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SCALING EARTHQUAKE GROUND MOTIONS USING MOUTH BROODING FISH ALGORITHM

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ABSTRACT

In this article, spectral matching of ground motions is presented via the Mouth Brooding Fish (MBF) algorithm that is recently developed. It is based on mouth brooding fish life cycle. This algorithm utilizes the movements of the mouth brooding fish and their children's struggle for survival as a pattern to find the best possible answer. For this purpose, wavelet transform is used to decompose the original ground motions to several levels and then each level is multiplied by a variable. Subsequently, this algorithm is employed to determine the variables and wavelet transform modifies the recorded accelerograms until the response spectrum gets close to a specified design spectrum. The performance of this algorithm is investigated through a numerical example and also it is compared with CBO and ECBO algorithms. The numerical results indicate that the MBF algorithm can to construct very promising results and has merits in solving challenging optimization problems.

Keywords: Mouth brooding fish algorithm, colliding bodies optimization, metaheuristic optimization algorithm; scaling ground motions.

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1. INTRODUCTION

Optimization algorithms can be divided into two general categories of Gradient-based methods and metaheuristics. Population-based meta-heuristic algorithms consists of two phases: an exploration of the search space and exploitation of the best solutions found. One of the most important subjects in a good metaheuristic algorithm is to keep a reasonable balance between the exploration and exploitation abilities [1].

Meta-heuristic optimization algorithms are becoming more and more popular in

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engineering applications because they: (i) rely on rather simple concepts and are easy to implement; (ii) do not require gradient information; (iii) can bypass local optima; (iv) can be utilized in a wide range of problems covering different disciplines [2].

Nature-inspired meta-heuristic algorithms can be grouped in three main categories: evolution-based, physics-based, and swarm-based methods. Evolution-based methods are inspired by the laws of natural evolution. The most popular evolution-inspired techniques are Genetic Algorithms (GA) that simulates the Darwinian evolution, Probability-Based Incremental Learning (PBIL), Genetic Programming (GP), and Biogeography-Based Optimizer (BBO).

Physics-based methods imitate the physical rules in the universe. The most popular algorithms are Simulated Annealing (SA), Gravitational Local Search (GLSA), Big-Bang Big-Crunch (BBBC), Gravitational Search Algorithm (GSA), Charged System Search (CSS) [3], Central Force Optimization (CFO), Artificial Chemical Reaction Optimization Algorithm (ACROA), Black Hole (BH) algorithm, Ray Optimization (RO) [4] algorithm, Small-World Optimization Algorithm (SWOA), Galaxy-based Search Algorithm (GbSA), Curved Space Optimization (CSO), water evaporation optimization (WEO) [5], Big Bang–Big Crunch algorithm (BB–BC), Colliding Bodies Optimization (CBO) [6], Imputation–Regularized Optimization (IRO) [7,8] and CBO-PSO [9].

The third group of nature-inspired methods includes swarm-based techniques that mimic the social behavior of groups of animals. The most popular algorithm is Particle Swarm Optimization (PSO) [10], Ant Colony Optimization (ACO) [11], Marriage in Honey Bees Optimization Algorithm (MBO), Artificial Fish-Swarm Algorithm (AFSA), Termite Algorithm, ABC, Wasp Swarm Algorithm, Monkey Search, Wolf pack search algorithm, Bee Collecting Pollen Algorithm (BCPA), Cuckoo Optimization Algorithm (COA), Dolphin Partner Optimization (DPO), Bat-inspired Algorithm (BA), Firefly Algorithm (FA), Hunting Search (HS), Bird Mating Optimizer (BMO), Krill Herd (KH), Fruit fly Optimization Algorithm (FOA) [12], Dolphin Echolocation (DE) and Mouth Brooding Fish algorithm(MBF) [13] and MBF-CBO [14].

