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ADVANCING SEISMIC RISK ASSESSMENT: LEVERAGING PRE-TRAINED NEURAL NETWORKS FOR SEISMIC FRAGILITY MODELS

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Abstract. Fragility curves are indispensable for quantifying the seismic risk of highway bridges, offering critical insights into the resilience and safety of transportation networks in earthquake-prone regions. Existing methodologies for developing fragility curves rely heavily on extensive post-event reconnaissance data or computationally intensive numerical simulation, posing significant challenges due to high resource demands and time constraints. While recent advancements in machine learning-based fragility models have introduced alternative approaches that reduce computational overhead, these methods typically require large training datasets, which are often inaccessible for older bridge structures or regions with limited seismic data. To address these challenges, this study introduces a novel transfer-learning-based fragility modeling framework designed to minimize data requirements without compromising accuracy or generalizability. The proposed approach leverages a sequential neural network pre-trained on a large fragility analysis dataset and fine-tunes it using a smaller, region-specific dataset of earlier bridge designs. By freezing all but the output layer and bottom-most hidden layers during fine-tuning, the transfer learning process effectively tailors the model to predict damage probabilities for underrepresented bridges while preserving the learned representations from the larger dataset. The model's performance was rigorously validated against traditional analytical fragility curves using R-squared values, demonstrating substantial improvements in predictive accuracy compared to models trained solely on smaller datasets. Ten-fold cross-validation confirmed the framework's robustness, ensuring generalizability without overfitting, even with limited training data. This innovative transfer learning approach offers a scalable, effective, and data-efficient solution for seismic fragility analysis, addressing critical data limitations while enhancing the accuracy of risk assessments. By enabling informed decision-making, this methodology contributes to the resilience of transportation infrastructure, supporting the design, retrofitting, and maintenance of highway bridges in seismic regions and promoting sustainable, disaster-resilient communities.

1 INTRODUCTION

Highway bridges are critical components of transportation networks and are particularly vulnerable to damage when subjected to ground shaking events. Such damage poses a risk of substantial economic impact, specifically in earthquake-prone regions. As a result, there has been a growing emphasis on developing advanced methodologies to assess the ability of existing infrastructure to withstand earthquakes. Among these methods, fragility models, which provide an estimate of the probability of exceeding a specific limit state threshold for a given earthquake intensity [1], have emerged as a key tool. The most prevalent approach used to derive fragility curves in recent literature is the analytical method, in which finite element modeling is employed to generate probabilistic seismic demand models (PSDMs) as part of the process [2, 3, 4]. Due to the relatively large amount of data required from nonlinear dynamic simulations and finite element analyses for the analytical approach, it can be computationally expensive and time-consuming to create reliable fragility curves, and alternative approaches with reduced computational cost and comparable accuracy are desirable. In this context, machine learning (ML) techniques have gained popularity for developing fragility models across various structure types. Although ML-based approaches can enhance prediction accuracy, they still generally require large training datasets to achieve reliable performance. This limitation is particularly challenging in scenarios where data is scarce or expensive to obtain.

To address these challenges, the objectives of the present study are twofold: (1) to develop multi-parameter ML-based fragility models that are capable of predicting bridge-specific results; and (2) to investigate the effectiveness of transfer learning techniques in generating accurate fragility models under data-limited conditions. To achieve these goals, fragility curves are developed for California (CA) box girder bridges across two distinct design eras, and artificial neural networks (ANNs) are trained to estimate the probability of exceeding various damage states based on bridge parameters and ground motion intensity measures. Subsequently, fragility curves for a third design era are constructed, and transfer learning is applied to adapt the pretrained ANN models for fragility prediction on this new dataset.

The following sections provide a detailed overview of the fragility curve generation process and the development and training of the neural network models.

