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A NEW HYBRID GENETIC AND SWARM OPTIMIZATION FOR EARTHQUAKE ACCELEROGRAM SCALING

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ABSTRACT

Earthquake time history records are required to perform dynamic nonlinear analyses. In order to provide a suitable set of such records, they are scaled to match a target spectrum as introduced in the well-known design codes. Corresponding scaling factors are taken similar in practice; however, optimizing them reduces extra-ordinary economic charge for the seismic design. In the present work a new hybrid meta-heuristic is developed combining key features from genotypic search and particle swarm optimization. The method is applied to an illustrative example via a parametric study to evaluate its effectiveness and less probability of premature convergence compared with the standard particle swarm optimization.

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KEY WORDS: particle swarm optimization, genetic algorithm, strong ground motion scaling, seismic design, building structures.

1. INTRODUCTION

Meta-heuristic algorithms are generally inspired by some natural processes to explore near optimal solution in reasonable and limited time. Their outstanding features in derivative free and parallel agent search, has made them popular in various fields of engineering optimization problems [1-5].

Social intelligence of less-intelligent natural individuals is simulated as *particle swarm optimization*, PSO, first introduced by Kennedy and Eberhart [6-7]. PSO has shown its search capability in several engineering problems; however, fine tuning its control parameters to balance between exploration and exploitation is a challenging task.

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Consequently, attempts are required to solve for probable premature convergence and weak local search exploitation in the standard form.

A number of strategies have already been proposed by investigators to enhance the swarm search capabilities [8-11]. Among them, tuning routines for the PSO parameters to alter the search intensification-to-diversification ratio, collapsing swarm, additional random direction term in the velocity relation, embedded local search features and special solutions for constraint handling problems have already been concerned in the literature [10-11].

The present study has made focus on the search space to enhance the PSO exploitation. In this regard, genotypic jumps in the coded variables space are mimiced from the well known *genetic algorithm*, GA and successfully employed in the new genetic swarm optimization, PSOGA. The problem of tuning required factors in the ground motion scaling is then formulated and treated with PSOGA well suited for such a continuous variable design space.

The basic features from the PSO and GA are first reviewed. Then hybridization methodology is presented through discussion. Consequently, numerical results in the treated example show high benefits in seeking optimal spectrum-compatible set of earthquake records with respect to the use of similar factors as in the common practice. Using a variation of control parameters it is found that the proposed method's effectiveness stands considerably higher than the conventional PSO.

2. KEY FEATURES IN THE GENETIC SEARCH

Since 1975 when genetic algorithm introduced by Holland [12], it has gained attention and been applied as a general effective search tool in various fields of optimization problems. The standard genetic algorithm and majority of its variants work in the search space of coded variables, called *genotypes* instead of the corresponding physical ones; i.e., *phenotypes*. Therefore, any genotype or *chromosome* consists of a number of *genes* containing coded value of a problem-specific design variable.

Each individual chromosome thus denotes a distinct alternative vector of design variables and should be decoded to a phenotype model for evaluating its corresponding fitness or objective function [13-15]. GA is based on three main operators; crossover, mutation and fitness-based selection to reproduce a new generation of chromosomes out of any current population.

The specific problem information is transmitted to the genetic search via the fitness evaluation and priority selection. The role of crossover is to search probable exchanges between genes of the current population; that is, exploiting the corresponding search island. Mutation is also crucial to enter new-comer information into the set of gene values already present in the current population of chromosomes. Thus, it is a pure explorative operator to enable GA to access points out of the current island from the whole search space. These distinguished exploitation and exploration operators, enable GA to fine tune the balance between intensification and diversification for more effective search.

3. BASICS OF PARTICLE SWARM OPTIMIZATION

The attempts in PSO to simulate natural swarm like bird flocks and fish schools behavior in a few simplified steps has made it a generalized tool to search various problems in their physical design variable spaces. In the PSO methodology, each design candidate variation is denoted by the movement vector from the current and the new position.

