Proceedings of the 10th World Congress on New Technologies (NewTech'24)
Barcelona, Spain - August 25-27, 2024
Paper No. ICCEIA 136
DOI: 10.11159/icceia24.136

Quantifying Seismic Resilience of Highway Bridges: A Case Study using Bayesian Neural Network

Jacob Atkins[1], Donya Hajializadeh[2], Farahnaz Soleimani[1]
[1]Oregon State University, School of Civil and Construction Engineering
Kearney Hall, 1491 SW Campus Way, Corvallis, Oregon, USA
atkijaco@oregonstate.edu; Farahnaz.Soleimani@oregonstate.edu
[2]University of Surrey
Guildford, Surrey GU2 7XH, United Kingdom
d.hajializadeh@surrey.ac.uk

***Abstract* -** Seismic resilience assessment of critical infrastructures is paramount for enhancing emergency mitigation planning and ensuring robust system performance in seismic hazard scenarios. This study focuses on evaluating the seismic resilience of highway bridges, crucial components of transportation networks whose proper functioning post-hazard events is essential for overall network integrity. While machine learning (ML) approaches have gained traction in earthquake engineering, their application to bridge resilience quantification remains underexplored. Improved ML algorithms, such as artificial neural networks (ANN), offer an alternative to labor-intensive computational analyses while enhancing model accuracy. This study introduces a novel Bayesian approach to quantify ANN-based bridge resilience. Applied to a typical class of highway bridges in California, the proposed methodology demonstrates its efficacy in estimating seismic resilience metrics. The findings indicate that the Bayesian network performs comparably to conventional neural network approaches, underscoring its potential significance in efficiently estimating network resilience and informing infrastructure resilience-based assessments and rapid decision-making processes. This research contributes to advancing computational frameworks for resilience estimation and offers valuable insights for enhancing infrastructure resilience and emergency preparedness efforts.

***Keywords*:** seismic resilience assessment, highway bridges, machine learning, bayesian approach, infrastructure resilience, emergency mitigation planning, artificial neural networks, seismic hazard

1. Introduction

Seismic events pose significant risks to critical infrastructures, making the assessment of seismic resilience crucial for effective emergency mitigation planning and ensuring robust system performance in seismic hazard scenarios [1]. Among these infrastructures, highway bridges stand out as crucial components of transportation networks, the proper functioning of which is essential for overall network integrity and societal resilience. However, traditional methods for assessing seismic resilience often entail labor-intensive computational analyses and may not fully capture the complex dynamics of bridge performance under seismic loading [2,3].

In recent years, machine learning (ML) approaches have received attention in earthquake engineering for their potential to enhance the accuracy and efficiency of risk assessment [4-7]. Among these approaches, Bayesian Neural Networks (BNNs) have emerged as promising tools for modeling complex relationships in data and making probabilistic predictions [8]. The large number of parameters during the training phase in ML can lead to overfitting, wherein the model achieves high accuracy on the training dataset but demonstrates comparatively lower accuracy on the validation dataset. To mitigate this issue, regularization methods like Bayesian regularization have been introduced for neural networks, offering promising outcomes in terms of prediction accuracy [9]. By leveraging the capabilities of BNNs, researchers aim to address the computational challenges associated with traditional methods while providing valuable insights into complex problems [10-13].

This paper presents a novel approach to quantifying the seismic resilience of highway bridges using BNN modeling. Through a case study focused on a class of representative highway bridges in California, the proposed methodology aims to demonstrate its efficacy in estimating seismic resilience metrics. By introducing a BNN-based framework for resilience assessment, this research contributes to advancing computational methods for infrastructure resilience evaluation and offers valuable insights for enhancing emergency preparedness efforts and decision-making processes in earthquake-prone regions.