2 LITERATURE REVIEW

In recent years, the implementation of ML techniques in probabilistic seismic assessment has gained significant traction in the earthquake engineering community [5-13]. For fragility analysis, a common use for ML methods is to develop surrogate models for structural seismic demands to reduce the computational cost associated with the complex nonlinear finite element modeling that previous methods rely upon [8, 14, 15, 16, 17, 18, 19, 20]. For highway bridges in particular, several studies have demonstrated the effectiveness of ML-based approaches in fragility modeling. Pang et al. [16] found that accurate fragility curves could be developed with significantly less data by training an ANN to predict incremental dynamic analysis (IDA) results. Similarly, Mangalathu and Jeon [15] used an ANN-based demand model to develop multi-parameter fragility curves for box-girder bridges and found that it performed better than traditional PSDM methods, even when attributes from several statistically different bridge classes were mixed together. Soleimani and Liu [17] further demonstrated that ANNs can effectively predict seismic demands for box-girder bridges and found that the complex nonlinear characteristics inherently involved in PSDMs were modeled efficiently and without systemic bias. This study also demonstrated that compared to classical regression-based models, the ANN-based models better capture the small and large values of median seismic demand. Another study attempted to use several ML models to directly predict the fragility curve parameters for buildings and found that ANNs reliably performed well, with an R^2 of 0.91 for predictions of the median and 0.75 for predictions of the dispersion [21].

Although the results of these studies have shown great promise for the implementation of ML methods in probabilistic seismic assessment, a persistent challenge in the use of ML for seismic fragility modeling is the need for large datasets to train and validate models. A potential solution lies in the use of transfer learning (TL), an ML paradigm that leverages knowledge from a well-trained model on a source dataset to improve learning on a related, often smaller, target dataset [22]. While several studies have been conducted using TL for structural engineering purposes [23, 24], its applications in probabilistic seismic assessment remain limited and have not been thoroughly explored.

To address this gap, the present study proposes a transfer learning framework tailored to predicting bridge fragility curves in data-scarce environments. The aim is to evaluate whether knowledge gained from data-rich bridge classes can be effectively transferred to develop reliable fragility models for bridges with limited seismic data.

3 METHODOLOGY

3.1 Dataset generation: bridge fragility curve framework

The dataset used in this study was generated according to the fragility assessment methodology proposed by Nielson and DesRoches [25], using OpenSees models developed by previous research [3, 4]. Specifically, unique bridge models from each design era (Era 1: pre-1971, Era 2: 1971-1990, Era 3: post-1990) were generated and randomly paired with one of the 160 ground motions (GMs) in the Baker suite, and a nonlinear time history (NLTH) analysis was performed for every bridge-GM pair to capture seismic demands. To expand the range of intensity measures (IMs), each ground motion was additionally scaled by a factor of two, effectively doubling its peak ground acceleration (PGA). This ensured adequate coverage of higher IM levels. The peak structural responses for all critical bridge components were extracted from each analysis. Subsequently, PSDMs were developed for each component according to the methodology prescribed in Cornell et al. [1]. These models relate seismic demands to IMs and serve as the foundation for deriving fragility curves. The component capacity models used in this study are the same as those described by Ramanathan [3].

Using these PSDMs and capacity models, component fragility curves were evaluated using Eq. (1).

$$P[D > C|IM] = \Phi\left(\frac{\ln(s_D/s_C)}{\sqrt{\beta_{D|IM}^2 + \beta_C^2}}\right) \quad (1)$$

In Eq. (1), D is component demand and C is component capacity; S_D and S_C are the demand and capacity medians, and β_D and β_C are the dispersions for demand and capacity, respectively. The fragility of the entire system was then estimated by developing a joint probabilistic seismic demand model and using a Monte Carlo simulation to compare realizations of demand and component capacities. Samples from both the demand and capacity models were taken and the probability of demand exceeding capacity for a particular *IM* value was evaluated. The procedure was repeated for increasing values of the *IM* and regression analysis was used to estimate the lognormal parameters of system fragility. Finally, the probability of a given bridge reaching a specified damage state was calculated using Eq. (2),

$$P[BSST_i > BSST_k | IM_i] = \Phi(\frac{\ln(IM_i/\mu_k)}{\beta_k}) \tag{2}$$

where $BSST_i$ is the damage state of the bridge in question, $BSST_k$ is the target damage state, IM_i is the intensity measure associated with the ground motion applied to that bridge in question during the NLTH phase, and μ_k and β_k are the lognormal distribution parameters of the fragility curve for the target damage state. The probability of each bridge sample from the NLTH phase reaching each of the four damage states was evaluated and used as training data for the ML models in this study.

