Chapter 6
A Comparative Study of Developing Seismic Fragility Models using Random Sampling Simulations and Machine Learning

Mohamed Tareq Soliman, Ufuk Yazgan, and Onur Avci

Abstract Seismic fragility analysis is an essential tool in evaluating structural reliability by quantifying the likelihood that a structure will exceed specific damage thresholds under varying ground motion intensities. Traditional approaches, such as Monte Carlo simulations, provide robust estimates by accounting for uncertainty in structural response; the approach's high computational demand, however, becomes particularly challenging for complex structures.

To address this issue, this study investigates developing fragility models of a structure exhibiting multiple failure modes using Monte Carlo simulations and machine learning driven techniques such as Response Surface Method (RSM) and Artificial Neural Networks (ANN). The structure's limit capacities are treated as random variables, and Incremental Dynamic Analysis (IDA) is used with scaled ground motions to capture record-to-record variability.

To ensure the invariability of the benchmark model, a sensitivity analysis was conducted to determine an appropriate size for the limit state set used in training, as well as to evaluate different sampling strategies. The results indicated that Latin Hypercube Sampling (LHS) demonstrated relatively lower variance in the fragility estimates compared to traditional random sampling methods, though it did not eliminate variance entirely and required a similar number of simulations to reduce this variability sufficiently. In addition, the variance of LHS-based estimates was observed to increase with the variance of the input random variables, reflecting the complexity of the relationship between the structural failure mechanisms.

Building on these findings, the study then evaluated RSM and ANN for developing fragility models. RSM offered a computationally efficient alternative by approximating fragility behavior through polynomial functions. However, it struggled to capture sharp transitions in mean fragility caused by sudden shifts of the dominant failure modes between the limit states, leading to inaccuracies, especially in highly nonlinear regions of the input domain. Conversely, ANN demonstrated superior performance, delivering more accurate and robust fragility models, even under high-variance conditions. Its ability to model complex nonlinear relationships without relying on predefined functional forms allowed it to outperform RSM in both predictive reliability and generalization.

Keywords Fragility · Monte carlo · Response surface · ANN.

Introduction

Seismic fragility models serve as a fundamental role in seismic risk assessment by quantifying the probabilistic relationship between ground motion intensity and structural damage states. These models express the conditional probability that a structure or component will exceed a designated damage state (e.g., collapse) given a specific ground motion intensity level measured through parameters like peak ground acceleration (PGA) or peak ground velocity (PGV). Fragility models are vital for several reasons, including: a) quickly assessing a structure's seismic performance [1]; b) informing government retrofitting and recovery plans [2]; c) developing mitigation strategies, such as for bridge design [2, 3]; d) creating vulner-

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ability models for insurance and risk analysis [4, 5]; e) improving guidelines through life-cycle cost assessment, including for aging structures [6, 7]; and f) managing risk in seismic mega-cities [1].

Traditionally, the fragility function parameters are estimated from three main approaches: a) engineering judgment, b) numerical simulation methods through data generated from structural analyses of building archetypes, and c) empirical approaches based on observed damage data. While engineering judgment provide statistical estimations of probable damage based on expert assessments for different earthquake intensities [8], the analytical approach has gained significant prominence within the Performance-Based Earthquake Engineering (PBEE) framework, which enables the estimation of earthquake-induced damage and loss while considering various sources of uncertainty [9–11]. The empirical fragility models are traditionally derived from larger post-earthquake databases for various building classes. Existing empirical fragility functions often rely on municipal-level damage data, which aggregates information across large, geologically diverse areas. Despite this variability, each ground motion intensity level is typically estimated—via a Ground Motion Prediction Model GMPE or ShakeMap—at the municipality's centroid and used to represent the entire area [12].

Research on seismic fragility models has evolved through several key studies. One investigation examined how the number of incremental dynamic analyses impacts the reliability of models built using regression and maximum likelihood methods [13]. A separate study created a flexible framework for developing models for any damage state, provided post-earthquake damage data is available [14]. Later work evaluated existing European fragility models and proposed new design maps for the region [15]. More recently, intensity-based fragility models were developed for specific mid-rise Turkish residential buildings, using the Modified Mercalli Intensity scale to accommodate models derived from on-site damage observations [5].

