Multi-Hazard Risk Assessment Using Bayesian Network and Fault Tree Analysis Considering Effects of Structural Damage

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ABSTRACT: Recently, South Korea experienced two strongest earthquake events in its modern history, i.e. 2016 Gyeongju (Mw 5.4) and 2017 Pohang Earthquakes (Mw 5.5). In the region generally considered as a low or moderate seismic zone, the occurrences of such earthquakes and their socio-economic consequences alarmed the general public. Moreover, those earthquake events featured a number of main- and after-shocks, which raised a significant concern about potential major catastrophes caused by multi-hazard effects. This paper presents a probabilistic framework being developed to assess such multi-hazard risk of nuclear power plants (NPPs). First, a ground motion prediction equation is represented by a Bayesian Network (BN). The relationship between main- and after-shocks, e.g. the modified Omori law is incorporated into the BN. Second, to overcome limitations in existing Probabilistic Risk Assessment (PRA) of NPPs, which often employs event tree and fault tree analysis, the BN representing the multi-hazard is connected with the fault trees constructed for the NPP. Finally, to address the impact of structural damage caused by earlier shocks on later events, the fragilities of NPP components are updated. These updated fragilities are incorporated into the fault trees connected with the BN for accurate after-shock risk assessment. The proposed methodology integrates our knowledge on the multi-hazard (BN), reliability of NPP (fault tree) and inter-hazard effect (system identification). The proposed framework is demonstrated by an NPP under main- and after-shock scenarios. Potential applications to other types of multi-hazards and future research needs are also discussed.

1. INTRODUCTION

For a probabilistic risk assessment (PRA) of nuclear power plant (NPP), the risk metric for a specific hazard, i.e. earthquake, can be calculated by convolution of system fragility and hazard curves. The hazard curve can be derived by probabilistic seismic hazard analysis (PSHA) to determine the annual probability of exceedance as a function of intensity measure, i.e. peak ground acceleration (PGA). Then, the fragility curve of each component in the NPP system is determined by computing the conditional probability of failure as a function of given intensity measure. The fragility curves can incorporate various uncertainties because of the use of available physical model, empirical, experimental, and/or numerical data. In this PRA, the plant-level risk can be calculated by incorporating fault and event trees generally with components' fragility curves.

Current PRA frameworks in use focus on estimating the risk about each type of hazard separately. One of the main reasons why multi-hazard scenarios have not been considered is that the probability of simultaneous occurrence of two different hazards such as earthquake and hurricane is extremely rare. However, it is noted that the possibility of occurrence of closely-related multiple hazards is relatively high and may result in significant damage or a major disaster. For example, the great Tohoku earthquake and flooding caused by the seismic sea wave resulted in the catastrophe at Fukushima Daiichi nuclear plant (Aoki and Rothwell, 2013). This disaster alarmed decision makers and stakeholders of various infrastructures worldwide, which is subject to multi-hazard risk. Recently, South Korea experienced two strongest earthquake events in its modern history, i.e. 2016 Gyeongju (Mw 5.4) and 2017 Pohang Earthquakes (Mw 5.5). Those areas are generally known as low or moderate seismic zones, but the occurrences of such earthquake including a number of main- and after-shocks raised a significant concern about potential major catastrophes caused by multi-hazard effects.

In this research, a probabilistic multi-hazard risk assessment framework is developed for NPP. To this end, first, after a literature survey on multi-hazard risk, the main- and after- shock is selected as a practical multi-hazard example for which the multi-hazard assessment can be developed. The selected multi-hazard is then modeled by Bayesian Network (BN). BN is a probabilistic graphical tool, and has been used as a decision-making tool for a variety of natural and man-made hazards. To establish the relationships between random variables in BN, the ground motion prediction equation (GMPE) proposed by Boore and Atkinson (2008) is adopted. By constructing the BN based on the GMPE, a probabilistic inference can be made regarding the multi-hazard effects. Two GMPE-based BNs for main- and after-shock are connected through the modified Omori law (Yeo and Cornell, 2009; Llenos and Michael, 2017), which has been used by a number of researchers to model aftershock rates immediately after the occurrence of a main-shock. Finally, the multi-hazard model can be constructed by BN, GMPE, and modified Omori law.

