ASPS Conference Proceedings 1: 631-637 (2022)

Proceedings of

12th Structural Engineering Convention - An International Event (SEC 2022)

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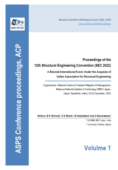

On the choice of ground motion intensity measure and the number of records for cloud analysis-based seismic demand assessment

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Paper ID - 060109

Abstract

Cloud analysis has emerged as a popular tool for the seismic demand/fragility assessment of structures. The output of cloud analysis is a seismic demand model which relates an Engineering Demand Parameter (EDP) indicative of structural distress to an Intensity Measure (IM) signifying the severity of ground shaking. IMs commonly used for probabilistic seismic demand assessment are quite heterogenous with respect to their "efficiency", i.e. their degree of correlation with a specific EDP. This feature has serious implications on the number of ground motion records that must be used to perform cloud analysis on a given structure in order to accurately describe the distribution of the EDP at various IM levels. In the current study, demand models for maximum interstorey drift (θ_{max}), based on a wide spectrum of IMs, are developed from the cloud analyses of a five-storey RC bare frame structure using a suite of fifty unscaled natural ground motion records. The method of bootstrap resampling is used to investigate the convergence of the regression coefficients in the demand model with the size of the bootstrap subsamples, each comprising of a limited subset of records drawn from the original suite with repetitions allowed. This procedure helps determine the minimum number of ground motion records necessary for the calibration of demand models without compromising its accuracy in predicting the drift demands. Results from the study indicate a strong correlation between the efficiency of various IMs and the optimal number of records required to produce reliable seismic demand models.

Keywords: Cloud Analysis, Intensity Measures, Ground Motion Records, Seismic Demand Assessment, Bootstrap Resampling

1. Introduction

Cloud analysis [1,2] has emerged as a popular tool for the seismic demand and fragility assessment of structures. Unlike other nonlinear dynamic analysis procedures such as incremental dynamic analysis [3] and multiple stripe analysis [4,5], which require a large number of nonlinear response history analyses (NLRHA) to be performed on a structure using ground motion records scaled to multiple intensity levels, cloud analysis may be performed using a set of as-recorded or unscaled accelerograms. Thus, the cloud method benefits from the need for lesser computational resources and run time compared to the other techniques.

The output from cloud analysis is represented in the form of a scatter plot (in logarithmic scale) comprising of ordered pairs of an intensity measure (IM) and the engineering demand parameter (EDP) of interest. Assuming an appropriate functional form for the IM-EDP relationship, classical regression techniques can be employed to assess the correlation between the above variables. The between the efficiency of IMs (E) and the optimum number of records (N_{opt}) necessary to calibrate a reliable seismic mathematical relationship established between the IM and EDP through statistical regression is commonly referred to as a 'seismic demand model'. Such models may be conveniently used for the estimation of seismic fragility using conventional reliability-based approaches [6].

A critical decision to be made while selecting ground motion records for cloud analysis, pertains to the size of the record bin to be used. The larger the size of the bin, the more time consuming will be the execution of NLRHA. The current study builds on the understanding that certain intensity measures are more efficient than others [7,8] and seeks to examine whether the choice of IM has a bearing on the minimum number of records necessary to accurately calibrate a demand model for cloud analysis. If so, the assessment framework could clearly benefit from the use of highly efficient IMs in formulating the demand model. In the present study, numerical investigation is carried out on a 2D RC bare frame model to examine the possible correlation demand model for maximum interstorey drift. Ten popular IMs are considered, which include five non-structure

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Proceedings of the 12th Structural Engineering Convention (SEC 2022), NCDMM, MNIT Jaipur, India | 19-22 December, 2022

Published online: December 19, 2022
doi:10.38208/acp.v1.563

specific and five structure specific descriptors. A modified version of the bootstrap resampling procedure proposed by [9] is used to determine N_{opt}. A mathematical model for the variation of N_{opt} with E is also proposed.

2. Numerical Investigation

2.1 Description of the numerical model

The numerical model used in the current investigation is that of a five-storey RC bare frame building, with configuration as outlined in Fig.1. The lateral load resisting system of the structure is a moment resisting frame comprising of beams and columns. In addition to its self-weight, each beam is assumed to carry a superimposed vertical load of 15kN/m over its entire span. The structure is designed to safely carry the gravity loads as per the guidelines of IS 456:2000 [10]. For the structural design, the characteristic compressive strength of concrete (f_{ck}) and the characteristic yield strength of the steel rebars (f_y) are assumed to be equal to 25 MPa and 415 MPa respectively. The geometric and reinforcement details of the beams and columns are furnished in Table 1 and Table 2 respectively.