Methodology

This study compares the advantages and limitations of employing machine learning algorithms to the traditional random sampling simulations in deriving fragility models for structures vulnerable to multiple failure modes. A key objective is the integration of two significant uncertainties that influence structural response during earthquakes: aleatoric and epismetic uncertainty. Aleatoric uncertainty stems from the inherent randomness in the strong motion characteristics. The epistemic uncertainty on the other hand arises from a lack of knowledge regarding material properties capacity of the structural elements and their load capacity.

The core architecture of our model is based on the work presented in [16, 17], which consists of a case study of an a 2D frame model with two columns and a beam. The structural configuration and load distribution are depicted in Figure 1. The reinforcement of the structural elements is configured as follows: the beam has a geometric percentage of 0.857%, with a top-to-bottom ratio of 2:1 at the ends (A-A) and 1:2 at midspan (B-B), while both columns have a reinforcement ratio of 1.2%, evenly distributed (C-C). The applied loads include 500 kN point loads on the columns and a 36 kN/m distributed load on the beam. the finite element analysis proceeds under the assumption that the concrete is unconfined, neglecting any confinement effects. OpenSeesPy was used in finite element analysis and dynamic analysis. This frame features three primary failure modes at the shorter column that represent the epistemic uncertainty: experiencing a shear force exceeding ultimate shear strength (Vu), and flexural failures due to concrete crushing at either top or bottom sections of the column. The shear strength is a random variable with a median of 170 kN and dispersion of 0.2, while the ultimate concrete crushing strain has a median of 0.006 and a dispersion of 0.35.

This structure is subjected to 12 ground motion records with a magnitude ranging between 6.0 and 7.6 with small epicentral distances up to 16 km, and soil profiles correspond to NEHRP C and D sites. The ground motions are listed in detail in the thesis work [17]. Incremental Dynamic Analysis (IDA) is performed such as that each earthquake is scaled to different levels, ranging from PGV = 5cm/s to PGV = 40 cm/s. The IDA process is performed for different limit state combinations meta-variables, and a fragility model is developed for each meta-variable by fitting the points to a log-normal cumulative density function. The cumulative distribution function of the equivalent log-normal fragility model (shown in Equation (1)) is characterized by the logarithmic mean (λ) and logarithmic standard deviation (ζ).

$$P(D > d \mid IM = x) = \Phi\left(\frac{\ln(x) - \lambda}{\zeta}\right) \tag{1}$$

To develop the benchmark model, random sampling simulations method is first employed, beginning with Monte Carlo simulations. This approach involves generating a large set of limit-state combinations and performing an Incremental Dynamic Analysis (IDA) for each. From the results, the probability of triggering each limit-state across various intensity measures is computed. Finally, a fragility model is fitted to the median probabilities using the maximum likelihood estimation method.