Any search agent in PSO is called a particle taking its location vector *X* a point or solution candidate in the search space. After completing the random initiation of the particles' population with a predetermined size, the new solution at iteration *k+1*, is discovered by any particle *i* using the following relations:

$$\underline{X}_i^{k+1} = \underline{X}_i^k + \underline{V}_i^k \tag{1}$$

$$\underline{V}_i^{k+1} = c_i \underline{V}_i^k + r_1 c_c (\underline{P}_i^k - \underline{X}_i^k) + r_2 c_s (\underline{B}^k - \underline{X}_i^k) \tag{2}$$

Where as c_i, c_c, c_s stand for *inertial* , *cognitive* and *social* factors and r_1, r_2 are random numbers uniformly distributed in the range [0,1]. P_i^k , denotes the best pervious position that a particle has already experienced while $\underline{B}^k$ is the global best position of the entire swarm up to the current search iteration. The former represents the cognitive and the latter models social terms in a natural (bird's) swarm to find their optimum position.

An artificial individual memory is provided in PSO and combined with the swarm *global best* result via such a vector-sum movement strategy among the search space. The inertia factor is used to transmit the previous-step direction of search to the current. Stochastic scaling of such movement in corresponding directions are also employed to enhance the PSO in global search, directly over the continuous phenotypic space.

4. THE PROPOSED GENETIC SWARM OPTIMIZATION

Any specific design vector, $\underline{X}$, is denoted by a chromosome when coded in GA while it is called a particle in the PSO terminology. Genotypic exploration and exploitation in GA provides powerful jumps in the phenotypic space to escape from local optima regions toward the global solution of the problem. GA is best suited for discrete problems but may require relatively large number of iterations to converge. In the other hand, PSO is best suited for phenotypic search in the continuous problem spaces. Hence, combining both genotypic and phenotypic movements of design vectors is expected to considerably enhance the search effectiveness in seeking the global optimum. The idea is utilized in this paper by substituting the Eq.(2) with the following modified relation (Figure 1):

$$\underline{V}_i^{k+1} = c_i \underline{V}_i^k + r_1 c_c (\underline{P}_i^k - \underline{X}_i^k) + r_2 c_s (\underline{B}^k - \underline{X}_i^k) + r_3 c_{GA} (\underline{G}^k - \underline{X}_i^k) \tag{3}$$

Whereas, c_i, c_c, c_s and c_{GA} are predetermined fixed factors multiplied by uniformly random numbers r_i in order to scale inertial, cognitive, social and genotypic search terms, respectively. The new contribution of the last genotypic term distinguishes new PSOGA feature with its additional search direction with respect to the standard PSO formulation. It is directed from any current design vector situation, $\underline{X}$, toward the new-comer $\underline{G}^k$ decoded from exploited genotypic space.

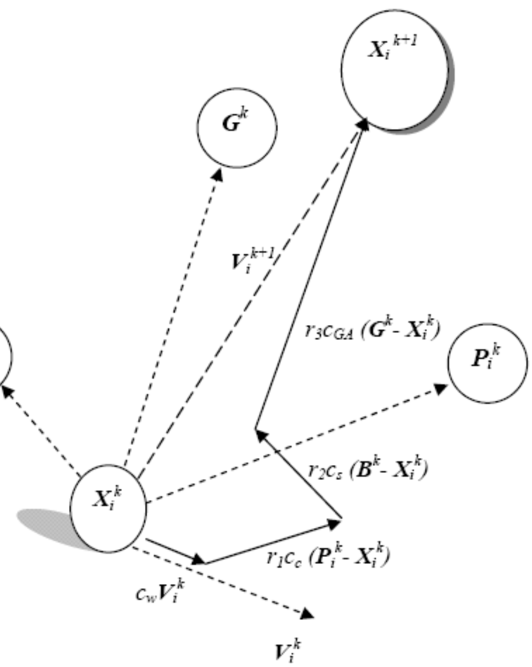

Figure 1. Schematic position update strategy in the PSOGA

The vector, $\underline{G}^k$, represents result of the genotypic search in any k^{th} iteration and is determined using the following sub-routine:

(i) Select the initial GA population identical to the encoded position vectors of all the particles in the current iteration state of PSOGA.

(ii) Perform standard genetic search for a few number of generations, $NumIter^{GA}$, and save the obtained elitist chromosome out of the final generation

(iii) Decode such an elitist chromosome from the genotypic space to new design vector, $\underline{G}^k$, to be returned into the PSOGA main algorithm.