It is worth mentioning here that there are also other meta-heuristic methods inspired by human behaviors in the literature. Some of the most popular algorithms are Teaching Learning Based Optimization(TLBO), Harmony Search (HS) [15], Tabu (Taboo) Search (TS), Group Search Optimizer (GSO), Imperialist Competitive Algorithm (ICA), League Championship Algorithm (LCA), Firework Algorithm, Interior Search Algorithm (ISA), Mine Blast Algorithm (MBA), Soccer League Competition (SLC) algorithm, Seeker Optimization Algorithm (SOA), Social-Based Algorithm (SBA), Exchange Market Algorithm (EMA), and Group Counseling Optimization (GCO) algorithm.

One of the recently developed metaheuristics is Mouth Brooding Fish algorithm (MBF) by Jahani and chizari. It is based on mouth brooding fish life cycle. This algorithm uses the movements of the mouth brooding fish and their children's struggle for survival as a pattern to find the best possible answer. The main objective of the present study is to minimize one objective function (Errors) under some specific limitations. Thus, in this paper, the MBF algorithm is used for the spectral matching of ground motions. The results of design are also compared with previous literature. For example, application of Mouth brooding fish algorithm for cost optimization of reinforced concrete slabs [16], optimum cost design of reinforced concrete slabs using a metaheuristic algorithm [17], Optimization of Haraz dam reservoir

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operation using CBO metaheuristic algorithm [18].

The present paper is organized as follows: In the next section, standard MBF algorithm is briefly introduced. Section 3 consisting of the study of optimization of one civil constrained function. Conclusion is presented in Section 4.

2. MOUTH BROODING FISH ALGORITHM (MBF)

In the sea, many underwater creatures have strategies to protect themselves from harm, such as camouflage, not all have methods for protecting their young, too. Mouth brooders, however, are well-known for their ability to take care and protect their offspring, largely due to a very unusual technique. Mouth brooders protect their young by using their mouths as a shelter. The way the mouth brooding fish (MBF) life cycle processes, has inspired the MBF algorithm [13]. this algorithm has 5 controlling parameters which the user determines. These parameters are the number of population of cichlids (nFish), mother's source point (SP), the amount of dispersion (Dis), the probability of dispersion (Pdis), and mother's source point damping (SPdamp). the most important base of a MBF algorithm, is how cichlids surround their mother or in other words move around her, and the impacts of nature on their movements. The flowchart of the MBF is shown in Figure 1 and the steps involved are given as follows: (i) the main movements, (ii) the additional movements, (iii) crossover, and (iv) shark attack.

2.1 The main movments

The main movements of each cichlid are calculated as follows:

$$\mathrm{A}_{sp} = \mathrm{SP} \times \mathrm{Cichlids} \cdot \mathrm{Movements} \tag{1}$$

where SP is the mother's source point and Cichlids.Movements is the last movements of cichlids.

$$\mathrm{SP} = \mathrm{SP} \times \mathrm{SPdamp} \tag{2}$$

where SP is mother's source point that changes for the next iteration and SPdamp is mother's source point damp and varies between 0.85 and 0.95.

$$\mathrm{A}_{lb} = \mathrm{Dis} \times (\mathrm{Cichlids} \cdot \mathrm{Best} - \mathrm{Cichlids} \cdot \mathrm{Position}) \tag{3}$$

where Cichlids.Best is the best position that the cichlid gets through the past iterations and Cichlids.Position is the current position of the same cichlid. Dis is the am ount of dispersion that is one of the controlling parameters which is selected by the user and could increase or

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decrease the effect of this movement.

$$\mathrm{A}_{gb} = \mathrm{Dis} \times (\mathrm{Global} \cdot \mathrm{Best} - \mathrm{Cichlids} \cdot \mathrm{Position}) \tag{4}$$

where Global.Best is the best position found of all cichlids colony through passed iterations and Cichlids.Position is the current position for each cichlid.

$$\mathrm{NewN} \cdot \mathrm{F} \cdot \mathrm{P} = 10 \times \mathrm{SP} \times \mathrm{NatureForce} \cdot \mathrm{Position}(\mathrm{SelectedCells}) \tag{5}$$

where NatureForce.Position(SelectedCells) is the selected cell from 60 percent difference cells of best position of last and current generation.

$$\mathrm{A}_{nf} = \mathrm{Dis} \times (\mathrm{NewN} \cdot \mathrm{F} \cdot \mathrm{P} - \mathrm{NatureForce} \cdot \mathrm{Position}) \tag{6}$$

where natureForce.Position is the best position of cichlids of the last iteration.

