



GA-BASED SELECTION AND SCALING OF STRONG GROUND MOTION RECORDS FOR STRUCTURAL DESIGN

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SUMMARY

A new approach in selection, scaling and classification of sets of recorded earthquake ground motions using soft computing methods is presented. First, the optimization basis of search and scaling procedure for site-specific design spectrum matching with minimum alteration of phase and shape of spectra is explained. Contrary to the prevailing scaling methods where a preset number of earthquake records (usually between a single component to seven pairs) are selected first and scaled to match the design spectrum next, the proposed method is capable of searching a set consisting of thousands of earthquake records and recommending a desired subset of records that match the target design spectrum. As a result, the phase and shape of the response spectra of earthquake ground motions are not tampered with. Second, pattern recognition is performed in the database of records by applying fuzzy classification in order to extract rules that can be used as data attributes in the search and scaling. The procedure is fast and reliable and results in records, which match the target spectrum with minimal alteration and the least mean square of deviation from the target spectrum.

INTRODUCTION

Structural design for seismic loading, which is traditionally done for most types of common structures by the means of equivalent lateral static loading or modal spectrum analysis, is no longer a preferred methodology for design of modern structures with complex topology and functionality under extreme loading scenarios. Nonlinear response history evaluation, on the other hand, is becoming a practical tool due to availability of high performance computing and recommendations of the new seismic guidelines. Code provisions governing design of seismic isolated structures, for example, have included nonlinear time history analysis provisions for over a decade (see Naeim and Kelly [26]). Modern seismic evaluation guidelines such as FEMA-356 (Federal Emergency Management Agency [12]) contain detailed and

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elaborate provisions for performing nonlinear analysis for all kinds of building structures. Since traditionally seismic hazard at a site for design purposes has been represented by design spectra, virtually all seismic design codes and guidelines require scaling of selected ground motion time histories so that they match or exceed the controlling design spectrum within a period range of interest (International Conference of Building Officials [19]; International Code Council [18]; Federal Emergency Management Agency [12]).

To this end, one important question that challenges design engineers in performing time history analysis is often the criteria by which to select SGM records as input to the mathematical model of the structure to accurately estimate structural demands for design objectives of interest. Due to exponential growth in size and number of the available earthquake motion records and databases around the globe and on the Internet (Northridge 1994 California earthquake, for instance, contributed to about 24% increase in the number of available data alone, with around 500 records added to the databases at the time, see Naeim and Anderson [24]), the crucial task of data mining and classification of ground motion records needs more attention. Currently, development of different search and scaling methodologies and computational tools necessary for finding and retrieval of near optimal and realistic sets of records in large databases with functionality to match any target design spectrum (enforced by site specific hazard analyses or design seismic codes) is underway. This study is a natural continuation on development of such a system (β -version available) by Naeim, *et al*, [23]. The optimization platform that is programmed by a GA makes it possible for the user to set up different constraints on a variety of parameters such as the range of acceptable scaling factors (that can be narrowed down to 1.0) and portions of the database to be searched by the software. The objective function to be minimized is the average digression from a given target design spectrum. The final bin of the selected records, in general, consists of entries of different distances, different soil types and different magnitudes, so it is appealing to extend the work to add more constraints (such as de-aggregation of hazard, site-soil types and regional tectonics) to the search and scaling procedure. This will result in more accurate estimation of hazard provided that the nature of expected seismic input motion in a site is understood. Even under these circumstances, since there is no guarantee that all possible causative faults in the region are known, one would better include many diverse records in the input design bin due to the random nature of ground motions generally expected. There has long been a consensus by researchers and practitioners that better representation of hazard can be obtained by including representatives from different types of motion that may be experienced at a site. In either cases, whether to have a “conforming” set of motions with site parameters and appropriate scaling factors to match the site’s design spectrum, or when “non-uniform” records are to be included, the first question to answer is whether or not there are patterns of similar records in the database so the task of search could be performed in any cluster of similar data or on any subset of few clusters. This can be addressed in the realm of pattern recognition, which is the mathematical technique of identification and classification of similar data in a set. Pattern classification has originally been developed and successfully applied in the areas of system sciences, speech and image recognition, and is possibly the most appropriate analytical vehicle to carry on this task with.

Pattern recognition techniques (supervised and unsupervised) are applied to the database of records in order to extract rules and clusters of similar data that can be used as data attributes in the search procedure through fuzzy classification. This has three major advantages:

1. Searching in clusters of smaller sizes can save computational time for the GA in large databases,
2. Having the benchmark database classified enables the user to have more choices when it comes to selection of data characteristics to be included in the design bin, and
3. By studying statistics of complex data, inference can be made to generalize rules to estimate unknown data properties based on the available information.

Soft computing, originated mainly by the pioneering work of Lotfi Zadeh in 60's to model the human mind's ability to "*Exploit the tolerance for imprecision, uncertainty and partial truth to achieve tractability, robustness and low solution cost,*" has now received considerable applications in structural and earthquake engineering practice (Ghaboussi *et al.*, [16], Pezeshk *et al.*, [27, 28], Alimoradi *et al.*, [1, 2], Foley *et al.*, [13, 14], and Zadeh [30]) This is due to the fact that the nature of seismic design, by itself, is involved with processing of uncertain data and processes. The dimensions of today's analytical models, especially in the area of nonlinear response estimation of complex dynamic systems, make it often difficult for the conventional "hard-computing" methodologies to efficiently meet all the real-world constraints necessitated by large-scale problems.

After a brief description of the GA-based scaling procedure, description of data dimensions, properties and feature selection is followed by classification techniques used, cluster validation, and discussion of the results.