3.2 Data preprocessing

For each bridge sample, 19 input parameters representing material, geometric, structural, and ground motion properties were used to train the ANN model. According to the statistical models for these parameters described in previous studies [3], several of these variables were transformed into logarithmic space to ensure that the resulting input features were approximately normally or uniformly distributed, thereby facilitating effective model training. A complete list of the input parameters is provided in Table 1. The correlation matrix for the input features in the source dataset is shown in Figure 1. While several features exhibit strong collinearity—typically undesirable for statistical modeling—there was no clear engineering basis to eliminate any of the correlated variables. To address potential issues arising from multicollinearity, a regularization strategy was incorporated into the ANN training process, mitigating its impact on model performance.

Table 1: Model input parameters

Parameter	Description	Parameter	Description
x_1	Soil type (class)	x_{11}	Foundation translational stiffness (k/in)
x_2	Span length (ft)	x_{12}	Foundation rotational stiffness (k-in/rad)
x_3	Column height (ft)	x_{13}	Concrete strength (ksi)
x_4	Deck width (ft)	x_{14}	Steel strength (ksi)
x_5	Girder spacing (in)	x_{15}	Abutment stiffness (k/in)
x_6	Top flange thickness (in)	x_{16}	Mass factor
x_7	Bottom flange thickness (in)	x_{17}	Damping ratio (%)
x_8	Girder depth (in)	x_{18}	Peak ground acceleration (g)
x_9	Number of columns per bent	x_{19}	Column reinforcement ration (%)
x_{10}	Abutment height (ft)		

Each parameter was scaled linearly using the Min-Max scaling approach, transforming values to a range of 0 to 1. This ensures equal contribution of features to the model and has been shown to significantly reduce estimation errors in neural networks [26]. A case study was conducted in this research to address the data scarcity issue for older bridges. Specifically, bridge fragility data from Era 2 and Era 3 were used as the source set (containing 640 samples) to develop the base model. Additionally, 160 samples from Era 1 were used as the target set to evaluate whether the proposed transfer learning framework could effectively create predictive models for older bridge cases.

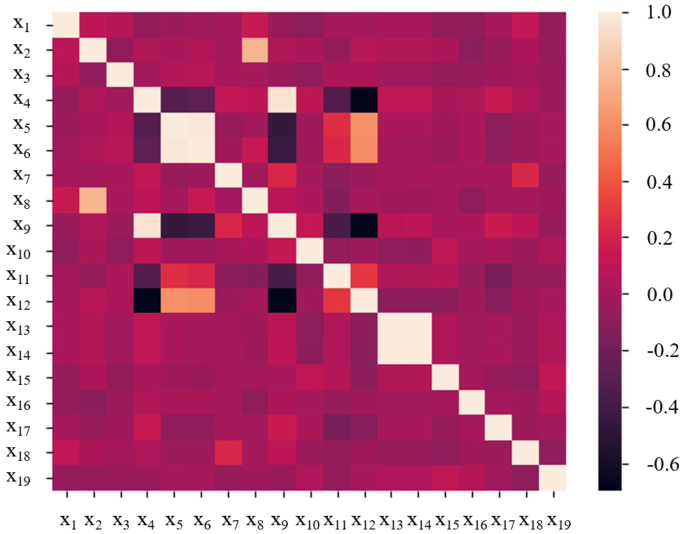

Figure 1: Correlation matrix for model input features

3.3 Transfer learning overview

The method of TL employed in this study involves pre-training ANN models on the source dataset, then freezing most of the model parameters and retraining on the target dataset. A schematic of an example TL scheme is shown in Figure 2, which depicts a typical regression ANN architecture consisting of an input layer, several hidden layers, and an output layer.

