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INTEGRATING BEST ESTIMATE PLUS UNCERTAINTY (BEPU) ANALYSIS INTO SEISMIC PERFORMANCE ASSESSMENT USING MACHINE LEARTNING TECHNIQUES

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ABSTRACT

This paper explores the need to integrate Best Estimate Plus Uncertainty (BEPU) analysis into seismic performance assessment, which is enhanced by machine learning methods, including ground motion generative models capable of directly generating ground motion time histories. The safety margin provided by the conventional deterministic assessment framework for the seismic performance of nuclear power plants remains implicit, making it difficult to identify potential weak points and provide meaningful insights for safety management. To address this, the proposed framework systematically varies key input parameters and ground motions while accounting for uncertainties, allowing for a more nuanced understanding of plant behavior under scenario-based ground motions. This approach helps identify critical factors influencing safety in extreme earthquake scenarios, thereby supplementing or potentially improving the current deterministic approach.

INTRODUCTION

Under the deterministic framework of seismic safety assessment, the design basis ground motion (DBGM) is established through, for example, fault rupture simulations incorporating conservative parameter settings for one or several specified earthquake sources. The safety-related systems, structures, and components (SSCs) are then verified with additional conservatism to ensure functionality under these conditions. IAEA SSG-9 (Rev. 1) states that “deterministic seismic hazard analyses are appropriate for regions where sufficient appropriate data exist for key parameters to identify the scenario earthquake.” (International Atomic Energy Agency, 2022)

However, the safety margin provided by this framework remains implicit rather than explicitly quantified, making it difficult to identify potential weak points and provide meaningful insights for management of safety. To complement this approach, probabilistic risk assessment is employed. Nevertheless, the deterministic approach itself also has room for improvement. A key limitation of the deterministic approach is its reliance on considered worst-case scenarios, even though determining the true worst case is inherently difficult due to uncertainties. The excessive focus on extremely rare scenarios can also lead to an overly pessimistic assessment, potentially resulting in overly rigid design constraints, while overlooking more probable scenarios. Moreover, it provides limited insight into how different parameters interact and influence overall safety performance.

To enhance this aspect, systematically varying key input parameters and ground motions while accounting for uncertainties, allows these techniques to provide a more nuanced understanding of plant behavior and to identify critical factors influencing safety in extreme earthquake scenarios, thereby supplementing or

potentially replacing the current deterministic approach. Such approaches are already being applied, for example, in the Best Estimate Plus Uncertainty (BEPU) analysis including Code Scaling, Applicability, and Uncertainty (CSAU) methodology, which is used for accident analysis (e.g., IAEA 2003; OECD/NEA 2007; Boyack et al., 1989). The introduction of a similar approach would enable more rigorous seismic performance assessments. Recent advancements in computational capabilities have made this kind of approach feasible. This procedure would be particularly useful for the performance assessment of a newly developed structural systems. Furthermore, its effective implementation could be enhanced by machine learning methods, including ground motion generative models capable of directly generating ground motion time histories (Matsumoto et al., 2023; Matsumoto et al., 2024) and surrogate models for seismic response analysis (Ishikawa et al., 2025).

PROPOSED FRAMEWORK

Outline of Proposed Procedure

The procedure of a proposed framework follows a similar approach to accident analysis and consists of the following steps:

1. Defining the target structure(s)
2. Identifying possible failures of SSCs and associated accident scenarios
3. Preparing the analysis tool
4. Analyzing sensitivities and identifying key parameters
5. Assessing the effects of uncertainties in the parameters
6. Comparing results against criteria related to the capacity of SSCs

Candidates for key parameters and their uncertainties in response analysis model of structures and in ground motion prediction are discussed in the following section.

