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SOFT COMPUTING BASED STRUCTURAL OPTIMIZATION FOR EARTHQUAKE

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ABSTRACT

An efficient methodology is proposed to optimal design of structures for earthquake loading. In this methodology to reduce the optimization overall time, a serial integration of wavelet transforms, neural networks and evolutionary algorithms are employed. In order to reduce the computational work of the structural time history analysis, a discrete wavelet transform is used by means of which the number of points in the earthquake record is decreased. Also, an advanced metamodel, called self-organizing generalized regression is employed to predict the time history responses. The optimization task is achieved by an evolutionary algorithm called virtual sub population method. A 6-storey space steel frame structure is designed for optimal weight for the El Centro earthquake induced loads. The numerical results demonstrate the efficiency and computational advantages of the proposed methodology.

Keywords: Earthquake; wavelet transform; genetic algorithm; neural networks

1. INTRODUCTION

The structural optimization for earthquake induced loads is a computationally intensive task. In order to deal with this problem an efficient hybrid soft computing strategy is proposed. A combination of wavelet transforms, neural networks and evolutionary algorithms are utilized to achieve the optimization task. In order to reduce the computational work of the structural time history analysis, a discrete wavelet transform (DWT) is used to decrease the number of points of the earthquake record involved. In this work, Daubechies [1] wavelet function (Db2) is selected to decompose the earthquake record. Also, the fast Mallat [2] algorithm is used to calculate the coefficients. The decomposition process is repeated in two stages, and the number of the points of the original record is reduced to 0.25 of the primary points. In the optimization process a great number of time history analyses should be performed; thus

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the overall time of the optimization process is still very long. To reduce the computational work, a neural system, called self-organizing generalized regression (SOGR), is employed to predict the time history responses of the structures. Training the SOGR is implemented in three phases. In the first phase, the input-output samples are classified as the similar data are divided into some clusters. Here, the similarity criterion is taken as the natural periods of the structures. It is obvious that the structures with similar natural periods yield the same patterns for dynamic structural responses. The classification is performed by a self-organizing map (SOM) [3] neural network. In the second phase, a distinct generalized regression (GR) [4] neural network is trained for each cluster using its training data. In the SOGR the natural periods of structures, during optimization process, should be computed and therefore the computational effort of the process is high. In the third phase, another GR network is trained to predict the natural periods of the structures. The evolutionary algorithm utilized in this paper is virtual sub-populations [5] (VSP) method. As demonstrated in [5-7] the computational effort by VSP is less than the standard GA. In order to investigate the efficiency of the proposed methodology, a 6-storey space steel frame structure is designed for optimal weight for the El Centro earthquake. The numerical results imply that the proposed methodology is a powerful tool for optimal design of structures subjected to earthquake loading.

2. FORMULATION OF OPTIMIZATION PROBLEM

In structural optimization problems, stress and displacement constraints are usually checked. In this paper only storey drift constraints for steel moment resisting frames are considered. A time-dependent discrete structural optimization problem of steel moment resisting frames is formulated as follows:

$$\begin{aligned} &\textit{Minimize} \quad W(X) \\ &\textit{Subject to} \quad g_{di}(X,t) = \frac{dr_i(X,t)}{dr_{i,all}} - 1 \le 0 \le 0 \quad , \quad i = 1,2,\cdots,m \\ &\qquad X_j \in R^d \quad , \quad j = 1,2,\cdots,n \end{aligned} \tag{1}$$

where $W(X)$ represents objective function, $g_{di}(X)$ is the drift constraint, m and n are the number of the stories and design variables, respectively. Drift of ith storey and its allowable value are represented by dr_i and $dr_{i,all}$, respectively. A given set of discrete values is expressed by R^d.

In this paper, Newmark's method is employed to solve the resulting equations and the conventional [8] method is employed to treat with the time-dependent constraints. In this method the time interval is divided into p subintervals and the time-dependent constraints are imposed at each time grid point.

The optimization method employed here is a variant of genetic algorithm (GA). GA has been quite popular and has been applied to a variety of engineering problems. In GA, constraints are mostly handled by using the concept of penalty functions, which penalize infeasible solutions. In the case of earthquake loading, a simple form of penalty function is employed as follows:

$$f_s(X)=\begin{cases} W(X) & \text{if} \quad X\in\tilde{\Delta} \\ W(X)+f_p(X) & \text{otherwise} \end{cases}, \quad f_p(X,t_k)=r_P\sum_{i=1}^{m}\left(\max(g_{di}(X,t_k),0)\right)^2, \quad k=0,1,\cdots,p \tag{2}$$

where $f_s(X)$ and $f_p(X)$ are supplemental and penalty functions, respectively. Also, $\tilde{\Delta}$ is the feasible search space. Also, r_p is an adjusting coefficient.