Hence, employing the new-comer, $\underline{G}^k$, introduces additional search direction to the main algorithm via the following steps

(1) Assign pre-determined values of PSOGA control parameters: $c_i, c_c, c_s,\ c_{GA}$, $PopSize^{PSO}$, $NumIter^{PSO}$, $PopSize^{GA}$, $NumIter^{GA}$ *and also* P_m^{GA}, P_c^{GA} as Mutation and crossover probability thresholds and also types of encoding, crossover, mutation and selection operators for the genotypic stage of the search. Set the

main iteration number, *k*, to 1.

(2) Initiate *PopSize* number of solution candidates; $\underline{X}_i^1$ and the corresponding velocity vectors, $\underline{V}_i^1$, randomly but satisfying the upper and lower bounds for design variables

(3) Evaluate fitness of the particles'

(4) Update $\underline{P}_i^k$ as the fittest position experienced by any i^{th} particle up to iteration, k and select $\underline{B}^k$ as the best among all $\underline{P}_i^k$ vectors in the entire swarm

(5) Use the genotypic search sub-routine to return the position vector, $\underline{G}^k$. Employ the control parameters $PopSize^{GA}$, $NumIter^{GA}$, P_m^{GA}, P_c^{GA} for such a partial search

(6) Increase main iteration number, *k*, by 1.

(7) Reposition particles according to Eq.(3) and Eq.(1) to form new population of particles

(8) Repeat the previous steps (3) to (7) for a fixed number of iterations, $NumIter^{PSO}$.

5. GROUND MOTION SCALING PROBLEM

Strong ground motion scaling is a procedure to utilize a set of records instead of only one acceleration record for further dynamic time-history analyses and seismic design of structures. According to this well-accepted procedure in seismic design codes [16-17] the pre-selected earthquake records are first normalized to their peak ground acceleration. Usually a pair of horizontal acceleration components is considered for each earthquake while their spectra are calculated for a given damping ratio [17-19]. Then, square root of sum of squares, SRSS for every pair of such spectra is evaluated and ensemble averaged dividing by a code-specific number; e.g., 1.4 due to the Iranian Standard No.2800 of practice [17]. Such an achieved acceleration spectral value for every earthquake is denoted, here-in-after, by *SA* for any period point T_j. The weighted average spectrum is calculated as Eq.(4) where s_i denotes the i^{th} primary scaling factor with *n* points in the pre-determined period range and *K* earthquakes in the record set:

$$SA_{Avg.}(T_j) = \frac{\sum_{i=1}^{K} s_i \times SA_i(T_j)}{\sum_{i=1}^{K} s_i} \qquad j = 1, 2, \dots, n \tag{4}$$

Consequently, the obtained average spectrum is re-scaled by a final value, β, so that falls not lower than the target standard spectrum in a specific period range.

$$\beta = \max_j \left\{ \frac{SA_{Target}(T_j)}{SA_{Avg.}(T_j)} \right\} \qquad j = 1, 2, \dots, n \tag{5}$$

The optimization problem is thus formulated as follows to tune the weight factors, s_i:

$$\begin{aligned} &Maximize \quad F(\underline{X}) = 1/Err \\ &S.t. \quad \underline{X} =< s_1,\ldots,s_K > \\ &\qquad\quad 0 < s_i \leq 1 \end{aligned} \tag{6}$$

Where, F, denotes the fitness function and the matching error, Err, is computed in (%) as:

$$Err = 100\frac{1}{n}\sum_{T=T_1}^{T_2}\left|\frac{\beta.SA_{Avg.}(T) - SA_{Target}(T)}{SA_{Target}(T)}\right| \tag{7}$$

6. NUMERICAL EXAMPLE

Sub-routine search stage in the proposed method is employed using control parameters as given in Table 1. The *direct encoding* (Figure 2) is used to verify if PSOGA stays superior to PSO even for such a simple coding method [13-15]. According to the *direct mutation* for continuous search spaces, any mutated gene is simply assigned a new value between its upper and lower limits when a random number falls below P_m threshold. Other controlling parameters for the main algorithm are also given in Table 2. The problem is solved for a few variants of control-parameter sets in this study identified by different present work IDs in Table 2.

