

## An integrated Bayesian Network Approach for Predictive Seismic Risk Assessment of Nuclear Power Plants

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### 1. Introduction

Risk of seismic events for nuclear power plants (NPPs) is typically quantified within the seismic probabilistic safety assessment (SPSA) framework [1]. In SPSA, seismic hazard and system response are modeled separately, and combined through a convolution process in order to quantify seismic risk. However, the separated procedure makes it restrictive to flexibly capture the causal influence from the seismic hazard to the system and the interaction between components of the system. To overcome such difficulties, this study proposes an integrated Bayesian network (BN) framework, in which seismic hazard and system response are described via a unified probabilistic model. The proposed BN model provides inference outcomes for predictive risk assessment and component behavior characterization.

### 2. Methods and Results

#### 2.1 BN for Seismic Hazard

Causal relationships in a seismic event, emulated using the ground motion model (GMM) proposed by Rezaeian and Der Kiureghian [2], are modeled as a BN model shown in Figure 1. The four variables  $F$ ,  $M$ ,  $R_{rup}$ , and  $V_{s30}$  in the top layer denotes fault type, moment magnitude, rupture distance, and shear-wave velocity, respectively. Then, the six variables in the middle layer represent physical properties of ground motions in time and frequency domain [2]. The variable in the bottom layer stands for peak ground acceleration (PGA).

In the GMM model, the six ground motion properties are predicted from the source and site characteristics using an empirical model, developed based on strong ground motion records. These six parameters are then used as input variables to generate nonstationary ground motion time series, from which PGA is computed.

The BN model in Figure 1 is developed by estimating conditional probability tables (CPTs) for random variables in the model using the GMM simulation results.

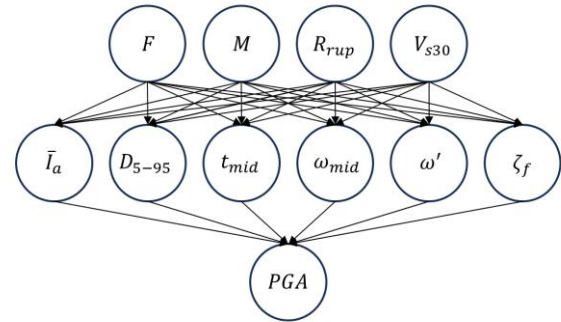


Fig. 1. BN for seismic hazard

#### 2.2 Integrated BN model with an NPP system

This study investigates Limeric Generating Station (LGS) NPP [3] for the proposed framework of integrated BN modeling. The core melt (CM) event of the NPP is defined as

$$CM = S_4 \cup S_6 \cap [A \cup (S_3 \cup C_R) \cap (S_{10} \cup SLC_R) \cup (S_{17} \cup W_R)], \quad (1)$$

$$A = S_{11} \cup S_{12} \cup S_{13} \cup S_{14} \cup S_{15} \cup S_{16} \cup DG_R \quad (2)$$

where  $S_j$  is the basic event representing the failure of NPP components, and  $DG_R$ ,  $W_R$ ,  $C_R$  and  $SLC_R$  are the random failure events corresponding to diesel generator common mode failure, containment heat removal failure, scram system mechanical failure, and standby liquid control failure, respectively. The failure probabilities of the basic events are defined using the seismic fragility. Detailed information of the fragility parameters as well as the random failure events can be found in [3].

The system model, namely the CM event, can be modeled as a BN model by developing CPTs for the corresponding AND and OR logic operators of the system model [4]. Furthermore, given that the failure probability is defined as seismic fragility, i.e., conational failure probability given PGA, the seismic hazard and the system response are concurrently modeled as a single BN model as shown in Figure 2.

