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EXTENDED ABSTRACT

Estimation of Structural Collapse Reliability via Response Surface Method and a Hybrid of Neuro-Fuzzy Networks with Meta-heuristic Algorithms

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1. Introduction

Earthquakes are catastrophic natural phenomena that occasionally lead to the collapse of structures. Considering the importance of collapse impacts, the present study primarily focuses on estimating the reliability of collapse probability for complicated structures for which no explicit limit state functions exist. Different simulation methods are used for combining uncertainties, including the Monte Carlo, Latin Hypercube Sampling, and the importance of sampling approaches. Simulation methods require several samples to cover the probabilistic distribution of uncertainties. To deal with this problem, the response surface method (RSM) and artificial neural networks (ANNs) integrated with the simulation method have been proposed for reducing the computation effort (Beheshti-Aval et al., 2015; Khojastehfar et al., 2015). Common methods applied to evaluate reliability include 1) reliability-based methods, involving the first-order reliability method (FORM) and second-order reliability method (SORM) and 2) Monte Carlo simulation methods (Nowak and Collins, 2000).

2. Methodology

Two in some reliability problems, the limit state function is implicit, and there is no explicit form of it. Particularly, no explicit forms of limit state functions are available for nonlinear dynamic problems, such as the seismic analysis of structures (Achintya, 2006). Various methods such as RSM and ANN have been proposed to evaluate the reliability of such problems. The RSM is based on estimating an explicit relation for a limit-state function consisting of random variables of the structure and using reliability evaluation techniques such as SORM, FORM, and simulation methods (Elhewy et al., 2006).

The present study incorporates the parameters of the modified Ibarra and Krawinkler (2005) moment-rotation curve in the concentrated plastic hinges of beams and columns in concrete moment frames as epistemic uncertainties. These uncertainties include 1) Effective initial stiffness, which is defined by the secant stiffness to 40% of yield force ($\frac{EI_{stf40}}{EI_g}$), 2) Bending (flexural) strength (M_y), 3) Plastic rotation capacity ($\theta_{cap,pl}$), 4) Post-capping rotation capacity (θ_{pc}), 5) Post-yield hardening stiffness or the ratio of the maximum moment and yield moment capacity ($\frac{M_c}{M_y}$), and 6) Energy dissipation capacity for cyclic stiffness and strength deterioration

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(λ), for the structural beams and columns. Thus, there are a total of 12 uncertainties including 6 beam uncertainties and 6 column uncertainties.

To evaluate the structure's reliability, 105 simulations are performed for the 12 uncertainties with the probabilistic distribution of the uncertainties and their correlations. Then, incremental dynamic analysis (IDA) is carried out on each simulation with 44 accelerogram records (Fema, 2009) and 15 incremental steps using the Hunt-Fill algorithm (Vamvatsikos and Cornel, 2002) to obtain the collapse drift of the simulation for the 44 accelerograms. In this way, the mean collapse drift is derived for each of the 105 simulations to produce an implicit limit state function for the uncertainties. Then, the RSM is performed to obtain an explicit limit state function, estimating the structure's collapse probability using the first-order [FORM] and second-order [SORM] reliability methods. In addition, the idea of using neuro-fuzzy networks is employed to estimate collapse reliability when the limit state function is implicit. However, when the number of uncertainties simulations is small in estimating the limit state function, hybrids of an adaptive neuro-fuzzy inference system with the genetic algorithm (ANFIS-GA), particle swarm optimization (ANFIS-PSO), differential evolution algorithm (ANFIS-DE), and ant colony optimization are used for continuous domains (ANFIS-ACOR). Finally, the reliability and failure probability of the structure is calculated by combining the Monte Carlo method with ANNs.

3. Results and discussion

3.1. Collapse drift-based structural reliability

The drift of structural collapse under an earthquake is one of the main criteria for evaluating structural collapse performance. Based on the collapse drift criterion, a collapse limit state function is defined as

$$G_{Drift_{collapse}}(X) = Drift_{collapse} - Drift(X) \tag{1}$$

Where $Drift_{collapse}$ the limit is the drift of the collapse limit state and $Drift(X)$ is the structural collapse drift based on basic random variables (i.e., the uncertainties). However, there is typically no explicit relation between structural collapse drift and uncertainties. Thus, it is required to employ simulation techniques to evaluate the performance reliability of a structure. Although simulation techniques are satisfactory for accurate structural reliability evaluation, the use of such techniques for real-life structural with many random variables requires considerable computation effort. The use of ANNs and RSM in reliability problems, which typically require a high computation effort, helps predict structural responses and estimate structural failure probability in a short time.

