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Artificial neural network based multi-dimensional fragility development of skewed concrete bridge classes

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ABSTRACT

Recent researches are directed towards the regional seismic risk assessment of structures based on a bridge inventory analysis. The framework for traditional regional risk assessments consists of grouping the bridge classes and generating fragility relationships for each bridge class. However, identifying the bridge attributes that dictate the statistically different performances of bridges is often challenging. These attributes also vary depending on the demand parameter under consideration. This paper suggests a multi-parameter fragility methodology using artificial neural network to generate bridge-specific fragility curves without grouping the bridge classes. The proposed methodology helps identify the relative importance of each uncertain parameter on the fragility curves. Results from the case study of skewed box-girder bridges reveal that the ground motion intensity measure, span length, and column longitudinal reinforcement ratio have a significant influence on the seismic fragility of this bridge class.

1. Introduction

One common approach to assess the seismic vulnerability is through the derivation of fragility curves. Fragility curves gives the likelihood that a structure or its components will reach a certain level of damage for a given ground motion intensity measure (IM). The usual strategy adopted to generate bridge class fragilities is to bin the bridges that have statistically similar performances and sample bridge classes in each group accounting for the variation in structural, material, and geometric attributes, and generate the fragility curves.

Numerous studies have been carried out to group bridge classes and suggest their fragility relationships [1–9]. HAZUS [1] is the most comprehensive document in grouping the bridge classes and suggested fragility relationships. However, the fragility relationships suggested in HAZUS are based on simple two-dimensional (2-D) analyses of bridges and do not reflect the material, structural, and geometric uncertainties. Mangalathu et al. [2] outlined the limitations of HAZUS fragilities such as the grouping of bridge classes based on engineering judgement and the use of capacity spectrum method to generate the fragility curves. Mackie and Stojadinovic [3] partially addressed the limitation of HAZUS and suggested fragility relationships for some specific bridge classes accounting for the variation in geometric properties. Banerjee and Shinozuka [4,5] suggested fragility relationships for bridge classes by grouping the bridge classes based on the number of spans (single versus multiple), bent type (single versus multiple), and skew angle (negligible versus significant, chosen to be > 30°). Ramanathan [6] classified the bridge classes in California based on the superstructure type, number of columns, design era, and abutment configurations, and suggested their fragility relationships. As noted by Mangalathu et al. [7], the above mentioned studies classified the bridge classes based on the engineering judgment which is subjective. These authors suggested a performance-based grouping based on a statistical technique called analysis of covariance. However, the scope of their study was limited to grouping bridge classes, not the generation of fragility curves. Mangalathu [8] suggested fragility relationships of California concrete bridges after grouping the bridge classes based on the structural response via the analysis of variance. This author classified the bridge classes based on the abutment type, pier-type, number of spans, column cross-section, span continuity, and seismic design. In all the aforementioned studies, the fragility relationships were conditioned only on IM. However, recent researches [10–13] highlighted that the fragility relationships conditioned on a single parameter (IM) might not be enough to capture uncertainties associated with other input parameters. The single-parameter fragility curves also suffer the limitation that it requires extensive re-simulation to update the fragility curves for a new set of input parameters.

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To mitigate the limitations of traditional single-dimensional fragility curves, recent researches [10–17] suggested multi-dimensional fragility curves, i.e., the fragility relationships are conditioned on input parameters including uncertain geometric, material, and structural parameters, in addition to IM. The multi-parameter fragility curves are generated using logistic regression on the demand-to-capacity estimates. However, the multi-parameter fragility curves are generated after an initial classification of bridges based on either engineering judgment or statistical performance. The performance based grouping of bridge classes is not always possible if one would like to perform the regional risk assessment of bridges with less computational efforts. As noted by Mangalathu [8], bridge attributes that dictate the bridge performance vary depending on the component under consideration, and the generation of fragility relations for the refined bridge group accounting for all the attributes is computationally expensive.

A few researchers [18–22] applied artificial neural network (ANN) in the field of structural engineering to estimate structural damage and seismic fragilities. ANN is one of machine learning techniques on the basis of a large connection of simple units called neurons, similar to axons in human brain [23]. It consists of an input layer of neurons (or nodes, units), hidden layers of neurons, and a final layer of output neurons. ANN has the capability in capturing the nonlinear behavior, and has an efficient input-out mapping. [23]. Compared to other machine learning methods such as Random Forest, ANN is robust in the presence of noisy or missing inputs and have the adaptively to learn in changing environment [23]. The comparison of the efficiency of ANN with other machine learning techniques is beyond the scope of the current study. Lagaros and Fragiadakis [18] evaluated the application of neural network–based methodology for a rapid estimation of the seismic demand of steel frames. Lautour and Omenzetter [19] explored the application of ANN in evaluating damage indices of 2-D reinforced concrete frames. Mitropoulou and Papadrakakis [20] generated fragility curves for buildings using ANN. The research by these authors pointed out that the computation time in the traditional fragility analysis can be reduced significantly with the use of ANN. Lu and Zhang [21] compared the fragility curve of steel buildings obtained by ANN and finite element analysis (FEA). These authors noted that if a sufficient amount of training data is available (with a set of 500 data points), ANN can produce accurate estimates of fragilities with less computational time compared to FEA. Pang et al. [22] simulated the median value and standard deviation of incremental dynamic analysis curves at various levels of IM using ANN.