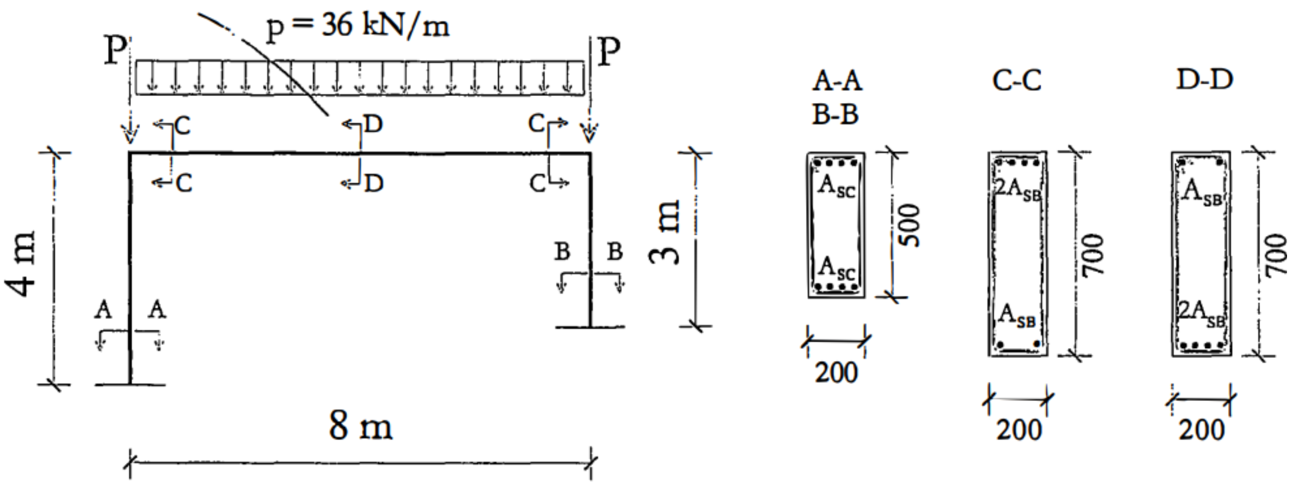

Fig. 1 Geometric and structural properties of the elements and sections

While the Monte Carlo method establishes a robust benchmark, its computational cost is prohibitive. To address this, our study focuses on reducing the computational effort relative to traditional MC sampling by employing more efficient techniques, such as Latin Hypercube Sampling (LHS). The LHS technique ensures uniform coverage of the input parameter space and a more accurate representation of distribution parameters with fewer samples compared to simple random sampling. In this approach, the distribution of each input variable is partitioned into N equal-sized intervals, and values are randomly paired across variables. LHS has been widely applied in many earthquakes and civil engineering fields; such as quantifying uncertainties in material properties that affect earthquake resistance of 9-story steel structure [18], deriving fragility models for masonry buildings [19], and capturing the influence of soil-foundation-structure interaction on system response [20].

The first machine learning tool used in this comparative study is the Response Surface Method (RSM) with Central Composite Design (CCD) as the sampling technique. CCD relies on experimental design points that are collected to cover the whole region of interest for the input limit states, while RSM fits these points into a polynomial bivariable surface. Then after fitting the surface, a mega set of randomly generated limit state combinations are generated into the RSM surface equation to determine their outcomes, and a log-normal cumulative density function is fitted using the median points of this mega set at each intensity measure level.

The second machine learning tool is Artificial Neural Networks (ANN) with grid sampling technique. The sample space is an evenly spaced region of dominating limit states divided into 7 combinations (total 49 training points) ranging from -2σ to 2σ each, which corresponds to the 3^{rd} and 97^{th} percentiles in the Z-score table. After developing fragility models for the 49 limit state combinations, a surface is fitted with the ANN model (MLP perceptron with back propagation) to fill the complete region. The ANN model consists of 5 neurons in 3 hidden layers each with L2 regularization parameter of 0.1%. And again, a mega set of randomly generated limit state combinations are generated into the neural networks model to develop fragility models, then fit an ultimate fragility model with the median points at each intensity measure level.

Discussion and Conclusions

In the process of developing benchmark model, a set of limit states was analyzed under 12 ground motion records to develop a fragility model that incorporates both structural and seismic uncertainties. These limit states were generated using two distinct random sampling techniques: the Monte Carlo simulations method and the Latin Hypercube Sampling method. A sensitivity analysis was performed to determine the optimal sample size for the limit state sets, ensuring the robustness of the benchmark fragility model. The results of this analysis (see Figure 2) indicate that at smaller sample sizes, the outcomes of different MC runs exhibited high variability. This variance decreased as the sample size increased. In contrast, LHS performed better with fewer samples, yielding a relatively lower variance in the estimated outcomes. However, for both methods, a non-negligible variance between different runs persisted even at larger sample sizes, requiring a comparable number of simulations to achieve stable results. This phenomenon is likely due to the complex relationships between the structural limit states.