Although this BN constructed to model the multi-hazard can effectively represent the probability distribution of PGA, it cannot be simply extended to assess the multi-hazard risk of NPP due to the complexity of the NPP system. On the other hand, the currently used PRA approach can estimate the risk about single hazard, but it has not been utilized for multi-hazard. Therefore, to develop a multi-hazard PRA method having the merits of the both approaches, the BN is connected with the main methodologies of PRA, i.e. the fault and event tree, which represent the relationship between components in the NPP system.

After providing theoretical backgrounds on BN, GMPE, modified Omori law, and fault-tree-based PRA, the paper will present the proposed multi-hazard risk assessment framework. Next, the proposed framework will be tested for several scenarios of main- and after-shock sequence. Finally, the paper is concluded with a summary and future research topics.

2. THEORETICAL BACKGROUNDS

In our efforts to construct a new multi-hazard risk assessment framework for NPP, a literature survey about multi-hazard risk assessment was first conducted as summarized below. Kameshwar and Padgett (2014) presented a parameterized fragility based multi-hazard risk assessment procedure for a portfolio of highway bridges subjected to earthquake and hurricane events. Coupling between the risk assessment procedure and the parameterized fragilities enables a comparative assessment of the contributions of different hazards to the total risk. However, in this research, the two hazards are not considered as concurrent, and thus the total probability is estimated by the summation of probabilities of two hazards. Kwag and Gupta (2017) proposed a Bayesian-network-based approach for probabilistic safety assessment of a nuclear facility. Because the BN enables us to consider general relations between various hazard events and conduct beyond-design-vulnerability assessment, the inference using BN makes it feasible to evaluate real-time risk for multi-hazard by accommodating field inspection data as observation for BN. However, this research also assumed that the likelihood of multi-hazard consisting of earthquake, wind, and flood is low.

On the other hand, there has been research efforts to consider causal relationship between sequential hazards. In a study to evaluate appropriate percentages of design snow load (Lee and Rosowsky 2006), the effect of snow load was incorporated into the seismic fragility analysis. Espinoza et al. (2016) presented a multi-phase resilience assessment framework that can be used to analyze any natural threat that may have multiple and/or continuous impact on critical infrastructures. These research efforts dealt with multi-hazard effects with focus on correlation or causal relation with short elapsed time between hazards.

To conduct practical risk assessment of NPP with multi-hazard effects of main- and after-shock sequence considered, it is important to develop an effective probabilistic model for the seismic hazard. In addition, the PRA of NPP should be able to incorporate the impact of structural damage caused by a main-shock on the after-shock damage by updating the fragility. To address these, the following background theories are used in the proposed framework.

2.1. Bayesian Network

Bayesian Network (BN) is a probabilistic graphical tool, which can describe random variables and their probabilistic relationship by using nodes and arcs, respectively. Each node in a BN is associated with a discretized probability distribution with a specific number of intervals. On the other hand, an arc represents probabilistic dependency of a child node on its parent nodes by Conditional Probability Table (CPT). There also exist BN methodologies that can model continuous random variables without discretization (Fenton and Neil, 2012; Lee and Song, 2017). Once a BN is constructed, full joint PMF about all random variables can be evaluated by multiplication rule. Then, using available marginalization algorithms, one can eliminate variables in the constructed full joint PMF to obtain the marginal PMF for each random variables in the BN model. Through this probabilistic inference process of BN with pre-calculated CPTs, the BN can provide efficient probabilistic inference for general selections of observed and unobserved nodes.

The BN methodology has been applied to various engineering areas including computer science, diagnosis engines, decision support systems, and social sciences, because of the following merits. First, a BN provides a graphical, powerful, and efficient tool for modeling complex systems consisting multiple components having uncertainties. Second, a BN allows for efficient probabilistic updating and assessments of each component and system performance. Lastly, the BN's graphical feature can help engineers or decision-makers to understand the current states of random variables and interdependencies between variables intuitively and visually. Recently, making use of these merits, Bensi et al. (2011) modeled multiple hazards on infrastructure systems by a BN with their interdependencies considered and extended the BN by including the utility as decision nodes. In this paper, the main- and after-shock sequence is modeled by BN based on the ground motion prediction equation and modified Omori law.

