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Estimating Structural Collapse Responses Considering Modeling Uncertainties using Artificial Neural Networks and Response Surface Method

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ABSTRACT: This research investigates the collapse responses of a concrete moment frame considering modeling uncertainties. These modeling uncertainties are considered for evaluating a collapse response related to the modified Ibarra-Krawinkler moment-rotation parameters for beam and column elements of a given structure. To analyze these uncertainties, the correlations between the model parameters in one component and between two structural components were considered. Latin Hypercube Sampling (LHS) method was employed to produce independent random variables. Moreover, Cholesky decomposition was adopted to produce correlated random variables. Performing 281 simulations for the uncertainties involved considering their inter-correlations, incremental dynamic analysis (IDA) was done using 44 far-field accelerograms to determine structural collapse responses. Collapse responses of each simulation, including mean collapse capacity, mean collapse drift and mean annual frequency, were obtained. Then, the collapse responses were predicted using the response surface method and artificial neural network. The results show that the Correlation coefficients (R) between the target data resulted from incremental dynamic analysis (IDA), output data resulted from response surface method (RSM), and artificial neural network (ANN) were obtained for the collapse responses above 0.98. The maximum prediction errors for mean collapse capacity and mean collapse drift are less than 5% and for mean annual frequency less than 10% under the response surface method (RSM) and artificial neural network (ANN).

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1- Introduction

The seismic performance of structures is evaluated based on probability rules. In this regard, the incorporation of uncertainty effects in modeling essentially changes the mean and dispersion values of responses. Thus, estimating parameters affecting uncertainty sources as accurately as possible provides more realistic responses of structures' seismic performance [1]. Modeling uncertainties in simulating the collapse responses of structures is of high importance because of the complicated and limited knowledge of model parameters and collapse-related behavior, as well as the high impact of the collapse level on the probability performance of structures [2, 3]. Due to the inability of available tools to evaluate structures' collapse, it is necessary to idealize the nonlinear behavior simulations and different deterioration, strength, and stiffness sources of structural components. Concentrated plastic hinge models are considered by researchers to model the collapse behavior of structures. Parameters used to define concentrated hinge models are typically calibrated by empirical equations, which functions as an important source of uncertainty in simulating structures' collapse responses [4, 5].

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2- Methodology

To incorporate the effects of epistemic uncertainties on collapse responses, the present study employs a four-story concrete structure with a moment frame system. A nonlinear concentrated plastic hinge model was employed to calculate collapse responses. In addition, OpenSees was used to perform modeling and nonlinear dynamic analyses. A total of 44 far-fault earthquake records proposed by FEMA-P695 were utilized in the incremental dynamic analysis (IDA) [6]. The concentrated plastic hinge models of concrete structures are developed using the material model proposed by Ibara et al. [7, 8]. Figure 1 illustrates a concentrated plastic hinge model with a tri-linear curve. The curve consists of an elastic area, a post-yield area, a pre-capping area with a negative slope, and a residual strength area. The yield moment is represented as M_y, The post-yield, pre-capping, and post-capping areas are defined by the plastic rotation capacity ($\theta_{cap,pl}$), maximum moment (M_c), and post-capping rotation capacity (θ_{pc}), respectively. The cycling stiffness and strength deteriorations are calculated based on the cycling energy damping (λ). Tables 1 and 2 represent the standard deviations and correlations of the concentrated hinge model parameters in a structural component and between structural components.

