

A new indicator of elastic spectral shape for the reliable selection of strong ground motion records*

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ABSTRACT:

The reliability of record selection based on ϵ -filtration is limited by the strength of the correlation between the structural non-linear response and the ϵ values. In this paper, an alternative indicator of spectral shape is proposed, which results in a more reliable prediction of the non-linear response. This new parameter, named eta (η), is a linear combination of ϵ and the peak ground velocity epsilon (ϵ_{PGV}). It is shown that η , as a non-linear response predictor, is remarkably more efficient than the well-known and convenient parameter ϵ . The influence of η -filtration in the collapse analysis of an eight story reinforced concrete structure with special moment-resisting frames was studied. Statistical analysis of the results confirmed that the difference between ϵ -filtration and η -filtration can be very significant at some hazard levels.

Keywords: ground motion record, spectral shape, collapse capacity assessment

1. INTRODUCTION

It has been shown that the shape of the uniform hazard spectrum (UHS) can be quite different from the shape of the expected response spectrum of a real ground motion record having an equally high spectral amplitude at a particular period [1]. For this reason, the current code-based practice is usually conservatively biased for structural analysis, especially in collapse capacity assessment [1].

It is quite well-known that the response spectra epsilon (ϵ) is an indicator of the elastic spectral shape of ground motion records [1]. The parameter ϵ is a measure of the difference between the spectral acceleration of a record and the mean value of the spectral acceleration, obtained from a ground motion prediction equation at a given period. It is noteworthy that the parameter ϵ has a seismological origin. The three parameters that can vary for a given site and a given fault are magnitude (M_w), distance (R), and ϵ [2]. Therefore, the most direct approach which can be used to account for the spectral shape in structural analysis is to select ground motion records that have M_w , R and ϵ values which match the target values obtained from the corresponding disaggregation analysis.

The parameter ϵ is not a perfect indicator of spectral shape due to the random nature of ground motion records. The ϵ values of ground motion records and the associated non-linear response of a given structure are in partial correlation. The ability of ϵ to predict the non-linear response of a given structure depends on the strength of this correlation.

The objective of this study is to establish a more reliable indicator of spectral shape which could lead to a better prediction of non-linear response. The main idea belonging to this goal is the incorporation of the time-domain intensity measures (i.e. PGA, PGV, and PGD) with the frequency-domain intensity

* This paper is based on a manuscript which is submitted to the Earthquake Engineering and Structural Dynamic journal, 2010.

measures (i.e. the spectral values) in order to create a more reliable indicator of the elastic spectral shape.

2. EPSILON; A PREDICTOR OF NON-LINEAR RESPONSE

In order to investigate the effect of ϵ on the non-linear response of a structure, a set of non-linear single-degree-of-freedom (SDOF) systems, as well as an appropriate bin of ground motion records, was considered. A period range of 0.1 to 2.0 sec, as well as a ductility range of 2 to 12, was used for the SDOF systems. The collapse capacity values were calculated using incremental dynamic analysis (IDA), and a precise trace of the collapse capacity point was performed using the Hunt and Fill algorithm [3]. The bin of applied ground motion records includes 78 records, with a magnitude range of 6.5 to 7.8. The selection criteria and the other information can be found in [4].

Figure 1 shows the correlation between the parameter ϵ and the collapse capacity values for two SDOF systems with periods of 1.0 and 2.0 sec, and ductility values equal to 6 and 12. The epsilon values were determined based on the Campbell and Bozorgnia attenuation relationship [5]. The correlation shown in the Figure 1 confirms the influence of the parameter ϵ on the non-linear response. Due to this correlation, it is anticipated that the selection of ground motion records based on ϵ -filtration results in a reduction in the potential bias in the prediction of the structural non-linear response. It is clear that the amount by which the potential bias can be reduced strongly depends on the size of the correlation between the non-linear response and the parameter ϵ_{Sa} .