PROBLEM FORMULATION

A typical code or guideline provision would require scaling of the two horizontal components of each ground motion (called a data set) such that the average square root of the sum of the squares (SRSS) of the 5% damped response spectra of the data set used does not fall below α times the 5% damped design spectrum for periods between T_0 and T_n . Typical value of α is either 1.3 or 1.4. For conventional buildings, T_0 and T_n are usually assigned values such as $0.2T$ and $1.5T$ where T is the fundamental period of the structure. For seismic isolated structures, some codes provide for a narrower range of matching around the fundamental period, T . Generally, for nuclear power plants and other critical facilities a broader range of matching is used.

Several methods of scaling time histories have been proposed. These include frequency-domain methods where the frequency content of the recorded ground motions are manipulated in order to obtain a match (Gasparini and Vanmarcke [15]; Silva and Lee [29]; Bolt and Gregor [5]; Department of the Army [11]; Carballo and Cornell [7]) and time-domain methods which limit themselves to manipulating only the amplitude of the recorded ground motions (Kircher [21]; Naeim and Bhatia [25]).

Regardless of the method (frequency-domain or time-domain), in virtually all of the existing approaches, the processes of selecting earthquake ground motions and their scaling to match the design spectrum are separate and distinct. In other words, first one or more time histories are selected and then appropriate scaling mechanisms for spectrum matching are applied. This is not the case for the method proposed in this paper where, as will be illustrated later, the search for appropriate time histories and corresponding scaling factors are completely intertwined and parts and parcels of a single process.

We present a scaling procedure based on genetic algorithms for the purpose of closely approximating a given target spectrum over a range of periods and tolerances specified by the user.

Optimization Statement

A genetic algorithm is to find the best combination of strong ground motion records and the corresponding scaling factors from a large database of earthquake records to minimize the deviation of the SRSS of the records' spectra from a given design spectrum (target). The deviation from the target is measured by the mean square of error between the square root of the sum of the squares (LMS-SRSS) of the average scaled spectrum and the target (see Figure 1). The search process is to obtain the best seven pairs of ground

motion and corresponding scaling factors. There is, however, no built-in limitation on the number of earthquake records and scaling factor pairs that the algorithm may select.

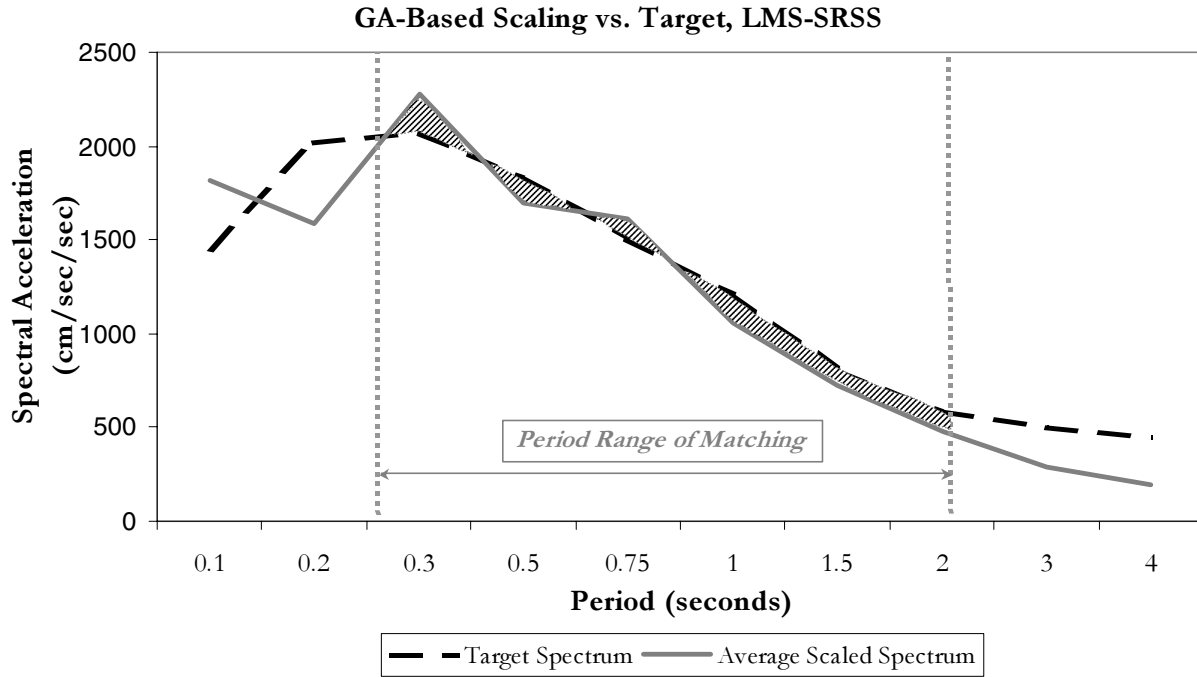


Figure 1. Graphical representation of the first optimization problem (minimization of the hatched areas.)

The problem is formulated as the minimization of the error function, Z , between the averaged scaled spectra and the target spectrum in a range of T_0 to T_n . The error function is defined as:

$$Z = \min \left\{ \sum_{T=T_0}^{T_n} \left(\sqrt{\frac{\sum_{i=1}^7 [S_i \cdot SA_i(T)]^2}{\sum_{i=1}^7 S_i^2}} - F_T(T) \right)^2 \right\} \quad (1)$$

in which:

- T = the fundamental vibration period of the structure
- S_i = the scaling factor corresponding to record number i
- $SA_i(T)$ = value of the spectral acceleration of record number i at period T
- $F_T(T)$ = value of the target design spectrum at period T
- T_0 = initial period to consider (i.e., $0.2T$)
- T_n = final period to consider (i.e., $1.5T$)

The optimization procedure is subject to:

$$S_{\min} \leq S_i \leq S_{\max}$$

and

$$S_{\min}, S_{\max} > 0 \quad (1-a)$$

where:

$$\begin{aligned} S_{\min} &= \text{is the lower bound of the acceptable scaling factors, and} \\ S_{\max} &= \text{the upper bound of the acceptable scaling factors.} \end{aligned}$$