Table 1. Parameters and operators used for the genotypic phase of search

Selection type	**Crossover type**	**Mutation type**	**Pm**	**Pc**	**Number of generations**
Tournament	1-point	Direct	0.05	0.9	2

0.4	0.0	1.0	0.9	0.4	0.2

Parent 1

0.1	**0.7**	1.0	0.9	0.4	0.2

Child 1

0.1	**0.7**	**0.6**	**0.5**	**0.3**	**0.0**

Parent 2

0.4	0.0	**0.6**	**0.5**	**0.3**	**0.0**

Child 2

Figure 2. Sample 1-point crossover applied to direct real coded parent chromosomes

A 24-pair set of horizontal earthquake records, is further treated by the proposed method. The range of scale factors variation is taken [0,1]. Zero scale means elimination of the corresponding earthquake from the optimal list. In another word, both selection and scaling of the earthquake records are simultaneously optimized in the present study. The accelerograms are elected with magnitudes larger than 5 and peak ground acceleration, PGA, greater than 0.2g recorded in distances more than 10km among the available database [20]. The target smooth and normalized spectrum is reconstructed using the soil type III and 5 % damping ratio in the high seismicity region according to *Iranian design standard No.2800* [17].

Table 2. Control parameters of the main PSOGA routine for the treated example

Present work ID	**C_i**	**Cc**	**C_s**	**C_{GA}**	**Number of particles**	**Number of iterations**
1	0.4	2.0	2.0	2.0	10	400
2	0.4	2.0	2.0	2.0	5	400
3	0.4	2.0	2.0	2.0	30	400
4	0.4	2.0	2.0	2.0	10	1000
5	1.0	1.0	1.0	1.0	10	1000

Once each pair of records are normalized to their PGA, the resulted linear spectra are driven and combined using SRSS, divided by 1.4 for further matching with the target. The corresponding period-range for matching is selected between 0.1 and 1.5 seconds in this example; that covers most periods in the spectral analysis of common building structures.

Table 3 shows statistics of the results obtained for the present work-1. The *Fitness Improvement*, F.I. with respect to the initial population is also given in Table 3 and Table 4 for all the treated cases. It is calculated as in Eq.8:

$$F.I. = \frac{F_{Elitist}^{NumItr} - F_{Elitist}^{1}}{F_{Elitist}^{1}} \tag{8}$$

whereas, $F_{Elitist}^{1}$ and $F_{Elitist}^{NumItr}$ stand for the best (ellitist) fitness in the initial and final iterations of the search, respectively. As given in Table 3, the standard deviation and its ratio over the mean results are less for PSOGA with respect to PSO so PSOGA is more stable. Table 4 gives the ratio of elapsed CPU time in PSO over PSOGA multiplied by F.I. ratio as a *performance index*, PI. It is obtained greater than 1 for parameter-tuned present works 1-4. According to Table 4, PSOGA is more effective than PSO for all the studied cases.

Table 3. Statistics of compared results for the present work-1 during several trial runs

Statistical parameter	**Err. PSO (%)**	**Err. PSOGA (%)**	**F.I. PSO**	**F.I. PSOGA**	**F.I.PSOGA/ F.I.PSO**
Mean.Value	9.51	5.13	1.46	3.44	2.61
σ	2.02	0.34	0.49	0.71	0.94
Min. ~ Max.	5.63~ 12.06	4.53~ 5.73	0.92~ 2.09	2.10~ 4.60	1.00~ 4.26
$\frac{\sigma}{mean}$	0.21	0.07	0.33	0.20	0.36

The *Err* value computed due to Eq.7 is 34% for manual selection with equal scale factors, optimized and decreased to 4.60% during present work-4 by PSOGA; that is about 7 times smaller. Hence, it is also realized that the proposed PSOGA has superior capability in achieving higher fitness values with respect to the PSO.

Table 4. Comparison of PSOGA and PSO results for various sets of control paramaters

Present work ID	**Err. PSO (%)**	**Err. PSOGA (%)**	**F.I. PSO**	**F.I. PSOGA**	**F.I. ratio**	**PI**
1	12.06	4.97	1.23	4.40	3.59	1.2
2	17.45	4.70	0.96	6.28	6.54	2.1
3	10.93	4.81	1.27	4.16	3.27	1.1
4	11.41	4.60	0.76	3.36	4.42	1.5
5	8.72	6.07	1.72	2.92	1.69	0.6

The matter is evident from the convergence curve of Figure 3, too. Getting closest to the target spectrum as depicted in Figure 4 again confirms such superiority. Employing either stochastic optimization methods has resulted in considerably more compatible spectrum to the target than manual implementation of identical scale factors.