3. OPTIMIZATION ALGORITHM

The VSP is a variant of GA that reduces the required computational burden of the GA. In the VSP, an initial population with a small number of individuals is selected and all the necessary operations of the genetic are carried out and the optimal solution is achieved. As the size of the population is small, the VSP algorithm converges to a pre-mature solution. In each generation, individual with the best fitness value satisfying the design constraints is saved. Then, the best solution is repeatedly copied to create a new population. In the new population, the majority of the individuals are the best repeated solution of the previous results and the remaining are randomly selected. Thereafter, the optimization process is repeated using standard GA with a reduced population to achieve a new solution. The process of creating the reduced population with repeated individuals in each iteration is continued until the method converges. These reduced populations are called virtual sub-populations (VSP) and the optimization process with VSPs is called adaptive VSP algorithm. The flowchart of VSP is illustrated in Figure 1.

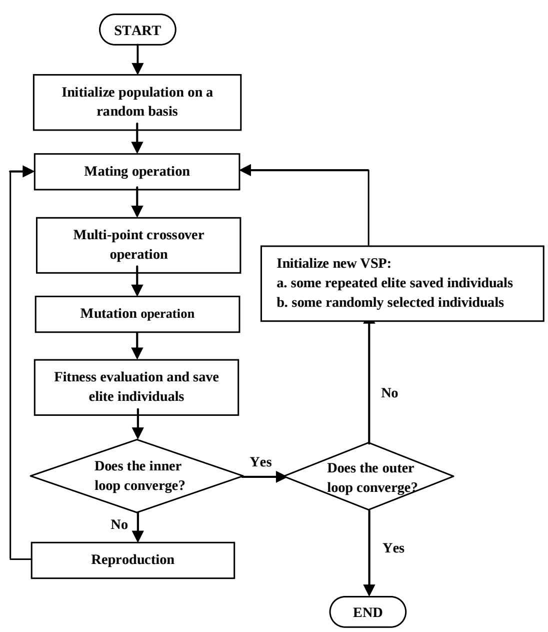


Figure 1. The flowchart of VSP Algorithm

4. EARTHQUAKE DECOMPOSITION BY WAVELET TRANSFORMS

Wavelets are mathematical functions that cut up data or function into different frequency components, and then study each component with a resolution matched to its scale. It turns out that the wavelet transform can be simply achieved by a tree of digital filter banks. The main idea behind the filter banks is to divide a signal into two parts; the first is the low-frequency part and the other is the high-frequency part. This idea can be achieved by a set of filters. A filter bank consists of a low-pass filter and a high-pass filter, which separate a signal into different frequency bands. A filter may be applied to a signal to remove or enhance certain frequency bands of the signal. By applying a low-pass filter to a signal, the high-frequency bands of the signal are removed and an approximate version of the original signal is obtained. A high-pass filter removes the low-frequency components of the original signal, and the result is a signal containing the details of the main signal. By combining these two filters into a filter bank, the original signal is divided into an approximate signal and a detail signal. The first part of coefficients (*cA*) contains the low-frequency of the signal, and the other (*cD*) contains the high-frequency of the signal. The low-frequency content is the most important part and this part is used for dynamic analysis of structures. A multilevel decomposition of the signal is obtained by repeating the decomposition process. The low-pass filtered output signal is used as input. In [9-10] decomposition of earthquake records has been achieved by employing Harr [11] wavelet function. In the present study, Daubechies wavelet function (Db2) [11] have been selected to decompose the earthquake record. The decomposition process can be inversed and the original record can be computed. This process is named as inverse discrete wavelet transforms (IDWT). The decomposition process is achieved in two stages, and the number of points of the original record is reduced to 0.25 of the primary ones. In Figure 2, a two level decomposition is illustrated.