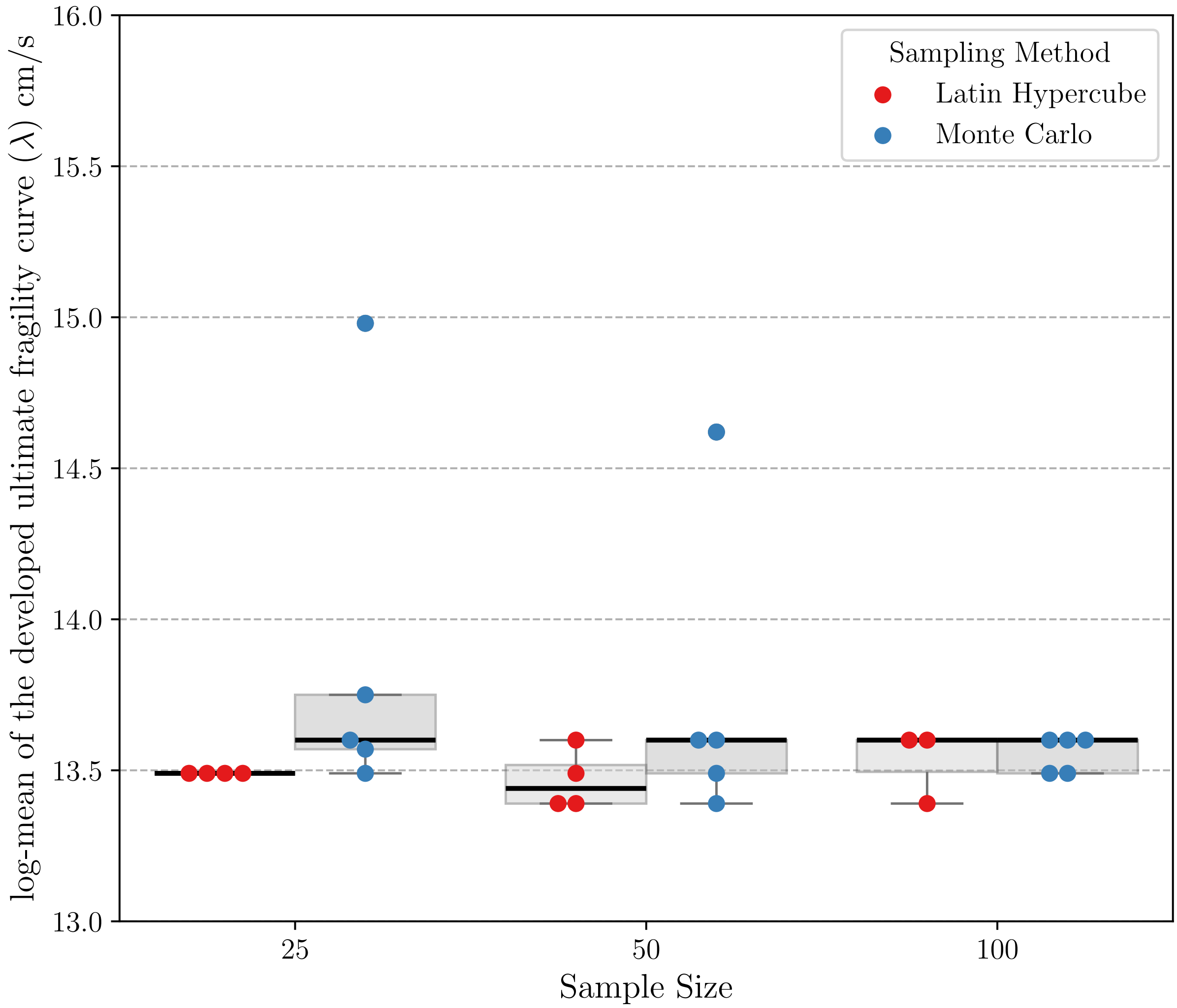

Fig. 2 Swarm plot of log-mean of the estimated ultimate fragility model for different sampling size and sampling techniques

Furthermore, as shown in Figure 3, the log-mean parameter from the MC simulations exhibits an increasing trend with the number of limit states. Conversely, Figure 4 demonstrates that for an equivalent sample size, both Monte Carlo and Latin Hypercube simulations produce nearly identical fragility models.

Looking into the two machine learning algorithms, RSM required little computational power to develop a predicting model for fragility function parameters. However, RSM failed to deal with the nonlinearity of the limit state function which has resulted in a sudden shift in the mean fragility, as shown in Figure 5. This has resulted in shifting the final fragility model developed by RSM to a lower mean value. On the other hand, ANN surface in Figure 6 is capable of detecting the plateau zone that the RSM failed to depict clearly. This plateau zone is the boundary line of shifting between the controlling limit states. In fact, ANN approach has demonstrated its effectiveness by delivering more accurate outcomes in predicting both fragility function parameters and final median fragility model compared to RSM approach (see Figure 7). Furthermore, the prediction errors (residuals) from RSM and ANN models are visualized for different levels of seismic intensity in Figure 8. The visualization uses violin plots, where the shape's width indicates how the errors are distributed at each intensity level. The results demonstrate that the ANN model consistently generates smaller errors than the RSM model at all intensity levels. This superior performance suggests that the ANN is more effective at modeling the complex, nonlinear behavior and inherent uncertainties of the structural system, leading to more precise fragility estimates. In contrast, the RSM model exhibits larger errors. This is attributed to the inherent smoothness of its fitted curves, which limits its capacity to accurately represent the system's nonlinear response.

