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FRAGILITY CURVES BY SAC FEMA AND ANN METHOD

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ABSTRACT

Performance-based seismic design is the modern approach to earthquake resistant design for buildings. Many parameters involved in seismic design have uncertainty associated with them. Characterizing the probabilistic nature of these parameters can be done through the use of 'Fragility Curves'. A fragility analysis assesses the probability that the seismic demand placed on the structure exceeds the capacity conditioned on a chosen IM representative of the seismic loading. Demand (D) and capacity (C) are assumed to follow a lognormal distribution, and the probability of exceeding a specific damage state for a particular component can be estimated with the standard normal cumulative distribution function as per Cornell et. al. (2002). There is a different approach for fragility analysis using by ANN (Artificial Neural Network Methodology). A two-dimensional building model is analyzed for a set of 30 ground motions, and in each case the peak demand measures (e.g., inter-storey drift etc.) are recorded. Thirty spectrum consistent (IS 1893:2002) time-history data are selected and used for the analyses. A four storeyed (G+3) RC frame designed as per relevant Indian standard is chosen for this study. Fragility curves are drawn based on the above mentioned two approaches and comparison is done based on the results obtained.

Key words: ANN Method, Fragility Curves, Ground Motions, SAC FEMA, Seismic Loading.

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1. INTRODUCTION

Due to the randomness in nature of seismic analysis for structures, it is not always possible to do deterministic approach to get accurate results. Randomness/Uncertainty caused may be due to change in Material properties, Time history data, loading profiles etc. A probabilistic based approach is the most appropriate to account the uncertainties. Fragility curve is probabilistic based approach to represent the safety of the structure incorporating the uncertainties involved. Mathematically, fragility curves can be defined as the probability of exceedance of damage at various levels of ground acceleration, which is considered as an Intensity Measure (IM). Out of the various existing methodologies for development of fragility curves, a method based on nonlinear time history analysis and the probabilistic demand model suggested by Cornell et al (2002) is considered in the present study and Artificial Neural network is also used to develop fragility curves for a RC frame. In the present study, a comparison of fragility curves based on the above mentioned approaches is presented.

2. DEVELOPMENT OF FRAGILITY CURVES: SAC FEMA METHOD

The fragility function represents the probability of exceedance of a selected Engineering Demand Parameter (*EDP*) for a selected structural limit state (*LS*) for a specific ground motion intensity measure (*IM*). Fragility curves are cumulative probability distributions that indicate the probability that a component/system will be damaged to a given damage state or a more severe one, as a function of a particular demand. The seismic fragility, $F_R(x)$ can be expressed in closed form using the following equation,

$$P(D \geq C \mid IM) = \phi\left(\frac{\ln \frac{S_D}{S_C}}{\sqrt{\beta_{D|IM}^2 + \beta_c^2}}\right) \tag{1}$$

where, D is the drift demand, C is the drift capacity at chosen limit state, S_D and S_C are the median of the demand and the chosen limit state (*LS*) respectively. $\beta_{d/IM}$ and β_c are dispersions in the intensity measure and capacities respectively. A fragility curve can be obtained for each limit state. The methodology adopted in this study has been used by many researchers (Nielson *et. al.*, 2005; Rajeev and Tesfamariam, 2012; Haran *et. al.*, 2016) in past to develop fragility curves of RC structures. The detailed methodology for development of fragility curves can be found above said papers.

3. DEVELOPMENT OF FRAGILITY CURVES: ARTIFICIAL NEURAL NETWORK (ANN) METHODOLOGY

A neural network is a computational structure inspired by the study of biological neural processing. There are many different types of neural networks, from relatively simple to very complex, just as there are many theories on how biological neural processing takes place.