2. Methodology

2.1. Bayesian Neural Network

The methodology employed in this study aims to quantify the seismic resilience of highway bridges using BNN modeling. The BNN model is constructed using a neural network architecture with Bayesian inference techniques. A BNN algorithm employs a statistical regularization approach aimed at mitigating overfitting and enhancing model fit [14]. This approach involves assigning Bayesian priors to the network parameters, enabling the incorporation of prior knowledge and uncertainty into the model. The architecture typically consists of multiple layers of interconnected neurons, with Bayesian inference methods such as Markov Chain Monte Carlo (MCMC) or Variational Inference (VI) used for probabilistic inference. Hyperparameters, including network depth, width, and regularization parameters, are optimized through techniques such as cross-validation or Bayesian optimization. By leveraging Bayesian inference, the BNN model captures uncertainty in the data and provides probabilistic predictions, enabling more robust and interpretable assessments of bridge resilience.

Unlike conventional neural networks, where hyperparameters such as weights and biases are singular values, a BNN assigns normal distributions to these parameters [15,16]. Consequently, each hyperparameter becomes variable over time, yielding a statistical distribution of potential outcomes [17], especially as the model progresses through training eras and epochs. This variability proves advantageous in scenarios with limited data, reducing the risk of overfitting by introducing variability, or "noise," into the model [18]. However, scaling BNNs to larger or more complex problems with extensive data can pose challenges, as the random variation of hyperparameters exacerbates the computational complexity already inherent in such tasks [19].

2.2. Implementation

Throughout this work, Python was utilized exclusively for programming tasks related to model training. The decision to use Python was motivated by its comprehensive range of ML libraries and resources, facilitating the implementation of a diverse array of ML techniques across various data structures and problem scenarios. Although BNNs are typically mathematically intensive and complex to implement, a Python library developed by Harry24k offers a straightforward solution that integrates with PyTorch [17, 20]. This library was utilized in the present study to construct a BNN for comparison with the standard artificial neural network (ANN) formulation. The BNN architecture closely resembled that of the ANN, with the exception that each layer was replaced by a Bayesian layer featuring a zero mean and a standard deviation ranging from 0.01 to 0.50, providing a diverse sampling of BNN architectures' impact on model accuracy.

Training data are fed into the model, and the network parameters are iteratively updated using gradient-based optimization algorithms such as stochastic gradient descent (SGD) or Adam. Throughout the training process, the model learns to make predictions while capturing uncertainty in the data. Model performance is evaluated using metrics such as mean squared error (MSE), coefficient of determination (R-squared), and probabilistic metrics such as predictive distributions and uncertainty estimates. The trained Bayesian Neural Network (BNN) model undergoes rigorous validation using holdout datasets or cross-validation techniques to assess its generalization performance.

3. Case Study: Seismic Resilience Assessment of Highway Bridges in California

As a case study to investigate the efficiency of employing BNN in the resilience assessment of bridges, we selected two-span box-girder concrete highway bridges in California. Seismic data relevant to this study area, including ground motion records and bridge characteristics, were collected from sources such as the National Bridge Inventory and previous works [21, 22]. The dataset comprises information on bridge geometry, material properties, and seismic loading conditions. This comprehensive dataset was essential for creating 3-dimensional finite element models of bridges in OpenSees and for capturing the diverse factors influencing bridge resilience and ensuring the accuracy and reliability of the the BNN model. By incorporating detailed information on bridge attributes and seismic events, the data collection process process lays the foundation for robust resilience assessment.

3.1. Resilience quantification using classical approach

In the analysis of complex systems like structures exposed to seismic excitations, assessing the resilience typically involves initially generating a fragility function. Seismic fragility quantifies the conditional probability, indicating the likelihood that a structure will reach or surpass a defined damage state (i.e., level of damage) for a given intensity measure (IM) of the seismic hazard [23]. A visual representation of this process is presented in Fig. 1 in the form of a flowchart.