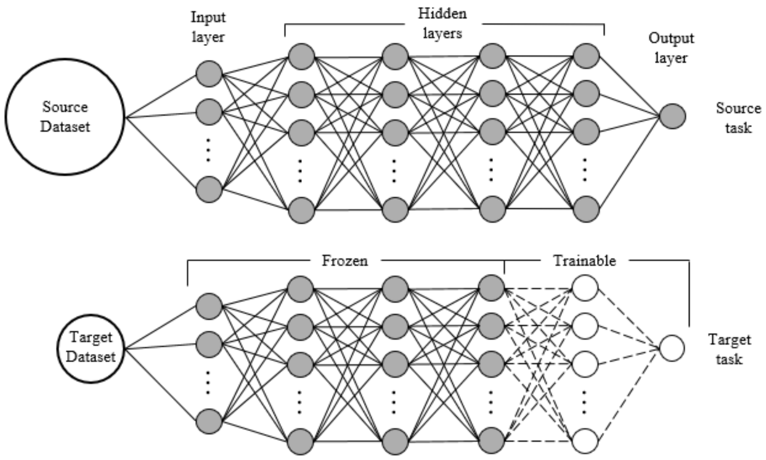

Figure 2: Example schematic of transfer learning process

Each layer is composed of a set of neurons each with an associated weight, bias, and activation function. During training, the weights and biases are adjusted to minimize a specified loss metric. By freezing all but the bottom-most (i.e., those nearest to the output) layers, much of the knowledge acquired from the larger source dataset can be retained while the remaining trainable parameters adapt the model to the smaller target dataset.

4 RESULTS

4.1 Model architecture and hyperparameter tuning

The primary goal of TL is to leverage a well-trained model to make reliable predictions on a target dataset that would typically be too limited in size to support robust model training independently. Thus, the initial step towards developing a TL framework was to develop an ANN model capable of predicting system-level fragility values for the source set. A grid search type algorithm was used to determine the ideal network architecture by exhaustively trying each combination of network depth and layer width selected from predefined candidate lists. For each combination, the model's performance was evaluated using the average R-squared value from 10-fold cross-validation. The results of this search, including performance trends across different configurations, are summarized in Figure 3.