This formulation does not guarantee that the final solution would not fall below the target in the period range under consideration, instead it would merely attempt to minimize the deviation of the solution from the target. A second constraint achieves the objective by adding a penalty function to the optimization formulation as follow:

$$\sqrt{\frac{\sum_{i=1}^7 [S_i \cdot SA_i(T)]^2}{\sum_{i=1}^7 S_i^2}} - F_T(T) \geq 0 \quad \text{for all periods } T_o \leq T \leq T_n \quad (2)$$

A search space of earthquake records is needed for the genetic algorithm to select from. For this paper a set of 1496 horizontal strong ground motion components were selected from the database compiled by Naeim and Anderson [24]. Obviously, any appropriate set of records may be used for the same purpose. It is worth mentioning that for a database of this size the search space is very large. Setting aside the scaling factors, 1496 records may be combined in groups of 7 records in more than 3×10^{18} different ways. Clearly, the use of conventional optimization techniques such as nonlinear programming would take an enormous number of computations and would not be feasible. Conversely, a genetic algorithm as demonstrated here can converge with a reasonable computing effort and a rather short computing time.

The operators of genetic algorithm are selected as follows:

Solution Variables/Population of Individuals:

Any arbitrary union of seven records and seven scaling factors is defined as a single “individual” or chromosome. The objective is to create the best individual using the pool of earthquake records in the database and scaling factors within the acceptable range specified by the user. Therefore, each individual has fourteen subdivisions to represent each variable (seven for identification of seven records in the database and seven for identification of the corresponding scale factors). We assigned a length of 10 binary digits to each subdivision making the total length of each individual equal to 140 binary digits. This, of course, can be changed and longer binary strings may be used to accommodate larger earthquake record databases. The first seven binary sub-strings provide the positions of the seven records in the database. The remaining seven sub-strings represent the corresponding scaling factors. Since the record numbers are integers and the scaling factors are real, the optimization method required a mixed integer-real process.

Fitness function:

This function is defined as the reciprocal of the objective function (1). Therefore, the lesser the error function for a given combination of selected records and scaling factors, the higher the fitness of the individual. The individuals may be penalized if their average scaled spectrum falls below the target. For these cases, a penalty function is defined to lower the fitness of the individual. The penalty function is proportional to the area under the target for the specific individual.

$$Fitness_Function(j) = \frac{C_1}{\left\{ \sum_{T=T_o}^{T_n} \left(\sqrt{\frac{\sum_{i=1}^7 [S_i \cdot SA_i(T)]^2}{\sum_{i=1}^7 S_i^2}} - F_T(T) \right)^2 \right\} + \left[C_2 \cdot \left(A_{T_o \rightarrow T_n}^- \right) \right]^2} \quad (3)$$

where:

- j = the individual number
- $A_{T_o \rightarrow T_n}^-$ = the area of the scaled spectrum under the target
- C_1 = fitness scaling
- C_2 = 0 if simple LMS or 1 if LMS and constraint on negative values is used.

We adapted and modified the backbone genetic algorithm routines from the LGADOS code placed in public domain by David Coley (Coley [8, 9]). The graphical user interfaces are programmed in Visual Basic and the analytical engine of genetic algorithm computations is in Fortran.

Software Utility

The input data consists of the ordinates of the target acceleration design spectrum, the period range for the matching, lower and upper bound acceptable values for scaling factors and a set of GA parameters. The GA parameters consist of a population size, number of generations, crossover ratio and mutation ratio. We have successfully used the default values, although other values may also prove promising.

1. Acceptable scale factor range: 0.5 to 1.5
2. Population of Individuals: 200
3. Number of generations: 300
4. Crossover ratio: 0.65
5. Mutation ratio: 0.025

The program is fast and it takes only a few seconds for it to converge to an optimum solution on a typical personal computer. A typical screen showing the selected input and obtained results and the match between the target and the selected individuals is presented in Figure 2.