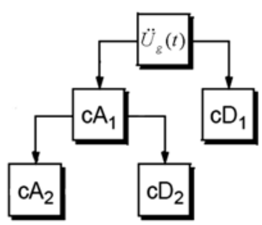


Figure 2. A two level decomposition of earthquake record $\ddot{U}_g(t)$

Despite the major reduction in the computational effort of time history analysis, the optimization process requires a great number of such analyses. In order to reduce the computational burden, a hybrid neural network is proposed in the present study to predict the time history responses of the structures.

5. SELF-ORGANIZING GR NEURAL NETWORKS

In this paper GR network and its extension is focused. In order to improve the performance generality of the conventional GR network, a new architecture and training algorithm for the GR network are proposed. The proposed neural network is a combination of SOM and GR networks and called self-organizing generalized regression (SOGR) networks. Similar neural systems were proposed in [12-13] employing RBF neural networks.

The SOM is a neural network algorithm developed by Kohonen [3]. The SOM learn to classify input vectors according to how they are grouped in the input space. In the SOM, neighbouring neurons learn to recognize neighbouring sections of the input space. Thus, SOM learn both the distribution and topology of the input vectors. A SOM network identifies a winning neuron using a simple procedure. However, instead of updating only the winning neuron, all neurons within a certain neighbourhood of the winning neuron are updated, using the Kohonen rule. Consequently, after many presentations, neighbouring neurons have learned vectors similar to each other.

Generalized regression (GR) neural networks are memory-based network that provides estimates of continuous and discrete variables and converges to the underlying (linear or nonlinear) regression surface. GR has a one pass learning algorithm with highly parallel structure. It does not require an iterative training procedure as in MLP. The principal advantages of GR are fast learning and convergence to the optimal regression surface as the number of samples becomes large. GR approximates any arbitrary function between input and output vectors, drawing the function estimate directly from the training data [14]. GR is two layers feed forward network. It is often used for function approximation. The first layer has as many neurons as there are samples in training set. Specifically, the first layer weight matrix is set to the transpose of the matrix containing the input vectors. The second layer also has as many neurons as input-output vectors, but here the weight matrix is set to the matrix containing the output vectors. Therefore training of GR network is fast.

5.1 SOGR Structure

Training of SOGR includes three stages. Firstly, the samples are divided into some classes so that the data located in each class have the same properties. In the case of dynamic analysis of structures the best criterion is the natural periods of the structures [12]. The classification task is achieved by a SOM network. The input vectors of the SOM consist of the first to third natural periods of the trail structures.

$$IV = \{T_1, T_2, T_3\}^{\mathrm{T}} \tag{3}$$

where IV is the input vector; T_1, T_2, and T_3 are the first to third natural periods of structures.

By presenting the input samples to the SOM, the network recognizes the similar ones and divides them into some classes. Now it is possible to train a GR network for each class using its training data. In this case, IV is used as the input vector of the GR networks and their outputs are the time history responses of structures as:

$$OV = \{dr_1(X,t),...,dr_i(X,t)\}^{\mathrm{T}} \tag{4}$$

Therefore, the input and output matrices of GR networks are as follows:

$$\text{IM} = [IV_l] \ , \ \text{OM} = [OV_l] \ , \ l = 1,...,n_{ts} \tag{5}$$

where IM and OM are matrices contained input and output vectors, respectively. The number of training samples is expressed by n_{ts}.

In order to train the SOM network and find the optimal number of data groups a simple procedure is performed. In this procedure, at first, some grids of SOM neurons with random topology are selected and the network is trained involving the grids. During the training process the SOM neurons concentrate on distinguishable regions. The number of these regions is taken into account as the optimal number of the SOM neurons. At last, a SOM network with the optimal number of SOM neurons is trained. Let m_s be the optimal number of SOM neurons. Then for each cluster a distinct GR network is trained.

$$\begin{cases} \text{Cluster 1}: \text{IM}_{C1} = [IV_j], \text{OM}_{C1} = [OV_j], \ j = 1,\dots,n_{C1} \Rightarrow \text{IM}_{C1}, \text{OM}_{C1} \rightarrow \text{GR NN 1} \\ \text{Cluster 2}: \text{IM}_{C2} = [IV_j], \text{OM}_{C2} = [OV_j], \ j = 1,\dots,n_{C2} \Rightarrow \text{IM}_{C2}, \text{OM}_{C2} \rightarrow \text{GR NN 2} \\ \vdots \\ \text{Cluster } m_s: \text{IM}_{C_{m_s}} = [IV_j], \text{OM}_{C_{m_s}} = [OV_j], \ j = 1,\dots,n_{Cm_s} \Rightarrow \text{IM}_{Cm_s}, \text{OM}_{Cm_s} \rightarrow \text{GR NN } m_s \end{cases} \tag{6}$$

where n_{C1}, n_{C2}, and n_{Cm_s} are the number of data located in clusters 1, 2, and m_s , respectively. Also, $\text{IM}_{Ci} \subset \text{IM}$, $\text{OM}_{Ci} \subset \text{OM}$, $i=1,\dots,m_s$. IM and OM are used to train the conventional GR network.