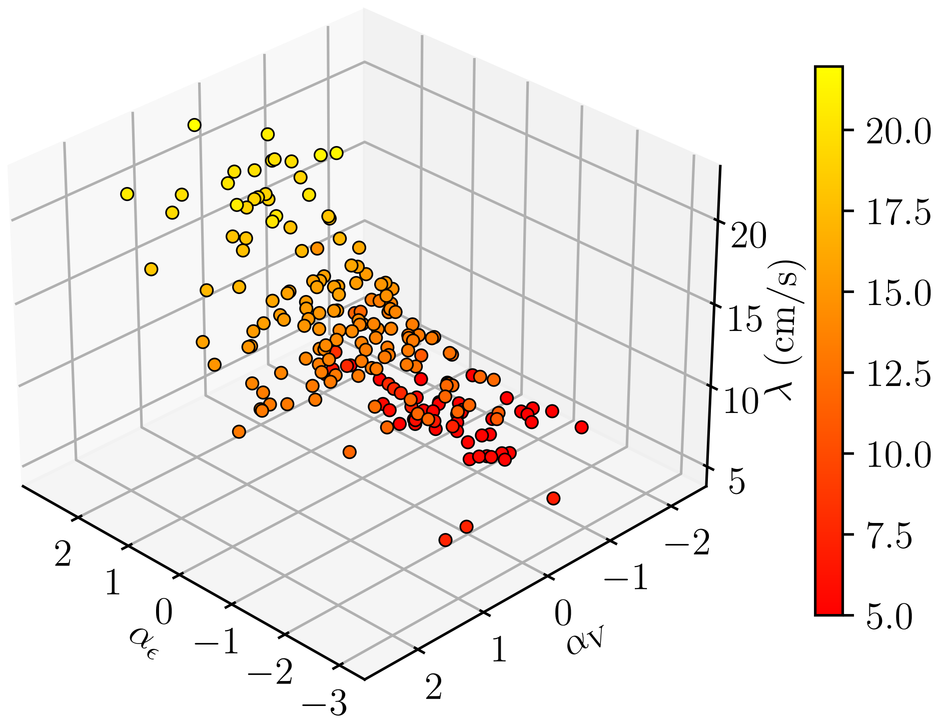

Fig. 3 Estimated median fragility (λ) of the Monte Carlo simulations using Maximum Likelihood Estimation and scaled to standard deviation

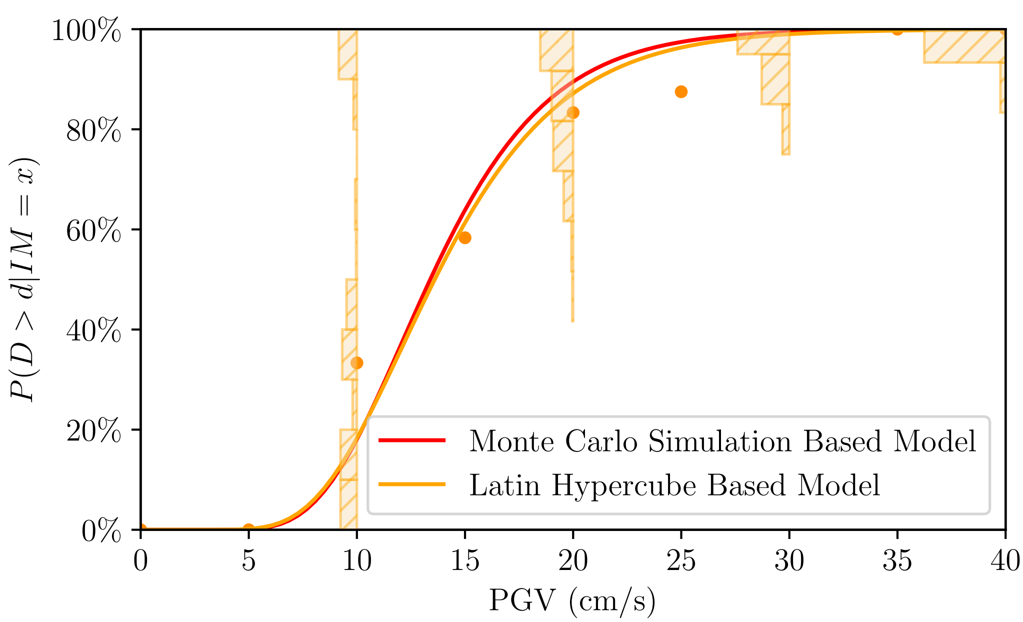

Fig. 4 Final fragility model estimated from Monte Carlo simulations and Latin Hypercube simulations