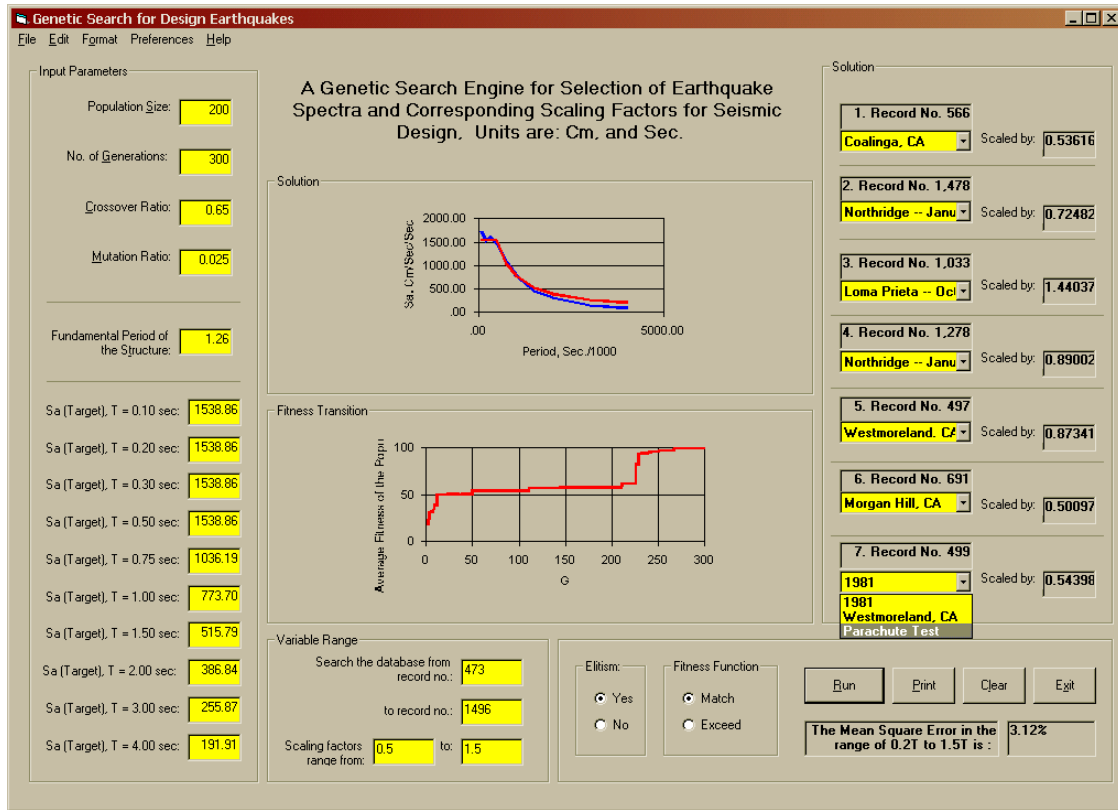


Figure 2. A computer display summarizing the input parameters and output results.

EXAMPLE

A sample 5% damped target spectrum is shown by the hatched thick line in Figure 3. A building period of 1.26 seconds is assumed with the range of 0.25 to 1.89 seconds for matching the target. A genetic search utilizing a 200-individual population over 300 generations with a crossover ratio of 65.0% and a mutation probability of 2.5% was performed. Acceptable range of scale factors was from to 0.5 to 1.5. The genetic algorithm selected seven records and the corresponding scale factors shown in Table 1, as representing the best match.

Table 1. The records and scaling factors selected by the genetic algorithm for Example 1

No.	Year	Earthquake Name	Station and Component	Scale Factor
1	1983	Coalinga, CA	Parkfield, Stone Corral 4 E, 0°	0.54
2	1994	Northridge, CA	LA, Wadsworth V.A. Hospital, 235°	0.72
3	1989	Loma Prieta, CA	Hollister - South & Pine, 0°	1.44
4	1994	Northridge, CA	Tarzana - Cedar Hill Nursery, 90°	0.89
5	1981	Westmoreland, CA	Niland, 0°	0.87
6	1984	Morgan Hill, CA	Coyote Lake Dam, 285°	0.50
7	1981	Westmoreland, CA	Parachute Test Facility, 0°	0.54

The mean square of error between the average spectra of the scaled records and the target in the range of 0.25 to 1.89 second is 3.12%. This represents an excellent match as can be observed in Figure 3 where the spectrum of individual scaled records is shown with narrow lines, the average of scaled records is indicated by a solid thick blue line and the target is represented by a hatched thick line. The fitness transition curve as a function of successive generations is shown in Figure 4.

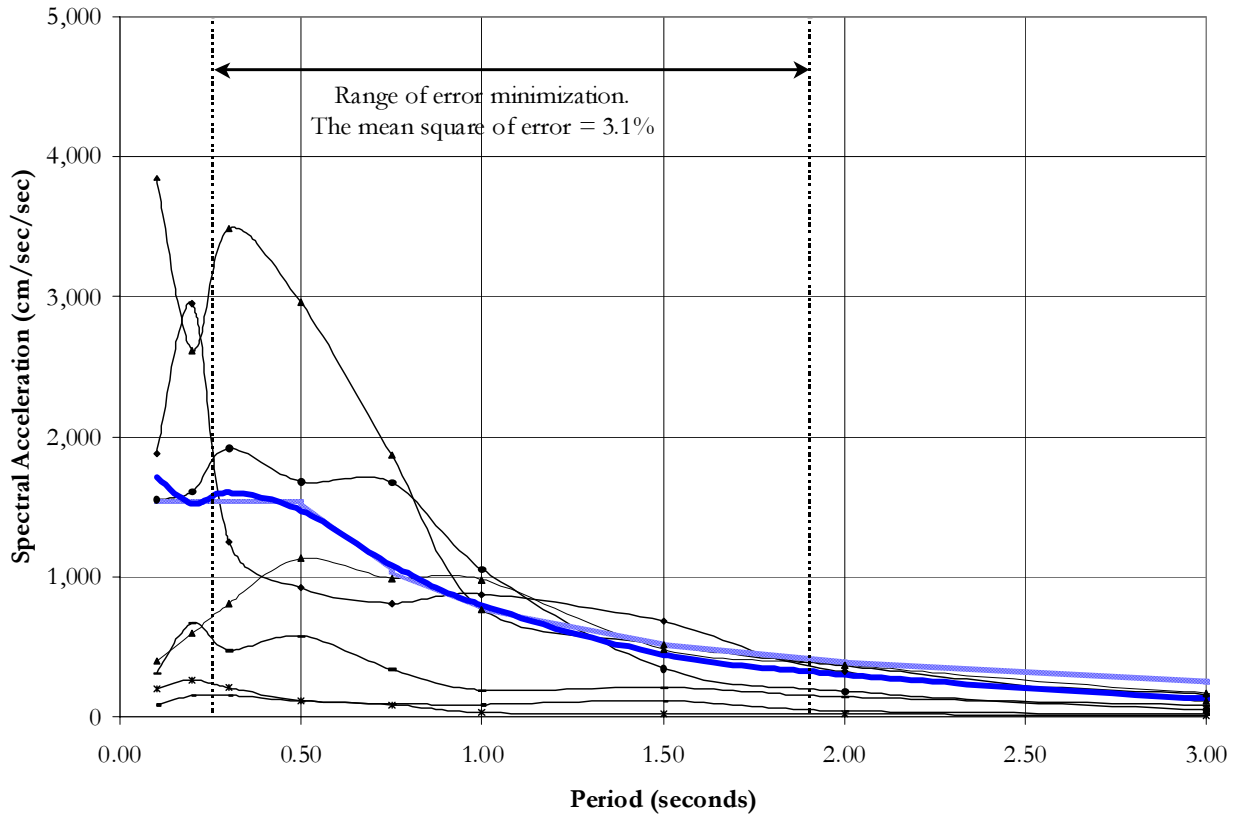


Figure 3. Spectrum matching of target in Example 1 using only Equation (1) as objective

