_U respectively.

$$A = A_m \cdot \epsilon_R \cdot \epsilon_U \tag{2}$$

Note that ϵ_R and ϵ_U are assumed to be lognormally distributed variables with unity as the median and logarithmic standard deviations β_R and β_U. An SSC will fail once the ground motion intensity a exceeds its ground acceleration capability A. As such, the fragility function can be described by the cumulative lognormal distribution in Equation (3), where Φ is the cumulative standard normal distribution, Φ^{-1} is the inverse cumulative standard normal distribution, and Q is the confidence level. Equation (4) shows the other commonly used fragility function is expressed in terms of the total uncertainty, β_C, without splitting into randomness and uncertainty [3].

$$P(a > A) = \Phi\left[\frac{ln\left(\frac{a}{A_m}\right) + \beta_U \Phi^{-1}(Q)}{\beta_R}\right] \tag{3}$$

$$P(a > A) = \Phi\left[\frac{ln\left(\frac{a}{A_m}\right)}{\sqrt{\beta_R^2 + \beta_U^2}}\right] = \Phi\left[\frac{ln(\frac{a}{A_m})}{\beta_C}\right] \tag{4}$$

3. NUMERICAL EXAMPLE

This section illustrates the application of seismic dependency modeling using an example of a three-component system recommended by the U.S. NRC [5]. Section 3.1 describes the component properties, system configuration, and seismic hazard data. Sections 3.2, 3.3, 3.4, and 3.5, discuss the results of Monte Carlo simulation (MCS), Reed-McCann, COREX, and Bayesian network methods, respectively. All the methods are implemented using the open-source R programming language [10] on a laptop with an Intel Core i7-12700H CPU and 32.00 GB RAM. The source codes are publicly available on GitHub: https://github.com/tzhou4/PSAM_seismic.

3.1. Problem Description

In this study, we establish four cases by varying the system configuration (i.e., series or parallel system) and the existence of dependencies (i.e., independent or partial dependent), as shown in Table 1. Specifically, the system comprises three safety-related components located in two separate buildings [5]. The components' fragility properties are shown in Table 2, and their dependencies are characterized by the group dependencies as displayed in Table 3. Note that the degree of seismic-induced dependencies is varied given the components' type, manufacturer, and location. Interested readers can find more details on the problem setup in Reference 4.

Table 1. Four cases to be considered in the numerical example

	Dependency	**System Configuration (Failure Logic)**	**Description**
Case 1	Independent	Series System (1/3)	At least one component fails
Case 2		Parallel System (3/3)	All three components fail
Case 3	Partial Dependent	Series System (1/3)	At least one component fails
Case 4		Parallel System (3/3)	All three components fail

Table 2. Properties of the three components in the system

Component	**Total Variability**			**Unique Variability**			**Median Capacity**
	$\boldsymbol{\beta_{C_i}}$	$\boldsymbol{\beta_{U_i}}$	$\boldsymbol{\beta_{R_i}}$	$\boldsymbol{\beta'_{C_i}}$	$\boldsymbol{\beta'_{U_i}}$	$\boldsymbol{\beta'_{R_i}}$	$\boldsymbol{A_{M_i}}$
a	0.85	0.60	0.60	0.38	0.28	0.26	0.9g
b	0.71	0.50	0.50	0.50	0.30	0.40	1.0g
c	0.72	0.40	0.60	0.44	0.19	0.40	1.1g

Table 3. Common attributes within the group of dependent components

Group	**Components**		**Common Variability**			**Composite Correlation**
	$\boldsymbol{i}$	$\boldsymbol{j}$	$\boldsymbol{\beta^*_{C_{ij}}}$	$\boldsymbol{\beta^*_{U_{ij}}}$	$\boldsymbol{\beta^*_{R_{ij}}}$	$\boldsymbol{\rho_{ij}}$
1	a	b	0.50	0.40	0.30	0.42
2	a	c	0.57	0.35	0.45	0.53

This study adopted the seismic hazard data developed for the Eastern United States and fitted to a power function of the form: $f(PGA) = 1 \times 10^{-5} \cdot PGA^{-1.61}$. Furthermore, as displayed in Table 4, we divide the seismic hazard curve into ten PGA intervals and choose the upper limit of each interval as the reference PGA. Depending on the type of seismic dependency method, the ground motion intensity would either need to be sampled from each ground motion interval or adjusted to match the reference PGA. Also, the following sections examine the results by referring to the impacts of dependencies for either parallel or serial system configuration. As all the components are positively correlated, we can establish the criteria [12] for examination purposes that the system fragility of Case 2 is always less than Case 1; the system fragility of Case 4 is always greater than Case 3.