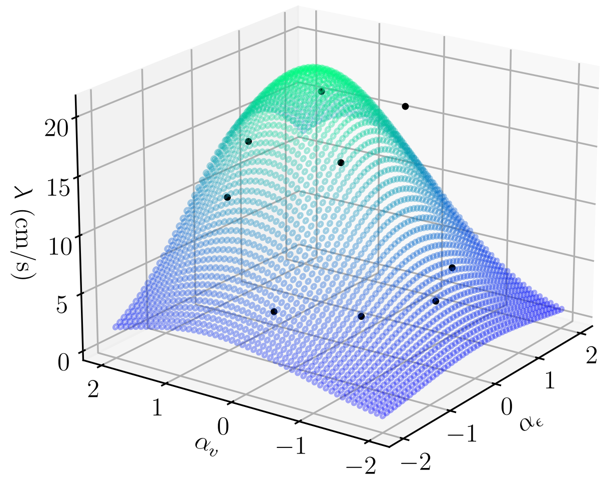

Fig. 5 Estimated median fragility (λ) of the Response Surface Method using Maximum Likelihood Estimation and scaled to standard deviation

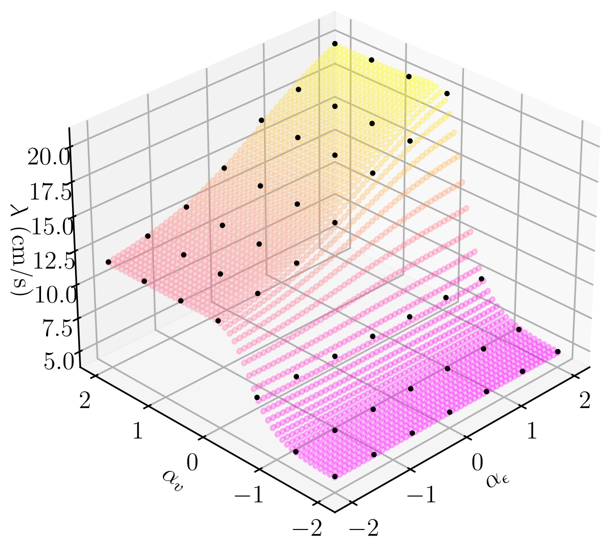

Fig. 6 Estimated median fragility (λ) of the ANNs using Maximum Likelihood Estimation and scaled to standard deviation

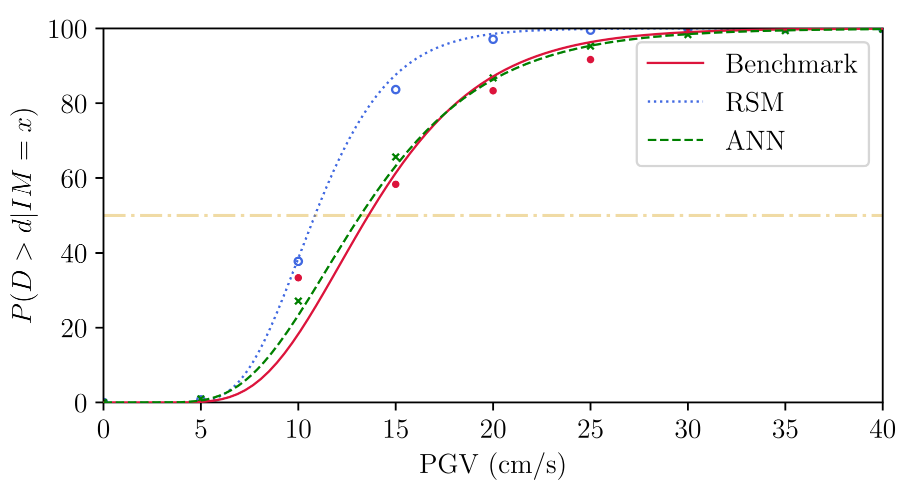

Fig. 7 Final fragility models of the benchmark Monte Carlo simulations, Response Surface Method, and ANNs