According to the main movements, each child can move no more than the additional surrounding dispersion positive or the additional surrounding dispersion negative (ASDP or ASDN).

The two parameters mentioned above are defined as:

$$\mathrm{ASDP} = 0.1 \times (\mathrm{VarMax} - \mathrm{VarMin}) \,.\, \mathrm{ASDN} = -\mathrm{ASDP} \tag{7}$$

where VarMin and VarMax are the minimum and maximum limits of the problems variation respectively.

After that, we find a new position for cichlids if we add the calculated movements of cichlids to their current position. Now if their current position is out of the search space area, new movement is added by using the mirror effect (i.e., by negativing the movement changing the direction of movement) and it is defined as follows:

$$\mathrm{Cichlids} \cdot \mathrm{Movements} = -\mathrm{Cichlids} \cdot \mathrm{Movements} \tag{8}$$

where Cichlids.Movements is the movements of cichlids before and after of mirror effects. Each position of cichlids is also checked with search space limits (VarMin and VarMax) therefore no cichlids have left the search space area.

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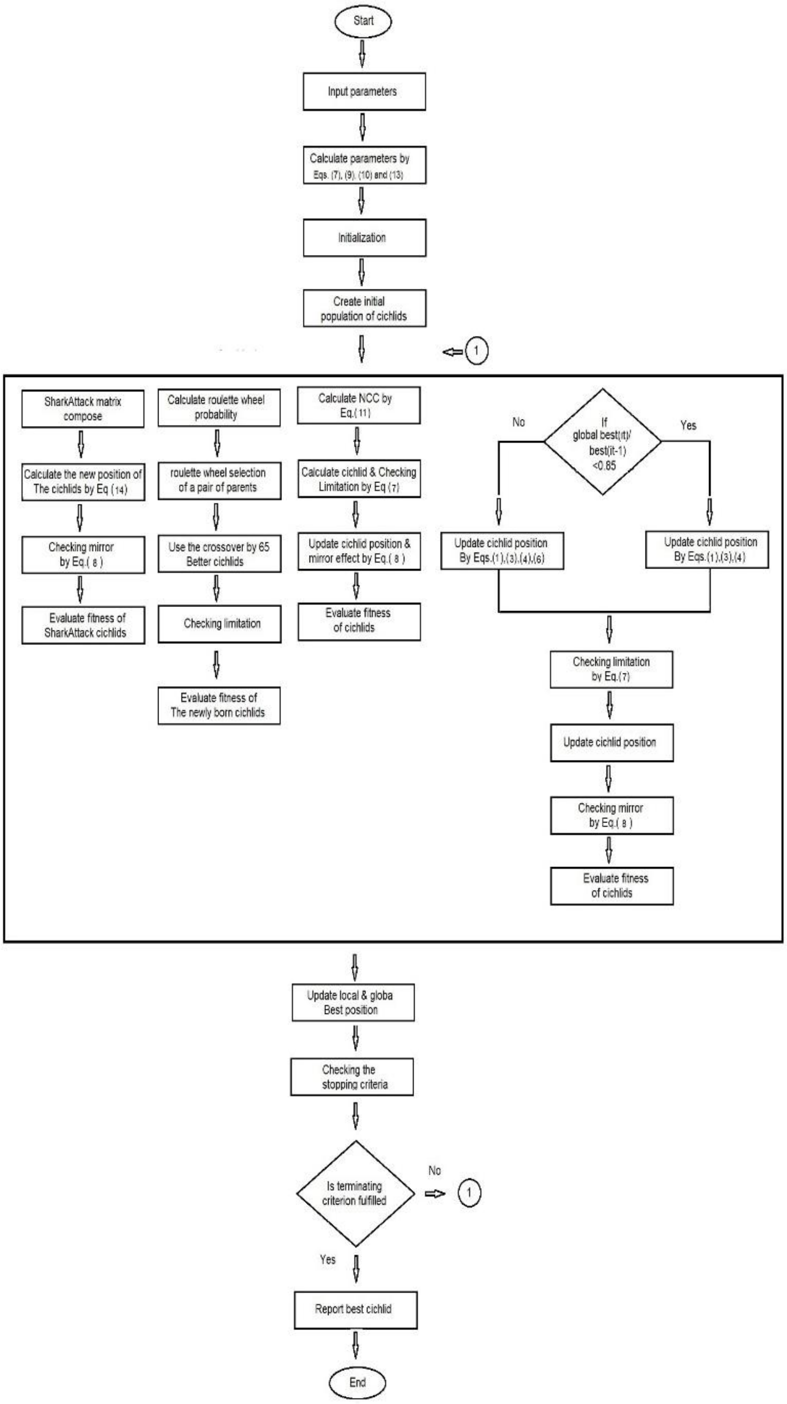