Uncertainty in Scenario-Based Ground Motion Prediction

Probabilistic Seismic Hazard Analysis (PSHA), which serves as an input to probabilistic seismic risk assessment (SPRA), accounts for uncertainties in both earthquake occurrence and ground motion prediction. Scenario-based ground motion prediction, on the other hand, is considered useful when a nuclear power plant is located near a limited number of contributing earthquake sources, and sufficient appropriate data exist for key parameters to identify the scenario earthquake. This approach assumes that a specific earthquake occurs at a specific location. In this case, uncertainties are only considered in ground motion prediction, given that the earthquake occurrence is assumed. The conventional design basis ground motion (DBGM) implicitly accounts for such uncertainties through conservative parameter settings. This study explicitly incorporates and evaluates these uncertainties. Several methods can be used for this purpose. One approach involves utilizing fault rupture simulations to synthesize ground motions by assigning probability distributions to each parameter. Another approach relies on statistical methods. In this study, a machine-learning-based approach is employed as one of the latter methods.

Uncertainty in Response Analysis Model

Typically, a response analysis model for deterministic analysis provides a conservative response. However, the response analysis model used in the proposed framework should be a best-estimate code and should explicitly account for uncertainties. For example, when applying this method to evaluate input ground motions, the key parameters may include:

- Soil parameters (e.g., soil profile including S-wave velocity profile, damping, stress-strain relationships)
- Soil-structure interaction
- Building model (e.g., stiffness, damping, hysteresis)

INPUT GROUND MOTIONS

Ground Motion Generative Model

Following a similar approach proposed by Matsumoto et al. (2024), a so-called Ground Motion Generative model (GMGM) is developed using a GAN model called styleGAN2 (Karras et al., 2020). Conventional ground motion prediction methods estimate ground motion intensity measure(s), and generating ground motions is not straightforward. This model, however, directly generates ground motion time histories along with associated parameters such as moment magnitude (M_{W}), the rupture distance (R_{rup}), and average shear-wave velocity in the top 30 m (V_{S30}).

The training dataset is compiled from observed records at K-NET stations (National Research Institute for Earth Science and Disaster Resilience, 2019), identical to the dataset used in Matsumoto et al. (2024). The earthquakes and observed records included in the dataset were selected based on the following criteria: (1) crustal earthquakes in Japan between 1997 and 2016, (2) moment magnitude $M_{\mathrm{W}} > 5$, (3) hypocenter depth less than 30 km, and (4) rupture distance $R_{\mathrm{rup}} \leq 100$ km. The training process of the GMGM is shown in Figure 1. StyleGAN2 incorporates a regularization term in the loss function during training to achieve a disentangled intermediate latent space, which is the output from the mapping network f. The generator is trained so that the generated data varies smoothly in response to changes in the intermediate latent variables $\mathbf{w}$. In this study, the dimension of $\mathbf{w}$ is set to 512.

Case Study

For demonstration purposes, a moment magnitude of $M_{\mathrm{W}} = 6.8$ and a rupture distance of $R_{\mathrm{rup}} = 11$km

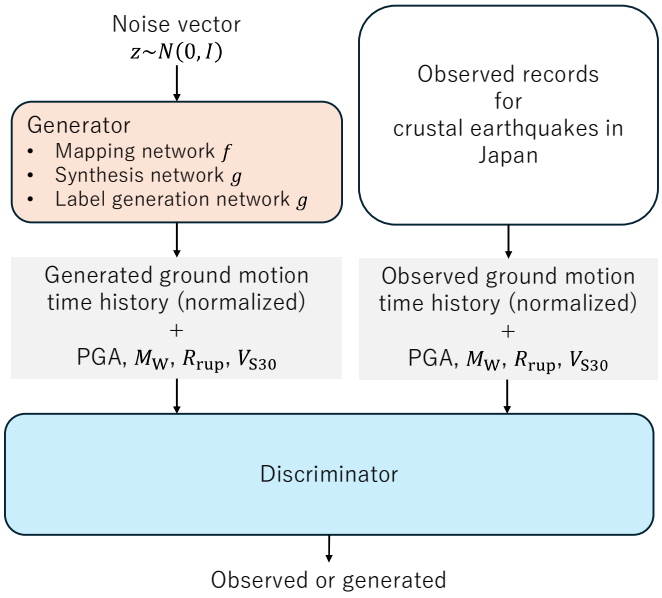

Figure 1. Training process of ground motion generative model (modified from Matsumoto et al. (2024)).

