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Appraisal of the evolutionary-based methodologies in generation of artificial earthquake time histories

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Abstract

Through the last three decades different seismological and engineering approaches for the generation of artificial earthquakes have been proposed. Selection of an appropriate method for the generation of applicable artificial earthquake accelerograms (AEAs) has been a challenging subject in the time history analysis of the structures in the case of the absence of sufficient recorded accelerograms. In this paper we have spotlighted the application of the evolutionary algorithms in the AEAs generation approaches. In this regard, we have statistically apprised the two novel methods; the genetic algorithm-based and the hybrid evolutionary neural network-based methods. The main feature of this paper is to provide some statistical information of the two proposed methods to make some quantitative criteria for assessing the future models and algorithms. The assessment is performed based on three major functions of the spectrum-compatibility, the stochastic diversity of generated seismographs and the computational efforts. The results demonstrate the practical advantages of the evolutionary algorithms in this context.

Keywords: Artificial earthquake accelerograms; Genetic algorithm; Response spectrum; Artificial neural network.

1. Introduction

In order to apply the time history analysis and the performance-based design of the special structures utilizing the spectrum-compatible artificial time histories is a promising solution in the absence of the appropriate and sufficient earthquake records at a specific site. There have been several seismological and engineering AEAs generation procedures. Improving the computational and programming tools, a number of time and frequency domain methods have been suggested in the recent years [1,2].

Iyama and Kuwamura [3], Mukherjee and Gupta [4,5], Hancock et al. [6], Suarez and Montejo [7] and Ghodrati Amiri et al. [8,9] have used the wavelet transforms as a powerful

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signal processing tool for analyzing transient variations in the frequency content in order to generate spectrum-compatible seismic ground acceleration time histories.

Ghaboussi and lin [10] and Lin and Ghaboussi [11] proposed the biologically motivated soft computing approaches in the generation of spectrum-compatible accelerograms using the multi-layer feed-forward (MLFF) neural network and the fast Fourier transform (FFT). Ghodrati Amiri and Bagheri [12] implemented the radial basis function (RBF) neural network and the wavelet transform to develop an ensemble of spectrum-compatible accelerograms. Lee and Han [13], Rajasekaran et al. [14], Fengxin et al. [15] proposed neural network based models, in which some characteristics of earthquakes, such as the magnitude, the epicenter distance, the site condition and the focal depth have also been directly considered . Ghodrati Amiri et al. [16] proposed a procedure to generate multiple earthquake accelerograms compatible with spectrum via wavelet packet transform and stochastic neural networks.

Recently the authors presented two novel AEAs generation approaches. In the first method, applying the genetic algorithm, principal component analysis (PCA), discrete wavelet packet transform (DWPT) and multi-layer feed-forward (MLFF) neural networks, a hybrid evolutionary neural network-based method is proposed in order to generate multiple SCAEAs in four duration groups of 10, 20, 30, and 40 seconds [17]. In the second method (evolutionary-based method), an ensemble of spectrum-compatible artificial earthquake accelerograms (SCAEAs) in five duration groups of 5, 10, 20, 30 and, 40 seconds are generated using genetic algorithm (GA) and discrete wavelet transform (DWT).

Different codes necessitate applying different numbers of time histories (either recorded or artificial) for the time history analysis of the structures. In the region with lake of sufficient and appropriate recorded earthquakes selecting and applying an appropriate AEA generation method has been a challenging issue for the structural engineers. Unfortunately, there is a discrepancy in providing some information about the performance of most of the previous proposed methods. So, either they compared their results with the previous ones visually, which is not precise and quantitative or they have ignored it. Here for the first time in this context, we have provided some statistical information about our previous methods [17] in order to make some quantitative evaluation criteria. Further discussions have also been done on the results of the neural network-based procedures Ghodrati Amiri et al. [16].

2. Evolutionary algorithms

Evolutionary algorithms (EAs) as the robust search techniques mimic the aspects of the natural evolution for the purpose of optimizing a solution to a predefined problem [18]. Following Darwin's principle of natural selection and the survival of the fittest, differential fitness advantages are exploited in a population of solutions to gradually improve the state of that population. Evolutionary algorithms as a whole, together with neural networks and fuzzy logic, are considered as the methods of computational intelligence. A comparatively novel research method in this context is GA [19,20]. A general evolutionary algorithm may be summarized as follows: [20,21]

1. Randomly initialize a population of individual solutions.
2. Select individuals from the population which are fitter than the others by using a certain selection method. The fitness measurement defines the problem that the algorithm is anticipated to solve.
3. Generate new individuals by applying the genetic operators such as reproduction, recombination and mutation with certain possibilities.
4. Process terminates when either a maximum number of generations has been produced, or a satisfactory fitness level has been reached for the population. If the termination criterion is not met, the algorithm restarts from the second stage.