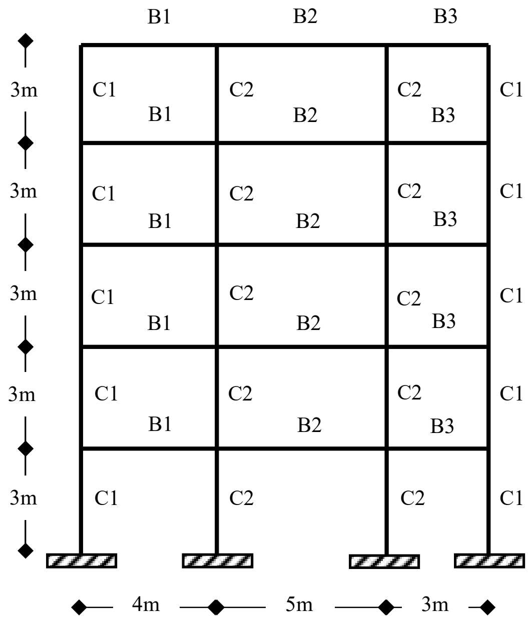

Fig.1 Elevation of the planar RC moment frame model used in the study

Table 1. Geometric and reinforcement details of beams

Property ID	Dimensions (mm)	Reinforcement details (mm)	
		L/R	M
B1	250 x 250	T: 2-16Y B: 2-12Y	T: 2-10Y B: 2-16Y
B2	250 x 300	T: 2-16Y B: 3-12Y	T: 2-10Y B: 2-16Y
B3	250 x 250	T: 2-12Y B: 2-12Y	T: 2-10Y B: 2-12Y
L: Left end R: Right end M: Mid-span T: Top face B: Bottom face			

Table 2. Geometric and reinforcement details of columns

Property ID	Dimensions (mm)	Reinforcement details (mm)
C1	250 x 250	Corners: 4-14Y
C2	300 x 300	Corners: 4-16Y

Table 3. Modal periods of vibration and mass participation factors for the model considered

Mode	Modal period T (s)	Modal mass participation factor U_X (%)
Mode 1	1.01	83.31
Mode 2	0.32	10.27
Mode 3	0.18	4.02
Mode 4	0.12	1.85

The seismic analysis platform Seismostruct 2020 [11] is used to execute the required NLRHA on the above structure. Inelastic force-based elements with five integration sections and fifty fibers per cross-section are used to define the frame members. The uniaxial stress-strain behavior of concrete under cyclic loading is defined using the nonlinear constitutive model proposed by Mander et al. [12] and the strength and stiffness degradation rules proposed by Martinez-Rueda and Elnashai [13]. The reverse cyclic behavior of the steel rebars is defined using the Menegotto-Pinto steel model [14] coupled with the isotropic hardening rules proposed by Filippou et al. [15]. The Newmark average acceleration method is used for the numerical evaluation of nonlinear seismic response and the Newton-Raphson solver is used in each time step.

Prior to the execution of nonlinear dynamic analysis, the modal properties of the structure (Table 3) are determined by carrying out an eigen value analysis post-application of the gravity loads. As can be seen from the table, the building is first mode dominated with the mass participation factor corresponding to the first mode (T_1=1.01s) amounting to 83.3%. The fundamental period T_1 will be used in the later parts of the study for the determination of certain structure specific descriptors of ground shaking severity.

2.2 Suite of Ground Motions

NLRHA of structures may be performed using natural records, artificial waveforms or synthetic records as the seismic input [16]. Here, a suite of fifty unscaled natural strong motion records, downloaded from the PEER NGAWEST database [17] is used to define ground shaking scenarios. The records originate from events covering a moment magnitude range of 5.5-7.5 and were recorded on NEHRP class C sites (360m/s < V_{S30} < 720m/s) [18] located at a distance of at least 15 km from the source of the earthquake. The records are selected to be free field or on the ground level. After filtering the records in the database based on the above pre-selection criteria, the final selection (Table 4) is made ensuring that the ensemble covers a broad