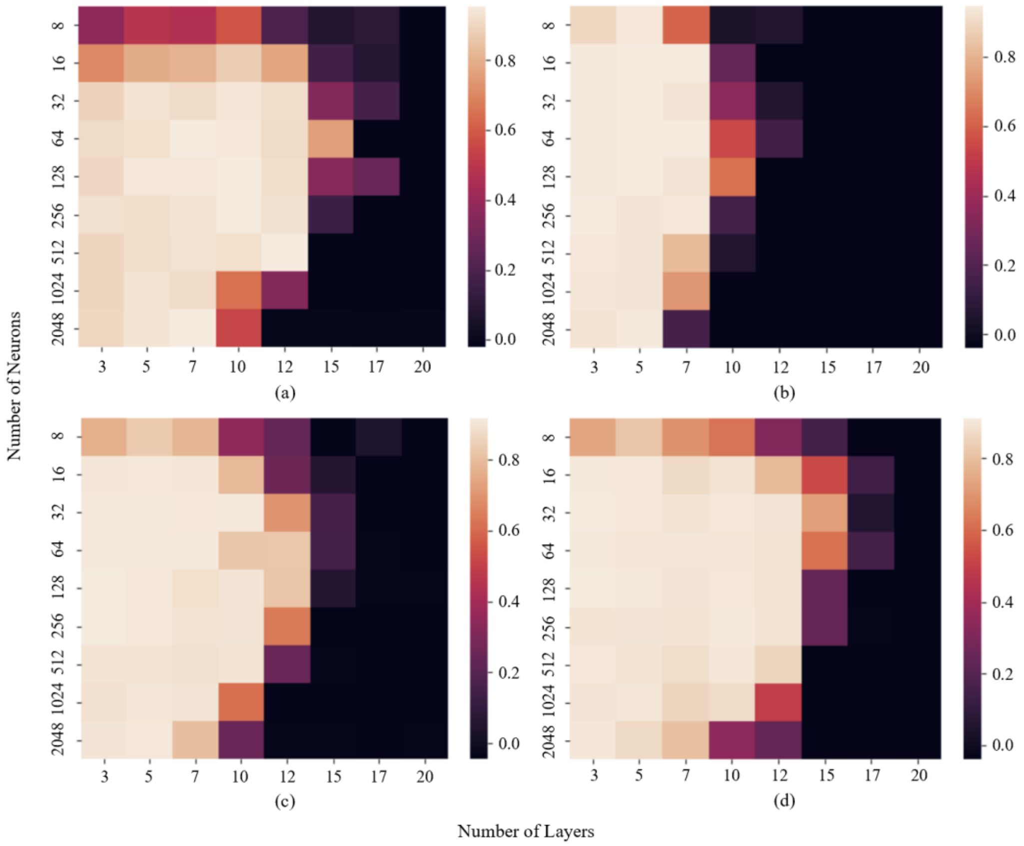

Figure 3: Optimization of model architecture on the source data set for (a) BSST-0, (b) BSST-1, (c) BSST-2, (d) BSST-3

As shown in Figure 3, many candidate ANN architectures yielded comparable performance across a broad range of model depths and layer sizes. To narrow down the possible architectures for the final model, a similar grid search algorithm was applied for the target dataset, and the results were compared against those from models trained exclusively on the source data. For each architecture, the model was first trained on the entire source dataset. Following this, a TL procedure was applied in which the model was fine-tuned on the target data. Specifically, all layers except the output layer and bottom-most hidden layer(s) were frozen to preserve learned representations from the source domain, and the model was retrained on the target data. The number of layers left unfrozen was determined relative to the total depth of the model: the output layer and last hidden layer were always unfrozen, and for models with 10 or more hidden layers, one additional layer was unfrozen for every five layers, ensuring that no more than 20% of the layers were retrained. This strategy aimed to balance knowledge retention from the source model with adaptability to the target dataset. Model performance was evaluated using 10-fold cross-validation on the target data only, and the resulting average R-squared values from each test are presented in Figure 4.