5. Stopping. The best individual represents the best solution found.

GA investigates the search space along different directions, simultaneously. With multiple searching points and the crossover and the mutation operations' abilities to swiftly move a searching point from one portion of the search space to another faraway portion, GA is less probable to be trapped at the local optimal points. All these characteristics significantly enhance the likelihood of finding the global optimal point, though there is no warranty to find global optimum. It is obvious that GA is not a random search algorithm. It is informed by the fitness of the individuals in the population. While search proceeds, the population is progressively accommodated to the portion of the search space containing good points [22].

3. Artificial neural networks

Artificial neural networks (ANNs) have been developed as generalization of mathematical model of the human cognition. ANNs can be most adequately characterized as the computational models with particular properties such as the capability to adopt or learn, to generalize, or to organize data. These networks are composed of a number of nonlinear computational elements which their operation are based on parallel processing and are arranged in a manner that is evocative of biological neural interconnections [23,24].

A multilayer perceptron (MLP) neural network model consists of feed-forward layered nets with one or more layers of nodes (so called hidden units between the input and output units). Each neuron in an MLP has a nonlinear activation function; especially sigmoid or hyperbolic tangent function, so it can provides a nonlinear mapping between input and output data [25]. In a Feed–forward nets, the signal flows from the input units to output units in a forward direction.

Training process or setting the weight values of the each interconnection is the fundamental problem in the neural network solutions. In multi-layer feed-forward (MLFF) neural networks the weight matrix are achieved through implementing the error back-propagation training method [25]. This training method involves the two phases of the forward and backward direction. In the former phase, the input values are presented and propagated forward through the network to compute the output values for each output unit and then the output is compared with its desired value, resulting in an error signal for each output unit. Latter phase involves a backward pass through the network, in which the error is passed to each network unit and the new modified weight matrix is computed [23]. This recurrent process might take a long time in order to achieve a desired level of training and so this concern is considered as an objective in order to implement the ANNs solutions.

4. Review of the methods and analytical discussion

The main feature of this paper is to discuss on the beneficial application of the evolutionary algorithms in the generation of SCAEAs by a statistical evaluation. Due to the lack of transparency in presentation the previous method's statistical data, the analytical discussion has been only performed based on the statistical results of the author's two new AEAs generation methods, i.e., the hybrid evolutionary neural network-based and the evolutionary-based methods. Also, a short discussion is made on the results of the neural network based method which is previously proposed by Ghodrati Amiri et al. [16]

The hybrid evolutionary neural network-based method consists of three main processes: initialization, mapping and generation. In the first process, the recorded accelerograms' response spectra and their wavelet packet coefficients have been computed. In the mapping process, using PCA and ANNs we have developed an inverse mapping from the spectrum coefficients to the wavelet packet coefficients. In the net's training phase we have utilized the genetic algorithm as a new strategy for finding the interconnection weights. Finally, non-unique artificial accelerograms (which are compatible with the target spectrum) are achieved from the trained neural network followed by passing from the alignment process [17].

On the other hand, the second approach is the evolutionary-based method in which GA has been used as the main tool (instead of the neural networks). In this method, we have computed the recorded accelerograms' response spectra and their discrete wavelet coefficients. Performing a GA, the appropriate spectrum-compatible artificial wavelet coefficients are achieved, Finally, SCAEAs are generated after passing from an alignment process for more matching.

As It has been discusses, the main difference in the two methods is the application of either biologically or evolutionary soft computing methods (ANN, and GA) in SCAEAs generation processes. Both the new methods are capable of generating an ensemble of spectrum-compatible artificial seismographs in different durations. For instance, a number of 10, 20, 30, and 40 seconds SCAEAs and their peak pseudo acceleration (PSA) spectra, generated by the evolutionary-based method are shown in Figure 1. This figure shows the good spectrum compatibility as well as the stochastic diversity of generated time histories.