Figure 1. Flowchart of the MBF algorithm [19]

2.2 The additional movements

The mother can keep as many cichlids as its mouth capacity allows and the remaining members, which have to face up with challenges in nature, are named left out cichlids.

The number of left out cichlids is calculated as follows:

$$\mathrm{nm} = 0.04 \times \mathrm{nFish} \times SP^{-0.431} \tag{9}$$

where nFish is the population size of cichlids and SP is the mother's source point and nm is the number of left out cichlids. These left out cichlids in order to survive from danger have to move further from the main movement that for this movement MBF algorithm uses another controlling parameter named probability of dispersion (Pdis) and it is between 0 and 1.

The number of cells for the chosen left out cichlids is calculated as follows:

$$\mathrm{NCC} = [\mathrm{nVar} \times \mathrm{Pdis}] \tag{10}$$

where NCC is the number of the cells that are to be changed. Left out cichlids have the second part of a movement; therefore, the limitation of movement is multiplied by 4 as follows:

$$\mathrm{LeftCichlids} \cdot \mathrm{Position} = \mathrm{UASDP} \pm \mathrm{Cichlids} \cdot \mathrm{P(SelectedCells)} \tag{11}$$

where UASDP and UASDN are the ultra-additional surrounding dispersion positive and negative limits for the left-out cichlid's movements.

The second part of movement is calculated as follows:

$$\mathrm{LeftCichlids} \cdot \mathrm{Position} = \mathrm{UASDP} \pm \mathrm{Cichlids} \cdot \mathrm{P(SelectedCells)} \tag{12}$$

where Cichlids.P(SelectedCells) are the randomly selected cells of cichlids by the number of NCC and LeftCichlids.Position is the new position of left out cichlids after the second part of movements.

2.3 Crossover

Mouth brooding fish allows its best cichlids to marry; thus, in the MBF algorithm by using a probability distribution or Roulette Wheel selection, we select one pairs of parents from each cichlid. The single point crossover by the probability of crossover of 65 percent of the better parent and 35 percent of another parent is conducted to generate the new fish. These newly born cichlids that have new position, take the place of their parents and their movement would

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be zero. Before evaluating the newly born fish with fitness function we should check that the new position for the generated children is in the search space area.

2.4 Shark attack

The number of cichlids for shark attack (effects of danger on cichlids) movements is calculated as follows:

$$\mathrm{nshark} = 0.04 \times \mathrm{nFish} \tag{13}$$

where nshark is the number of cichlids that is chosen for shark attack effect.