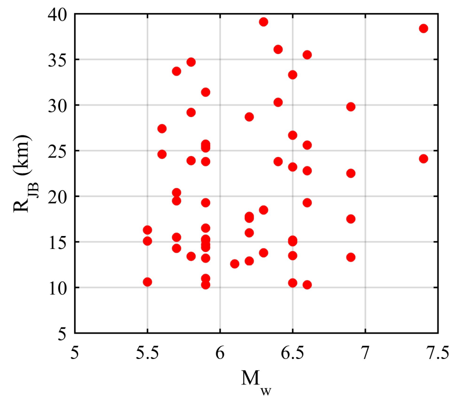

Fig.2 Variability in moment magnitudes and Joyner Boore distances among the selected ground motions

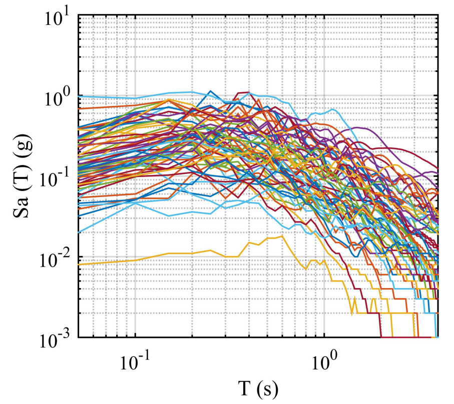

Fig.3 5% damped acceleration response spectra for the suite of fifty unscaled ground motion records

range of intensity values. No specific constraints related to spectral matching are imposed during this process. Fig.2 demonstrates the diversity among the ensemble of ground motion records in terms of their moment magnitude (M_w) and Joyner-Boore distances (R_{JB}). Fig.3 highlights the variability among the chosen ground motion records in terms of their 5% damped acceleration response spectra.

2.3 Intensity Measures

A total of ten popular IMs are used in the current numerical investigation. They include peak ground acceleration (PGA), peak ground velocity (PGV), peak ground displacement (PGD), specific energy density (SED), cumulative absolute velocity (CAV), first mode spectral acceleration ($Sa(T_1)$) [19], acceleration spectrum intensity (ASI), velocity spectrum intensity (VSI) [20], Housner intensity (HI) [21] and average spectral acceleration (Sa_{avg}) [22]. The first five IMs fall into the category of non-structure specific IMs while the latter five are structure specific in nature [23]. Previous studies [24] have shown that these measures are characterized by different levels of efficiency; i.e. their degree of correlation with an EDP of interest. The procedure adopted in the present study for the determination of IM efficiency is described in the next sub-section.

Table 4. Suite of ground motion records used in the study

ID	Event Name	Year	Station Name
1	Imperial Valley-03	1951	El Centro Array #9
2	Kern County	1952	Taft Lincoln School
3	Imperial Valley-04	1953	El Centro Array #9
4	Parkfield	1966	Cholame - Array #12
5	Parkfield	1966	Cholame - Array #8
6	Parkfield	1966	Temblor Pre-1969
7	Northern California-05	1967	Ferndale City Hall
8	San Fernando	1971	Castaic - Old Ridge
9	San Fernando	1971	Fairmont Dam
10	San Fernando	1971	LA - Hollywood Store FF
11	San Fernando	1971	Pearblossom Pump
12	Point Mugu	1973	Port Hueneme
13	Friuli-01	1976	Tolmezzo
14	Fruili-03	1976	Buia
15	Fruili-03	1976	Forgaria Cornino
16	Friuli-02	1976	Buia
17	Friuli-02	1976	Forgaria Cornino
18	Friuli-02	1976	San Rocco
19	Santa Barbara	1978	Cachuma Dam Toe
20	Tabas	1978	Boshrooyeh
21	Coyote Lake	1979	Halls Valley
22	Coyote Lake	1979	SJB Overpass
23	Coyote Lake	1979	San Juan Bautista
24	Coyote Lake	1979	San Juan Bautista Polk St
25	Norcia Italy	1979	Bevagna
26	Norcia Italy	1979	Spoleto
27	Imperial Valley-06	1979	Calexico Fire Station
28	Imperial Valley-06	1979	Calipatria Fire Station
29	Imperial Valley-06	1979	Cerro Prieto
30	Imperial Valley-06	1979	Compuertas
31	Livermore-01	1980	APEEL 3E Hayward
32	Livermore-01	1980	Antioch - 510 G St
33	Livermore-01	1980	Del Valle Dam (Toe)
34	Livermore-01	1980	Fremont - San Jose
35	Mammoth Lakes-01	1980	Long Valley Dam
36	Mammoth Lakes-02	1980	Long Valley Dam
37	Mammoth Lakes-03	1980	Long Valley Dam
38	Mammoth Lakes-03	1980	Long Valley Dam (L)
39	Victoria	1980	SAHOP Casa Flores
40	Irpinia-01	1980	Brienza
41	Irpinia-01	1980	Mercato San Severino
42	Irpinia-02	1980	Auletta
43	Irpinia-02	1980	Bagnoli Irpinio
44	Taiwan-05	1981	SMART1 C00
45	Taiwan-05	1981	SMART1 I06
46	Taiwan-05	1981	SMART1 I12
47	Corinth	1981	Corinth
48	Westmorland	1981	Brawley Airport
49	Westmorland	1981	Niland Fire Station
50	Westmorland	1981	Superstition Mtn Camera