are assumed. The V_{S30} value for the site under consideration is set to 356 m/s. Ground motion time histories are generated based on these parameter settings. To generate ground motions for a specific source at a specific site using the GMGM, MCMC sampling is performed in the intermediate latent space. MCMC sampling needs $p(\mathbf{w}|M_{\mathrm{W}}, R_{\mathrm{rup}}, V_{\mathrm{S30}})$ to be obtained as follows:

$$p(\mathbf{w}|M_{\mathrm{W}}, R_{\mathrm{rup}}, V_{\mathrm{S30}}) \propto p(M_{\mathrm{W}}, R_{\mathrm{rup}}, V_{\mathrm{S30}}|\mathbf{w})p(\mathbf{w}) \quad (1)$$

where, the prior distribution $p(\mathbf{w})$ is estimated using normalizing flow-based model (Dinh et al., 2014; Papamakarios et al., 2021). The likelihood $p(M_{\mathrm{W}}, R_{\mathrm{rup}}, V_{\mathrm{S30}}|\mathbf{w})$ is defined theoretically as the delta function and is approximated by the narrow distribution. In this study, No-U-Turn Sampler (NUTS) (Hoffman et al. 2014), an extension of Hamiltonian Monte Carlo (HMC) (Duane et al. 1987), is employed as the MCMC algorithm. For more details, see Matsumoto (2025). The generated 100 samples of ground motions are shown in Figure 2. Both amplitude and temporal characteristics exhibits scatter following the characteristics of observed ground motions.

DISCUSSION

Response Analysis Model for Case Study

A linear elastic 9-degree-of-freedom (9DOF) lumped mass model representing a boiling water reactor