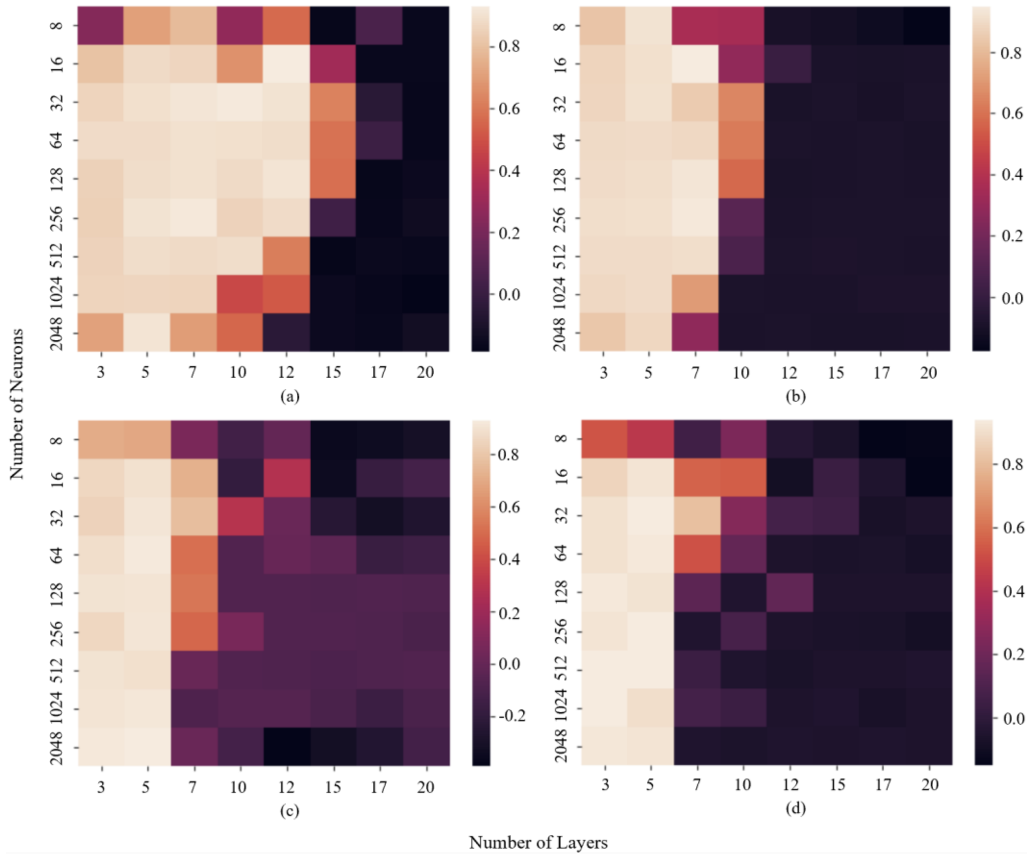

Figure 4: Optimization of model architecture on the target data set for (a) BSST-0, (b) BSST-1, (c) BSST-2, (d) BSST-3

As shown in Figure 4, deeper ANN models generally exhibited lower performance in the TL setting compared to shallower architectures. Among the tested configurations, the model with five hidden layers and 64 neurons per layer consistently ranked among the top performers across both the source and target datasets. This architecture was therefore selected as the final model for further evaluation.

With the final model architecture established, the next step involved tuning key hyperparameters, including activation functions, regularization technique and coefficient, and the number of training epochs. Given their widespread use in ANN applications, both the rectified linear unit (ReLU) and sigmoid activation functions were considered. Several configurations were evaluated using the source dataset, and the comparative results are summarized in Table 2.

Table 2: Average R-squared from 10-fold CV for considered activation function configurations

Hidden layer activation	Output layer activation	Average R-squared			
		BSST-0	BSST-1	BSST-2	BSST-3
ReLU	ReLU	0.84	0.69	0.69	0.67
ReLU	Sigmoid	0.94	0.94	0.91	0.89
Sigmoid	Sigmoid	-0.037	-0.024	-0.011	-0.013
Sigmoid	ReLU	-3.42	-0.73	-0.93	-0.29

The configuration with ReLU activation for the hidden layers and sigmoid activation for the output layer performed the best and was selected for the final model. Two regularization techniques were also tested for this model: Lasso (L1) and Ridge (L2). These regularizers apply a penalty term to each layer of the model to prevent overfitting by reducing reliance on certain features or patterns. Figure 5 shows the average R-squared value from 10-fold cross validation for a range of coefficients of L1 and L2 regularization.