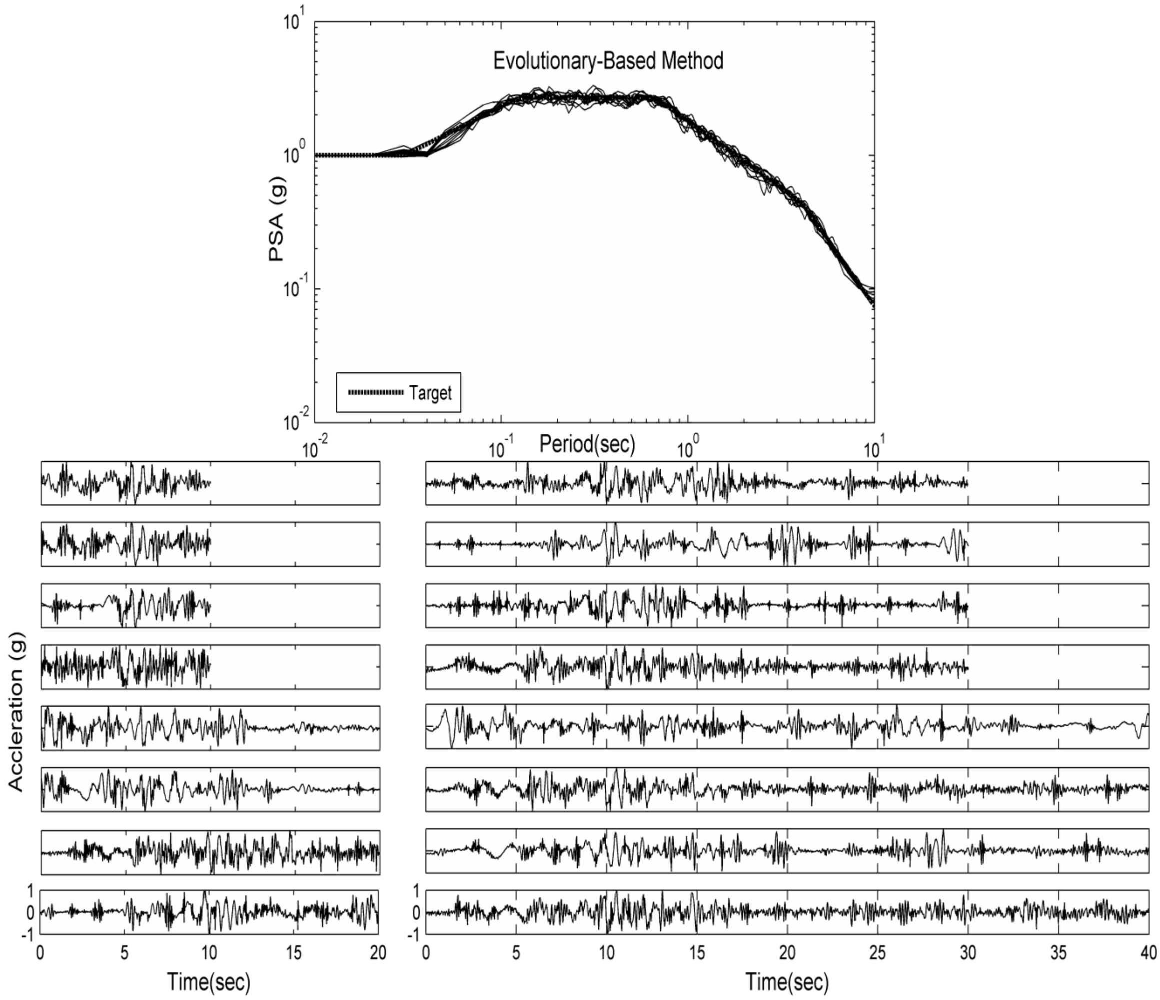

Figure 1. Generated AEAs and their PSA spectra-compatibility in evolutionary-based method.