In order to study the effect of population size decrease on the optimization performance, the present work-2 is executed with half the number of particles in the present work-1. Sample results depicted in Figure 5 and Figure 6 show higher sensitivity of the PSO to *PopSize* reduction with respect to the developed PSOGA. It can also be concerned that premature convergence occured by PSO for such a small number of particles.

In addition, the effect of increasing population size is studied and revealed in Figure 7 and Figure 8 which led to higher performance of both optimization algorithms.

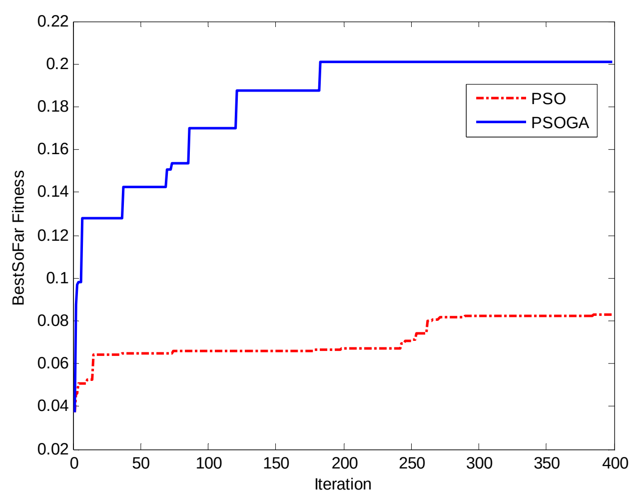

Figure 3. Convergence curve for the present work-1 with 10 particles

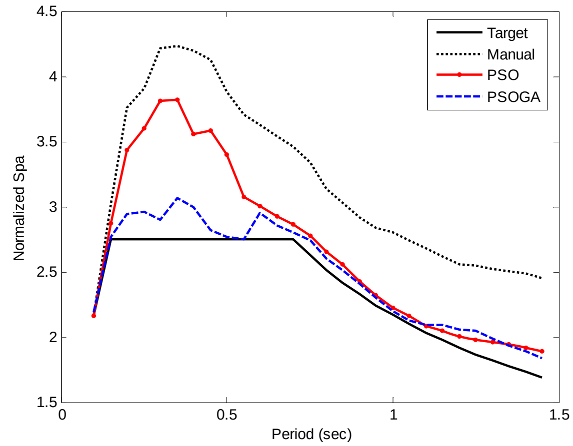

Figure 4. Mean spectra results of different scaling procuders vs. the target in the present work-1

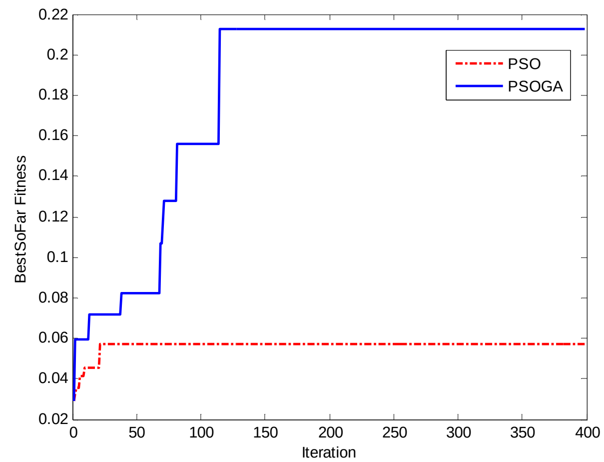

Figure 5. The present work-2, less number of particles led to premature convergence in PSO