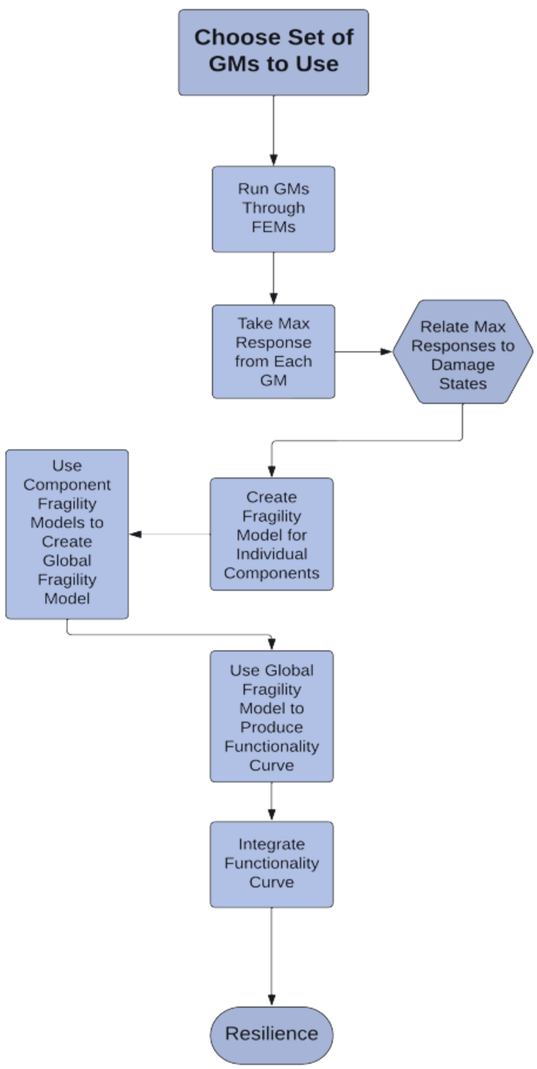

Fig 1: Traditional structural resilience calculation process. GM = Ground Motion, FEM = Finite Element Model.

An analytical fragility calculation process based on numerical analysis, employing Finite Element Method (FEM) and probabilistic computational methods, may require several days or even weeks for a single bridge, contingent upon its complexity. This leads to an exponential escalation in computational costs. Furthermore, traditional computational methods may overlook several significant parameters. Previous studies have typically modeled fragility as depicted in Equation (2.1), primarily dependent on the ground motion parameter IM, without directly integrating various other potentially crucial structural parameters [24, 25].

$$PF_{p|IM} = P[DS_s|IM] = \Phi\left[\frac{\ln(IM)-\ln(\mu_d)}{\beta_d}\right] \quad (1)$$

In Equation 1, μ_d and β_d denote to the median and logarithmic standard deviation of the seismic demands, respectively. The variable DS_s represent the designated damage states. As outlined in the seismic fragility models summary by Gidaris et al., the majority of models incorporate four consistent damage states: "slight, moderate, extensive, and complete" [23]. In this study, we adopted the normalized performance indicator function (Q) (Equation 2) as the fundamental component for formulating the seismic resilience of structures.

$$\bar{Q}(t) = \sum_{d=1}^{nDS_s}(1 - PF_{p|IM}) \times \Phi(\frac{t-\mu_{t,d}}{\sigma_{t,d}}) \quad (2)$$

The recovery trajectory function used in this paper is aligns with the recommendation provided by Hazus-MH. It incorporates four predefined damage states, with mean recovery times ($\mu_{t,d}$) set at 0.6, 2.5, 75, and 230 days, respectively; and standard deviation ($\sigma_{t,d}$) set at 0.6, 2.7, 42, and 110 days, respectively [26].

From Equation 2, bridge resilience (R) is determined by computing the area under the performance indicator function subsequent to the occurrence of the hazard. This corresponds to integrating the performance indicator function over time, starting from the onset of the hazard (t_h) until the conclusion of the recovery process and the attainment of the new standard operational level (t_r):

$$R(t) = \int_{t_h}^{t_r} \bar{Q}(t)dt \quad (3)$$

3.2. Resilience estimation using Bayesian Neural Network

ML methodologies, as explored in this study, offer a chance to enhance resilience modeling and mitigate certain simplifications that were previously unavoidable. ML techniques like artificial neural networks can alleviate the computational constraints that imposed some limitations during the development of fragilities. This capability stems from ML algorithms' capacity to conduct regression analysis on extensive datasets by identifying emerging patterns and learning from their mistakes.