2.4 Efficiency Analysis

The efficiency of a given IM in predicting the maximum interstorey drift demands (θ_{max}) on the test structure is determined by cloud analysis using the suite of fifty ground motion records. In the present study, the widely adopted log-linear model (Equation 1) for seismic demand [25,8] is used to represent the functional relationship between the predictor variable (IM) and the response variable (θ_{max}).

$$\ln\hat{\theta}_{max} = a + b \cdot \ln(IM) + \varepsilon \tag{1}$$

In the above equation, 'a' and 'b' are regression coefficients and ε is a normal random variable with zero mean and standard deviation given by Equation 2.

$$\sigma = \sqrt{\frac{\sum_{i=1}^{N}\left(\ln\theta_{max,i} - \left[a + b\cdot\ln(IM_i)\right]\right)^2}{N-2}} \tag{2}$$

where IM_i and $\theta_{max,i}$ are the intensity and maximum interstorey drift values corresponding to the 'i^{th}' observation and N is the number of input signals. The complete definition of the seismic demand model requires all the three parameters- a, b and σ to be estimated with a desired level of confidence.

The degree of correlation between the predictor and response variables or efficiency (E) is quantified in terms of the coefficient of determination for the above regression. A value close to zero is indicative of statistical independence, where as a value equal to one signifies perfect correlation between the IM and θ_{max}. The output from the IM efficiency analyses are presented in section 3.

2.5 Determination of optimal number of records

The reliability of a seismic demand model depends on the confidence with which its parameters are estimated. In the log-linear representation of IM- θ_{max} relationship, there are three unknown constants (a, b and σ). Using a larger suite for input records to calibrate the demand model could enable the estimation of the mean value of these constants with better confidence. However, beyond a certain number, adding more records to the bin is known to result only in a marginal reduction in the width of the confidence interval for these statistics [26].

In the current study, the method of bootstrap resampling [27] is used to examine the rate at which the estimates of the demand parameters converge with increase in the size of the bin of records. Bootstrapping involves generating a large number of subsamples of a particular size from a parent set with repetitions of elements allowed. From the parent suite of fifty records, 100000 bootstrap samples of size 5 are first generated. Estimates of the regression constants are made using the NLRHA output corresponding to each such subsample. Naturally, there will be a variability among the estimates of the constants obtained using different samples. The coefficient of variation (δ) is a good measure of the inter-sample variability of these estimates. The coefficient of variation for the estimate of a, b and σ are denoted by δ_a, δ_b and δ_σ respectively. The process is repeated for bootstrap sample sizes from 6 to 50 in increments of one. The bin size 'N' is considered sufficient when the coefficient of variation for all three parameters reduce to a small value (δ_0); i.e. when the constraints given by Equations 3, 4 and 5 are simultaneously satisfied.

$$\delta_a(N, IM) < \delta_0 \tag{3}$$

$$\delta_b(N, IM) < \delta_0 \tag{4}$$

$$\delta_\sigma(N, IM) < \delta_0 \tag{5}$$

The minimum value of N which satisfies the above criteria is referred to as the optimum number of records (N_p). The magnitude of N_p will vary with the value chosen for the tolerance δ_0. For discussions in the subsequent section, the value of δ_0 is assumed as 0.2. Since the demand model may be conditioned on different IMs, an investigation is carried out on the sensitivity of N_{opt} to the choice of IM (section 3).