Employing the above explained neural system during the optimization process necessitates that the natural periods of structures be computed. Computing the periods with analytical methods can impose an additional computational burden to the optimization process. In order to eliminate this difficulty another GR network is trained to predict the natural periods of the structures. In this GR network, the inputs and outputs are the cross-sectional area assignments and the natural periods of the structures, respectively.

$$I_{ppn} = \{I_1, I_2, ..., I_{ni}\}^{\text{T}} \ , \ O_{ppn} = IV \tag{7}$$

where I_{ppn} and O_{ppn} are the input and output vectors of the period predictor GR network. The number of the input vector components is ni.

Therefore, the input and output vectors of the SOGR neural system are I_{ppn} and OV, respectively. In order to evaluate the accuracy of approximate time history responses, the SOGR prediction results are compared with the corresponding exact responses through Rrmse and Rsquare.

The main steps of training the SOGR networks are summarized as follows:

a) Employing the Db2 for decomposition of the El Centro earthquake record.
b) Selecting a number of input vectors from the design variables space.
c) Evaluating responses of the structures for the low-pass filtered record by Newmark's method.
d) Recovering the evaluated responses by IDWT to determine the responses on the original time points.
e) Evaluating natural periods of the structures by conventional FE analysis.

f) Selecting data for training and testing the neural networks on a random basis.
g) Considering two or three dimensional grids of SOM neurons with random topology.
h) Training the SOM network to classify the samples and find the optimal number of clusters (m_s).
i) Selecting a grid with the order of $m_s \times 1$ and training a new SOM network to cluster the data.
j) Training a GR network for each cluster using its corresponding data.

Figure 3 shows the architecture of the SOGR.

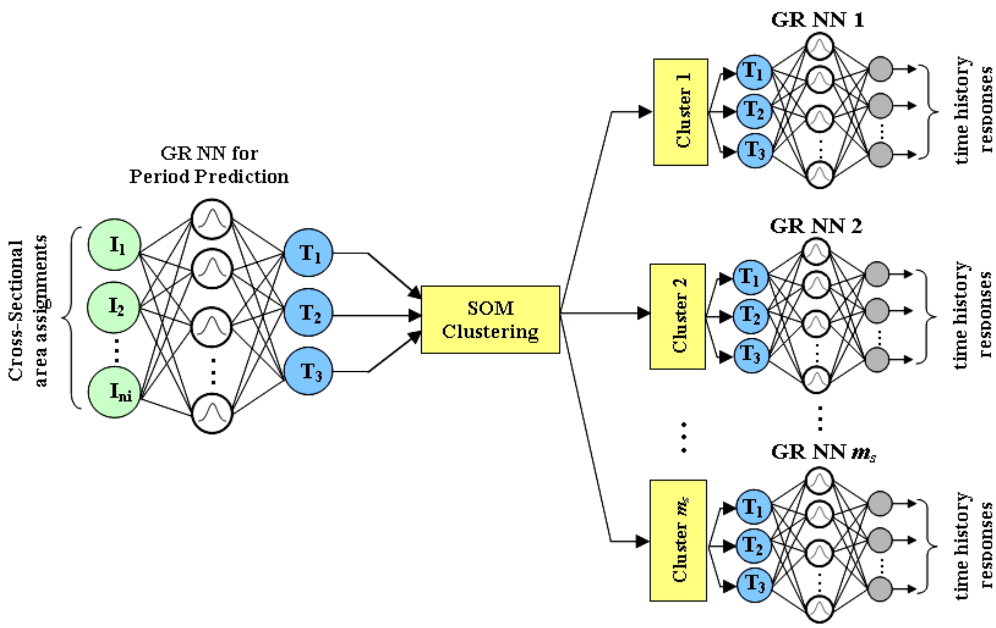


Figure 3. Architecture of SOGR

6. OPTIMIZATION BY VSP USING SOGR

For optimization an initial population including 20 individuals is selected on a random basis. The first to third natural periods of each individual are predicted by the trained period predictor GR network. The periods predicted are then presented to the SOM network to determine the cluster number, in which the individual is located. Afterward the GR networks associated with each cluster predicts the time history responses. The evolution is achieved by VSP using the genetic operators.