2.2. Ground Motion Prediction Equation

In PRA of an NPP, the final risk of the target system is calculated by convolution of the system fragility and the hazard curve. Especially, to derive the hazard curve, we need to conduct PSHA, which combines the probabilities of all earthquake scenarios with different magnitudes and distances in order to compute seismic hazard at a site. PSHA often uses an GMPE, i.e. an empirical model to estimate ground motion intensities at the site. A general form of GMPE is expressed as

$$\ln Y_{ij} = f\left(M_j, R_{ij}, \theta_i\right) + \sigma_{ij}\varepsilon_{ij} + \tau_j\eta_{ij} \quad (1)$$

where Y_{ij} denotes the selected ground-motion intensity measure, e.g. peak ground acceleration (PGA) at site i for the earthquake event j, $f(M_j,R_{ij},\theta_i)$ is the attenuation law to predict the median value of Y_{ij} given as a function of M_j (magnitude of event j), R_{ij} (seismological distance to site i in earthquake j), and θ_i (a set of other explanatory variables assigned at site i). The random variable ε_{ij} is the intra-event residual to represent site-to-site uncertainty within the same event j while η_j is the inter-event residual to represent event-to-event uncertainty. Finally, the parameters σ_{ij} and τ_j represent the standard deviations of the intra- and inter- event residuals, respectively.

There are various GMPEs using different attenuation laws, and PSHA usually incorporates uncertainties in ground motion prediction, by considering multiple GMPEs. Then, those GMPEs are integrated with probability distribution conditioned on parameters in GMPEs to derive the final hazard curve. More details of PSHA can be found in Yeo et al. (2009). This PSHA process require good understanding about earthquake at the specific site, and proper selection of GMPEs with corresponding several conditional probability distributions.

Apart from the selection problem, it is not easy to describe the whole process of PSHA using BN, because the corresponding BN would be highly complex because of numerous nodes representing selections of GMPEs. Therefore, the BN model in this study utilizes a single GMPE model (Boore and Atkinson 2008) to derive probability distribution of PGA based on given information such as magnitude or distance of occurred earthquake.

2.3. Modified Omori Law

It has been generally observed that several earthquakes occur as a cluster within a limited period of time and confined to a limited interval in space. The main-shock is generally defined to be the main event representing the earthquake, which shows the largest magnitude among events in the sequence. Immediately following the occurrence of a main-shock, the rate of occurrence of the after-shocks is at its maximum, and then decreases. In order to achieve a multi-hazard framework addressing such relationship between main- and after-shocks, this study adopts the modified Omori law as follows.

The statistical records indicate that the occurrence rate of the after-shocks should be represented by a power-law, which is generally referred to as the modified Omori law, i.e.

$$\lambda\left(t, M\right) = 10^{a+b(M_m-M)}\left(t+c\right)^{-p} \quad (2)$$

where $\lambda(t,M)$ denotes the mean daily rate of aftershocks with magnitude M or larger at time t after main-shock with M_m, a and b are the productivity parameter and the slope of the magnitude-frequency distribution respectively, and c and p are so-called Omori-Utsu parameters characterizing a particular after-shock sequence with specific main-shock. These constant values can be estimated by regression with earthquake data in a specific period (Lienos and Michael, 2017). The modified Omori law has been used by a number of researchers to model after-shock rates immediately after the occurrence of main-shock.

For example, 62 California after-shock sequences with main-shock magnitudes M_m greater than 5.0 were fitted to the modified Omori law using the maximum likelihood method. The mean after-shock rates were described by the modified Omori law and the Gutenberg-Righter relationship. As a result, “generic California model” (Llenos and Michael, 2017) was developed. Actually, the after-shock sequences data from two strongest earthquake events in South Korea are not enough to be fitted to the modified Omori law. So, in this paper, the values of Omori-Utsu parameters (c, p), productivity parameter (a), and slope (b) in the California model are adopted in numerical examples.

2.4. Fault Tree Analysis

As discussed above, PRA of NPP often incorporates fault and event trees generally with components' fragility curves. These curves are convoluted with the hazard curve to evaluate the plan-level risk. The event trees are essential for plant-level risk assessment, but only fault tree are utilized in this study to propose a new framework.

A fault tree diagram is a graphical decomposition of an undesirable event representing system failure into intermediate events and basic events through the use of logical gates, e.g. AND and OR gates. The basic events are represented by Boolean states, which mean "failure" or "safe" state generally. These basic events are linked to the logical gates to characterize intermediate events. These events can be connected to other logic gates as well. Through the fault tree analysis (FTA), the minimal cut-sets of system can be identified in the form of a fault tree.