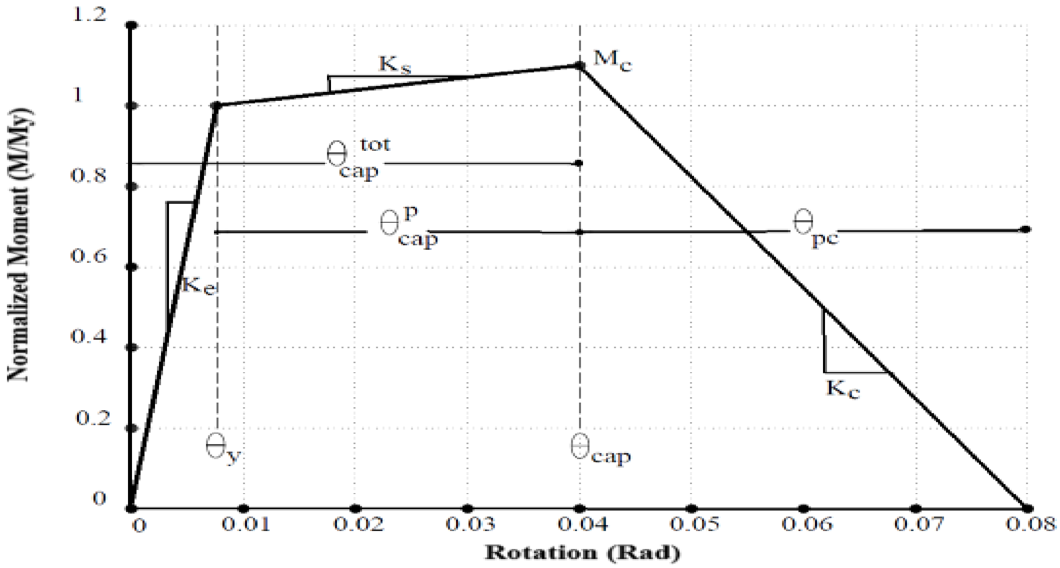

Fig. 1. Tri-linear backbone curve of the plastic hinge model

Table 1. The standard deviation of model parameters

	$\theta_{cap,pl}$	θ_{pc}	$EI_{stf\,40}$	M_y	$\frac{M_c}{M_y}$	λ
σ_{LN}	0.63	0.86	0.42	0.3	0.12	0.64

Table 2. Correlations between parameters of a component and two structural components

		COMPONENT 1						COMPONENT 2					
		$\theta_{cap,pl1}$	θ_{pc1}	EI_{stf1}	M_{y1}	M_c/M_{y1}	γ_1	$\theta_{cap,pl2}$	θ_{pc2}	EI_{stf2}	M_{y2}	M_c/M_{y2}	γ_2
COMPONENT 1	$\theta_{cap,pl1}$	1	0.3	0	0.1	0.3	0.1	0.6	0.3	0	0.1	0.2	0
	θ_{pc1}		1	0.1	0.1	0.1	0.3		0.8	0.1	0.1	0.1	0.3
	$EIstf_1$			1	0.1	0	0			0.9	0.1	0.1	0
	M_{y1}	(sym.)			1	0.4	0.1	(sym.)			0.9	0.4	0.1
	M_c/M_{y1}					1	0.2					0.8	0.1
	γ_1						1						0.6
COMPONENT 2	$\theta_{cap,pl2}$	(symmetric)						1	0.3	0	0.1	0.3	0.1
	θ_{pc2}								1	0.1	0.1	0.1	0.3
	EI_{stf2}									1	0.1	0	0
	M_{y2}							(sym.)			1	0.4	0.1
	M_c/M_{y2}											1	0.2
	γ_2												1

3- Discussion and Result

In this study, 281 dependent samples were produced and simulated to determine the input data and make response levels for 12 epistemic uncertainties. Then, IDA was performed using the Hunt-Fill algorithm with the 44 records for each simulation under uncertainty conditions. The collapse responses, including $Sa_{collapse}$ and $Drift_{collapse}$, were obtained for each of the 44 records. Then, the mean collapse capacity μ_{sa} and mean collapse drift μ_{Drift} were obtained for each simulation by the mean values of the collapse responses. This was repeated for 281 simulations to obtain the mean collapse capacity and a mean collapse drift for each simulation. The results were used as the target inputs in artificial neural networks (ANNs) and the response surface method (RSM). A total of 185,460 nonlinear dynamic time-history analyses were carried out for 281 simulations by the Hunt-Fill algorithm with epistemic uncertainties, 44 records, and 15 incremental steps for each record. The Pareto chart was applied to represent the contribution percentages of the uncertainties in the mean collapse capacities. According to Figure 2, the contribution percentages of uncertainties in the beams in the collapse capacity response are 15.16%,