Shark attack affects 4 percent of cichlids population on position and movements as follows:

$$\mathrm{Cichlids} \cdot \mathrm{NewPosition} = \mathrm{SharkAttack} \times \mathrm{Cichlids} \cdot \mathrm{Position} \tag{14}$$

where SharkAttack is the matrix that holds the number of cells and how many times they have changed and Cichlids.Position is the randomly selected cichlids from 4 percent population.

3. NUMERICAL EXAMPLE: SCALING EARTHQUAKE GROUND MOTIONS

In this section, the performance of the MBF algorithm is studied for scaling of ground motions taken from the optimization literature [20] and [21]. This example is independently optimized 30 times, and the algorithm ran 1000 iterations.

In this paper for spectral matching of ground motions utilizing the wavelet transform and a metaheuristic optimization algorithm as MBF. For this purpose, wavelet transform (db10 in matlab) is used to decompose the original ground motions to 8 levels (Figure 2), where each level covers a special range of frequency, and then each level is multiplied by a variable (Eq. (15)). Then the response pseudo-acceleration spectrum of the ground motions is determined (Eq. (16)). wavelet transform modifies the recorded accelerograms until the response spectrum gets close to a specified design spectrum. Comparisons are made through the error between the target spectrum and modified maximum response spectrums (Eq. (17)). Subsequently, the MBF algorithm is employed to calculate the variables such that the error between the response and target spectra is minimized.

$$f_m(t)=\sum_{j=1}^{n}(\alpha_j D_j)+\alpha_{n+1} A_n \tag{15}$$

where D_j and A_n are the detailed and approximate signals at level j and n, respectively, and α_j is the j_{th} modified value ($\alpha_j \geq 0$). In fact, this value is a variable in the optimization process.

$$\ddot{x}(t)+2\,\zeta\,\omega\dot{x}(t)+\,\omega_2\,x(t)=-\,f_m(t) \tag{16}$$

where ω, ζ and $f_m(t)$ are the fundamental frequency, the damping coefficient of the single degree of freedom system, and the earthquake ground acceleration, respectively.

$$\mathrm{Err(X)} = 100\sqrt{1/N\sum_{i=1}^{N}(log\mathrm{Sa} - logA)^2} \tag{17}$$

where S_a is the elastic acceleration response spectrum for oscillators with 5% ratio of critical damping and natural period T, is defined by the European seismic code provisions (CEN 2003); A is the pseudo-acceleration spectrum of the i_{th} modified ground acceleration in period T and N is the number of specified periods (here, 500 are considered in the range [0-5] s with period steps of 0.01s).

In this paper, penalty method is utilized to satisfy the code requirements:

$$\text{Penalty} = q_1 + q_2 \tag{18}$$

$$q_1 = \max(0, \max(0.9 * S_a(T_i) - A(T_i)), \qquad 0.2T_n \le T_i \le 2T_n \tag{19}$$

$$q_2 = \max(0, S_a(T_1) - A(T_1)), \qquad T_1 = 0 \tag{20}$$

Here, q_1 and q_2 are considered in order to prevent the maximum response spectrum to fall below the target spectrum within the code-specific period range and zero period, respectively. S_a and T_n are the target spectrum and fundamental period of structure, respectively.

In this step the objective function in optimization process is computed as:

$$\mathrm{F(X)} = \mathrm{Err(X)} * (1 + \gamma * \mathrm{penalty(X)}) \tag{21}$$

where x is the vector of the optimization variables (i.e., the modified values in Eq. (15), γ is a large number which is selected to magnify the penalty effects, and Err is calculated using Eq. (21)). The algorithm is also coded in MATLAB.