The pseudo code of the VSP + SOGR hybrid optimization process is shown in Figure 3.

Step 1: Selecting 20 parent vectors from the design variables space.
Step 2: Evaluating the natural periods of the structures by the GR networks.
Step 3: Recognizing the corresponding cluster of the structures.
Step 4: Evaluating the time history responses of the structures located in each cluster
Step 5: Evaluating the objective function.
Step 6: Checking the constraints at the grid points for feasibility of parent vectors.
Step 7: Generating offspring vectors by adaptive crossover and mutation operators.
Step 8: Evaluating the natural periods of the offspring vectors by the GR network.
Step 9: Recognizing the corresponding cluster of the offspring vectors.
Step 10: Evaluating the time history responses of the offspring vectors.
Step 11: Evaluating the objective function.
Step 12: Checking the constraints; if satisfied continue, else reject the solution.
Step 13: Checking convergence; if satisfied stop, else go to *Step* 7.
Step 14: Creating a VSP.
Step 15: Repeating *Steps* 7 to 15 until the proper solution is met.

Figure 4. The pseudo code of the optimization process by VSP + SOGR

7. NUMERICAL RESULTS

In this paper an illustrative examples is considered. A 3D steel frame, shown in Figure 5, subjected to the El Centro (S-E 1940) earthquake is designed for optimal weight. Rigid diaphragms are assigned to all the floors. The structural members are divided into six groups. The loads consist of 700 kg/m^2 gravity load on all floor levels and the El Centro earthquake applied in the *y* direction. Due to one-way action of the diaphragms the gravity loads are only supported by the beams of groups 1 and 2.

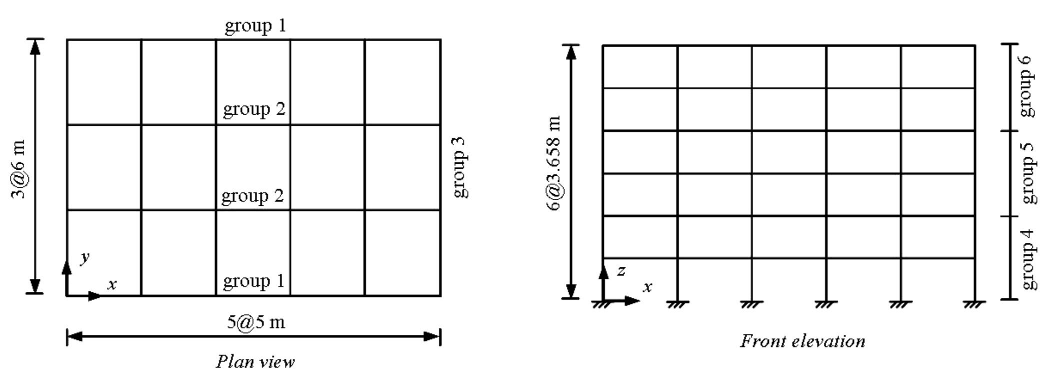


Figure 5. A 6-storey space steel frame

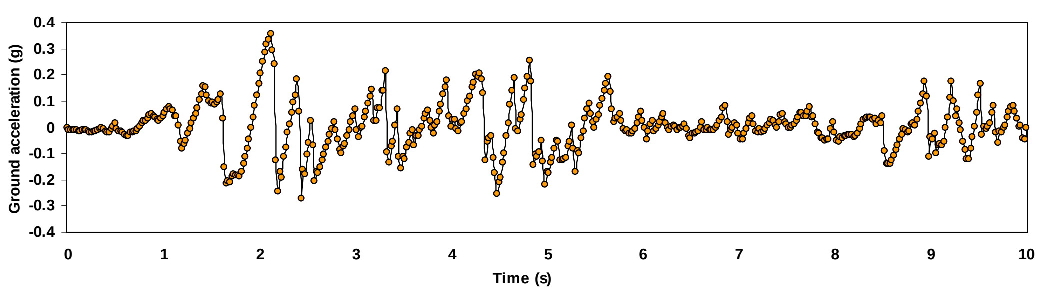
The time of optimization is computed in clock time by a personal Pentium IV 2000MHz. Young's modulus and weight density are 2.1×10^{10} kg/m^2 and 7850 kg/m^3, respectively. The optimization is carried out by VSP using the following analysis methods: (a) full dynamic analysis (FDA), (b) approximate analysis by conventional GR network (GR), and (c) approximate analysis by the SOGR metamodel (SOGR). In order to practical demands, the cross-sectional area assignments of elements are selected from European profile list given in Table 1.