3. Results and Discussions

Based on the procedure outlined in section 2.4, efficiency analyses for the ten IMs are carried out and the results thereof are presented graphically in Fig. 4.

It can be seen that there is significant heterogeneity among the considered IMs in terms of their degree of correlation with θ_{max}. PGA is observed to be the least efficient, with E=0.53 and Sa_{avg} is observed to be the most efficient with E= 0.89. Once the efficiency analysis is complete, the bootstrap resampling procedure was used to deduce δ_a, δ_b and δ_σ for different subsample sizes and different choices of the IM. The output from this exercise is illustrated in Fig.5.

A summary of IM efficiencies and the corresponding optimum number of records is presented in Table 5. The functional dependence of N_{opt} on E is illustrated in Fig.6. It can be observed that N_{opt} is highly sensitive to the efficiency of the intensity measure used to define the demand model. A degrading power law model is found to capture the variation of N_{opt} with E. Larger the efficiency of an IM, fewer the number of ground motion records necessary to accurately calibrate the demand model. This highlights the importance of selecting the number of records for cloud analysis only after giving due attention to the efficiency of the intensity descriptor used within the assessment framework.
If the optimum number of records necessary to develop a demand model conditioned on an intensity measure IM_1 of efficiency E_1 is known to be N_{opt1}, then the optimal number of records (N_{opt2}) that must be used to develop an equally accurate demand model using an intensity measure IM_2 of efficiency E_2 is given by Equation 6.

$$\frac{N_{opt2}}{N_{opt1}} = \left(\frac{E_2}{E_1}\right)^{-1.57} \tag{6}$$

Adopting the values of E_1, E_2 and N_{opt1} from reliable sources of literature, once could deduce a priori, an appropriate number of records that must be used when a particular IM is used as the basis for seismic demand assessment.