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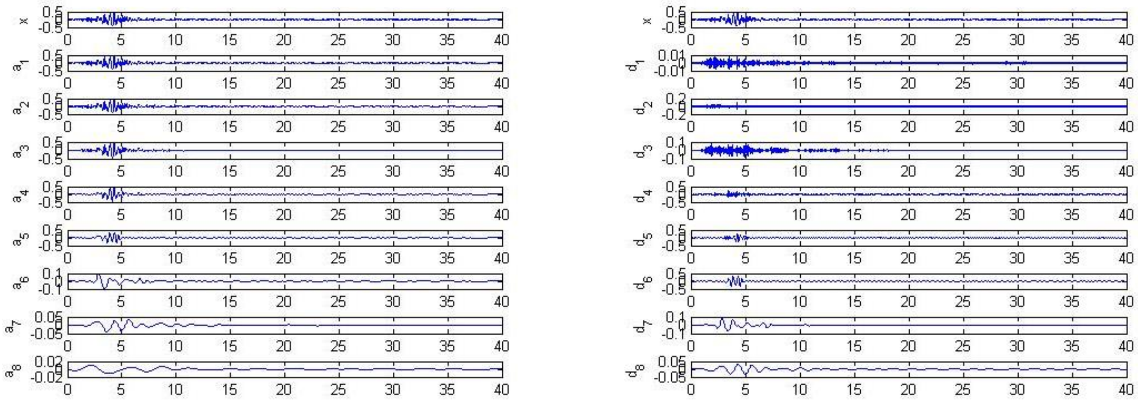

Figure 2.-Decompose the original ground motions (LOMAP/G01090)

For illustrating the proposed method, three recorded ground motions have been modified so as to be compatible with Eurocode-8 design spectrum of soil class A. According to Eurocode-8, the minimum number of records for this selection is 3. In this paper, three horizontal ground motion components with identical soil conditions are selected from the PEER NGA (2014) STRONG MOTION DATABASE RECORD. All of the records are discretized at 0.01 s with different durations for the strong ground motions. After considering records, one fundamental period of 0.45s, is selected for controlling the requirements of Eurocode-8 in the range of the considered periods [22]. The example motions are: (i) ANZA/PFT135 component recorded at Anza (Horse Canyon) site during on 2/25/1980, (ii) KOCAELI/GBZ000 component recorded at Kocaeli Turkey site during on 8/17/1999, (iii) LOMAP/G01090 component recorded at Loma Prieta site during on 10/18/1989.

Figure 3 is displayed the original and modified acceleration time-history of loma Prieta. From this figure, it can be seen that the frequency content of the modified acceleration time-history is different compared to its original ones.