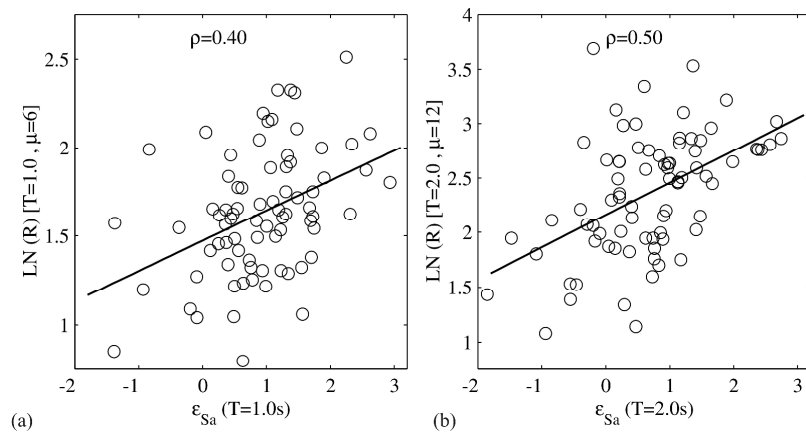


Figure 1. The correlation between the parameter ϵ and the collapse capacity values

The above analysis for all of the considered SDOF systems showed that the average correlation coefficient is just 0.43. It is reasonable to take this correlation coefficient as an index of efficiency of the parameter ϵ for reducing bias in the non-linear response.

The main contribution of this study is that a more robust predictor of non-linear response has been obtained by considering the parameter η as a linear combination of different epsilons, i.e. ϵ_{PGA} and ϵ_{PGV} . This hypothesis is studied in the following sections.

3. ETA, A MORE ROBUST PREDICTOR OF NON-LINEAR RESPONSE

Each of the IM epsilons can reflect a part of information hidden in a given ground motion record. Here it is shown that a combination of IM epsilons can result in a more robust prediction of the structural response, due to the inherent distinction between the time domain and frequency response domain parameters, which have a high potential to enhance each other as response predictors.

Again, let us assume a SDOF system with a period of 2.0 sec and ductility equal to 12. A linear trend, as expected, exists between ϵ_{Sa} and the non-linear response as shown in Figure 2a. The coefficient of

correlation between these variables was determined to be equal to 0.50. Now consider the parameter η as a linear combination of ε_{Sa} , ε_{PGA} , ε_{PGV} and ε_{PGD} as written in Equation 1:

$$\eta = \varepsilon_{Sa} + c_1\varepsilon_{PGA} + c_2\varepsilon_{PGV} + c_3\varepsilon_{PGD} \quad (1)$$

The objective is to find the best values for the constant coefficients (c_1 , c_2 and c_3) which result in the maximum correlation between η and the non-linear response. By application of the Genetic Algorithm (GA) [6], as a powerful tool for optimization, the optimum constant coefficients were determined to be equal to:

$$c_1 = 0.50 \quad c_2 = -0.74 \quad c_3 = -0.42$$

The achieved coefficient of correlation is 0.75, and is significantly greater than the previously obtained value, as shown in Figure 2b. It is thus reasonable to claim that the potential of η is greater than ε_{Sa} to predict the non-linear response.

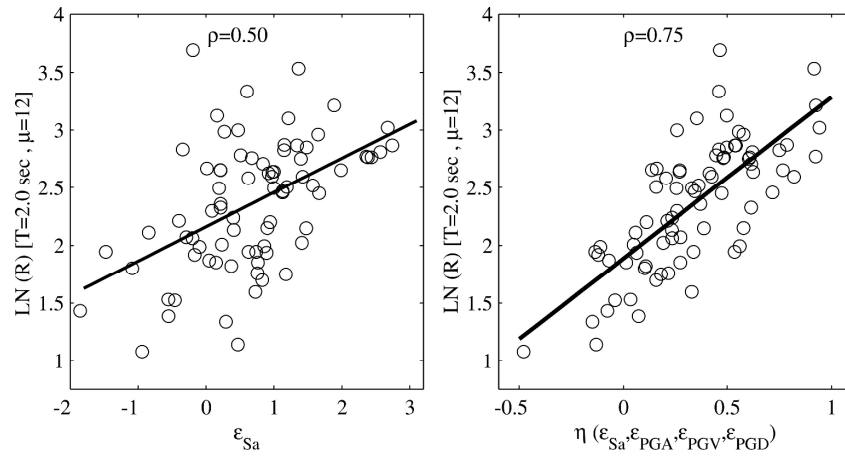


Figure 2. The correlation between the response predictors and the collapse capacity: (a) ε_{Sa} as a response predictor, (b) η as a response predictor.