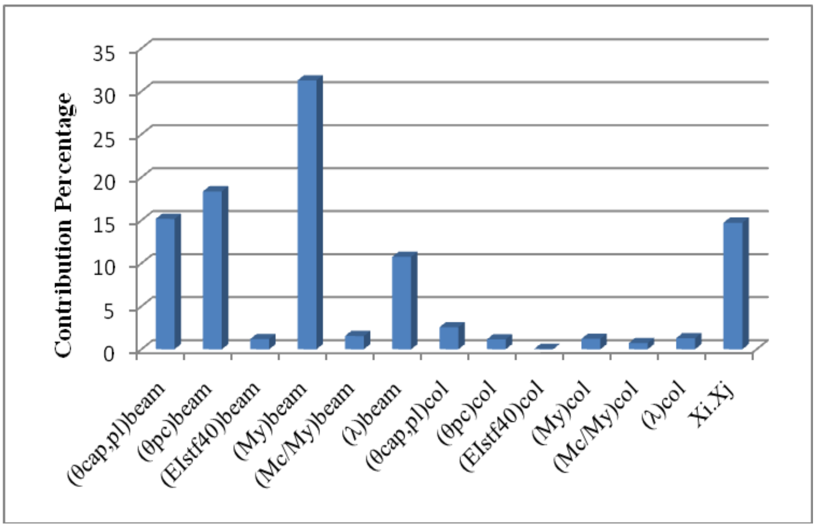

Fig. 2. The contribution percentages of the uncertainties to the collapse capacity

Table 3. The estimated µSa, µDrif, and MAF values at the levels of 16%, 50%, and 84%

		IDA	RSM	ANN	RSM	ANN
N. Samples		281	281	281	10000	10000
μ_{sa}	16%	0.889815	0.894587	0.901919	0.91179	0.89639
	50%	1.341208	1.387041	1.348254	1.3641	1.3547
	84%	1.946592	1.945388	1.951696	1.9411	1.9714
μ_{Drift}	16%	0.32655	0.032235	0.033337	0.033634	0.0331
	50%	0.049541	0.051078	0.050261	0.051604	0.0497
	84%	0.075671	0.07321	0.075747	0.07279	0.0755
MAF	16%	9.293E-05	9.674E-05	0.0001015	9.579E-05	9.718E-05
	50%	0.0002146	0.0002123	0.0002109	0.0002069	0.0002163
	84%	0.0004638	0.0004525	0.0004768	0.0004534	0.0004767

18.37%, 1.19%, 31.28%, 1.54%, and 10.75% for $\theta_{cap,pl}$, θ_{pc}, EI_{stf40}, M_y, $\frac{M_c}{M_y}$, and λ, respectively. Also, the contribution percentages of the column uncertainties were all below 5%, and the interactions between the uncertainties accounted for 14.72% of the structure's collapse capacity response.

This study adopted the RSM and an ANN to predict collapse responses while incorporating epistemic uncertainties. The input data of the ANN were specifications of 12 epistemic uncertainties. The target data were the mean collapse capacity, mean collapse drift, and mean collapse annual frequency (MAF) obtained from IDAs performed on 281 simulations. Also, the output data of the ANN's output layer were the mean collapse capacity, mean collapse drift, and mean collapse annual frequency predicted by the ANN. The correlation coefficients of the target and output data for the mean collapse capacity were 0.9875 and 0.9877 in the RSM and ANN approaches, respectively. The correlation coefficients of the target and output data for the mean collapse drift were 0.9811 and 0.987 in the RSM and ANN approaches, respectively. Finally, the correlation coefficients of the target and output data for the mean annual collapse frequency were 0.9875 and 0.9814 in the RSM and ANN approaches, respectively. Table 3 provides the structure's collapse responses at the levels of 16%, 50%, and 84% for the 281 simulations and the values obtained from the IDA, RSM, and ANN approaches. In the next step, 10^4 simulations were produced for the 12 epistemic uncertainties using the Latin hypercube sampling (LHS) method. However, since a total of 6,600,000 nonlinear dynamic time-history analyses are required for 10^4 simulations with 44 records and 15 incremental steps in the Hunt-Fill algorithm, it is difficult or even impossible to perform this number of IDAs. Thus, the structure's collapse responses for the 10^4 simulations were predicted only by the RSM and ANN methods. Table 3 represents the collapse responses at the levels of 16%, 50%, and 84%.

4- Conclusions

As mention previously, applying a correlation coefficient of above 98% between the IDA collapse responses and RSM and ANN collapse responses and an error of below 10% in collapse response predictions, it can be concluded that RSM and ANN can be employed as high-accuracy prediction methods to estimate structural collapse responses. Thus, time-consuming dynamic time-history analyses are not required for other simulations since RSM and ANN can predict structural responses in a short time.

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