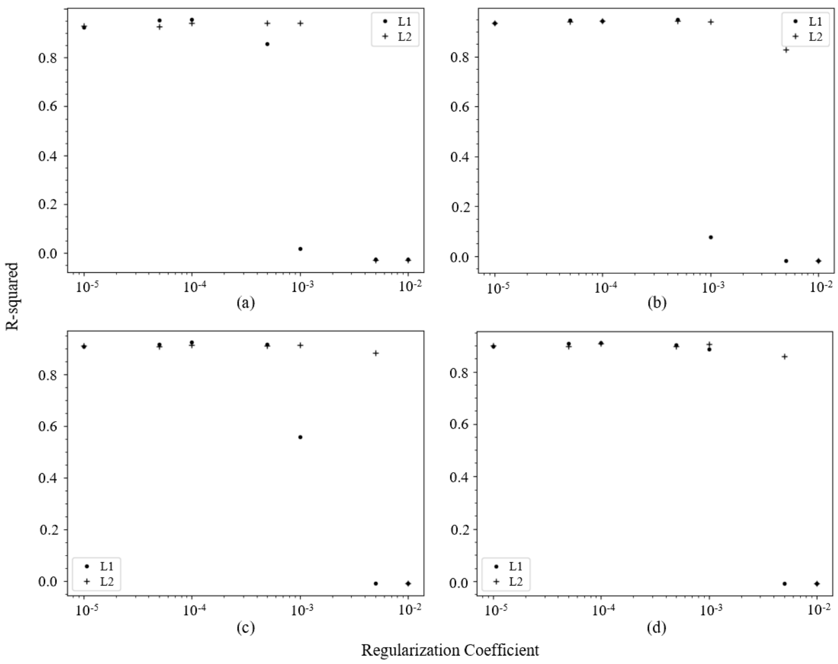

Figure 5: Average R-squared versus regularization coefficient for L1 and L2 regularizers for (a) BSST-0, (b) BSST-1, (c) BSST-2, (d) BSST-3

From Figure 5, it can be seen that for very low regularization values, both methods perform relatively consistently. This is likely because the coefficients are so small that regularization is not impacting the model meaningfully. For values greater than 5E-4, the performance of the model trained with an L1 regularization term declines significantly. The model trained with an L2 regularization term also performs worse as the coefficient increases but maintains a high R-squared up to a value of 1E-3. Because the source data is known to have some multi-collinearity, an L2 regularizer with a coefficient of 1E-3 was included in the final model to help prevent possible overfitting.

Finally, the ideal number of training epochs for both the source set and the target set were determined by training the models over a wide range of epochs. Learning curves for BSST-0, based on both the source and target dataset, are shown in Figure 6. Similar curves were developed for the other three damage states and used to select the number of training epochs.

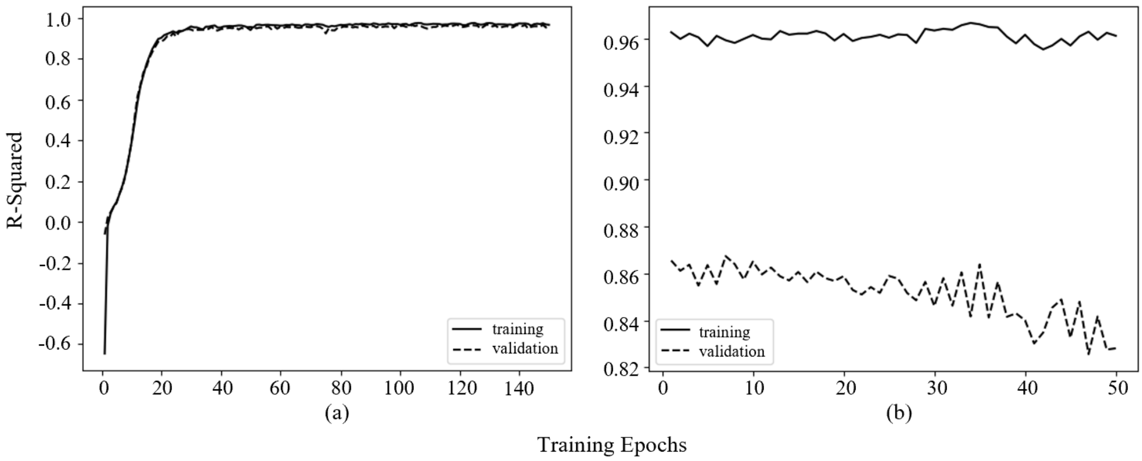

Figure 6: Average R-squared versus number of training epochs at BSST-0 for (a) source dataset only and (b) TL to target dataset

From Figure 6 (a), it is observed that after approximately 40 epochs the R-squared on training and validation data stops improving, and this pattern held true for all bridge damage states. For testing the ideal number of epochs to train the unfrozen layers of the TL models for, the base models were first trained for 40 epochs on the source data, then tested over a range of epochs on the target data. Figure 6 (b) shows the results of a TL model when training the last hidden for an increasing number of epochs. The TL model performs well even with very few training epochs, but it should be noted that the output layer was trained for 100 epochs prior to the hidden layer being trained. The validation R-squared generally decreases as the hidden layer is trained more, potentially indicating overfitting or an inability of the limited target dataset to support deeper model adaptation. Like the model trained only on the source dataset, this pattern is consistent for all three damage states BSST-1, BSST-2, and BSST-3. As the models consistently achieved their highest R-squared through 10 hidden layer training epochs, this configuration was selected for the final model to maintain optimal predictive performance while minimizing the risk of overfitting.