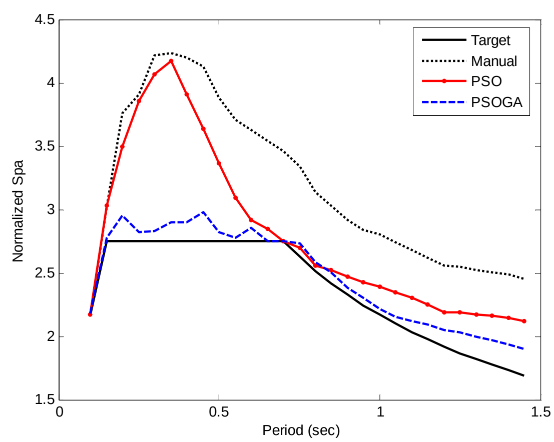

Figure 6. Compared effect of smaller population size in the present work-2

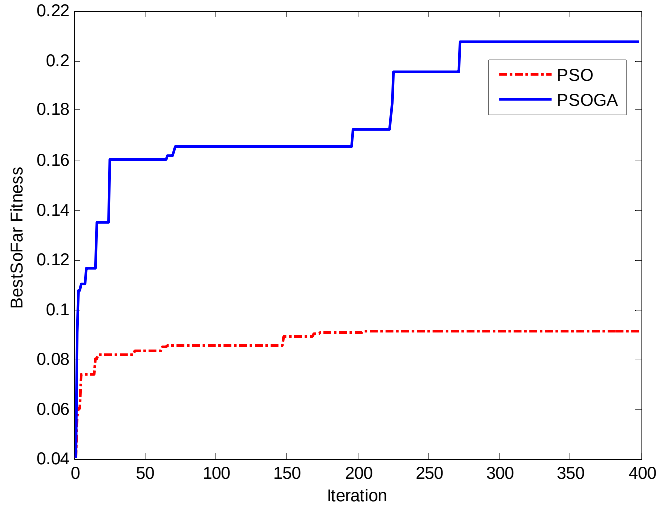

Figure 7. Convergence curve for in the present work-3 with 30 particles

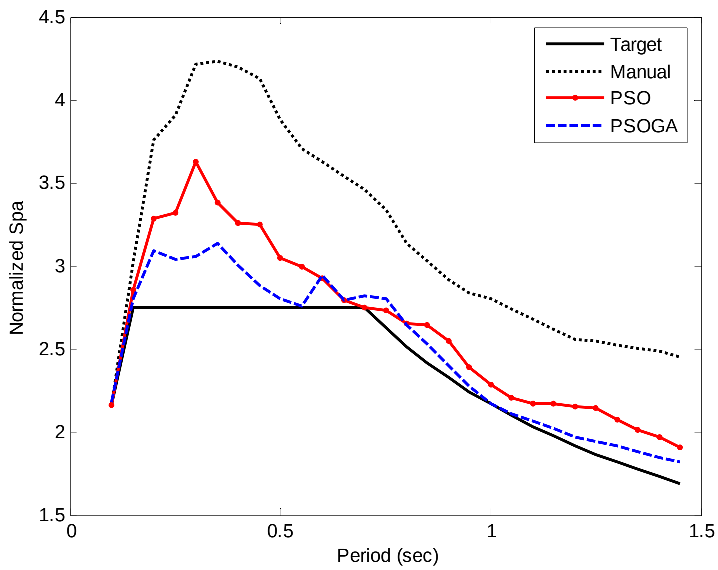

Figure 8. Comparison of the mean spectra results vs. the target in the present work-3

According to Figure 9, exploration of higher fitness levels in further iterations of search may be stopped in PSO but PSOGA shows its higher effectiveness and convergence stability. The matter resulted in improved spectrum compatibility in charge of higher computational effort via more search iterations, as in Figure 10.

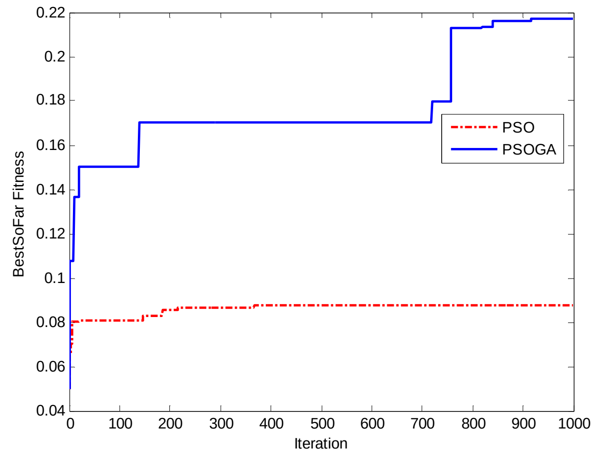

Figure 9. Convergence curve for the treated example in the present work-4

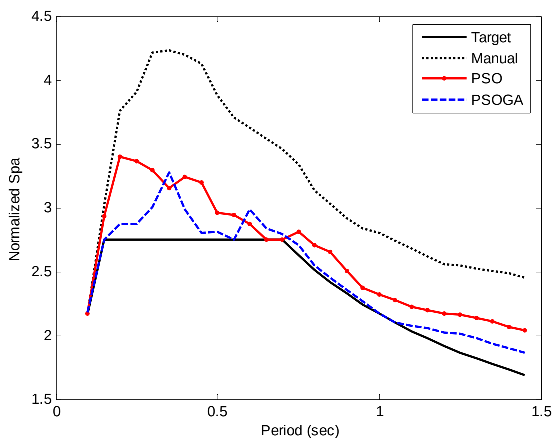

Figure 10. Comparison of the mean spectra results vs. the target in the present work-4