FUZZY PATTERN CLASSIFICATION OF INPUT DATABASE

Current state of knowledge treats the processes of earthquake generation (and the properties of signals temporally and globally) as non-deterministic, non-stationary random processes. However, should enough accurate data parameters be available to take into consideration all the processes involved (tectonics of the region, focal mechanism, background seismology, geological and topographical features of different wave propagation media, and local geotechnical site effects) it may be possible to physically classify the nature of motion in few distinct types. Some practical benefits of classifications may be added choices for the user of the search and scaling program as well as a new way of modeling earthquake ground motion records in synthetic earthquake motion generation.

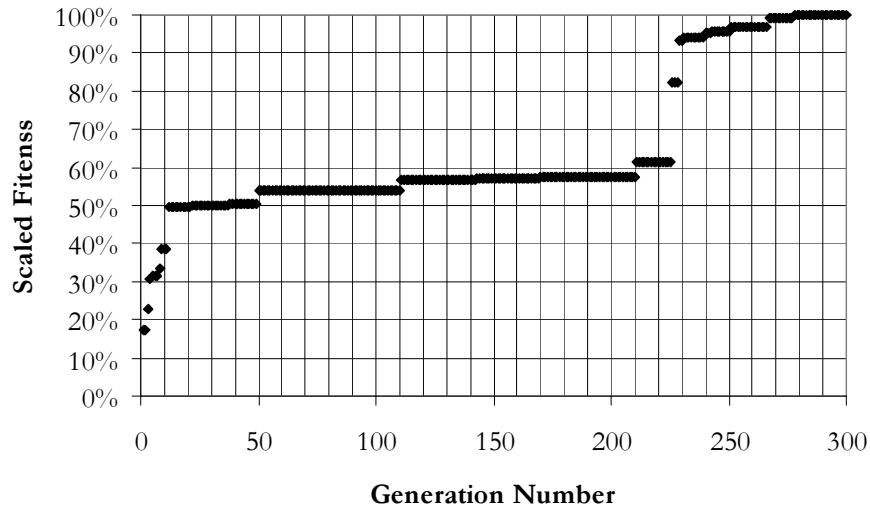


Figure 4. Fitness transition of solutions as a function of generations for the Example.

The criteria used in this study for feature selection and class description was based on some simple observations on the past recorded ground motions and the fact that SGM records are in general:

1. Narrowed in time domain (as spike) or are pronounced intensively during a long duration of shaking, and/or
2. Wide band or narrow band in frequency domain, and/or
3. Have large pulses of displacement accompanied by rapid forward/backward velocity pulses or of a far-field type.

It is assumed that these three criteria, in essence, summarize many of the aspects of earthquake ground motion generation. For instance, the contribution of low frequencies and wide-band nature of the response spectra of motions recorded on top of soft soil deposits is a well-recognized fact. Besides generating insight into earthquake ground motion processes, such classification makes it possible for a design engineer to have more control on the type of data he/she uses out of a database.

The following parameters are available for our benchmark problem and are used to describe the classes:

1. Peak Ground Acceleration (PGA),
2. 5%g bracketed duration, ([D]),
3. Effective Peak Acceleration (EPA) and Effective Peak Velocity (EPV) - (average response spectral ordinates in selected period bands; *i.e.*, 0.1-0.5 second for EPA and about 1.0 second for EPV - ATC-3-06, ATC [4]), and
4. Maximum Incremental Velocity (IV) and maximum Incremental Displacement (ID) – sudden changes in velocity and displacement due to existence of near-source pulses (Anderson and Bertero, [3]).

Although the general behavior of earthquake ground motion parameters is erratic and difficult to classify into groups, when plotted two-by-two, earthquake parameters are more or less statistically correlated and grow monotonically together with higher dispersion associated with higher levels of intensities. This is due to the fact that most ground motion characteristics are defined, in a way or another, to measure the

severity of an event. Therefore, good localization of similar data is hard to achieve when only simple characteristics are used. Extraction of new variables in the feature space is necessary, in these cases, to physically define similarity measures.

Feature Extraction

The idea behind this study is the hypothesis that earthquake strong ground motion records in a large database naturally come into clusters of similar forms, should the data description be performed utilizing enough independent appropriate features. Because of the problem with the simple data characteristics, ground motion parameters were nonlinearly combined to create a set of new features that can meaningfully describe higher dimensions in a reliable physical sense with significant design implications. The form of nonlinear combination is derived based on the quality of classification, statistical distribution of the new features, experience, and by checking the error rate.

For the preliminary analyses of this study, it was aimed to explore the clusters with significant design implications such as:

1. Long duration records, for systems with deteriorating properties during vibration,
2. Wide frequency band/Narrow frequency band records,
3. Near-fault ground motions, when the burst input of energy is important, and
4. Moderate records.

The following features were computed based on their strong relationship with the aforementioned categories, the form of their probability density function, and the quality of classification. They were obtained by trail and error and by using previous experience with the data that is essential in learning “the priori” information in pattern recognition:

$$\begin{aligned}
 & \text{Scaled } \left\{ \frac{PGA^{3.1}}{[D]} \right\} \\
 & \text{Scaled } \left\{ (EPA + EPV)^{2.1} \right\} \\
 & \text{Scaled } \left\{ (IV \cdot ID)^{1.15} \right\}
 \end{aligned} \tag{4}$$

Two common scaling schemes were tried on the database; scaling based on the length of the features (from 0 to 1) and scaling for mean and standard deviation in a logarithmic scale as follow:

$$\text{Scaled Feature } \mathfrak{K}_i = \log \left| \frac{\mathfrak{K}_i - \text{mean}(\Xi)}{\sigma(\Xi)} \right| \tag{5}$$

in which, \mathfrak{K}_i is the i^{th} component of feature set Ξ . The results of scaling based on the length of features were presented in Alimoradi, *et. al*, [2]. The second scaling scheme is presented in this paper.