Actual fault trees used in current practice of PRA of NPP have been designed mostly for single hazard such as an earthquake event, and such a fault tree cannot be used for other types of hazard, i.e. flood, hurricane, etc. In addition, the basic events of a fault tree represent components of the system, each of which is modeled by fragility curves. These fragility curves are also derived for single earthquake event. So, therefore, it is noted that the current FTA used in NPP is not able to deal with multi-hazard effects. This creates a significant limitation for the entire process of PRA including event and fault tree. Therefore, an alternative framework utilizing the current process of PRA is proposed as shown in the next section to facilitate multi-hazard PRA of NPP.

3. PROBABILISTIC FRAMEWORK FOR MULTI-HAZARD

By describing ground motion prediction equation and modified Omori law of main- and after-shock multi-hazard in a Bayesian Network framework, and combining the BN with fault tree analysis used in existing PRA methods, a probabilistic risk assessment framework is developed as follows.

3.1. Bayesian Network for main- and after-shock

Ground motion prediction equation (GMPE) proposed by Boore and Atkinson (2008) is modeled by a Bayesian Network (BN). Details of the selected GMPE can be found in the reference.

First, the random variables M (magnitude of event), R_{JB} (closest distances to the surface projection of the fault plane), and θ (a set of other explanatory variables) in Equation (1) are selected as the nodes of the BN (See Figure 1). Specifically, θ for the selected GMPE is shear wave velocity, V_{s30}. There are other variables often adopted as θ to characterize the earthquake hazard. For simplicity, however, such variable, e.g. fault type being strike-slip ("ST:SS" in Figure 1) is considered deterministic variable. Two additional deterministic variables are added as nodes in BN to represent the uncertainties in the intra- and inter-residuals. The target intensity measure in the GMPE, which is peak ground acceleration (PGA) in this study, is described as a child node (Y) of the deterministic and random nodes described above. It is generally known that BN has to be constructed based on causal relations between the nodes. The BN model described above represents the causal relation between the parent nodes (M, R_{JB}, V_{s30}, σ_{intra} and τ_{inter}) and the child node (Y).

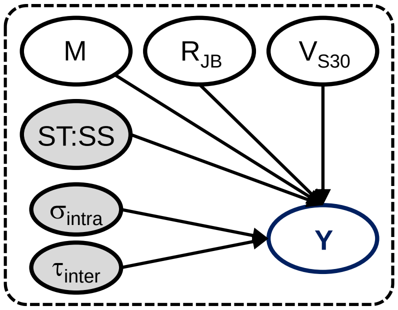


Figure 1: Bayesian Network model representing Ground Motion Prediction Equation (GMPE-BN)

The constructed GMPE-based BN (GMPE-BN) is then utilized to describe a main- and after-shock sequence. This is accomplished by connecting GMPE-BNs which are developed for main- and after-shocks separately. This connection should represent probabilistic information in the modified Omori law as shown in Figure 2. Because the magnitude of main-shock influences on after-shock, the parameters a and b in Equation (2) are connected to the M_m. If an observation of M_m is available from the main-shock event, the distribution of the mean daily rate of aftershock, λ can be derived by inference. The distribution of magnitude for after-shock, $M_{A.S}$, is then generated based on the updated λ by sampling. Finally, GMPE-BNs for main- and after-shock can be constructed by above BN for the modified Omori law.

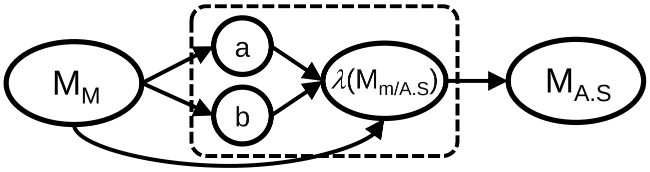


Figure 2: Bayesian Network representing the modified Omori law

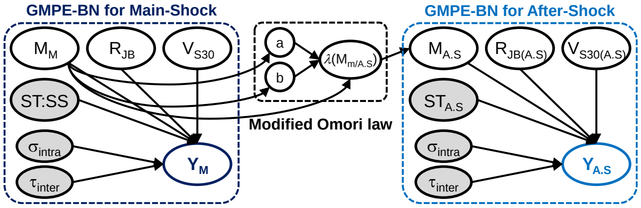


Figure 3: GMPE-BN developed for sequential shocks ($GMPE\text{-}BN_{SS}$)

Basically, the GMPE-BN model in Section 3.1 could be used for after-shock events as well. Instead of modeling and using GMPE-BN's separately, the BNs developed for the main- and the corresponding after-shocks are connected through the BN model representing the modified Omori law (Figure 2) to describe the causal relation between the earthquake events in the sequence. Figure 4 shows the final BN structure describing main- and after-shock, termed as "GMPE-BN for sequential shocks (GMPE-BN_{SS})" for the rest of this paper. The GMPE-BN_{SS} covers the multi-hazard modeling, and will be connected with the conventional fault-tree-based PRA framework as described in the next section.