Table 1: Available box and I-shaped profiles

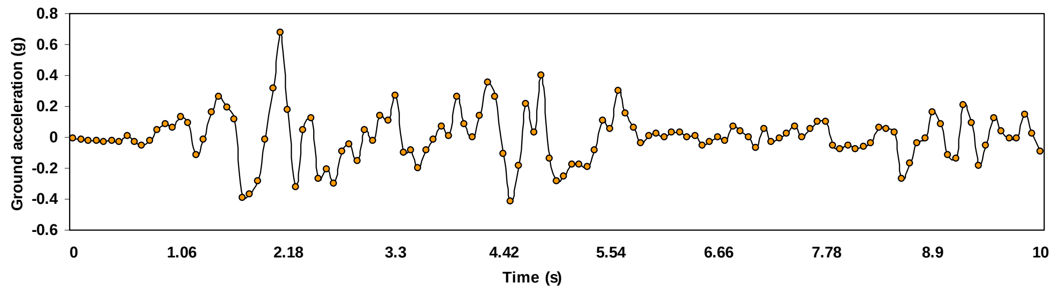
Columns		**Columns**		**Beams**	
1	Box 200×200×12.5	9	Box 260×260×16.0	17	IPE 220
2	Box 200×200×14.2	10	Box 260×260×17.5	18	IPE 240
3	Box 220×220×12.5	11	Box 280×280×14.2	19	IPE 270
4	Box 220×220×14.2	12	Box 280×280×16.0	20	IPE 300
5	Box 240×240×12.5	13	Box 280×280×17.5	21	IPE 330
6	Box 240×240×14.2	14	Box 300×300×16.0	22	IPE 360
7	Box 240×240×16.0	15	Box 300×300×17.5	23	IPE 400
8	Box 260×260×14.2	16	Box 300×300×20.0	24	IPE 450

In this study, drift constraints under allowable drift design requirements are expressed by the drift ratio of the following formula, in which the value of allowable drift ratio is 0.005.

The constraints are checked at 500 grid points with the time step of 0.02 second. In the data generating phase, 150 structures are randomly generated. From which 100 and 50 samples are employed to train and test the performance generality of the neural networks, respectively. The number of points of the original earthquake record is 500. The number of the points is reduced to 127 using DWT with Db2 wavelet at the 2nd level. The original and filtered earthquake points are shown in Figure 6.



(a)



(b)

Figure 6. The El Centro earthquake points of (a) original, (b) filtered records

The generated structures are analyzed for the filtered earthquake records and the approximate responses are obtained using the IDWT. The test samples are also analyzed for the original earthquake record to compute the actual responses. The approximate (DWT/IDWT) responses are compared with their corresponding actual ones in terms of mean *Rsquare* and mean *Rrmse* in Table 2.

Table 2: Mean *Rsquare* and *Rrmse* of the approximate (DWT/IDWT) drift responses

Wavelet function	**Evaluation metrics**	**Storey**					
		1	**2**	**3**	**4**	**5**	**6**
Db2	Rsquare	0.9876	0.9922	0.9964	0.9929	0.9775	0.9464
	Rrmse	0.1096	0.0866	0.0590	0.0831	0.1471	0.2291

As the second step in training the SOGR metamodel, a SOM network is trained to detect the data clusters. A grid of 5×1 of SOM neurons is employed. After training the SOM neural networks with the mentioned grid it is observed that the SOM neurons tend to concentrating about four main clusters. Therefore, the optimal number of SOM neurons is set to 4 (i.e. m_s=4) and a grid of 4×1 SOM neurons is adopted for this example. As the optimal number of cluster is determined (m_s=4), therefore 4 parallel GR networks are incorporated into the SOGR. The Approximate responses are employed to train the conventional GR network and the SOGR metamodel. The predicted responses are compared with their corresponding actual ones. The performance generalities of the conventional GR network and the SOGR metamodel are investigated through the testing data. The mean *Rsquare* and mean *Rrmse* of the inter-storey drift ratios predicted by the GR and the SOGR networks are summarized in Table 3.