Fuzzy C-Means Method

Fuzzy c-means (FCM) can be taken as a modification of hard c-means classification. These are unsupervised minimum variance partitioning of data, in which no training (labeled data) is required. During classification, the algorithm initializes a number of clusters as well as cluster centers and then assigns every data point to a cluster to which the data point has the closest distance. This consists one

step of an iterative procedure that converges to a solution when there is a least amount of dispersion due to the location of cluster centers (minimization of objective function of Equation 6). At each step, new cluster centers are updated by finding the mean value of data points associated to the cluster at the previous step (Duda *et. al.*, [10])

The objective function to be minimized is a measure of intraclass dispersion summed over all the classes, (Duda *et. al.*, [10]):

$$L = \min \sum_{i=1}^c \sum_{j=1}^n \left[\hat{P}(\omega_i | \mathbf{X}_j, \hat{\theta}) \right]^b \|\mathbf{X}_j - \mu_i\|^2 \quad (6)$$

in which:

$$\begin{aligned} \mathbf{X}_j &= \text{feature } \mathbf{X} \text{ of point } j, \\ \mu_i &= \text{center of cluster } i, \\ \hat{P}(\omega_i | \mathbf{X}_j, \hat{\theta}) &= \text{“fuzzy” cluster membership of point } j \text{ in cluster } i, \\ b &= \text{“blending” parameter, usually taken as 2.0,} \\ n &= \text{total number of data points, and} \\ c &= \text{number of clusters.} \end{aligned}$$

$$P(\omega_i | \mathbf{X}_j) = \frac{(1/d_{ij})^{1/(b-1)}}{\sum_{r=1}^c (1/d_{rj})^{1/(b-1)}}, \quad d_{ij} = \|\mathbf{X}_j - \mu_i\|^2 \quad (7)$$

$$\mu_j = \frac{\sum_{j=1}^n \left[P(\omega_i | \mathbf{X}_j) \right]^b \mathbf{X}_j}{\sum_{j=1}^n \left[P(\omega_i | \mathbf{X}_j) \right]^b} \quad (8)$$

$$\sum_{i=1}^c \hat{P}(\omega_i | \mathbf{X}_j) = 1, \quad j = 1, \dots, n. \quad (9)$$

Fuzzy c-means differ from hard c-means in that every point belongs to every cluster to some degree, based on its fuzzy membership (Equation 7), whereas in hard c-mean a point can only belong to one cluster.

Fuzzy c-means clustering is applied to the data with $c = 2, 3, \dots, 8$ assumed for each clustering case. The best clustering strategy is obtained by verifying, for each case, the optimization trajectories and by checking the resulting clusters as shown in Figures 5. Six distinct clusters are detected in the data with clusters 1 and 6 presented as dense data around the center with the rest of clusters with higher dispersion surrounding the core. Further investigations in time and frequency domain show that FCM clustering has successfully identified similar data within the database (Figure 6).

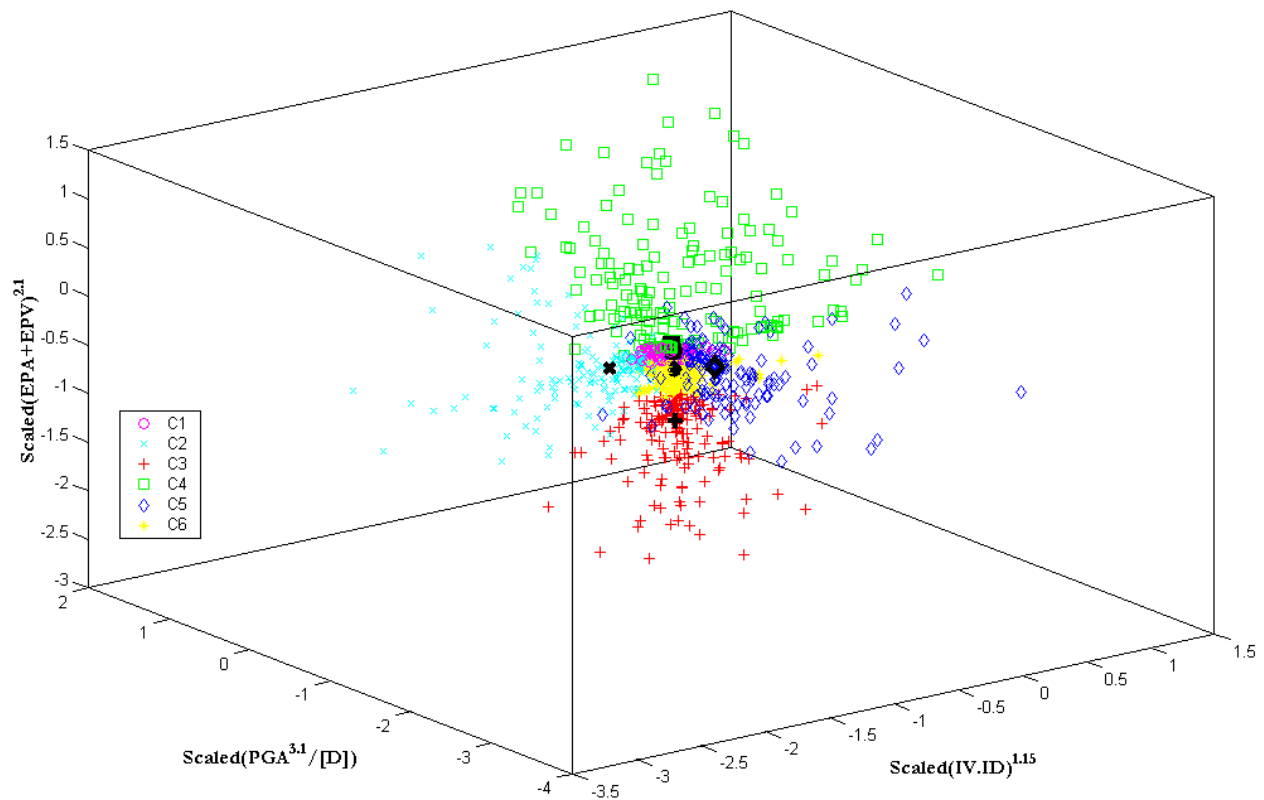


Figure 5. Six Distinct Data Clusters Plotted With Clusters Centers in the Feature Space..