3.2. Bayesian Network Connected with Fault Tree Analysis

The conventional PRA framework has limitations in its applications to deal with multi-hazard effects. However, it is difficult to modify the event- and fault-tree-based framework and the PRA-based practice. Therefore, the conventional PRA is rather connected with the proposed GMPE-BN_{SS} in this study. As the first attempt of such approach, the proposed framework utilizes fault tree analysis only for simplicity. In this research, the target system is the Hanul NPP located at Ulchin in South Korea. Among several fault trees available for the Hanul NPP, the tree about 'seismic-induced loss of essential power (LEP)' is selected, and constructed by using Simulink of MATLAB® 2017b.

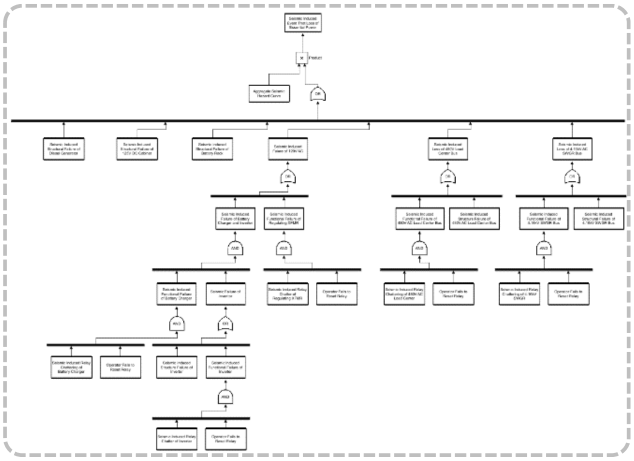


Figure 4: LEP Fault Trees of NPP at Ulchin in South Korea

The basic events in the LEP tree include seismic fragility curves. The probability of the top event is calculated by convolution of these fragility curves with the hazard curve. In this research, to be able to assess the risk of an ongoing multi-hazard event, the probability distributions of intensity measure is updated by the proposed GMPE-BN_{SS}, and convoluted with the fragility curves in PRA of NPP. Figure 5 illustrates the proposed PRA framework that connects GMPE-BN_{SS} of main- and after-shocks, and fault-trees of NPP.

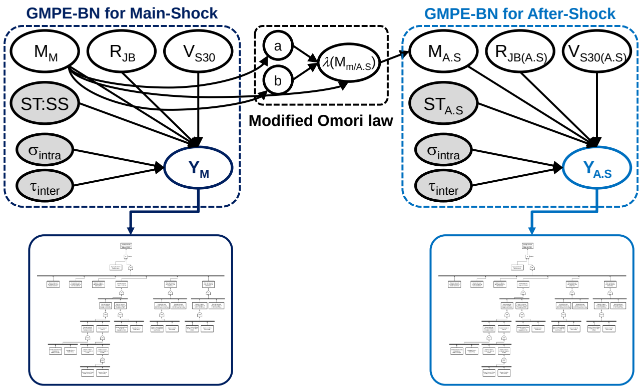


Figure 5: GMPE-BN$_{ss}$ connected with Fault Tree

4. NUMERICAL INVESTIGATIONS

This research utilizes some specific values for parameters in Equation (2) because the data from two recent earthquakes in South Korea do not provide enough information to estimate the parameters of the modified Omori law. Therefore, the information from generic California model is utilized. To test the proposed framework, a scenario about main- and after-shock is created by using the parameter values in Table 1.