Equation 1 was based on just one particular case, and so it does not represent all of the investigated SDOF systems. A regression analysis for the response of all of the SDOF systems is needed in order to develop a general response predictor. After normalization of all of the SDOF response values, a vector of size 6552 (84x78) was obtained. Corresponding to this vector, a 6552x4 matrix, including four epsilon values for each record and each SDOF system, was considered. Similarly to the above approach, the response predictor (η) can be defined. For sensitivity analysis, too, different combinations of epsilons are involved in the regression analysis, and the results are summarized in Table 1.

The last case, which involves all of the epsilons, provides, as shown in Table 1, the most efficient response predictor, with $\rho = 0.65$. However, it can be seen that the efficiency of the dual combination of ε_{Sa} and ε_{PGV} (the sixth item in Table 1) is approximately equal to that of the last combination. Thus, a simple definition of the parameter η can be introduced as:

$$\eta = \varepsilon_{Sa} - b\varepsilon_{PGV}, \quad b = 0.823 \quad (2)$$

Table 1. Determination of the coefficients for η for different linear combinations of ε

No.	ε_{Sa}	ε_{PGA}	ε_{PGV}	ε_{PGD}	ρ
1	1	-	-	-	0.43
2	-	1	-	-	0.18
3	-	-	1	-	0.08
4	-	-	-	1	0.13
5	1	-0.373	-	-	0.47
6	1	-	-0.823	-	0.64
7	1	-	-	-0.676	0.54
8	1	0.123	-0.958	-	0.65
9	1	-0.289	-	-0.540	0.56
10	1	0.186	-1.016	0.057	0.65

Figures 3a and 3b show, respectively, the coefficient of correlation between the parameters η and ε_{Sa} and the non-linear response for all of the investigated SDOF systems. The parameter η is a more robust predictor of response as shown in Figure 4, with an average of a 50% improvement in the coefficient of correlation.

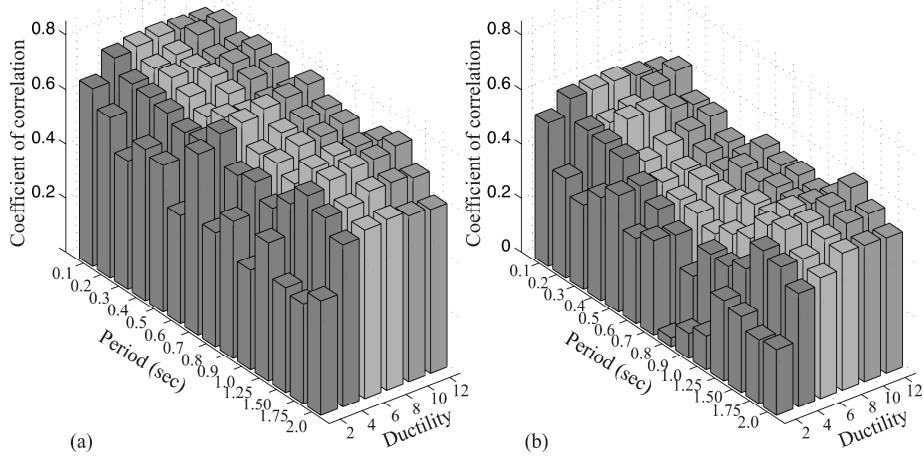


Figure 3. Comparison of the efficiency of η and ε as response predictors
(a) correlation of the response and η (b) correlation of the response and ε_{PGV} .