Table 3: Mean *Rsquare*, mean and Max *Rrmse* of the predicted responses by GR and SOGR

Structural response	**GR**		**SOGR**	
	Rsquare	**Rrmse**	**Rsquare**	**Rrmse**
dr_1	0.9751	0.1486	0.9856	0.1134
dr_2	0.9801	0.1272	0.9913	0.0877
dr_3	0.9855	0.1050	0.9954	0.0646
dr_4	0.9822	0.1202	0.9925	0.0832
dr_5	0.9614	0.1851	0.9749	0.1498
dr_6	0.9283	0.2549	0.9446	0.2251
Ave.	0.9688	0.1565	0.9807	0.1206

It is observed that the SOGR has a better generality comparing with the conventional GR network. Mean *Rsquare* and mean *Rrmse* of the predicted responses in all the clusters are given in Tables 4.

Table 4: Mean *Rsquare* and *Rrmse* of test data for four clusters

Outputs	**Cluster 1**		**Cluster 2**		**Cluster 3**		**Cluster 4**	
	Rsquare	**Rrmse**	**Rsquare**	**Rrmse**	**Rsquare**	**Rrmse**	**Rsquare**	**Rrmse**
dr_1	0.9913	0.0890	0.9904	0.0945	0.9835	0.1236	0.9768	0.1481
dr_2	0.9949	0.0675	0.9945	0.0727	0.9904	0.0942	0.9856	0.1166
dr_3	0.9976	0.0478	0.9964	0.0586	0.9946	0.0717	0.9932	0.0799
dr_4	0.9954	0.0665	0.9947	0.0718	0.9916	0.0890	0.9882	0.1062
dr_5	0.9818	0.1291	0.9835	0.1240	0.9728	0.1593	0.9615	0.1885
dr_6	0.9588	0.1950	0.9629	0.1887	0.9412	0.2354	0.9190	0.2762
Ave.	0.9866	0.0992	0.9871	0.1017	0.9790	0.1289	0.9707	0.1526

Another GR network is also trained to predict the first to third natural periods of the structures. Results of testing this GR network reveal that the errors of first to third approximated periods are 2.441%, 1.459%, and 1.733%, respectively. Therefore, it can be employed in the optimization process. The total time spent to data generating, earthquake filtering, computing the approximate responses, computing the exact responses and networks training phases is about 300 minutes. The results of optimization using full and approximate dynamic analyses are given in Table 5.

Table 5: Optimum designs obtained by VSP using full and approximate analyses

Element groups No.	**Optimum designs**		
	FDA	**GR**	**SOGR**
1	IPE 300	IPE 300	IPE 300
2	IPE 360	IPE 360	IPE 360
3	IPE 330	IPE 330	IPE 330
4	Box 280×280×16.0	Box 300×300×17.5	Box 300×300×16.0
5	Box 260×260×14.2	Box 260×260×14.2	Box 280×280×14.2
6	Box 220×220×12.5	Box 220×220×12.5	Box 200×200×12.5
Weight (kg)	118476.63	122446.23	120426.97
Generations	52	85	68
Time (min)	2500.00	1.51	1.23

As given in this table, the optimum design obtained by FDA is better than the other solutions but it is very extensive in terms of the optimization overall time. The optimum design attained by SOGR is better than that of the conventional GR.

In order to assess the accuracy of the optimum designs obtained by the approximate analyses, their final responses are computed by the conventional FE analysis and are compared with their approximate responses. The results of the comparison are summarized in Tables 6 and 7. Also, third and fifth time history drifts of the optimum designs obtained using approximate analyses respectively by GR and SOGR are compared with their corresponding actual ones in Figures 7 and 8.