The BNN model, crafted through the methodology outlined in this research, is deployed to the representative highway bridges, enabling the estimation of seismic resilience metrics tailored to each bridge's specifications. A wealth of bridge-specific data, encompassing geometric attributes, material properties, and seismic loading parameters, serves as input to the BNN model, facilitating the prediction of resilience outcomes (refer to Fig. 2). In this regard, we considered the following list of 16 input variable: soil type, girder type, span length, column height, deck width, superstructure depth, number of columns per bent, column diameter, reinforcement ratio, abutment height, foundational translational and rotational stiffness, concrete strength, reinforcement strength, abutment stiffness, and Peak Ground Acceleration (PGA). The model's application yields a spectrum of resilience metrics, including fragility curves, damage probabilities, and post-earthquake functionality assessments, furnishing critical insights into the vulnerability of highway bridges to seismic events and the ensuing ramifications for transportation network functionality.

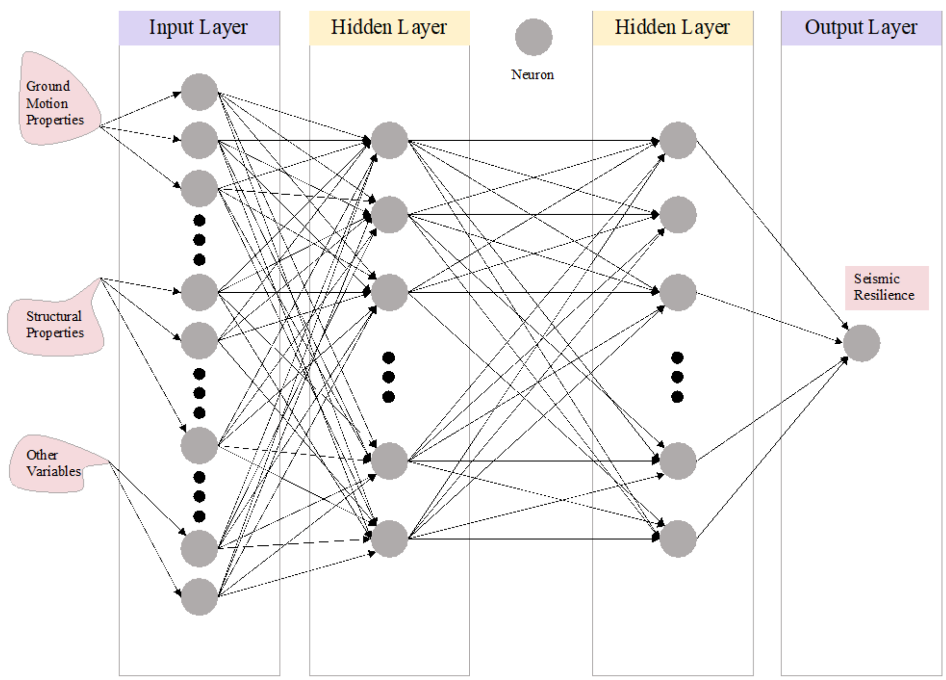

Fig. 2: Standard MLP-style ANN, with fully connected neurons in multiple hidden layers.

Moreover, the case study entails a comparative analysis, pitting the results derived from the BNN-based resilience assessment against those garnered through traditional computational methods. Through this comparative lens, the advantages of the BNN approach come to the fore, encompassing superior accuracy, efficiency, and nuanced uncertainty quantification. Ultimately, the findings derived from the case study offer actionable insights into the seismic resilience landscape of highway bridges, that could pave the path towards serving as a cornerstone for infrastructure resilience planning, risk mitigation strategies, and emergency response preparedness efforts in the future. Through this investigation, the case study underscores the promising role of BNN modeling in infrastructure resilience assessment and decision-making endeavors in seismic hazard-prone regions.