The improved efficiency of η as a response predictor may be due to the fact that η is a better indicator of the spectral shape than ε_{Sa} . This hypothesis is demonstrated in Figure 4. The ground motion records were sorted based on the ε_{Sa} value and also based on η , and then two higher and lower subsets with N elements were selected from each sorted list. The mean of the response spectra of both subsets were then plotted, so that the left-hand figures are based on ε_{Sa} sorting, and the right-hand figures are based on η -based sorting. Two subsets with size 8, as shown in Figure 4a, result in different spectral shapes. This finding is similar to the results obtained in other studies [i.e. 1]. The procedure is repeated for η filtration in Figure 4b. The difference between two resulted spectra is more significant for the η filtration case in comparison with the ε_{Sa} -filtration approach. This analysis was repeated for a selection of 16 records, and the corresponding results are shown in Figure 4c and 4d, for each of the filtration approaches. This case fully confirms the better ability of η to make a distinction between records with different spectral shapes.

4. DETERMINATION OF THE TARGET ETA FOR DIFFERENT HAZARD LEVELS

A practical challenge faced when using η for record selection is the choice of target epsilons. The standard hazard disaggregation analysis only provides the target ε_{Sa} , but the target ε_{PGV} is still

undetermined. Assuming equal values for epsilons may be challengeable since equal epsilons may not necessarily correspond to a particular hazard level.

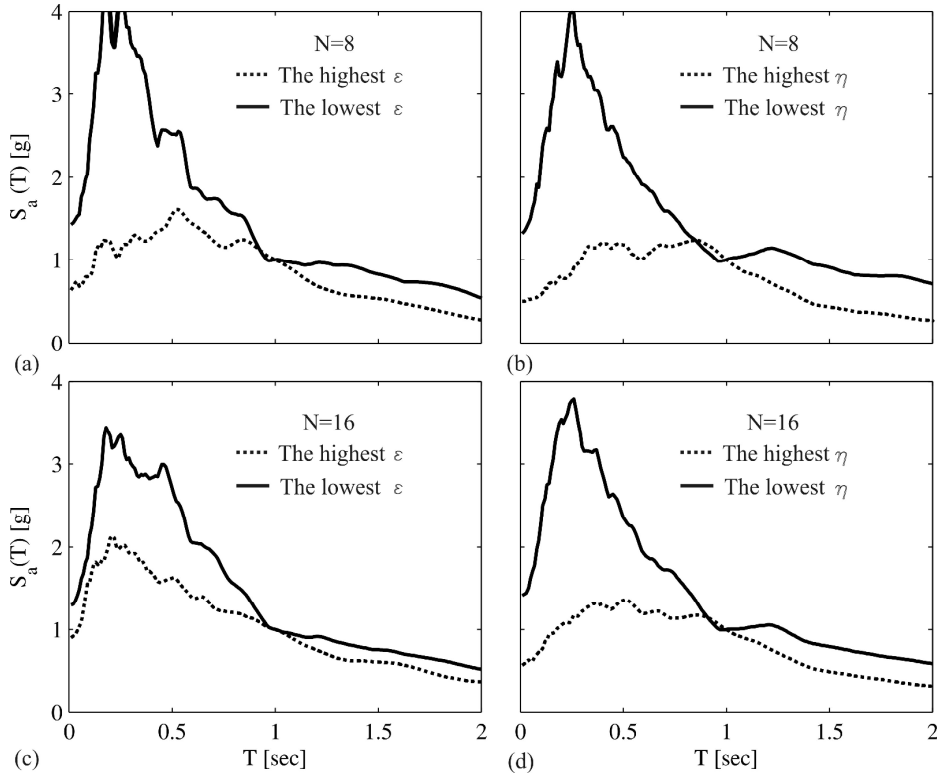


Figure 4. Comparison of η and ε_{Sa} indicators of spectral shape
(a), (b) selection of 8 ground motions with highest/lowest values of η and ε_{Sa}
(c), (d) selection of 16 ground motions with highest/lowest values of η and ε_{Sa}

The correlation between ε_{PGV} and ε_{Sa} in different period ranges is studied in this section, and linear regression is implemented in order to develop an analytical equation for the evaluation of ε_{PGV} for a given ε_{Sa} .

The results presented in this section were derived empirically from a strong ground motion records (SGMR's) data set based on worldwide recordings of shallow crustal earthquakes. This set, which was used by Baker and Cornell [7] to analyze the correlation of response spectral values, includes 267 pairs of horizontal ground motion records with magnitudes greater than 5.5 and source-to-site distances of less than 100 km.