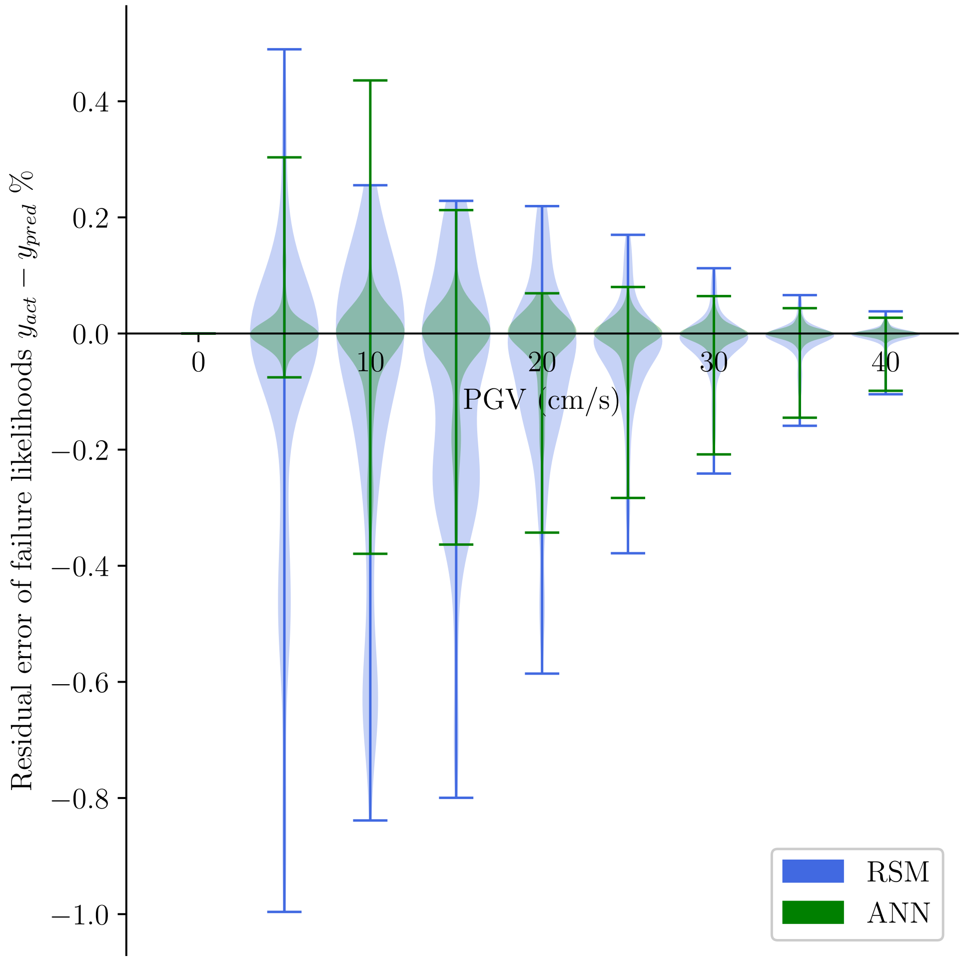

Fig. 8 Comparison between distribution of residuals for different seismic intensity measure of Response Surface Method, and ANNs to the benchmark model

Future work

To address the limitations of this study, future research should focus on:

1) Developing hybrid models that combine multiple algorithms with the Response Surface Method (RSM) to improve accuracy and reduce computational cost.
2) Testing these techniques on more complex, real-world structures with higher degrees of freedom to better assess their efficiency.
3) Enhancing the RSM approach by integrating adaptive algorithms to optimize Incremental Dynamic Analysis (IDA) that will pre-determine the necessary range of ground motion intensities, avoiding wasteful calculations at extreme levels.

Pursuing these questions will help overcome current limitations and advance the field.

References

1. L. Di Sarno, A. Elnashai, Seismic Fragility Relationships for Structures, in: 2021: pp. 189–222. https://doi.org/10.1007/978-3-030-68813-4_9.
2. A. Elnashai, L. Di Sarno, Fundamentals of Earthquake Engineering, From Source to Fragility, 2015.