4.2 Final model results

The final neural network architecture selected for this study consists of an input layer with 19 neurons, followed by five hidden layers, each containing 64 neurons, and a single-neuron output layer. The neurons in the hidden layers employ a ReLU activation function and an L2 regularization term with a coefficient of 1E-3 to mitigate overfitting. The output layer employs a sigmoid activation function, enabling the prediction of probabilities associated with exceeding specified damage states. The model is trained using the Adam optimizer and mean squared error as the loss metric.

For the TL process, the model was initially trained for 40 epochs on a source dataset consisting of bridge parameters and fragility values for CA box-girder bridges designed after 1971, then frozen. The output layer was then unfrozen and trained for 100 epochs on a target dataset consisting of bridge parameters and fragility values for CA box-girder bridges designed prior to 1971. Next, the bottom-most hidden layer was unfrozen, and the model was trained for another 10 epochs on the target dataset. The predictive performance of the model for estimating fragility values on the target dataset is summarized in Table 3, along with the performance of a baseline model with the same architecture trained solely on the target dataset without employing TL.

Table 3: Model performance without transfer learning on source and target data and with transfer learning on target data

	No Transfer Learning				With Transfer Learning	
	Source		Target			
	R^2	MSE	R^2	MSE	R^2	MSE
BSST-0	0.960	0.0285	0.110	0.0953	0.864	0.0125
BSST-1	0.954	0.0470	0.105	0.1114	0.890	0.0102
BSST-2	0.921	0.0367	0.406	0.1003	0.900	0.0075
BSST-3	0.899	0.0322	0.357	0.1162	0.947	0.0068

5 CONCLUSION

The development of fragility curves for highway bridges using traditional analytical methods is often both time-consuming and computationally intensive. Recent studies have demonstrated that ML techniques can serve as effective surrogate models, capable of capturing the complex nonlinear behavior inherent in probabilistic seismic demand modeling while requiring significantly less data than conventional approaches. Nevertheless, the performance of ML models still heavily depends on the availability of large, high-quality datasets for training and validation.

This study aimed to address this limitation by investigating the feasibility of applying TL techniques to seismic fragility assessment of highway bridges. In TL, knowledge gained from a well-labeled, data-rich source domain is leveraged to improve model performance in a data-scarce target domain. In this case, an ANN was first trained to predict fragility values on a source dataset of 640 bridge samples designed after 1971, and subsequently adapted to predict fragility values for a target dataset of 160 bridge samples designed prior to 1971. The adapted model achieved strong predictive performance and was able to reliably predict the probability of unseen bridge samples reaching each damage state with an R-squared of at least 0.86 across all damage states, compared to a significantly lower maximum R-squared of only 0.41 for a model trained solely on the target dataset. An additional advantage of this approach is its ability to generate bridge-specific fragility estimates by incorporating structural, geometric, and material properties—unlike traditional fragility models that are typically conditioned on a single intensity measure and generalized to an entire bridge class. Moreover, the proposed TL framework is agnostic to the fragility data source, meaning source and target data could be acquired from empirical, expert-based, or analytical fragility curves.

This initial application was limited to two-span box-girder bridges with rigid diaphragm abutments designed in California, with knowledge transfer confined to bridge design eras. Future research should explore the generalizability of this framework to other bridge types (e.g., T-girder, I-girder, slab bridges) and evaluate its applicability across geographically distinct regions, accounting for variations in seismic hazard and design practices. Further studies should also investigate modeling parameters in greater detail, including the optimization scheme and loss metric, as well as the influence of source and target dataset sizes.

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