The correlation between ε_{PGV} and ε_{Sa} can be represented by the following model:

$$\varepsilon_{PGV} = 0.24 + 0.72\varepsilon_{Sa} \quad (3)$$

In this simple model, different values of ε_{Sa} associated with a range of periods were employed in order to develop a unique equation. The range of applied periods was 0.1 to 3.0 sec, including 58 data points. Figure 5 shows ε_{PGV} versus ε_{Sa} for the stated data points.

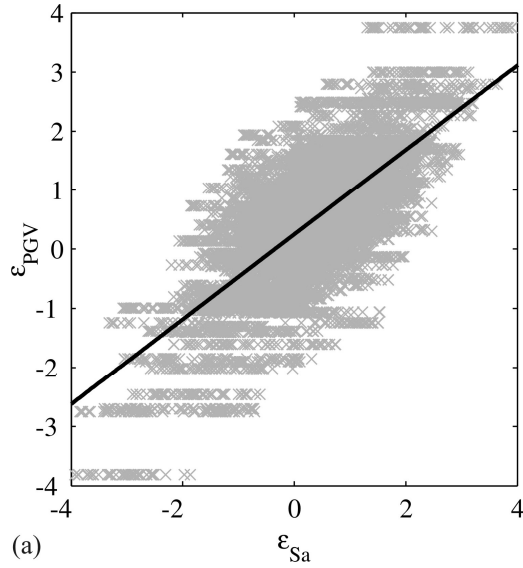


Figure 5. The relationship between ε_{PGV} and ε_{Sa}

A direct method to account for the target η in structural collapse assessment is to determine the expected ε_{PGV} value from Equation (3) for any considered hazard level, then to calculate the target η from Equation (2), and finally, to select the ground motions that are consistent with the target η . For the purposes of simplicity, Equation (2) can be revised to normalize the target η values to the target ε_{Sa} values, as described below.

$$\eta = 0.485 + 2.454\varepsilon_{Sa} - 2.020\varepsilon_{PGV} \quad (4)$$

The target η value can now be considered to be equal to the target ε_{Sa} which is achievable from the disaggregation analysis. In the following section, a η based selection of ground motion records is presented for the collapse simulation of a MDOF structure.

5. EXAMPLE: COLLAPSE CAPACITY ASSESSMENT OF A MDOF STRUCTURE

In this section the seismic collapse capacity of a MDOF test structure based on an η -based record selection is discussed. The considered structure is an eight story reinforced concrete building with special moment resisting frames. The building is 36.5x36.5 m in plan, uses a 3 bay perimeter frame system with a spacing of 6.1 m, and has a fundamental period (T_1) of 1.71 sec. This building is ID 1011 from [8].

It was assumed that this structure is located at an idealized site where the ground motion hazard is dominated by a single characteristic event with a return period of 200 years, $M_w = 7.2$, $R = 11.0$ km and $Vs_{30} = 360$ m/s. From basic probability, the target epsilons for different hazard levels are given in Table 2.

Table 2. The target parameters for different hazard levels.

Return Period (Year)	Probability in 50 years	Target epsilon
125	33%	-0.80
200	22%	0.00
475	10%	+0.80
2475	2%	+1.75

For each hazard level, 20 ground motion records were selected using both η -filtration and ε -filtration procedures. The resulting fragility curves for different hazard levels are shown in Figure 6; where the differences between the ε and η filtrations are, in the case of some of the epsilons, significant, whereas in the case of the remaining epsilons they are not significant.