Table 4. Seismic hazard data and its discretization in the numerical example

Ground Motion Interval	PGA Interval (g)		Reference PGA (g)
	Lower Limit	Upper Limit	
PGA-1	0.05	0.25	0.25
PGA-2	0.25	0.45	0.45
PGA-3	0.45	0.65	0.65
PGA-4	0.65	0.85	0.85
PGA-5	0.85	1.00	1.00
PGA-6	1.00	1.10	1.10
PGA-7	1.10	1.20	1.20
PGA-8	1.20	1.30	1.30
PGA-9	1.30	1.40	1.40
PGA-10	1.40	1.50	1.50

3.2. Monte Carlo Simulation-Based Results

The MCS method is widely used to propagate uncertainty from ground acceleration capacity and ground motion interval to assess the seismic risk in terms of system fragility. The four fundamental steps of the MCS method for assessing seismic risk are as follows:

1) Identify the group of components with common sources of randomness and uncertainty.
2) Generate a sample set of ground motion intensity based on the power function of the seismic hazard curve to propagate the uncertainty of the seismic hazard;
3) Generate a sample set of ground acceleration capacity using the multivariate normal distribution or a more generic joint probability distribution using copulas when dependencies exist;
4) Use the random sample sets of ground motion and ground acceleration capacity to determine the component state in accordance with the limit-state function and quantify the system risk in terms of conditional failure probability considering the configuration of the system.

In this study, we follow the recommendations from Reference 6 to use the self-normalized importance sampling technique to propagate the uncertainty in each ground motion interval and use the Gaussian copula to construct a multivariate distribution that characterizes the mutual dependencies among components. Table 5 displays the results based on the MCS method, which satisfies the criteria as defined in Section 3.1.

Table 5. Results of the Monte Carlo Simulation Method

Ground Motion Interval	Series System		Parallel System	
	Independent (Case 1)	Dependent (Case 2)	Independent (Case 3)	Dependent (Case 4)
PGA-1	1.59E-02	1.48E-02	1.13E-06	2.36E-05
PGA-2	2.19E-01	1.89E-01	6.50E-04	3.40E-03
PGA-3	5.04E-01	4.29E-01	9.67E-03	2.77E-02
PGA-4	7.20E-01	6.27E-01	4.19E-02	8.50E-02
PGA-5	8.40E-01	7.49E-01	9.41E-02	1.58E-01
PGA-6	8.92E-01	8.13E-01	1.43E-01	2.17E-01
PGA-7	9.22E-01	8.51E-01	1.85E-01	2.65E-01
PGA-8	9.43E-01	8.80E-01	2.31E-01	3.13E-01
PGA-9	9.58E-01	9.05E-01	2.77E-01	3.60E-01
PGA-10	9.70E-01	9.24E-01	3.23E-01	4.05E-01

3.3. Reed-McCann Method-Based Results

The Reed-McCann method was first proposed by Reed et al. [4] and was endorsed by the U.S. NRC [5]. There are three main parts for assessing the system's fragility as follows:

1) Determine which components have a common source of uncertainty and randomness.
2) Generate a sample set of the median capacities, considering the dependencies among uncertainties, for instance, by applying the Latin Hypercube Sampling (LHS) method.
3) Integrate the dependencies among randomness based on a multiple-integration approach to compute the system fragility without directly using the correlation.

In this study, we implement the Reed-McCann method as described by the NUREG/CR-7237, and the results are shown in Table 6. It is observed that some results in bold red violate the criteria we established in Section 3.1. This implies that the Reed-McCann technique has certain limitations when accurately assessing the contribution from seismic-induced dependencies. This was also demonstrated in the authors' previous research [7, 12] and Segarra et al. [11].

Table 6. Results of the Reed-McCann method

Ground Motion Interval	**Series System**		**Parallel System**	
	Independent (Case 1)	**Dependent (Case 2)**	**Independent (Case 3)**	**Dependent (Case 4)**
PGA-1	**1.11E-01**	**1.18E-01**	**2.08E-02**	**6.77E-04**
PGA-2	3.84E-01	3.34E-01	**3.87E-02**	**2.08E-02**
PGA-3	6.44E-01	5.30E-01	6.80E-02	7.84E-02
PGA-4	8.18E-01	6.81E-01	1.21E-01	1.56E-01
PGA-5	9.00E-01	7.67E-01	1.77E-01	2.17E-01
PGA-6	9.39E-01	8.12E-01	2.20E-01	2.59E-01
PGA-7	9.69E-01	8.51E-01	2.67E-01	3.00E-01
PGA-8	9.93E-01	8.83E-01	3.16E-01	3.41E-01
PGA-9	1.01E+00	9.10E-01	3.66E-01	3.81E-01
PGA-10	1.03E+00	9.33E-01	4.16E-01	4.19E-01

3.4. COREX Method-Based Results

The COREX method [13] is a hybrid approach that applies simulation-based techniques to derive the CCF probabilities at the group level of dependent components and then integrate those CCF probabilities into the system-level model for assessing system fragility [6]. The COREX method has four fundamental steps as follows:

1) Use simulation-based techniques (i.e., MCS or Reed-McCann method) to calculate the seismic failure probabilities of all possible combinations for each group of dependent components.
2) Formulate a system of equations, i.e., seismic failures probabilities are the dependent variables and seismic CCF probabilities are the independent variables;
3) Solve the system of equations to estimate seismic CCF probabilities of all the possible combinations.
4) Input the seismic CCF probabilities to the system-level model developed using the CCF module of the standard PRA software tools.