4. Results and Discussion

The optimal BNN architecture identified for this problem consists of two hidden layers, each containing 32 neurons, utilizing a rectified linear activation function, a commonly used ANN activation function. The Adam optimizer, a popular choice for ANN optimization, was employed due to its computational efficiency, particularly suitable for datasets with large volumes of data and parameters. Training involved 50 epochs, with each epoch iterating over the entire test set using a 2% step without replacement, ensuring no duplication of training data within the same epoch. The training data comprised 80% of the original dataset, while the test data comprised 16% and the validation data comprised 4%. To facilitate comparison, a separate ANN with the same architecture but without Bayesian inference incorporation was also created.

The ANN-based model demonstrated a validation data resilience prediction accuracy of 89.4% and a test data accuracy of 91.1%. Upon evaluating various standard deviations ranging from 0.01 to 0.50, we found that a standard deviation of 0.01 yielded the highest levels of test and validation accuracy within the given range. The Bayesian distribution yielding optimal accuracy in both validation and test sets exhibited a mean of zero and a standard deviation of 0.01, yielding average accuracies of 86.4% and 82.9%, respectively, as depicted in Fig. 3. These accuracies were slightly lower than those achieved by the standard ANN structure. Despite having the same network architecture, the Bayesian model necessitated significantly longer training times compared to the ANN. This disparity can be attributed to the BNN's inherent complexity, which demands continuous value spectrum computation for each parameter, thereby imposing a higher computational burden relative to an equivalent-dimensional ANN. In general, the BNN model exhibited accuracy values comparable to those of the ANN, with the added advantage of mitigating the overfitting problem often encountered in ANN models.

In comparison with traditional computational methods, the BNN approach demonstrates notable advantages in terms of accuracy, efficiency, and uncertainty quantification. By leveraging Bayesian inference techniques, the BNN model effectively captures the inherent uncertainties in seismic hazard modeling and bridge response prediction, thereby enhancing the reliability of resilience assessments. The results highlight the potential of advanced ML methodologies, such as BNNs, in revolutionizing infrastructure resilience assessment practices, offering more robust and interpretable predictions.

Despite the advancements facilitated by the BNN framework, several limitations and avenues for future research warrant consideration. Model uncertainties stemming from inherent complexities in seismic hazard modeling and data limitations underscore the need for continued refinement and validation of the BNN model. Moreover, efforts to enhance data availability, quality, and interoperability are essential for improving the accuracy and robustness of resilience assessments. Future research directions may focus on refining the BNN model architecture, integrating additional data sources, and exploring innovative ML techniques to further advance the state-of-the-art in infrastructure resilience assessment methodologies.

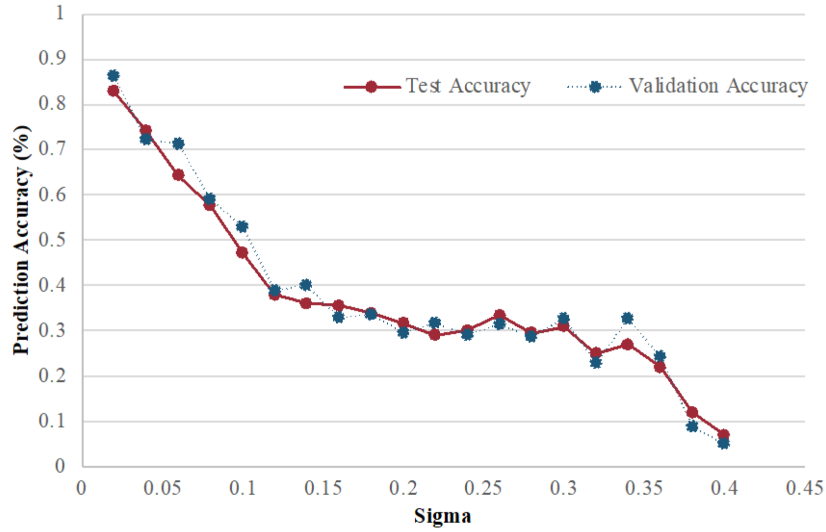

Fig. 3: Model accuracy on test and validation data for different Bayesian standard deviation inputs in BNN model

5. Conclusion

In conclusion, the seismic resilience assessment of highway bridges utilizing the Bayesian Neural Network (BNN) framework tested in this work, showed promising results compared to the traditional finite-element-based approach. This project found the key advantages of BNN-based resilience estimations over traditional calculations as lower computational costs, a multi-parametrized resilience model, elimination of the need for finite element modeling of complex structures, avoidance of nonlinear time history analyses, and a reduction in human errors associated with the process. In essence, this results in a potentially more dependable estimation of resilience. Moreover, the BNN approach accounts for various sources of uncertainty in the estimation process, treating them as random input variables within the framework.