CONCLUDING REMARKS

A new method for selection of earthquake ground motions that in combination match a given site-specific design spectrum was presented. This method uses a genetic algorithm which treats any random union of seven records and corresponding scale factors as a single “individual” with 14 variables (7 record identifiers and 7 scale factors). The first generation of individuals is modified through the processes that mimic mating, natural selection and mutation. The process continues until an optimum individual (seven pairs, and scaling factors) is obtained.

Pattern recognition was applied to the database of recorded earthquake ground motions in order to localize clusters of data with significant similar characteristics. A feature extraction experiment was performed to find parameters that could physically distinguish data based on their sharpness in time and frequency domain, existence of large input velocity pulses accompanied by large displacement pulses and the bandwidth in the spectral ordinates. Fuzzy c-means was shown as a promising analytical tool in classification of design ground motion records. The results obtained can be utilized for increased

functionality and performance of the GA-based software system developed earlier to find optimum or near optimal sets of input motion records for a given target design spectrum.

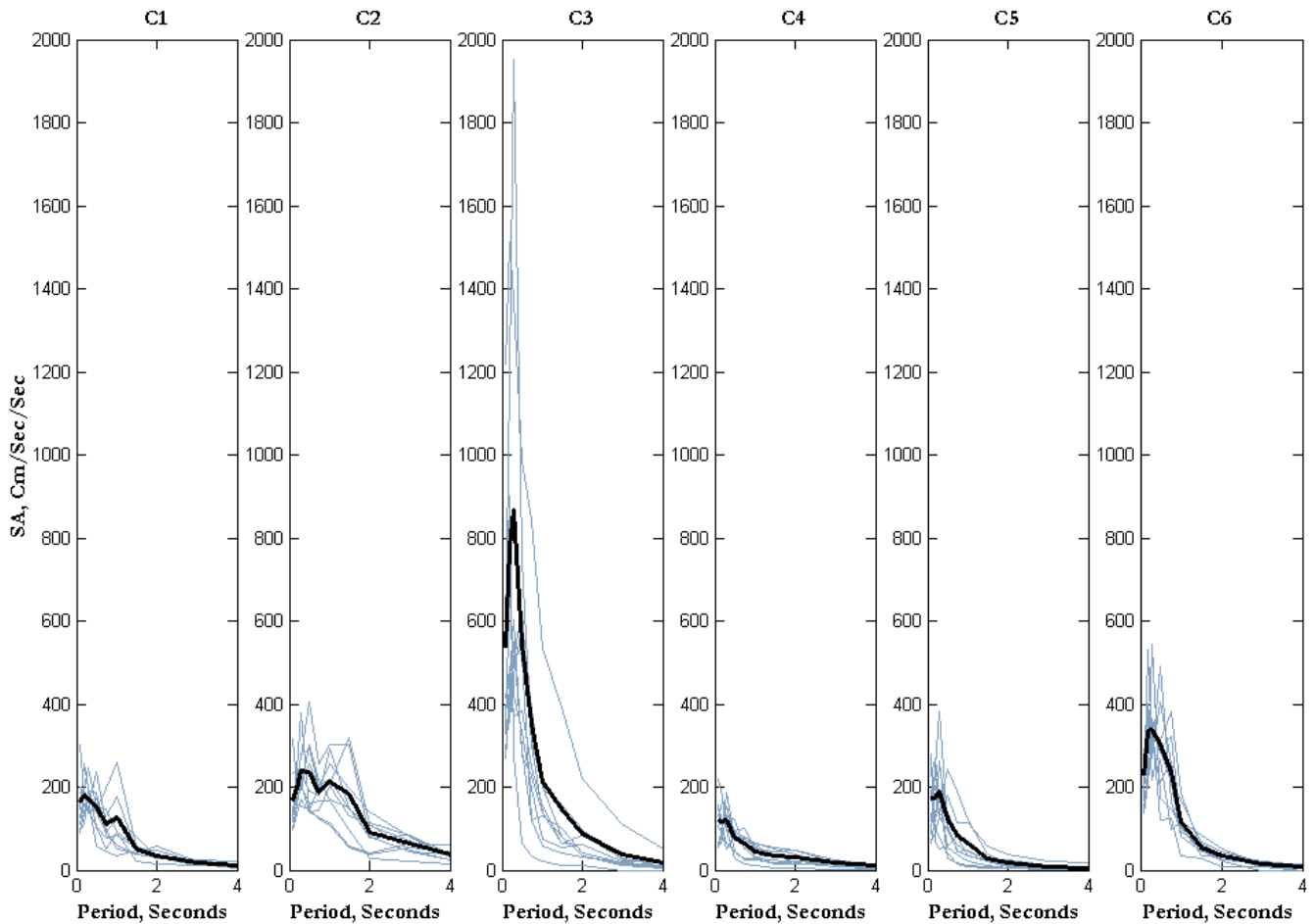


Figure 6. Sample of Response Spectra of Ten Closest Records to Each Cluster Center Plotted with the SRSS Spectra of Data in Each Group.