3.1. Mathematical Model for Feed Forward Neural Network

A layered feed forward neural network has layers, or subgroups of processing elements. A layer of processing elements makes independent computations on data that it receives and passes the result to another layer. The next layer may in turn make its independent computations and pass on the result to yet another layer. Finally, a subgroup of one or more processing elements determines the output of the network. Each processing element makes its computation based upon a weighted sum of its inputs and the activation functions. The first layer in the input layer and the last layer is the output layer. The layers that are in between these two layers are the hidden layers. The processing elements are seen units that are similar to neurons working in the brain, and hence, they are referred to as cells, neuromines, or artificial neurons. Even though our subject matter deals with artificial neurons, we will simplify them as neurons. Synapses between neurons are referred to as connections, which are represented by edges of a directed graph in which the nodes are the artificial neurons.

4. FORMULATION OF METAMODEL

The first step in calculating the seismic fragility curves utilizing the meta model concept is to define the input and output (response) variables. A response measure that best describes damage from seismic loadings should be selected. Damage limit states or performance limit states corresponding to the selected damage measure must also be identified. Parameters such as base shear, maximum roof displacement, peak inter-storey drift, damage indices, ductility ratio, and energy dissipation capacity can be used to identify the damage states depending on the types of structure being investigated. Input variables include aleatory uncertainties caused due to the randomness in construction material properties and uncertainties from earthquakes are defined together with their statistical parameters. Uncertainties from earthquakes are implicitly incorporated in the analysis by using a suite of ground acceleration records. Seismic intensity parameter is defined and the ground motion records in the suite are scaled to have the same level of intensity. Computational seismic analyses are performed on the models which represent different earthquake-structure scenarios. Scaled earthquake records are used as the loading inputs for these analyses and the chosen seismic response is extracted from each analysis. This is repeated for different combinations of input variables. The response resulting from the analysis is recorded for each ground motion, and the mean and standard deviation for each particular combination is calculated. Metamodels for the mean and standard deviation of the responses are formulated by applying the different techniques. Once the metamodel for mean and standard deviation are formed, they are combined to form the overall metamodel as given in Eqn 2.

$$y = y_{\mu} + N[0, y_{\sigma}] \tag{2}$$

The first term in Eqn. 2 predicts an expected or a mean value of the maximum displacements due to a suite of ground motions, while the second term represents the earthquake-to-earthquake dispersion in response computation and consequently incorporates randomness in earthquake excitations.

4.1. Performance Limit States attached

Limit states define the capacity of the structure to withstand different levels of damage. The median inter-storey drift limit states for RC moment resisting frame structures defining the capacity of the structure at various performance levels (S_C) are suggested by Ghobarah (2000) and ASCE/SEI 41-06 (2007). Drift limits for RC frames as per ASCE/SEI 41-06 (2007) as has considered in the present study as light repairable damage (IO), moderate repairable damage (LS) and near collapse (CP) as 1%, 2% and 4% respectively.

4.2. Selection of Earthquake Ground Motion

Selection of earthquake ground motions for a dynamic analysis is a more challenging task as each earthquake has its unique property involving so many uncertainties. FEMA P695 (2012) gives some guidelines on the selection of earthquake ground motion for structural analysis. Haselton *et. al.* (2012) has worked on selection of earthquakes for time history analysis and shared time history data for far field and near field ground motions based on FEMA P695 (2012). All far field earthquake data from this set of earthquake ground motions is used in the present study. These earthquakes are converted to match with IS 1893 (2002) spectrum using a program, WavGen developed by Mukherjee and Gupta (2002). WavGen uses a wavelet-based procedure to decompose a recorded accelerogram into a response spectrum compatible time-history with non-overlapping frequency contents such that the temporal variations in its frequency content are retained in the synthesized accelerogram.

4.3. Material uncertainty

Material properties of concrete and steel and used in the construction are random in nature. It is important to incorporate the uncertainties in all possible material and modelling parameters in the computational model to have a more realistic representation of the responses in a probabilistic assessment. For Indian conditions, Ranganathan (1999) studied the randomness in the strength of concrete and steel and proposed normal distributions for these properties with statistical parameters. It is also reported in many studies (Celik and Ellingwood, 2010; Davenport and Carroll 1986, etc) that damping can be random in nature. Randomness in damping is considered in the present study.