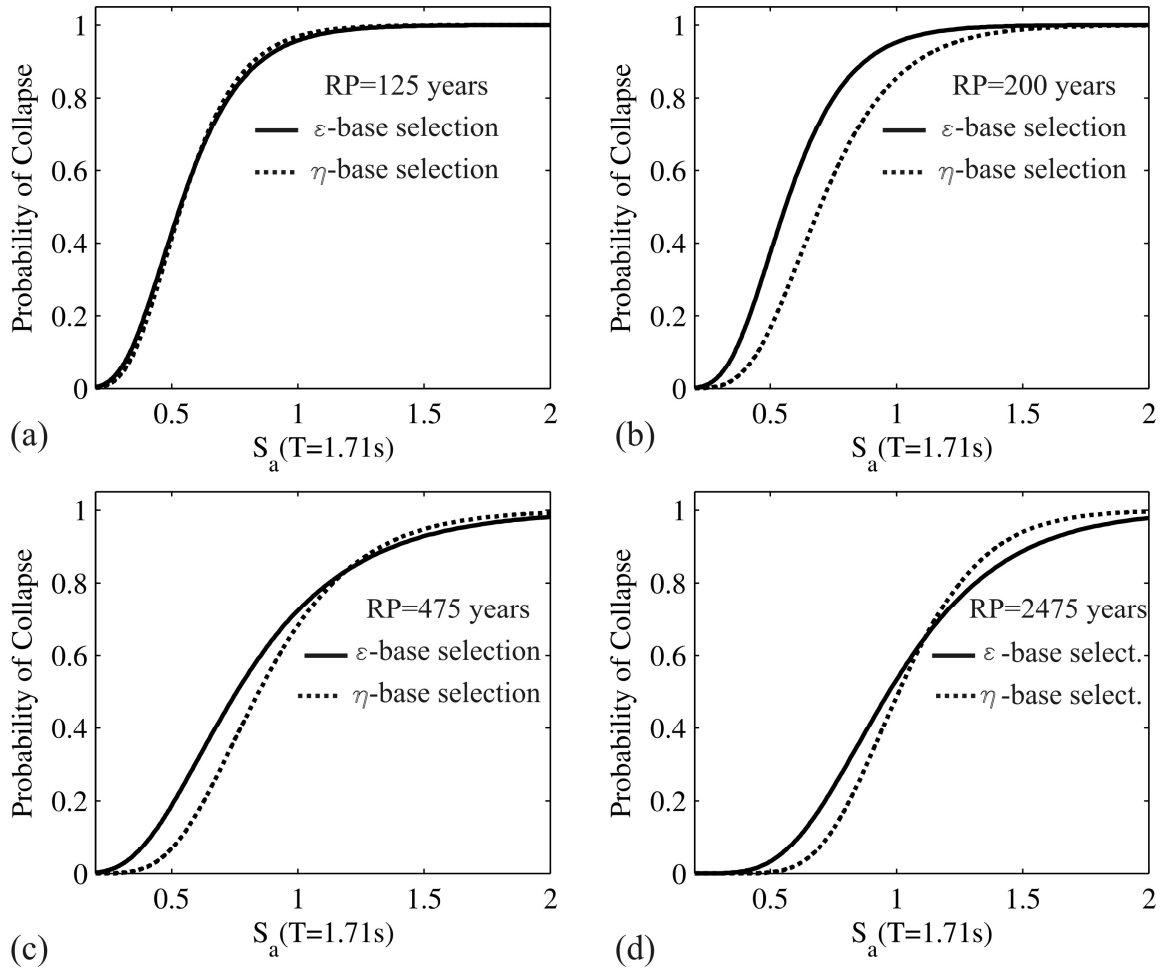


Figure 6. The fragility curves for different hazard levels

For further investigation, the mean annual frequency (MAF) of collapse was computed based on each of the filtration approaches. Figure 7a shows the hazard curve for the assumed site. The MAF of collapse due to $S_a(T=1.71\text{sec})=x$ is shown in Figure 7b, for both record selection methods. The MAF of collapse is also shown in Figure 7b for the case when all the records were used (without any filtration). The MAF of collapse is less for ε -filtration in comparison with the no-filtration approach which has also been addressed by other studies [e.g. 1]. Also this Figure shows that the MAF of collapse for η -filtration is remarkably lower than that for the ε -filtration. The absolute value of MAF, calculated by integrating MAF over S_a , was 6.4×10^{-5} , 3.6×10^{-5} and 1.6×10^{-5} for the no-filtration, ε -filtration and η -filtration approaches, respectively.