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REFERENCES

1. Alimoradi, A., 2001. "Performance Study of a GA-Based Active/Hybrid Control System Under Near Source Strong Ground Motion," *2001: A Structural Engineering Odyssey, Proceedings of the 2001 Structures Congress and Exposition*, Washington, D.C., ASCE.
2. Alimoradi, A., S. Pezeshk, and F. Naeim, 2004. "Identification of Input Ground Motion Records for Seismic Design Using Neuro-Fuzzy Pattern Recognition and Genetic Algorithms," *2004: Proceedings of the ASCE Structures Congress*, Nashville, Tennessee, ASCE.
3. Anderson, J.C., and Bertero, V.V., 1987. "Uncertainties in Establishing Design Earthquakes," *Journal of Structural Engineering*, ASCE, Vol. 113, No. 8, pp. 1709-1724.
4. Applied Technology Council, 1978. *Tentative Provisions for the Development of Seismic Regulations for Buildings*, ATC-3-06, Palo Alto, CA.
5. Bolt, B.A., and Gregor, N.J. 1993. "Synthesized Strong Ground Motions for the Seismic Condition Assessment of the Eastern Portion of the San Francisco Bay Bridge," Report UCB/EERC-93/12, University of California, Earthquake Engineering Research Center, Berkeley, CA.
6. Camp, C.V., Pezeshk, S., and Cao, G., 1998. "Optimized Design of Two-Dimensional Structures Using a Genetic Algorithm," *ASCE Journal of Structural Engineering*, Vol. 124, No. 5, May, pp. 551-559.
7. Carballo, J.E., and Cornell, C.A., 2000. *Probabilistic Seismic Demand Analysis: Spectrum Matching and Design*, Department of Civil and Environmental Engineering, Stanford University, Report NO. RMS-41.
8. Coley, D.A., 2001. *An Introduction to Genetic Algorithms for Scientists and Engineers*, World Scientific.
9. Coley, D.A., 2002. David Coley's GA: <http://www.ex.ac.uk/cee/ga/software.htm>
10. Duda R.O., Stork D.G., and Hart P.E., 1999. *Pattern Classification, Vol. 1*, Wiley, John & Sons, Incorporated.
11. Department of the Army, 2000. *Dynamic Analysis of Concrete Hydraulic Structures*, Circular No. EC 1110-2-6051, Washington, D.C.
12. Federal Emergency Management Agency (FEMA), 2000. *Prestandard and Commentary for the Seismic Rehabilitation of Buildings*, FEMA-356, Washington, D.C.
13. Foley, C.M., and Schinler D., 2001. "Optimized Design of Partially and Fully-Restrained Steel Frames Using Distributed Plasticity," *2001: A Structural Engineering Odyssey: Proceedings of the 2001 Structures Congress and Exposition*, Washington, D.C., ASCE.
14. Foley, C.M., Pezeshk, S., and Alimoradi, A., 2003. "State of the Art in Performance-Based Design Optimization," *2003: Proceedings of the ASCE Structures Congress*, Seattle, Washington, ASCE.
15. Gasparini, D., and Vanmarcke, E.H. 1976. "SIMQKE: A Program for Artificial Motion Generation," Department of Civil Engineering, Massachusetts Institute of Technology, Cambridge, MA.
16. Ghaboussi, J., Lin, C.J., 1998. "New Method of Generating Spectrum Compatible Accelerograms using Neural Networks," *Earthquake Engineering & Structural Dynamics*, 27, 4, pp. 377-396.
17. Goldberg, D.E., 1989. *Genetic Algorithms in Search, Optimization, and Machine Learning*, Addison-Wesley.
18. International Code Council, 2000. *International Building Code*, Falls Church, Virginia.

19. International Conference of Building Officials (ICBO), 2001. *California Building Code*, Whittier, California.
20. Kim, Y., and Ghaboussi, J., 1999. "A New Method of Reduced-Order Feedback Control Using Genetic Algorithms," *Earthquake Engineering & Structural Dynamics*, 28, 3, pp. 235-254.
21. Kircher, C., 1993. *Private Communications with Farzad Naeim and Marshall Lew*.
22. Levy, S., 1992. *Artificial Life*, Vintage Books, New York.
23. Naeim, F., A. Alimoradi, and S. Pezeshk, 2004. "Selection and Scaling of Ground Motion Time Histories for Structural Design Using Genetic Algorithms," *Earthquake Spectra*, Vol. 20, No. 2, May 2004.
24. Naeim, F., and Anderson J., 1996. *Design Classification of Horizontal and Vertical Earthquake Ground Motion (1933-1994)*, John A. Martin & Associates. Inc. Report 7738.68-96.
25. Naeim, F., and Bhatia, H., 2000. *Private Communications*.
26. Naeim, F., and Kelly, J.M., 1999. *Design of Seismic Isolated Structures – From Theory to Practice*, John Wiley and Sons, New York.
27. Pezeshk, S., Camp, C.V., and Chen, D., 1999. "Genetic Algorithm for Design of Nonlinear Framed Structures," *Proceedings of the 1999 Structures Congress*, New Orleans, Louisiana, ASCE.
28. Pezeshk, S., Camp, C.V., and Chen, D., 2000. "Design of Framed Structures by Genetic Optimization," *ASCE Journal of Structural Engineering*, Vol. 126, No. 3, Paper No. 19107, pp. 382-388.
29. Silva, W., and Lee, K. 1987. "State-of-the-art for Assessing Earthquake Hazards in the United States; Report 24, WES RASCAL Code for Synthesizing Earthquake Ground Motions," Miscellaneous Paper S-73-1, U.S. Army Engineer Waterways Experiment Station, Vicksburg, MS.
30. Zadeh L., What is BISC? <<http://www-bisc.cs.berkeley.edu/bisc/bisc.memo.html>>