Table 6: Mean *Rsquare* and *Rrmse* of the optimum designs

Outputs	GR		SOGR	
	Rsquare	Rrmse	Rsquare	Rrmse
dr_1	0.9780	0.1484	0.9869	0.1144
dr_2	0.9850	0.1221	0.9924	0.0871
dr_3	0.9958	0.0646	0.9947	0.0725
dr_4	0.9889	0.1055	0.9925	0.0865
dr_5	0.9521	0.2187	0.9827	0.1315
dr_6	0.8964	0.3218	0.9567	0.2079
Ave.	0.9660	0.1635	0.9843	0.1167

Table 7: Comparison of maximum value of responses of the optimum designs with their allowable values

Outputs	Maximum values			Allowable values
	FDA	GR	SOGR	
dr_1	0.00329	0.00275	0.00290	0.00500
dr_2	0.00497	0.00464	0.00480	0.00500
dr_3	0.00500	0.00503	0.00475	0.00500
dr_4	0.00454	0.00435	0.00392	0.00500
dr_5	0.00473	0.00463	0.00502	0.00500
dr_6	0.00279	0.00276	0.00307	0.00500

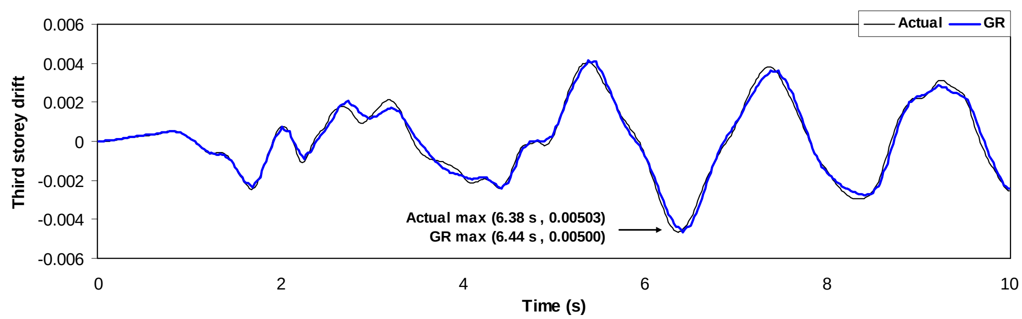


Figure 7. Third storey drift of optimum structure obtained by GR vs. its actual response

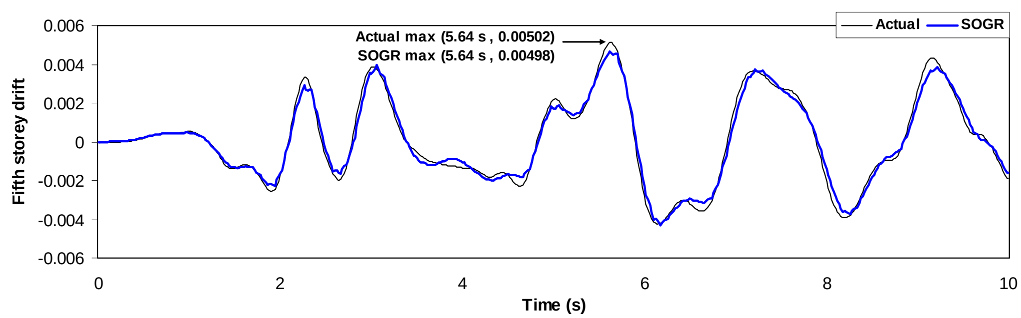


Figure 8. Fifth storey drift of optimum structure obtained by SOGR vs. its actual response

It can be observed that the performance generality of the SOGR metamodel is better than that of the conventional GR network. In this example the time of optimization employing neural networks, including data generating, earthquake filtering and networks training is about 0.12 times of optimization employing full dynamic analysis while, the errors due to the approximation are low.

8. CONCLUSIONS

In this study, an optimization procedure has been developed to optimal design of structures for earthquake loading. In this procedure, a combination of the wavelet transform, neural networks and an adaptive evolutionary algorithm has been utilized. The evolutionary algorithm employed is virtual sub population (VSP) method. Performing the structural optimization using the full time history analysis imposes disproportionate computational burden to the optimization process. In order to reduce the computational effort a serial integration of discrete wavelet transform (DWT) and a neural system (SOGR) is employed. The DWT is employed to reduce the design points of earthquake record. A combination of self organizing map (SOM) and generalized regression (GR) networks, the so-called SOGR, and a conventional GR network are used to this purpose. The numerical results of testing the networks performance generality, demonstrate the computational advantages of SOGR compared to the conventional GR network. The numerical results of optimization indicate that by using the proposed methodology, the time of optimization including data generating, earthquake filtering and neural networks training time is reduced to about 0.12 of the time required for optimization employing full dynamic analysis; while the errors is small.

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