3.2. Collapse drift-based structural reliability

A sensitivity vector represents the importance of each random variable in the failure probability of a structure. Using such information, the most important parameters affecting the reliability index can be identified. Considering the interaction effects between the uncertainties, the beam and column uncertainties account for 88.9% and 11.1%, of the structure's collapse probability, respectively.

3.3. Seismic reliability evaluation under collapse by RSM and ANN

The hybrids of the RSM and FORM, SORM, and Monte Carlo methods (i.e., RSM-MCS, RSM-SORM, and RSM-FORM) are used to estimate collapse reliability. The limit state function is brought in an explicit form. Then, the structure's collapse probability is calculated by the above-mentioned reliability methods.

In the hybrid of the Monte Carlo method and neuro-fuzzy networks, 10^6 simulations are produced based on a (variation coefficient of ≤ 0.05) using the simulation technique to predict the mean structural collapse drift for the 10^6 simulations. For this purpose, the hybrid of the neuro-fuzzy approach and meta-heuristic algorithms is used. Next, the implicit limit state function is formed for different drift limit values (i.e., $Drift_{collapse}$), calculating the structure's failure probability by using the Monte Carlo method. Fig. 1 illustrates the structural collapse probability curves for different drift limit values (i.e., $Drift_{collapse}$=0 to 0.1) obtained from RSM and the hybrids of neuro-fuzzy networks and meta-heuristic algorithms.

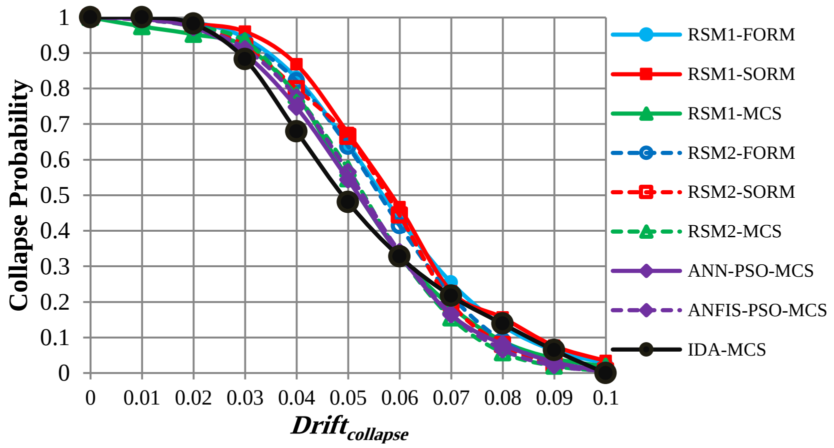

Fig. 1. Structural collapse probability for different $Drift_{collapse}$ values

Table 1. provides the RMSE values obtained in predicting structural collapse probability curves in the combination of IDA with Monte Carlos for RSM-FORM, RSM-SORM, RSM-MCS, ANFIS-GA-MCS, ANFIS-PSO-MCS, ANFIS-DE-MCS, and ANFIS-ACOR-MCS.

Table 1. RMSE values from IDA-MCS in different methods

	RSM-FORM	RSM-SORM	RSM-MCS	ANFIS-GA-MCS	ANFIS-PSO-MCS	ANFIS-DE-MCS	ANFIS-ACOR-MCS
RMSE	0.08067	0.09923	0.4616	0.04247	0.04034	0.4872	0.04933

4. Conclusions

The lowest error in predicting structural collapse probability curves was obtained in the Monte Carlo method. The RMSE values for ANFIS-PSO-MCS, ANFIS-GA-MCS, RSM-MCS, ANFIS-DE-MCS, and ANFIS-ACOR-MCS from IDA were estimated to be 0.04034, 0.04247, 0.04616, 0.04872, and 0.04933, respectively.

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