For making a precise comparison between the methods and developing quantitative criteria for the performance evaluation of the future methods with the current ones, we have presented the statistical information of both methods in Tables 1 to 5. Tables 1 to 4 present the statistically evaluation of differences between target and artificial PSA spectra in two evolutionary-based and the hybrid evolutionary neural network-based methods for the selected samples of generated seismographs with durations of 10, 20, 30, and 40 seconds generate, respectively. For example, the samples' mean values of *maximum*, *minimum*, *standard deviation* and *average* of difference values between target and artificial PSA spectra in 40 second duration group in the evolutionary-based algorithm are 0.49729g, 5.877E-05g, 0.05796g, and 0.03459g, respectively. While, the corresponding values in the hybrid method are 0.63780g, 1.339E-0.5g, 0.07074g, and 0.04059g, respectively. Table 5 show the performance of both methods in all duration groups. The results demonstrated the appropriate spectrum-compatibility in the both methods, although the evolutionary-based method has developed more superior outcomes (approximately 20%) than the hybrid evolutionary neural network-based method.

Table 1. The statistical information of the two evolutionary and the hybrid methods for duration groups of 10s.

Samples	Difference Value† in Samples with 10 Sec. Duration (g)							
	Evolutionary-Based Method				Hybrid Evolutionary Neural Network Method			
	Max.	Min.	S_D	Ave.	Max.	Min.	S_D	Ave.
Sample 1	0.64985	6.920E-06	0.06415	0.04210	0.64985	6.920E-06	0.06415	0.04210
Sample 2	0.23842	9.134E-06	0.03272	0.01987	0.23842	9.134E-06	0.03272	0.01987
Sample 3	0.38034	4.529E-06	0.04735	0.02761	0.35192	1.059E-06	0.04934	0.03312
Sample 4	0.76266	4.631E-05	0.08420	0.05723	0.48217	3.284E-04	0.05914	0.05581
Ave. Samples	0.50782	1.672E-05	0.05710	0.03670	0.43059	8.639E-05	0.05134	0.03773

† Difference value between target and artificial PSA spectra

Table 2. The statistical information of the two evolutionary and the hybrid methods for duration groups of 20s.

Samples	Difference Value† in Samples with 20 Sec. Duration (g)							
	Evolutionary-Based Method				Hybrid Evolutionary Neural Network Method			
	Max.	Min.	S_D	Ave.	Max.	Min.	S_D	Ave.
Sample 1	0.40851	6.016E-06	0.05257	0.03302	0.85638	6.172E-05	0.13836	0.09086
Sample 2	0.54968	6.184E-06	0.06572	0.04297	0.77026	4.296E-05	0.11903	0.08918
Sample 3	0.55021	1.304E-06	0.06562	0.03731	0.64010	2.159E-05	0.07843	0.05045
Sample 4	0.42099	6.098E-07	0.06017	0.03340	0.45228	1.451E-05	0.04178	0.02367
Ave. Samples	0.48235	3.528E-06	0.06102	0.03668	0.67975	3.519E-05	0.09440	0.06354

† Difference value between target and artificial PSA spectra

Table 3. The statistical information of the two evolutionary and the hybrid methods for duration groups of 30s.

Samples	Difference Value† in Samples with 30 Sec. Duration (g)							
	Evolutionary-Based Method				Hybrid Evolutionary Neural Network Method			
	Max.	Min.	S_D	Ave.	Max.	Min.	S_D	Ave.
Sample 1	0.38977	7.434E-06	0.04872	0.02611	0.38977	7.434E-06	0.04872	0.02611
Sample 2	0.32823	1.574E-05	0.04556	0.02787	0.51665	2.847E-05	0.06842	0.03290
Sample 3	0.47725	7.223E-08	0.07663	0.04747	0.59047	1.075E-05	0.07617	0.05396
Sample 4	0.48374	1.925E-05	0.07671	0.06097	0.56023	5.157E-06	0.09449	0.05037
Ave. Samples	0.41975	1.063E-05	0.06191	0.04060	0.51428	1.295E-05	0.07195	0.04083

† Difference value between target and artificial PSA spectra

Table 4. The statistical information of the two evolutionary and the hybrid methods for duration groups of 40s.

Samples	Difference Value† in Samples with 40 Sec. Duration (g)							
	Evolutionary-Based Method				Hybrid Evolutionary Neural Network Method			
	Max.	Min.	S_D	Ave.	Max.	Min.	S_D	Ave.
Sample 1	0.53360	1.123E-05	0.06002	0.03324	0.53360	1.123E-05	0.06002	0.03324
Sample 2	0.60493	4.824E-06	0.06783	0.03469	0.75799	1.302E-05	0.07503	0.04181
Sample 3	0.37987	8.783E-06	0.05065	0.03706	0.69548	1.889E-05	0.08755	0.04570
Sample 4	0.47074	2.102E-04	0.05336	0.03338	0.56414	1.044E-05	0.06035	0.04160
Ave. Samples	0.49729	5.877E-05	0.05796	0.03459	0.63780	1.339E-05	0.07074	0.04059

† Difference value between target and artificial PSA spectra

Table 5. The average of the statistical information of the two evolutionary and the hybrid methods for all the duration groups.