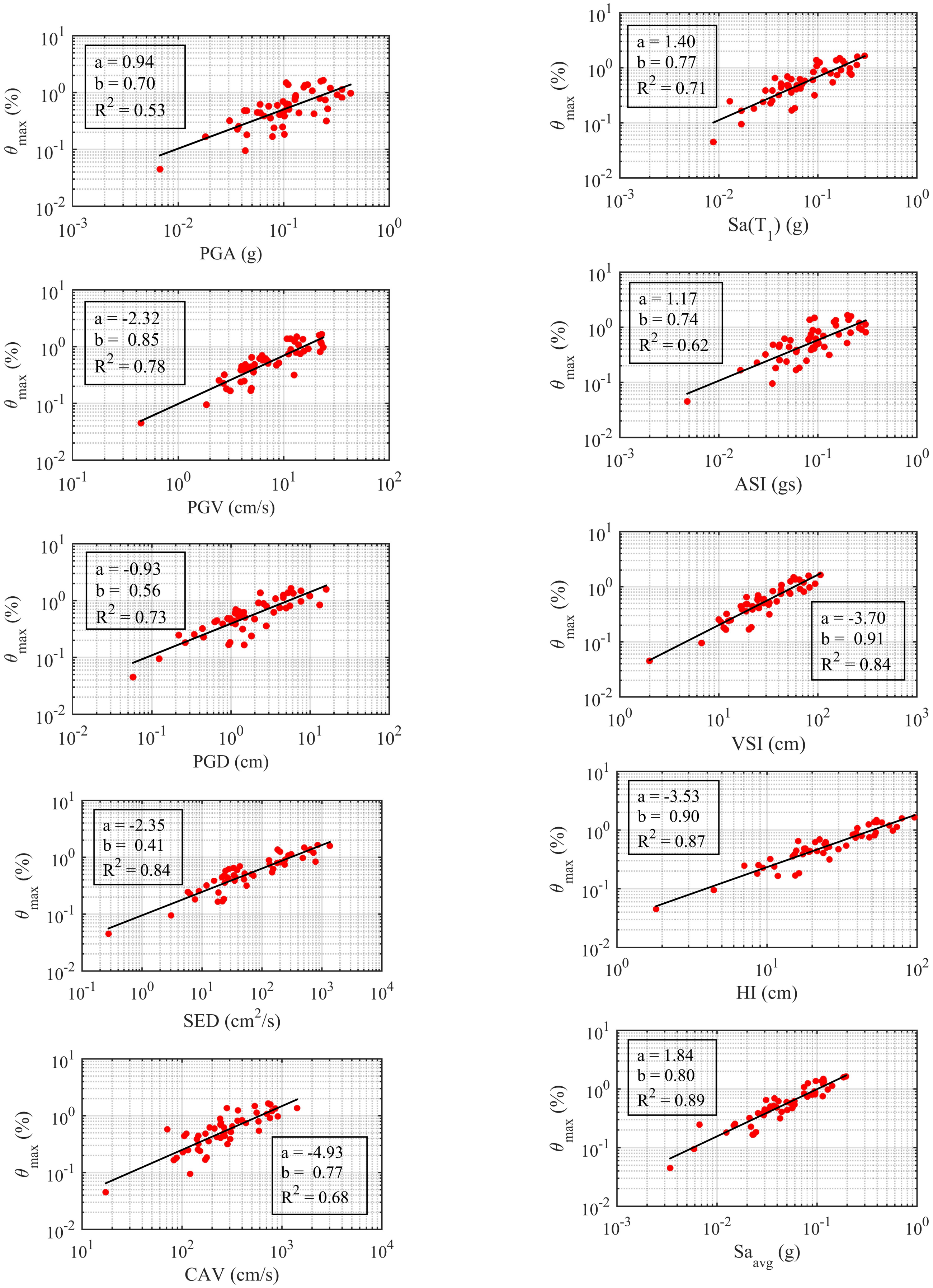

Fig.4 Efficiency analysis of various ground motion intensity measures

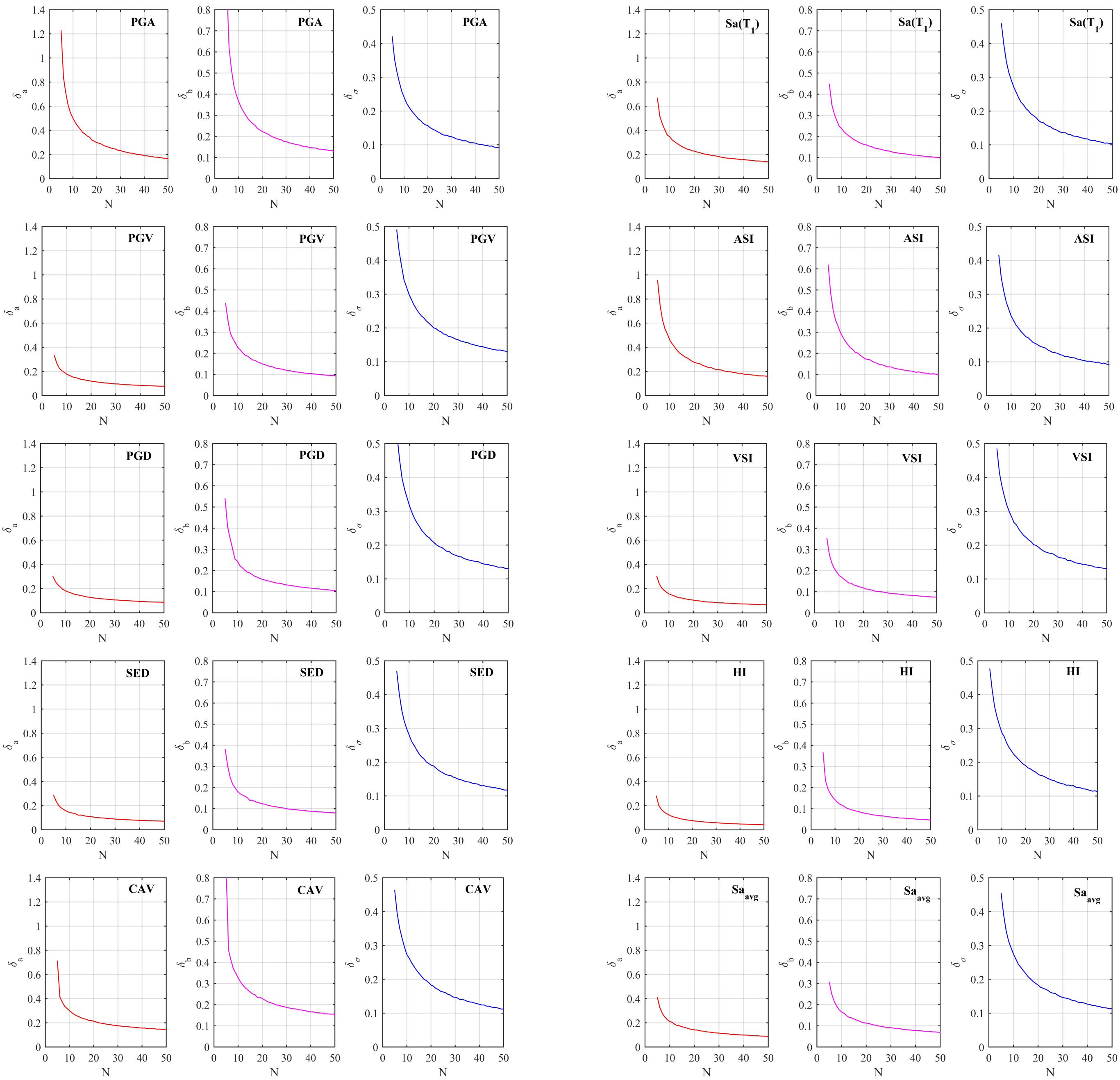

Fig.5 Coefficient of variation in the estimates of demand model parameters from bootstrap samples of different sizes.

Table 5. Efficiency (E) of various IMs and the corresponding values of N_{opt}

IM	E	N_{opt} ($\delta_0 = 0.2$)
PGA	0.53	37
PGV	0.78	21
PGD	0.73	22
SED	0.84	18
CAV	0.68	26
$Sa(T_1)$	0.71	26
ASI	0.62	33
VSI	0.84	20
HI	0.87	18
Sa_{avg}	0.89	17

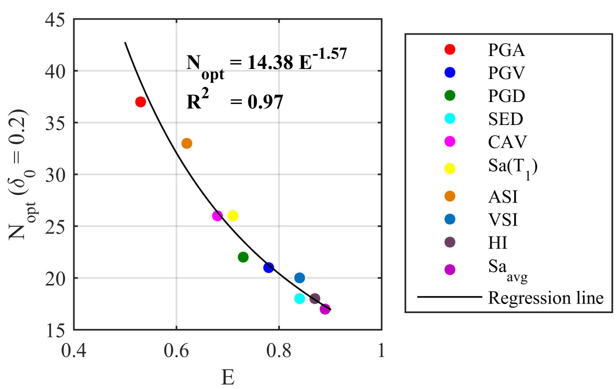

Fig.6 Variation in N_{opt} with the efficiency of IMs

4. Summary and Conclusions

In this study, the method of bootstrap resampling is used to investigate the potential relationship between the efficiency (E) of various IMs and the minimum number of ground motion records necessary to develop a reliable demand model for maximum interstorey drift using cloud analysis. Ten popular IMs are considered in the study, the efficiencies of which are quantified in terms of the R^2 value corresponding to their regression with θ_{max} (considering fifty different ground shaking scenarios in total). Bootstrap resampling is carried out on the parent set of fifty records to generate 100000 subsamples each, of sizes 5 to 50. The constants (a, b and σ) in the log-linear regression model for θ_{max} is then estimated using the NLRHA output corresponding to each subsample of a particular size 'N'. The coefficient of variation for the estimates of each constant across subsamples of the same size is further calculated. The optimum number of records (N_{opt}) for cloud analysis is defined herein as the lowest value of 'N' for which the coefficients of variation for the estimates of all three regression constants in the demand model drop to less than 20%.

The results indicate a strong correlation between the efficiency of IMs and N_{opt}. The value of N_{opt} is as high as 37 for the least efficient measure PGA (E= 0.53) and as low as 17 for the most efficient descriptor Sa_{avg} (E= 0.89). The observed variation of N_{opt} with E highlights the need to give the choice of IM due consideration while determining the number of ground motion records to be used for cloud analysis. Clearly, the use of a highly efficient IM to define the seismic demand model brings down the number of required nonlinear response history analyses, easing a framework which is otherwise computationally exorbitant.

Disclosures

Free Access to this article is sponsored by SARL ALPHA CRISTO INDUSTRIAL.