This work primarily contributes to the advancement in infrastructure resilience assessment methodologies. The findings offer broader impacts on actionable insights into vulnerability, damage probabilities, and post-earthquake functionality metrics, highlighting the transformative potential of advanced computational methods in addressing the multifaceted challenges posed by seismic hazards. The resilience assessment findings inform infrastructure planning, risk mitigation, and emergency preparedness efforts, guiding prioritization of retrofitting measures in vulnerable regions or bridge types. Additionally, they facilitate targeted risk mitigation strategies, enhancing design standards and emergency response protocols to bolster infrastructure resilience and mitigate societal impacts of seismic disasters. Through ongoing efforts to refine model architecture, enhance data quality, and address uncertainties, future research endeavors may further advance infrastructure resilience assessment practices, ultimately contributing to the safety, reliability, and resilience of transportation networks and communities.

Acknowledgements

The authors acknowledge the support and funding provided by the School of Civil and Construction Engineering at Oregon State University.

References

[1] M. Bruneau and A. Reinhorn, “Overview of the Resilience Concept,” 8th US Natl. Conf. Earthq. Eng., no. Paper No. 2040, Apr. 2006.

[2] G. P. Cimellaro, A. M. Reinhorn, and M. Bruneau, “Framework for analytical quantification of disaster resilience,” Eng. Struct., vol. 32, no. 11, pp. 3639–3649, Nov. 2010, doi: 10.1016/j.engstruct.2010.08.008.
[3] F. Soleimani and D. Hajializadeh, “Bridge seismic hazard resilience assessment with ensemble machine learning,” Structures, vol. 38, pp. 719–732, Apr. 2022, doi: 10.1016/j.istruc.2022.02.013.
[4] Soleimani F, Vidakovic B, DesRoches R, Padgett J. Identification of the significant uncertain parameters in the seismic response of irregular bridges. Engineering Structures. 2017 Jun 15;141:356-72.
[5] Xie Y, Ebad Sichani M, Padgett JE, DesRoches R. The promise of implementing machine learning in earthquake engineering: A state-of-the-art review. Earthquake Spectra. 2020 Nov;36(4):1769-801.
[6] Mangalathu S, Sun H, Nweke CC, Yi Z, Burton HV. Classifying earthquake damage to buildings using machine learning. Earthquake Spectra. 2020 Feb;36(1):183-208.
[7] F. Soleimani, “Probabilistic seismic analysis of bridges through machine learning approaches,” Structures, vol. 38, pp. 157–167, Apr. 2022, doi: 10.1016/j.istruc.2022.02.006.
[8] Jeon, Jong-Su, and Taehyo Park. "Seismic fragilities of curved concrete bridges via bayesian parameter estimation method." In *World Congress on Civil, Structural, and Environmental Engineering*, pp. 1-9. Avestia Publishing, 2017.
[9] Y. Wong, “Why You Shold Use Bayesian Neural Network,” Medium: Towards Data Science. Accessed: Mar. 13, 2024. [Online]. Available: https://towardsdatascience.com/why-you-should-use-bayesian-neural-network-aaf76732c150#:~:text=Bayesian%20neural%20network%20(BNN)%20combines,that%20best%20fit%20the%20data.
[10] Li B, Zhang XS, Li GY, Sichuan U. Improving performance of retention modeling in ion chromatography using Bayesian regularization for neural network training. In7th Asian International Conference of Leather Science and Technology Sect 2006 (Vol. 1).