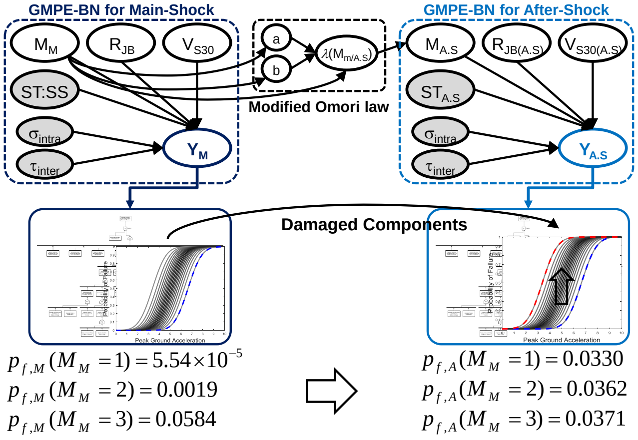
Table 1: Parameters of main- and after-shock scenario for GMPE-BN$_{ss}$

Name	Assumed values	Unit
R_{JB}	*Normal*(30, 5^2)	km
V_{s30}	*Normal*(700, 50^2)	m/s
σ_{intra}	0.502	-
τ_{inter}	0.260	-
c	1.08	-
p	0.05	-
a	*Normal*(-1.67, 0.1^2)	-
b	*Normal*(0.91, 0.04^2)	-

In addition to 8 parameters listed in Table 1, the magnitude of main-shock is assumed as 0, 1, 2, and 3. In calculating the failure probability using the fault-tree about the assumed scenario, an important assumption should be made regarding the seismic performance of the structures damaged during the main-shock event. To incorporate this point, the fragility of such structures need to be updated accordingly. To this end, system identification (SI), i.e. estimation of changes in system parameters based on measurement data such as acceleration or displacement, can be utilized. To obtain an effective SI method for this purpose, the research is currently underway to detect main-shock damage by use of Kalman or Particle Filter (Kim and Song, 2018). In this paper, to develop a prototype risk assessment framework, it is assumed that the fragility curves of all components in the LEP fault tree will increase by changing uncertainty index (Q) from 5% to 95% in the fragility (Kim et al., 2010).

$$F(a)=\Phi\left[\left(\ln\left(a/A_m\right)+\beta_U\times\Phi^{-1}(Q)\right)/\beta_U\right] \quad (3)$$

where a, A_m, β_R, β_U, and Q are intensity measure, logarithmic standard deviation of inherent randomness and uncertainty, and index introduced to consider uncertainty respectively.



$$p_{f,M}(M_M=1)=5.54\times10^{-5}$$
$$p_{f,M}(M_M=2)=0.0019$$
$$p_{f,M}(M_M=3)=0.0584$$

$$p_{f,A}(M_M=1)=0.0330$$
$$p_{f,A}(M_M=2)=0.0362$$
$$p_{f,A}(M_M=3)=0.0371$$

Figure 6: Numerical investigation using assumed increase of failure probabilities

Figure 6 shows an example of multi-hazard risk assessment in which the fragility curves of the damaged components increase because of damage from main-shock. Then, the failure probabilities of top event of constructed fault tree are calculated about main- and after-shock sequentially when the magnitude of main-shock is 0, 1, 2, and 3, respectively. The calculated probabilities increase as the magnitude of main-shock increases. In addition, because of the increased fragility of components in basic events of fault tree, the probabilities of after-shock are bigger than those of main-shock in LEP, whose components are vulnerable to low magnitude. If there is no damage in each component, the failure probabilities for after-shock (M_M = 1, 2, and 3) are 0.0081, 0.0087, and 0.0092 respectively. Except for M_M=1, the probabilities for after-shock are smaller than those for main-shock, because the magnitude of after-shock is small generally.

5. CONCLUSION AND FUTURE WORK

Because of the limited applicability of conventional probabilistic risk analysis (PRA) to multi-hazard phenomena, e.g. main- and after-shock sequences, the ground motion prediction equation-based Bayesian network representing sequential shocks (GMPE-BN$_{ss}$) is proposed and connected with fault tree as the first attempt of developing a practical risk assessment framework for multi-hazard. In the proposed framework, only fault tree is exploited for simplicity, but both event- and fault trees will be connected with GMPE-BN$_{ss}$ finally in future research.

The numerical investigations demonstrate that the proposed methodology can evaluate the risk of sequential shocks while considering causal relationship between main- and after-shocks, and the impact of main-shock-caused damage on after-shock fragility. In particular, to address the latter, the fragility curves are increased for components damaged by main-shock. Although the fragility curves are increased by arbitrarily changing an index in this research, filter-based system identification (SI), which can identify changed system parameters from given output data of structures, is expected to help incorporate the effect into the proposed framework. By incorporating an effective SI method, the proposed framework is expected to facilitate practical multi-hazard risk assessment for complex engineering systems such as NPP.

6. ACKNOWLEDGEMENT

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