5. EXAMPLE FRAMES CONSIDERED

The building frame considered for numerical analysis in the present study is designed for the highest seismic zone (zone V with PGA of 0.36g) as per Indian standard IS 1893 (2002) considering medium soil conditions (N-value 10 to 30). The characteristic strength of concrete and steel are taken as 25MPa and 415MPa respectively. The buildings are assumed to be symmetric in plan, and hence a single plane frame is considered to be representative of the building along one direction. Typical bay width and column height in this study are selected as 5m and 3.2m respectively, as observed from the study of typical existing residential buildings. A configuration of four storeys and two bays is considered. The dead load of the slab (5 m × 5 m panel) including floor finishes is taken as 3.75 kN/m^2 and live load as 3 kN/m^2. The design base shear (V_B) is calculated as per equivalent static method (IS 1893, 2002). The structural analysis for all the vertical and lateral loads is carried out by ignoring the infill wall strength and stiffness (conventional). The design of the RC elements are carried out as per IS 456 (2000) and detailed as per IS 13920 (1993).

6. MODELING FOR NONLINEAR ANALYSIS

As per the methodology adopted, it is required to conduct a series of nonlinear dynamic time history analyses of all the selected frames. Opensees Laboratory tool developed by Frank *et. al*. (2014) is used for the present study for nonlinear time history analyses. The concrete is modelled by considering the effect of confinement due to the special confining detailing in the beams and columns using the Kent and Park (1971) model. The cover concrete is modelled as unconfined concrete. Steel reinforcing bars are modelled using uniaxial Giuffre-Menegotto-Pinto steel material model with isotropic strain hardening.

7. FRAGILITY CURVES

The 40 models where developed with PGA of ground motions are scaled linearly from 0.1g to 1g. Then each model is allowed to run for 44 set of earthquake for each PGAs. A total of 1760 nonlinear dynamic time history analyses are performed and the maximum inter-storey drift (EDP) for each storey are monitored. Concrete compressive strength (f_{ck}), steel yield strength (f_y), Damping Ratio (ξ) and Peak ground acceleration (PGA) are considered as Input parameters. Mean and standard deviation of inter-storey drift for each models is found out for the same PGAs and considered as Output parameters.