3. M. Salkhordeh, E. Govahi, M. Mirtaheri, Seismic fragility evaluation of various mitigation strategies proposed for bridge piers, Structures 33 (2021). https://doi.org/10.1016/j.istruc.2021.05.041.
4. K. Pitilakis, H. Crowley, A.M. Kaynia, SYNER-G: Typology Definition and Fragility Functions for Physical Elements at Seismic Risk: Buildings, Lifelines, Transportation Networks and Critical Facilities, Geotechnical, Geological and Earthquake Engineering 27 (2014). https://doi.org/10.1007/978-94-007-7872-6.
5. S. Akkar, Earthquake Physical Risk/Loss Assessment Models and Applications: A Case Study on Content Loss Modeling Conditioned on Building Damage, in: Springer Tracts in Civil Engineering, 2021. https://doi.org/10.1007/978-3-030-68813-4_10.
6. G.M. Calvi, R. Pinho, G. Magenes, J.J. Bommer, L.F. Restrepo-Vélez, H. Crowley, Development of seismic vulnerability assessment methodologies over the past 30 years, ISET Journal of Earthquake Technology 43 (2006). https://doi.org/10.63898/busy2147.
7. J.G. Xu, Z.K. Cai, D.C. Feng, Life-cycle seismic performance assessment of aging RC bridges considering multi-failure modes of bridge columns, Eng Struct 244 (2021) 112818. https://doi.org/10.1016/J.ENGSTRUCT.2021.112818.
8. A. Hadlos, A. Opdyke, S.A. Hadigheh, Deriving expert-driven seismic and wind fragility functions for non-engineered residential typologies in Batanes, Philippines, Sci Rep 13 (2023). https://doi.org/10.1038/s41598-023-49398-2.
9. M. Shinozuka, M.Q. Feng, J. Lee, T. Naganuma, Statistical Analysis of Fragility Curves, J Eng Mech 126 (2000). https://doi.org/10.1061/(asce)0733-9399(2000)126:12(1224).
10. D. Lallemant, A. Kiremidjian, H. Burton, Statistical procedures for developing earthquake damage fragility curves, Earthq Eng Struct Dyn 44 (2015). https://doi.org/10.1002/eqe.2522.
11. J. Kohns, L. Stempniewski, A. Stark, Fragility Functions for Reinforced Concrete Structures Based on Multiscale Approach for Earthquake Damage Criteria, Buildings 12 (2022). https://doi.org/10.3390/buildings12081253.
12. I. Ioannou, R.E. Chandler, T. Rossetto, Empirical fragility curves: The effect of uncertainty in ground motion intensity, Soil Dynamics and Earthquake Engineering 129 (2020). https://doi.org/10.1016/j.soildyn.2019.105908.
13. P. Gehl, J. Douglas, D.M. Seyedi, Influence of the number of dynamic analyses on the accuracy of structural response estimates, Earthquake Spectra 31 (2015). https://doi.org/10.1193/102912EQS320M.
14. U. Yazgan, Empirical seismic fragility assessment with explicit modeling of spatial ground motion variability, Eng Struct 100 (2015). https://doi.org/10.1016/j.engstruct.2015.06.027.
15. V. Silva, H. Crowley, P. Bazzurro, Exploring risk-targeted hazard maps for Europe, Earthquake Spectra 32 (2016). https://doi.org/10.1193/112514EQS198M.
16. M.T.M. Soliman, U. Yazgan, Exploring the benefits and limitations of alternative machine learning techniques in seismic fragility assessment, in: DEU INTERNATIONAL SYMPOSIUM SERIES ON GRADUATE RESEARCHES-2022 GeoScience, 2023.
17. M.T. Soliman, Application of machine learning algorithms in seismic fragility analysis of structures, M.Sc. Thesis, Istanbul Technical University, 2023.
18. D. Vamvatsikos, Seismic Performance Uncertainty Estimation via IDA with Progressive Accelerogram-Wise Latin Hypercube Sampling, Journal of Structural Engineering 140 (2014). https://doi.org/10.1061/(asce)st.1943-541x.0001030.
19. S. and F.T.M. and R.P. and U.M. Del Carlo Federica and Caprili, Deriving Analytical Fragility Curves for Masonry Churches Based on Stochastic Nonlinear Analyses, in: P.B. and O.D.V. and B.J. and P.D. and S.R.A. and S.H.S. Matos José C. and Lourenço (Ed.), 20th International Probabilistic Workshop, Springer Nature Switzerland, Cham, 2024: pp. 115–124.
20. A. Karatzetzou, Uncertainty and Latin Hypercube Sampling in Geotechnical Earthquake Engineering, Geotechnics 4 (2024) 1007–1025. https://doi.org/10.3390/geotechnics4040051.