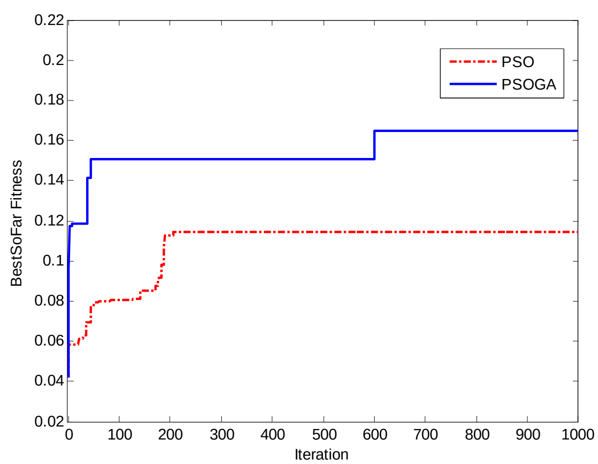

Figure 11. Convergence curve for the present work-5 without fine parameter tuning

Sensitivity of the results to parameter tuning is also tested in the current study. Superior effectiveness of PSOGA over PSO and both of them over manual procedure stayed reliable as shown in the convergence curve of Figure 11 while all the swarm coefficients are taken equal to unity instead of being tuned. Figure 12 shows relatively close spectra of the optimization methods. For the sake of true comparison in all convergence curves of this study, whenever a population of particles is randomly initiated in PSO, it is saved and transmitted to the PSOGA as its initial positions of particles.

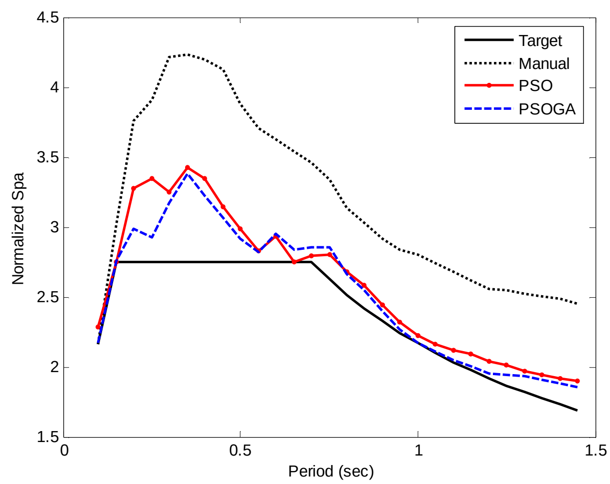

Figure 12. Comparison of the mean spectra results vs. the target in the present work-5

6. SUMMARY AND CONCLUSION

A new hybrid procedure is developed combining the directional search in PSO with genotypic jumps in GA to enhance effectiveness of the artificial swarm intelligence in searching global optimum. Strong ground motion scaling problem was formulated so that the corresponding scale factors be assigned floating-point values in range 0 to 1. While zero choice means omitting the record, the proposed method not only tunes the scale factors but also simultaneously selects earthquakes that are most compatible with the target design spectrum.

Optimization results showed considerable decrease in the compatibility error using either PSO or PSOGA with respect to manual practice; i.e. using identical scale factors for all the available earthquakes. It declared high economical benefits of optimization for seismic design.

Treating the available record list with various parameter sets in the optimization algorithms, superiority of the proposed PSOGA over PSO was shown even starting from the same randomly initiated population of particles.

Some further points were investigated by parametric study. The proposed PSOGA showed to be less sensitive to the population size variation as a major control parameter, as well as being more powerful than PSO in passing over premature convergence. It stayed more effective than PSO even by altering such control parameters to non-tuned values, however, not so efficient in this case.

PSOGA reliability is confirmed by various sets of parameters studied in such an illustrative example. As a result the proposed method can be recommended for optimal ground motion scaling problem being enhanced by its additional genotypic search and convergence stability with respect to the standard particle swarm optimization.

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