Samples	Difference Value† in Samples with 10 - 40 Sec. Durations (g)							
	Evolutionary-Based Method				Hybrid Evolutionary Neural Network Method			
	Max.	Min.	S_D	Ave.	Max.	Min.	S_D	Ave.
Ave. Samples 40 sec.	0.49729	5.877E-05	0.05796	0.03459	0.63780	1.339E-05	0.07074	0.04059
Ave. Samples 30 sec.	0.41975	1.063E-05	0.06191	0.04060	0.51428	1.295E-05	0.07195	0.04083
Ave. Samples 20 sec.	0.48235	3.528E-06	0.06102	0.03668	0.67975	3.519E-05	0.09440	0.06354
Ave. Samples 10 sec.	0.50782	1.672E-05	0.05710	0.03670	0.43059	8.639E-05	0.05134	0.03773
Ave. All Samples	0.47680	2.241E-05	0.05950	0.03714	0.56561	3.698E-05	0.07211	0.04567

† Difference value between target and artificial PSA spectra

The computational time in both methods has taken from a few minutes to the several hours and it has depended on the various factors such as the desired level of spectrum-compatible accuracy, the number of generations in GA, structure of neural networks, level of decomposition in wavelet transform and etc. However, in the same level, the hybrid evolutionary neural network-based algorithm has been accomplished in 1.35 to 1.65 times longer than the evolutionary–based algorithm.

Therefore, from all the three discussed viewpoints, the application of the evolutionary algorithms in AEAs generation process not only is beneficial, but also it could be superior to the neural network-based methods.

As compare to the previous methods, the hybrid evolutionary neural network-based method is a modified version of Ghodrati Amiri et al. [16] algorithm, where the authors have implemented PCA and genetic GA to evolve the algorithms' efficiency. The computational time in the new method has been decreased with applying the PCA which caused a dimension reduction in the calculative matrices along with applying the GA which enhanced the net's training process rate. Therefore, the new method is more efficient than the previous neural network-based method. Beneficial application of PCA has also been verified in other scholar's research [14]. Also, utilizing the GA in the new method has improved the root mean square error between the target and generated spectrum from an average of 0.18g to the 0.08g [17] in a shorter computational time.

5. Conclusion

There are some discrepancies in providing some statistical evaluation of the previous AEAs generation methods, while, these significant information are the basis for assessing the past and the future AEAs methods with the current ones. The novelty of this paper is to present the statistical information of the new AEAs generation methods recently proposed by the authors for the first time in this context. This paper presents an assessment on the implementation of the evolutionary algorithms in AEAs generation procedures. The evaluation has been mainly performed based on the outcomes of the two evolutionary-based and the hybrid evolutionary neural network-based methods along with considering a neural network-based algorithm. Spectrum-compatibility, the stochastic diversity of the artificial time histories, and the computational time were the three main criteria in this assessment. The statistical results show that:

- Utilizing the evolutionary algorithms like GA in training process of artificial neural networks will increase the efficiency of SCAEAs generation processes in all three major aspects. Furthermore, applying the PCA has resulted in more reduction in computational time in the hybrid evolutionary neural network-based algorithm.
- Applying GA, as a new strategy in AEAs generation procedures have resulted in the generation of exceptional SCAEAs (an improvement of about 20% in matching the spectrum in compare with the hybrid method). The evolutionary-based algorithm proposed by the authors could generate multiple stochastic PSA spectra-compatible accelerograms in only a few minutes (the program runs about 1.35-1.65 times faster than the hybrid method). All the three aspects of the generated AEAs in this method are superior to the previous approaches.
- Although both the hybrid evolutionary neural network-based and the evolutionary-based methods lead to the acceptable and the superior results (in compare with the previous methods from all three major criteria viewpoints), the new evaluation demonstrates the higher efficiency of the latter than the former with simple programming. Therefore, the authors recommended using the evolutionary programming in this context for the practical applications.

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