[11] Hu XH, Zhan LJ, Xue Y, Liu GX, Fan Z. Energy Consumption Forecasting Using United Grey System–Bayesian Regularization Neural Network Model. Advanced Materials Research. 2012 Sep 5;524:3087-92.
[12] Zhang, Xiaodan, Lu Yao, and Zhenxiong Zhou. "Rolling force prediction algorithm based on Bayesian regularization neural network." In *2nd International Conference on Electronics, Network and Computer Engineering (ICENCE 2016)*, pp. 790-795. Atlantis Press, 2016.
[13] Shi J, Li X, Khan F, Chang Y, Zhu Y, Chen G. Artificial bee colony Based Bayesian Regularization Artificial Neural Network approach to model transient flammable cloud dispersion in congested area. Process Safety and Environmental Protection. 2019 Aug 1;128:121-7.
[14] A. Gupta, “Regularization in Machine Learning,” Geeks for Geeks. Accessed: Mar. 04, 2024. [Online]. Available: https://www.geeksforgeeks.org/regularization-in-machine-learning/
[15] V. Mullachery, A. Khera, and A. Husain, “Bayesian Neural Networks,” 2018, doi: 10.48550/ARXIV.1801.07710.
[16] J. Lampinen and A. Vehtari, “Bayesian approach for neural networks—review and case studies,” Neural Netw., vol. 14, no. 3, pp. 257–274, Apr. 2001, doi: 10.1016/S0893-6080(00)00098-8.
[17] J. McCaffrey, “An Example of a Bayesian Neural Network Using PyTorch,” James D. McCaffrey. Accessed: Mar. 04, 2024. [Online]. Available: https://jamesmccaffrey.wordpress.com/2021/08/30/an-example-of-a-bayesian-neural-network-using-pytorch/
[18] “Bayesian Neural Network.” Databricks, Inc. Accessed: Mar. 04, 2024. [Online]. Available: https://www.databricks.com/glossary/bayesian-neural-network
[19] M. White, “What are the pros and cons of Bayesian and neural network machine learning algorithms?,” Quora. Accessed: Mar. 04, 2024. [Online]. Available: https://www.quora.com/What-are-the-pros-and-cons-of-Bayesian-and-neural-network-machine-learning-algorithms#:~:text=Limited%20scalability%3A%20Due%20to%20their,function%20of%20the%20human%20brain.
[20] Harry24k, “Bayesian-Neural-Network-Pytorch.” Accessed: Mar. 04, 2024. [Online]. Available: https://github.com/Harry24k/bayesian-neural-network-pytorch.
[21] K. Ramanathan, J. E. Padgett, and R. DesRoches, “Temporal evolution of seismic fragility curves for concrete box-girder bridges in California,” Eng. Struct., vol. 97, pp. 29–46, Aug. 2015, doi: 10.1016/j.engstruct.2015.03.069.

[22] F. Soleimani, “Fragility of California bridges-development of modification factors,” Doctoral Dissertation, Georgia Institute of Technology, Georgia, 2017.
[23] Gidaris, I., Padgett, J. E., Barbosa, A. R., Chen, S., Cox, D., Webb, B., & Cerato, A. (2017). Multiple-hazard fragility and restoration models of highway bridges for regional risk and resilience assessment in the United States: State-of-the-art review. Journal of structural engineering, 143(3), 04016188.
[24] J. Zhang, Y. Huo, S. J. Brandenberg, and P. Kashighandi, “Effects of structural characterizations on fragility functions of bridges subject to seismic shaking and lateral spreading,” Earthq. Eng. Eng. Vib., vol. 7, no. 4, pp. 369–382, Dec. 2008, doi: 10.1007/s11803-008-1009-2.
[25] A. K. Agrawal, M. Ghosn, S. Alampalli, and Y. Pan, “Seismic Fragility of Retrofitted Multispan Continuous Steel Bridges in New York,” J. Bridge Eng., vol. 17, no. 4, pp. 562–575, Jul. 2012, doi: 10.1061/(ASCE)BE.1943-5592.0000290.
[26] Hazus-MH, “Multi-Hazard Loss Estimation Methodology: Earthquake Model Hazus-MH MR5 Technical Manual.” Federal Emergency Management Agency (FEMA), 2011.