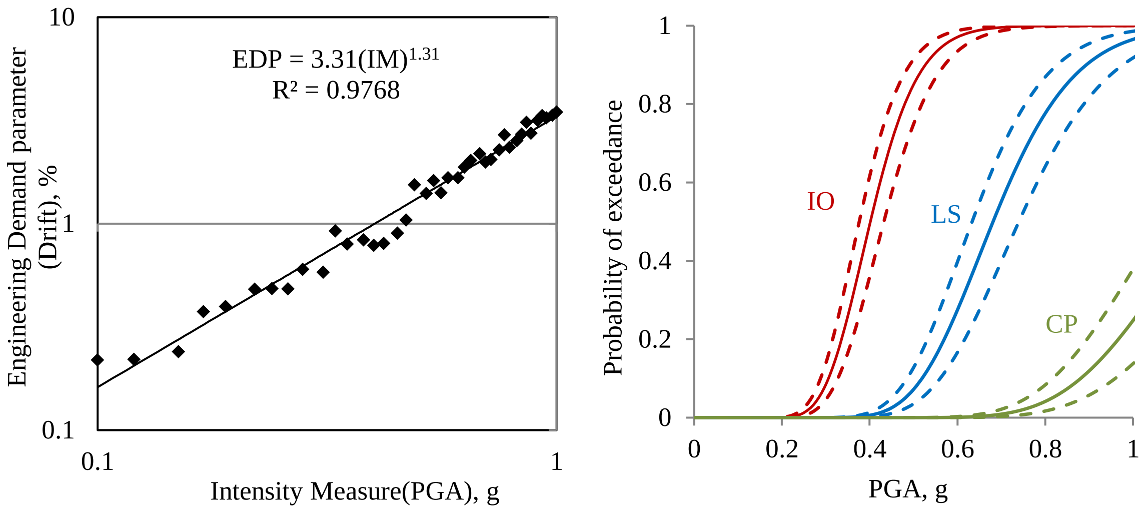


Figure 1 Time history data and corresponding displacement history

7.1. Fragility curves by SAC-FEMA method

Probabilistic seismic demand model (PSDM) is developed as per the Eq. 1 and results are shown in the Fig. 1. The regression coefficients *a* and *b* are found to be 3.31 and 1.31 respectively. Dispersions $\beta_{D/IM}$ are found and fragility curves for different performance levels are developed as per Eq.3 and shown in the Fig. 1 along with the 95% confidence intervals.

7.2. Fragility curves by Artifical Neural Network

Neural network tool available in Matlab (2013) is used for fitting the data points. So many trials have been made and arrive that one hidden layer with 5 neurons gave the reasonable results, tansig and purlin functions are used as activation functions as shown in Eq.3. Equation 4 & 5 is arrived for mean (y_m) and standard deviation (y_σ) of responses using ANN methodology.

$$f(x) = \tan sig(x) = \left(\frac{2}{1+e^{-2x}} - 1\right);\ f(x) = purlin(x) = x; \qquad (3)$$

$$A_{11} = \tan sig \cdot (-0.2669\, f_c - 0.40216\, f_y - 16.58275\,\xi - 2.22303\, PGA + 2.1366)$$

$$A_{12} = \tan sig \cdot (-8.38697\, f_c + 0.76033\, f_y + 16.40306\,\xi - 19.44919\, PGA - 10.62997)$$

$$A_{13} = \tan sig \cdot (0.57265\, f_c - 0.12895\, f_y - 4.08978\,\xi - 1.94873\, PGA + 8.56411)$$

$$A_{14} = \tan sig \cdot (0.00826\, f_c + 0.00031\, f_y + 1.38436\,\xi - 1.77692\, PGA + 0.90108)$$

$$y_m = purlin \cdot (1.03079\, A_{11} - 0.10921\, A_{12} - 0.72211\, A_{13} - 2.649244\, A_{14} + 0.7813) \tag{4}$$

$$A_{21} = \tan sig \cdot (0.18078\, f_c - 0.07665\, f_y + 16.66341\,\xi - 2.10798\, PGA - 3.86661)$$

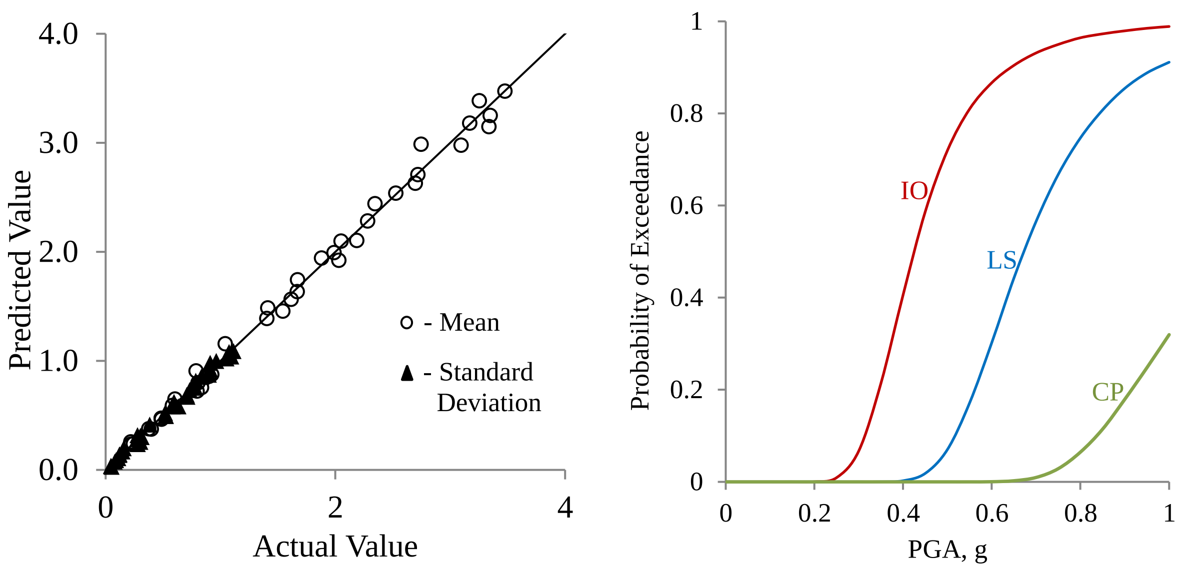
$$A_{22} = \tan sig \cdot (0.02482\, f_c - 0.03818\, f_y - 39.59424\,\xi - 0.08261\, PGA - 0.09837)$$