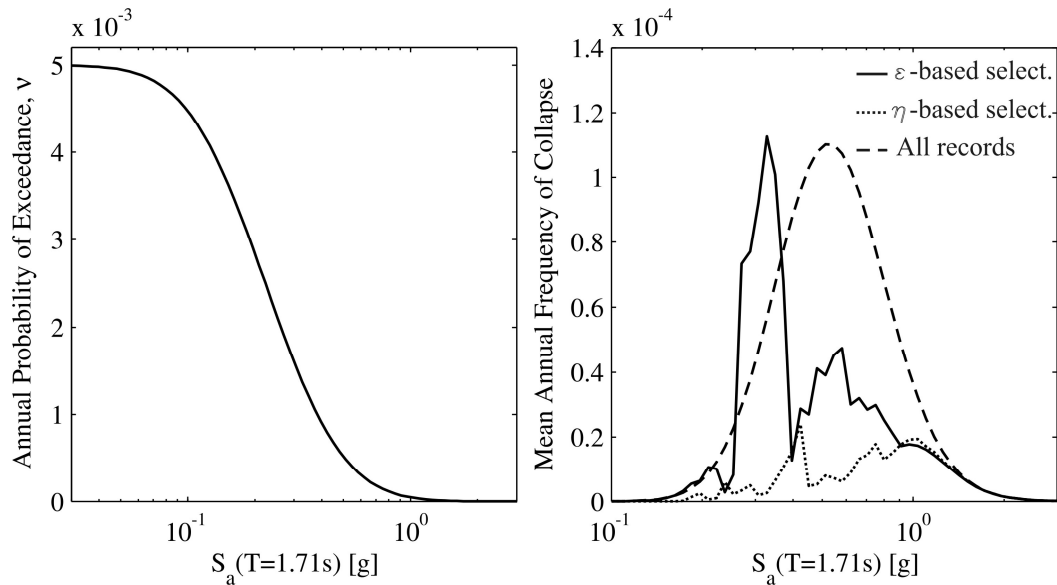


Figure 7. The effect of different filtration approaches in MAF analysis (a) the hazard curve (b) the MAF of collapse due to $S_a(T = 1.71 \text{ sec}) = x$

6. CONCLUSION

In order to improve the reliability of the record selection procedure, a new parameter named eta (η) has been proposed as a linear combination of ε and ε_{PGV} . It was shown that the correlation between η and the non-linear response is about 50% better than the correlation between ε and the response. It has also been shown that the parameter η is a better indicator of spectral shape compared with the parameter ε . Finally, the absolute MAF of collapse for the η -filtration approach is remarkably lower than that corresponding to ε -filtration.

ACKNOWLEDGMENT

The research conducted by the authors has been funded by the International Institute of Earthquake Engineering and Seismology (IIEES) under Award Number 7134. This support is gratefully acknowledged.

REFERENCES

1. Baker J.W, Cornell CA. Spectral shape, epsilon and record selection. *Earthquake Engineering and Structural Dynamics* 2006; **35**(9):1077–1095.
2. Kramer S.L. Geotechnical earthquake engineering, *Prentice Hall*, Upper Saddle River, N.J., 653 pp, 1996.
3. Vamvatsikos D., Cornell C.A. Incremental dynamic analysis. *Earthquake Engineering and Structural Dynamics* 2002; **31**(3):491–514.
4. Haselton C.B., Deierlein G.G. Assessing Seismic Collapse Safety of Modern Reinforced Concrete Moment-Frame Buildings, *PEER Report 2007/08*, Pacific Engineering Research Center, University of California, Berkeley, California.
5. Campbell K.W., Bozorgnia Y. Campbell-Bozorgnia NGA ground motion relations for the geometric mean horizontal component of peak and spectral ground motion parameters. *PEER Report 2007/02*, Pacific Engineering Research Center, University of California, Berkeley, California.
6. Goldberg DE. *Genetic Algorithms in search, Optimization, and Machine Learning*. Addison-Wesley: Reading, MA, 1989.
7. Baker J.W., Cornell C.A. Correlation of response spectral values for multicomponent ground motions. *Bulletin of the Seismological Society of America*, 2006; **96**(1): 215–227.
8. Haselton C.B, Baker J.W, Liel A.B, Deierlein G.G. Accounting for ground motion spectral shape characteristics in structural collapse assessment through an adjustment for epsilon. *ASCE Journal of Structural Engineering*; (in press).