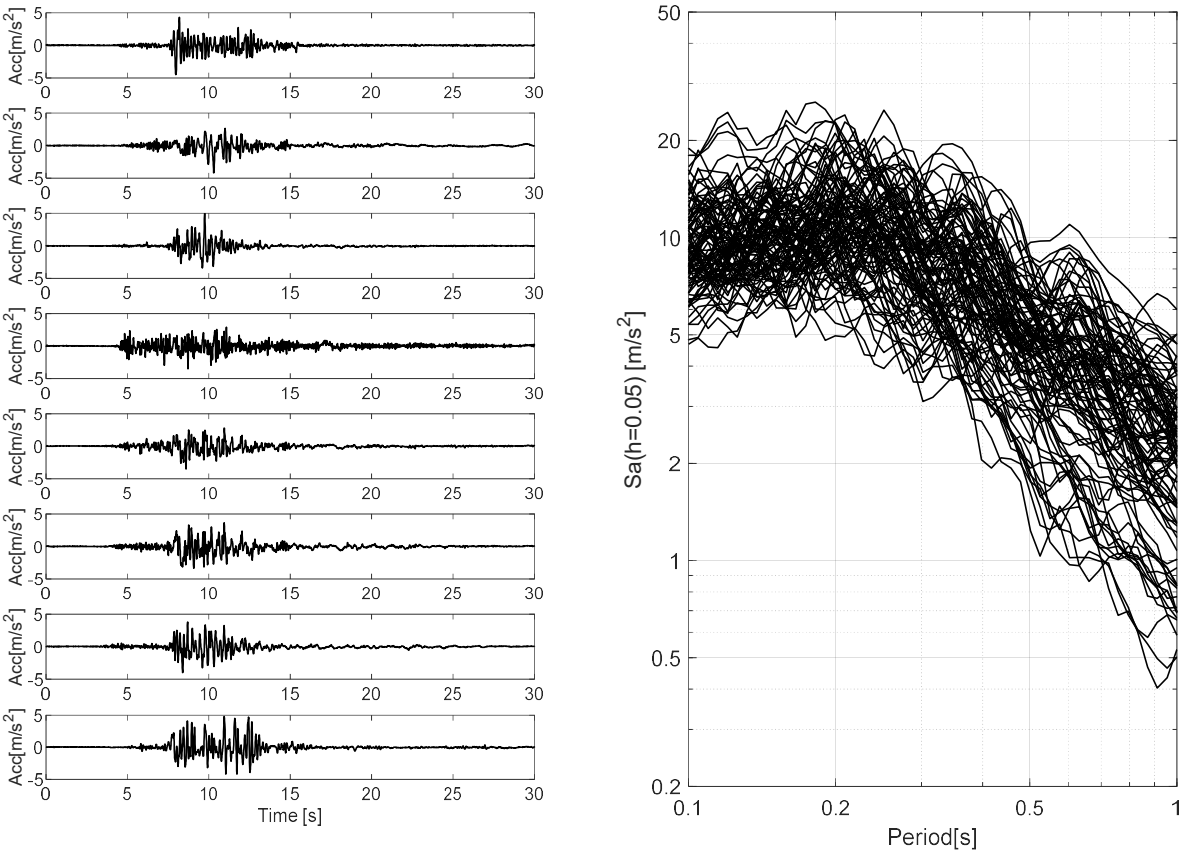

Figure 2. Examples of acceleration time histories and response spectra (h=0.05) of ground motions generated by the proposed ground motion generative model ($M_{\mathrm{W}} = 6.8, R_{\mathrm{rup}} = 11\mathrm{km}, V_{\mathrm{S30}} = 356\mathrm{m/s}$).

(BWR) reactor building is considered, as shown in Figure 3 and Table 1. This model is modified from an example in JEAC 4601-2015 (Japan Electric Association, 2017). The model assumes a shear modulus of 9.6×10^6 kN/m^2, and a Poisson's ratio of 0.167. Rayleigh damping is applied with a damping ratio of 0.05 for both the fundamental and second modes. Time history analysis is performed using OpenSeesPy.

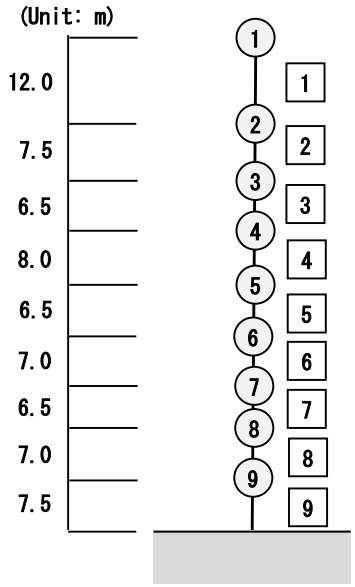

Figure 3. Linear elastic 9-degree-of-freedom (9DOF) lumped mass model for a reactor building.

Table 1: Parameters for the response analysis model.

(a) Mass-related parameters

Mass No.	Mass [$\times 10^3$kg]	Moment of Inertia [$\times 10^6$kg$\cdot$m^2]
1	4500	1400
2	5200	2000
3	25500	15400
4	34900	19400
5	48700	27100
6	48100	30300
7	46300	29800
8	62100	37700
9	65000	44300

(b) Stiffness-related parameters

Member No.	Shear Cross-section Area [m^2]	Second Moment of Area [$\times 10^3$m^4]
1	49	34
2	64	54
3	298	262
4	340	335
5	473	473
6	586	601
7	656	662
8	733	736
9	804	808

In this case study, only uncertainties in ground motions are considered, while uncertainties in the response analysis model are omitted for simplicity.

Results

Response analyses are conducted for 59 randomly selected input ground motions, where the maximum response corresponds to the 95% confidence and 95% cumulative probability (95/95) levels, as per Wilks (1941). Figure 4 shows histograms and scatter plots of the selected responses, which include the interstory drift ratio (IDR) at spring No. 9 and the peak floor accelerations (PFAs) at nodes No. 2, 6, and 9. The red dashed lines indicate the estimated 95/95 values for each response. Scatter plots are also useful for assessing the possibility of common-cause failures of SSCs located in the reactor building that could lead to a cliff-edge effect. It could also be informative if these results are compared with those of the conventional deterministic approach to explicitly illustrate its conservatism for this scenario earthquake.