$$A_{23} = \tan sig \cdot (-0.07388\, f_c - 0.21937\, f_y - 27.21051\,\xi - 0.64384\, PGA + 7.74235)$$

$$A_{24} = \tan sig \cdot (0.00703\, f_c + 0.00071\, f_y + 2.33686\,\xi - 2.212\, PGA + 0.63151)$$

$$y_\sigma = purlin \cdot (-0.04119\, A_{21} - 0.10696\, A_{22} - 0.14116\, A_{23} - 0.7\, A_{24} + 0.29323) \tag{5}$$

Fig 2a shows the fit of computational responses and the predicted values by ANN approach. It can be seen that, ANN models using LHS sampling can be predict responses reasonably accurate. Using equation 11 & 12 Metamodel is developed as per the equation 8. Then a set of one lakh input variables are generated randomly and montecarlo simulations is done to find the probability of exceedance for each limit states as a function of PGA and shown in Fig. 2b.



ANN output vs Actual value

Fragility curve

Figure 2 Computational fir and Fragility curve for selected frame

Further comparative study is carried out between developed methods Fig 3. Shows the comparison of fragility curve at IO performance level. It can be seen from the figure that both methods predicts similar observation and slight variation in probability of exceedance (greater than 0.5). This can be further achieved good correlation by selecting more number of samples while training ANN and also by increasing the network size.

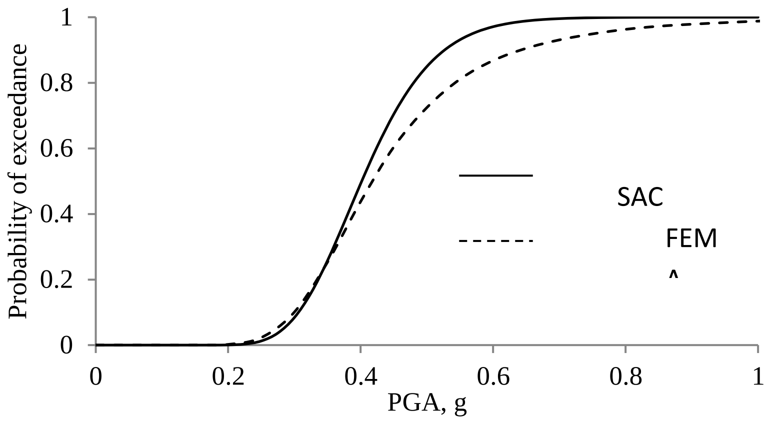


Figure 3 Fragility curve at IO performance level by different methods

8. CONCLUSIONS

Four storey RC frames has been chosen in this study and fragility curves were drawn by two methods namely by SAC FEMA method and Artificial Neural network method. To develop this fragility curves, uncertainties are considered on material strength and damping. Further earthquake uncertainties are considered by selecting 30 ground motions and converted it to match Indian code spectrum. A non-linear time history analysis was performed using selected time history and building maximum response are noted in terms of inter storey drift. Finally fragility comparison is made among both the methods; it shows that ANN method can also predict the fragility curve with a reasonable accuracy. Though there is little difference at higher PGA level. It can be tuned further by modifying ANN network and increasing number of training parameter.

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