This research employs ANN to generate fragility curves for bridge classes in California. Unlike previous studies on the application of machine learning techniques for bridge fragilities [8,10], this research explores the use of ANN without grouping bridge classes based on skew angle, number of spans and columns per bent. Unlike previous studies on the application of machine learning techniques for bridge fragilities [8,10], this research explores the use of ANN without grouping bridge classes based on skew angle, number of spans and columns per bent. Per Mangalathu [8], eight bridges classes with statistically different performances are possible with these combinations (the number of columns per bent: one versus two, abutment skewness: straight versus skewed, the number of spans: two-span versus three-to-four-span). Especially, skewed bridges can be classified into five different bins based on their response: low (0–15°), medium (15–30°), high (30–45°), very high (45–60°), and extreme (60–77°) [24]. The establishment of a predictive equation between uncertain input (modeling) parameters and output (structural response) parameter enable to perform the rapid risk assessment and generation of bridge-specific fragility curves for a set of input parameters. To examine the capability of ANN, this research selects two-span, three-span, and four-span skewed box-girder bridges with single-column and two-column bents and with seat abutments. Thus, 20 (five levels of skew angle × two types of column bent × two numbers of span) bridge classes are possible with these combinations. The skewed bridges occupy more than 60% of the California bridge inventory, and their risk assessment is getting considerable attention these days [24–28]. The scope of the study is limited to seismically designed (constructed after 1970) pre-stressed concrete box-girder bridges with seat abutments.

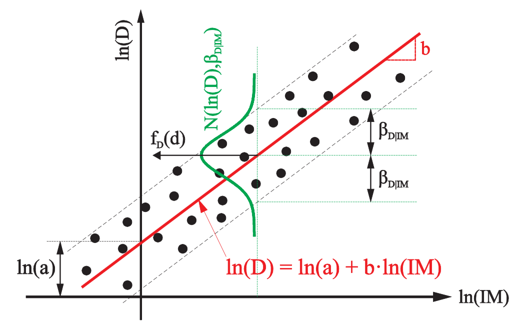

Fig. 1. Illustration of single-parameter PSDM.

2. Proposed probabilistic seismic demand models

2.1. Traditional probabilistic seismic demand models

The probabilistic seismic demand model (PSDM) is a linear regression of pairs of input (demand, *D*) and output (*IM*) variables in the log-transformed space. Fig. 1 shows the scatter plot of the seismic demand or response (*D*) of a bridge group versus the *IM* in the logarithmic space, along with the probability distribution of the seismic demands. Note that the PSDM shown in the figure is single parameterized, i.e., conditioned only on IM. Per Cornell et al. [29], the PSDM can be written as

$$\ln(S_d) = \ln(a) + b\ln(IM) \tag{1}$$

where a and b are the regression coefficients, S_d is the median estimate of the demand in terms of *IM*. The coefficients a and b are obtained by performing a linear regression analysis on *D* and *IM* pairs in the logarithmic space. Dispersion, $\beta_{d|IM}$, is evaluated based on statistical analysis of ln(*D*) and ln(*IM*) pairs:

$$\beta_{d|IM} = \sqrt{\frac{1}{N-2}\sum\nolimits_{i=1}^{N}[\ln(d_i)-\ln(S_d)]^2} \tag{2}$$

where d_i is the demand for the *i*th ground motion and N is the number of dynamic analyses.

2.2. Artificial neural network for probabilistic seismic demand models

ANN is a mathematical model inspired by the organization and functioning of biological neurons. The data from the dynamic analyses are split randomly in this research into a training set (70%), a validation set (15%), and a test set (15%). ANN consists of the input layer, hidden layer, and output layer, as shown in Fig. 2. Each line connecting neurons is associated with a weight. The output (h_i) of the neuron i in the hidden layer is

$$h_i = s\left(\sum_{j=1}^{N} V_{ij}x_j + T_i^{hid}\right) \tag{3}$$

where $s()$ is called the activation or transfer function. N is the number of input neurons, V_{ij} is the weights, x_j is the input value, and T_i^{hid} is the threshold term of hidden neurons. The activation function used in this research is sigmoid to introduce the nonlinearity in the model [23,30] and is defined as

$$s(u) = \frac{1}{1+e^{-u}} \tag{4}$$

The network is trained with the training data to minimize the error function in predicting the demand model, by adjusting the weights