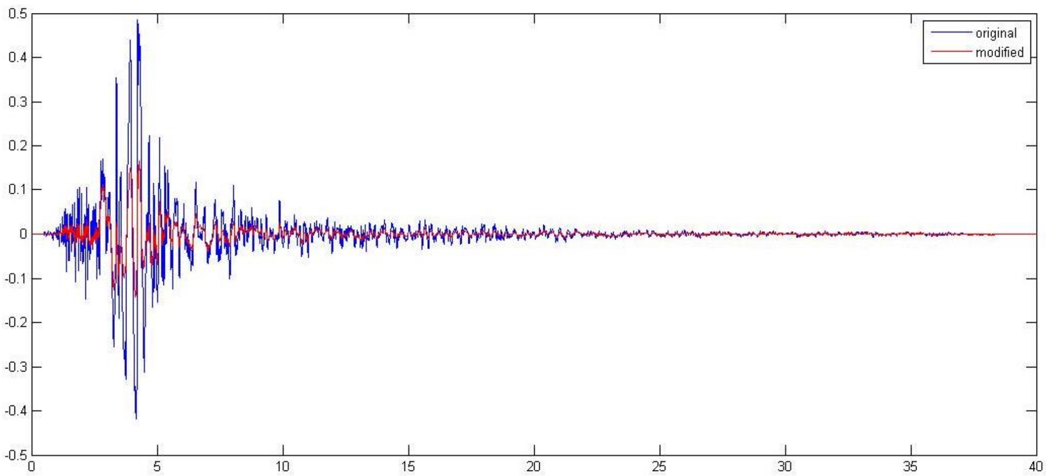

Figure 3. Original and modified acceleration time-histories of Loma Prieta

The maximum response spectrum of the ground motions obtained by algorithm for fundamental period, and target spectrum are shown in Figure 4. In the optimization process of all the recorded ground motions, the number of agents is set as 50 individuals, SP = 0.6, SPdamp = 0.95, Dis=1.8, Pdis = 0.2, pro=0.3, cMs=2 and the maximum number of iterations is considered as 300.

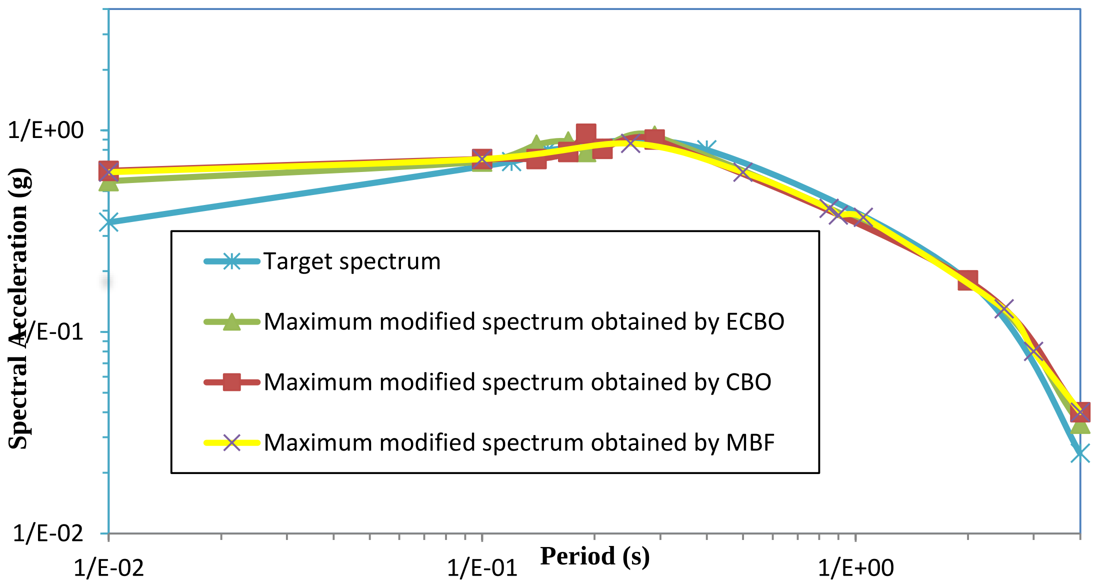

Figure 4. Comparison of maximum response spectrum with the target spectrum

Table 1 shows the optimized error obtained by MBF. As shown in this table, the errors obtained by MBF are better than that obtained for the CBO algorithm (but not relative to ECBO), which it indicates the importance of the enhancement of the algorithm for this problem.

Table. 1 The errors obtained using the MBF algorithm (%)

Record No.	Earthquake name	Record ID	CBO [20]	ECBO [20]	Present study (MBF)
1	Anza (Horse Canyon)	ANZA/PFT135			
2	Kocaeli Turkey	KOCAELI/GBZ000	5.84	3.43	5.27
3	Loma Prieta	LOMAP/G01090			

4. CONCLUSIONS

This study uses the MBF for solving optimization problems and in particular for spectral matching of ground motions. The results obtained show that the MBF method is powerful and efficient approaches for finding the optimum solution to structural optimization problems.

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Furthermore, for the scaling of ground motions, the comparison of the optimization results of MBF with CBO and ECBO shown the superiority of the MBF to achieve better results than the CBO algorithm but not relative to ECBO. This simple meta-heuristic algorithm can be used in many other engineering design problems to decrease the construction costs.

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