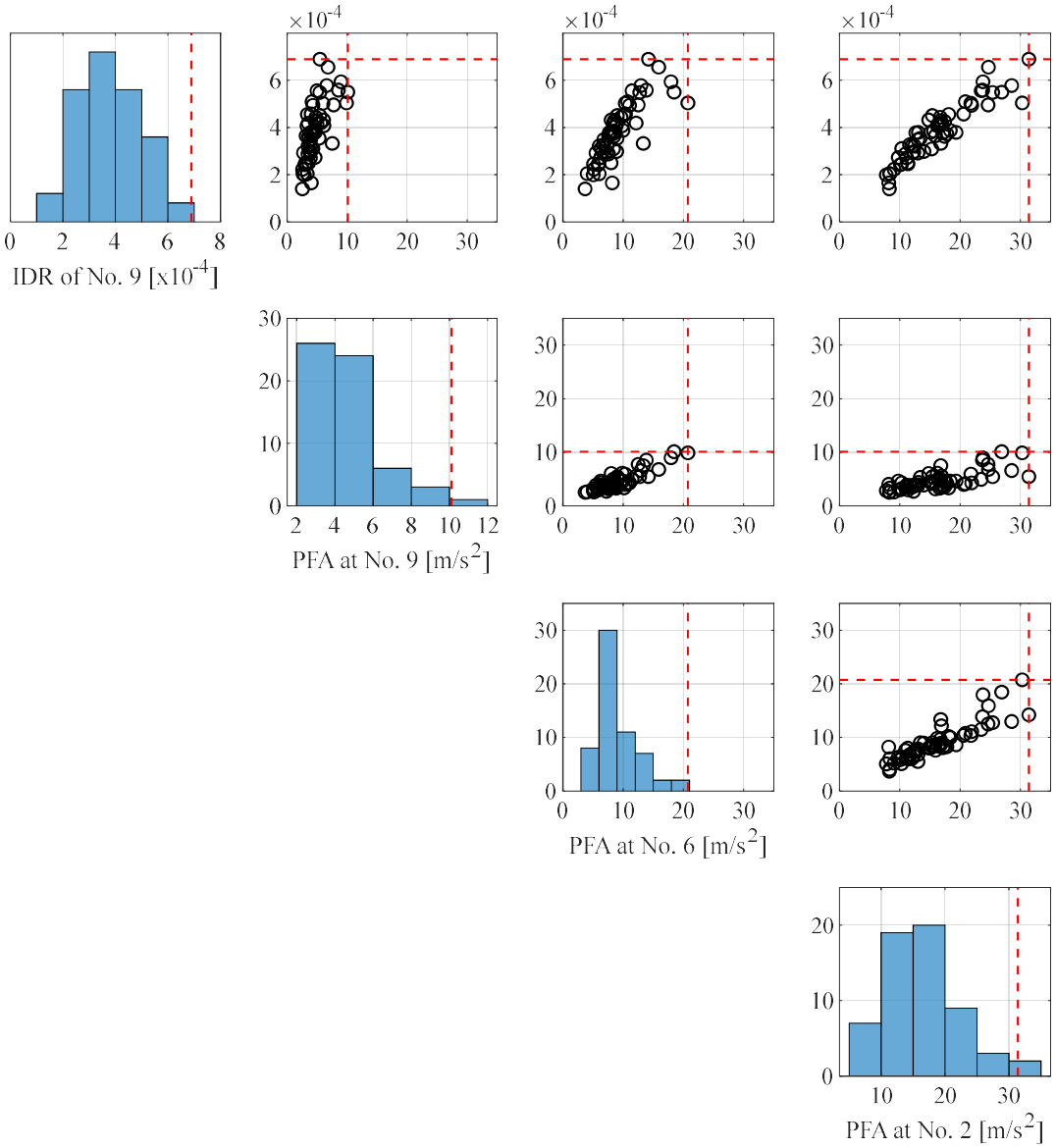

Figure 4. Histograms and scatter plots of selected responses.

CONCLUSION

This paper explored the need to integrate Best Estimate Plus Uncertainty (BEPU) analysis into seismic performance assessment. Its effective implementation could be enhanced by machine learning methods, including ground motion generative models capable of directly generating ground motion time histories. The safety margin provided by the conventional deterministic assessment framework for the seismic performance of nuclear power plants remains implicit, making it difficult to identify potential weak points and provide meaningful insights for safety management. To address this, the proposed framework systematically varied key input parameters and ground motions while accounting for uncertainties, allowing for a more nuanced understanding of plant behavior under scenario-based ground motions. This approach was considered to help identify critical factors influencing safety in extreme earthquake scenarios, thereby supplementing or potentially improving the current deterministic approach.

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