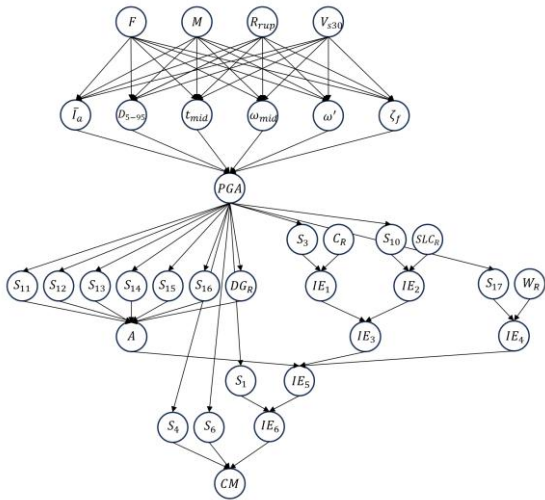


Fig. 2. Integrated BN model for LGS NPP under seismic events

### 2.3 Probabilistic inference using integrated BN model

The developed BN model provides predictive risk estimates for different earthquake scenarios. For example, Figure 3 shows the occurrence probability of CM for earthquake scenarios with different  $M$  and  $R_{rup}$  intervals. Here,  $M$  is discretized into six intervals: (6.0, 6.5), (6.5, 7.0), (7.0, 7.5), (7.5, 8.0), (8.0, 8.5), and  $R_{rup}$  (km) is discretized into three intervals: (10, 30), (30, 50), (50, 70). It is noted that earthquake scenarios with higher moment magnitude and shorter rupture distance exhibit higher system failure probabilities.

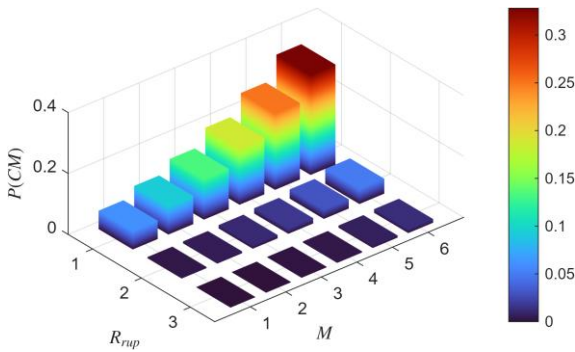


Fig. 3. System failure probability (CM) for various earthquake scenarios

Furthermore, to investigate the effect of components on the system failure, the probability that two basic events occur given CM, i.e.,  $P(S_i, S_j|CM)$  is evaluated. The outcomes are displayed as a heatmap, as shown in Figure 4, where off-diagonal and diagonal entries correspond to  $P(S_i, S_j|CM)$  and  $P(S_i|CM)$ , respectively. The pair of components with lower median seismic capacities tend to show higher probability outcomes, which implies that the correlation between components

are mainly considered through the seismic fragility functions in current system analysis.

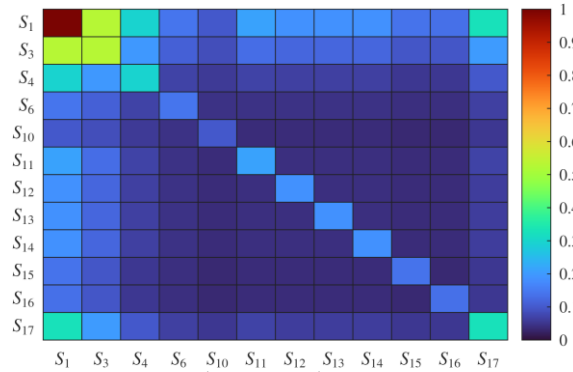


Fig. 4. Heatmap of  $P(S_i \cap S_j|CM)$  and  $P(S_i|CM)$  for off-diagonal and diagonal entries, respectively

### 3. Conclusions

An integrated BN model was proposed for risk analysis of NPPs under seismic events. BNs for seismic hazard and system response are modeled, and subsequently combined by linking PGA of the hazard model to the basic events of the system. The inference capability of the BN model was demonstrated by predicting system failure probability for various earthquake scenarios and evaluating effect of components on the system failure.

The proposed integrated BN framework is expected to facilitate more reliable risk-informed decision-making under future seismic events by explicitly quantifying the risk associated with specific rupture scenarios. Furthermore, the capability to infer component states can serve as a basis for post-earthquake inspection and recovery strategies of NPPs.

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