References

1. Jalayer F, Ebrahimian H, Miano A, Manfredi G, Sezen H. Analytical fragility assessment using unscaled ground motion records. Earthquake Engineering & Structural Dynamics 2017; 46:2639–63.
2. Miano A, Jalayer F, Ebrahimian H, Prota A. Cloud to IDA: Efficient fragility assessment with limited scaling. Earthquake Engineering & Structural Dynamics 2017; 47:1124–47.
3. Vamvatsikos D, Cornell CA. Incremental dynamic analysis. Earthquake Engineering & Structural Dynamics 2002; 31:491–514.
4. Baker JW. Efficient Analytical Fragility Function Fitting Using Dynamic Structural Analysis. Earthquake Spectra 2015; 31:579–99.
5. Bhasker R, Menon A. Torsional irregularity indices for the seismic demand assessment of RC moment resisting frame buildings. Structures 2020; 26:888–900.
6. Melchers RE, Beck André T. Structural reliability analysis and prediction. John Wiley & Sons, Inc.; 2018.
7. Ebrahimian H, Jalayer F, Lucchini A, Mollaioli F, Manfredi G. Preliminary ranking of alternative scalar and vector intensity measures of ground shaking. Bulletin of Earthquake Engineering 2015; 13:2805–40.
8. Bhasker R, Menon A. Characterization of ground motion intensity for the seismic fragility assessment of plan-irregular RC buildings. Structures 2020; 27:1763–76.
9. Sinha R, Sapre A. Optimal number of seismic time-history records for assessment of fragility functions of RC buildings using cloud method. In 16th symposium on earthquake engineering 2018.
10. Indian Standard IS. 456: 2000. Plain and reinforced concrete code of practice. Bureau of Indian Standards; 2000.
11. SeismoSoft. SeismoStruct—a computer program for static and dynamic nonlinear analysis of framed structures; 2018. http://www.seismosoft.com
12. Mander JB, Priestley MJ, Park R. Theoretical stress-strain model for confined concrete. Journal of Structural Engineering 1988; 114(8): 1804-26.
13. Martínez-Rueda JE, Elnashai AS. Confined concrete model under cyclic load. Materials and Structures 1997, 30(3): 139-47.
14. Menegotto M, Pinto E. Method of analysis for cyclically loaded reinforced concrete plane frames including changes in geometry and non-elastic behavior of elements under combined normal force and bending. Proceedings of the IABSE Symposium, Lisbon; 1973.
15. Filippou FC, Popov EG, Bertero VV. Effects of bond deterioration on hysteretic behavior of reinforced concrete joints. EERC Report No. UCB/EERC-83/19, University of California, Berkeley; 1983.
16. Bommer JJ, Acevedo AB. The Use of Real Earthquake Accelerograms as Input to Dynamic Analysis. Journal of Earthquake Engineering 2004; 8:43–91.
17. Pacific Earthquake Engineering Research Center (PEER). PEER ground motion database 2011.
18. Federal Emergency Management Agency (FEMA). NEHRP Recommended Provisions for Seismic Regulations for New Buildings and Other Structures, Rep. No. 450-1/450-2, FEMA; 2004.
19. Kramer SL. Geotechnical earthquake engineering. Pearson Education India; 1996.
20. Von Thun JL. Earthquake ground motions for design and analysis of dams. Earthquake engineering and soil dynamics II-recent advances in ground-motion evaluation. 1988.
21. Housner GW. Spectrum intensities of strong-motion earthquakes. In proceedings of the symposium on earthquake and blast effects on structures 1952 (pp. 20-36).
22. Bianchini M, Diotallevi P, Baker JW. Prediction of inelastic structural response using an average of spectral accelerations. In 10th international conference on structural safety and reliability 2009.
23. Kostinakis K, Fontara I-K, Athanatopoulou AM. Scalar Structure-Specific Ground Motion Intensity Measures for Assessing the Seismic Performance of Structures: A Review. Journal of Earthquake Engineering 2017; 22:630–65.
24. Fontara IK, Athanatopoulou AM, Avramidis IE. Correlation between advanced, structure-specific ground motion intensity measures and damage indices. In 15th world conference on earthquake engineering 2012.
25. Cornell CA, Jalayer F, Hamburger RO, Foutch DA. Probabilistic basis for 2000 SAC federal emergency management agency steel moment frame guidelines. Journal of structural engineering. 2002; 128(4):526-33.
26. Kiani J, Camp C, Pezeshk S. On the number of required response history analyses. Bulletin of Earthquake Engineering 2018; 16:5195–226.
27. Efron B, Tibshirani RJ. An introduction to the bootstrap. CRC press; 1994.