In this study, we implement the COREX method using the MCS method, as discussed in Section 3.2 in the first step, and the results are displayed in Table 7. It is worthwhile noting that explicitly treating seismic CCF probability enables handling the asymmetrical CCF problems, achieving a balance between risk estimation accuracy and computational simplicity.

Table 7. Results of the COREX method

Ground Motion Interval	**Series System**		**Parallel System**	
	Independent (Case 1)	**Dependent (Case 2)**	**Independent (Case 3)**	**Dependent (Case 4)**
PGA-1	1.59E-02	1.48E-02	1.81E-06	1.85E-05
PGA-2	2.18E-01	1.89E-01	6.09E-04	3.36E-03
PGA-3	5.05E-01	4.30E-01	9.76E-03	2.90E-02
PGA-4	7.19E-01	6.27E-01	4.17E-02	9.34E-02
PGA-5	8.40E-01	7.50E-01	9.42E-02	1.80E-01
PGA-6	8.93E-01	8.13E-01	1.43E-01	2.56E-01
PGA-7	9.22E-01	8.51E-01	1.86E-01	3.18E-01
PGA-8	9.43E-01	8.81E-01	2.32E-01	3.84E-01
PGA-9	9.59E-01	9.05E-01	2.76E-01	4.50E-01
PGA-10	9.70E-01	9.24E-01	3.25E-01	5.15E-01

Table 8. Results of the Bayesian Network Method

Ground Motion Interval	**Series System**		**Parallel System**	
	Independent (Case 1)	**Dependent (Case 2)**	**Independent (Case 3)**	**Dependent (Case 4)**
PGA-1	3.45E-02	5.79E-03	**7.85E-07**	**1.98E-07**
PGA-2	2.44E-01	1.33E-01	5.59E-04	8.26E-04
PGA-3	5.21E-01	3.83E-01	9.40E-03	1.45E-02
PGA-4	7.26E-01	6.17E-01	4.11E-02	6.29E-02
PGA-5	8.40E-01	7.63E-01	9.34E-02	1.39E-01
PGA-6	8.93E-01	8.35E-01	1.42E-01	2.06E-01
PGA-7	9.22E-01	8.76E-01	1.85E-01	2.63E-01
PGA-8	9.44E-01	9.07E-01	2.32E-01	3.20E-01
PGA-9	9.59E-01	9.30E-01	2.77E-01	3.77E-01
PGA-10	9.69E-01	9.47E-01	3.19E-01	4.32E-01

3.5. Bayesian Network-Based Results

The Bayesian network has been widely used for external hazard risk assessment due to its advantages in dependencies modeling. In this study, we implement the Bayesian network-based method, as suggested by Segarra et al. [11]. There are four main steps as follows:

1) Establish the network topology to characterize the state of each component. Particularly, the nodes of component states depend on a node of ground motion intensity, a node of earthquake of engineering significance (EES) event, and nodes of two sources of variability, which are either component-specific or common to multiple components. Note that the node of EES events implies that only the ground motion beyond a certain intensity of ground motion can have the potential to meaningfully affect the component states.
2) Discretize continuous variables according to the manner of equal probability or equal width.
3) Use the MCS method to generate the conditional probability tables (CPTs) for the node of component states.
4) Establish the network topology and CPTs to determine the system state according to its system configuration and the states of each component.

We use equal-probability discretization and the MCS method, as discussed in Section 3.2, to address the uncertainty within each ground motion interval under the power function of the seismic hazard curve. EES events happen when the PGA exceeds 0.05g in this numerical example. The results are shown in Table 8, where the bold red results violate the criteria discussed in Section 3.1.

4. CONCLUSION

This paper summarized the state-of-the-art methods for dependency modeling and illustrated their application using a numerical example of a three-component system. The R programming language was used to develop four methods (MCS, Reed-McCann, COREX approaches, and Bayesian network), and the source codes are made available to the public on GitHub. The findings showed that Reed-McCann and Bayesian network methods fail to accurately capture the effects of dependencies; the level of conservatism varies quite differently across the four methods mentioned above. Therefore, it would be insightful to investigate the performance of those methods from the perspective of conservatism and precision of estimates. Interested readers will find a critical review and benchmark of the four methods in the authors' recent research [7].

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