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Research Article

STRUCTURAL OPTIMISATION FOR EARTHQUAKE LOADING USING NEURAL NETWORKS AND GENETIC ALGORITHM

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ABSTRACT
Optimum design of structures subject to earthquake requires that the time history analysis to be performed many times. This makes the optimal design process inefficient. In this study, in order to reduce the overall time of optimisation two strategies are adopted. In the first strategy, an intelligent neural system (INS) consisting of competitive (CNN) and radial basis function (RBF) neural networks is used to predict the responses of structures subject to earthquake. In the second one, an improved genetic algorithm (GA) is employed to achieve optimisation task. Computational performance of the hybrid INS-GA method is demonstrated by two numerical examples.

Keywords: *Optimum Design, Earthquake, Evolutionary Algorithm, Competitive, Radial Basis Function, Intelligent Neural System*

INTRODUCTION
This paper is an updated and revised version of the conference paper (Salajegheh *et al*., 2006). In the present paper further enhancements are accomplished on presenting of the materials. In order to clarity some new sections and figures are added to the paper. Also, a more efficient evaluation metric (Jiang *et al.*, 2006) is included to assess performance generality of neural networks. All the neural network models are retrained and the neural based optimisation processes are re-achieved and the obtained results are reconfirmed. Finally, a deeper analysis of the results is included.
Structural optimisation requires that the structural analysis to be performed many times for the specified external loads. This makes the optimal design process inefficient, especially when a time history analysis is considered. This difficulty will be resonated when the employed optimisation method has the stochastic nature such as evolutionary algorithms. A few researchers (Jiang *et al*., 2006; Lagaros *et al.*, 2006; Zou and Chan, 2005; Kocer and Arora, 2002) employed traditional and evolutionary search techniques to optimal design of structures subject to response spectrum and earthquake loadings. Salajegheh and Heidari (2005) incorporated wavelet neural network techniques in the optimisation process to predict structural time history responses. In the recent years, neural networks are broadly utilized in civil and structural engineering applications (Adeli and Jiang, 2006; Pu and Mesbahi, 2006; Zhang *et al*., 2006; Jung and Ghabousi *et al*., 2006; Fang *et al.*, 2005). In the case of neural networks application to predict structural time history responses it is probable that a single neural network model cannot provide sufficient performance generality. In order to attain proper performance generality an intelligent neural system (INS) is proposed by Gholizadeh and Salajegheh (2006). The INS is a combination of competitive (CNN) and radial basis function (RBF) neural networks.
In this study, the INS is used to predict the time history responses of the structures subject to earthquake. By implementing this approximation the exact dynamic analysis of the structure is not necessary in the optimisation process. Training of INS is implemented in two phases. In the first phase, the input and target spaces are classified as the similar data is located in some subspaces. The similarity criterion may be taken as natural periods of the structures. In fact, the structures with similar natural periods appear the same patterns for time history responses. The classification task is performed by a CNN. The CNN can learn to detect regularities and correlations in its input and adapt its future responses to that input accordingly. The neurons of CNN learn to recognize groups of similar input vectors. In the second phase,

a distinct RBF is trained for each subspace using its data. Therefore, INS consists of an intelligent classifying unit and a set of RBF networks. Illustrative examples demonstrate the computational advantages of INS. In all the examples, the input space includes the natural periods of the structures and target space consists of the corresponding time history responses of structures. In order to provide training data and to design the neural networks ANSYS (2004) and MATLAB (2006) are employed, respectively.
The evolutionary algorithm used in this study is virtual sub population (VSP) method (Salajegheh and Gholizadeh, 2005). In the present work, a 10-bar steel truss and a 25-bar space tower subjected to the El Centro (S-E 1940) and Naghan (1977 Iran) earthquakes, respectively are considered as the numerical examples. The numerical results reveal efficiency of the proposed method for finding the optimal design of structures subjected to the earthquakes, spending low computer effort.

Formulation of the Optimal Design Problem

In sizing optimisation problems the aim is usually to minimize the weight of the structure, under some constraints on stress and displacements. The design variables are considered as cross-sectional properties of the structural elements. Due to the practical demands the cross-sections are selected from the sections available in the manufacture catalogues. Therefore, the design variables are discrete.
A discrete structural optimisation problem can be formulated in the following form:

$$\begin{aligned} &\text{Minimize} && F(X) && \\ &\text{Subject to} && g_i(X) \le 0 && i = 1,2,\cdots,m \\ & && X_j \in R^d && j = 1,2,\cdots,n \end{aligned} \tag{1}$$

where $F(X)$ represents objective function $g(X)$ is the behavioural constraint, m and n are the number of constraints and design variables, respectively. A given set of discrete values is expressed by R^d and design variables X_j can take values only from this set.
In the optimal design of structures the constraints are the member stresses, nodal displacements, or frequencies. The stress constraints can be written as

$$|S| \le |S_a| \tag{2}$$

where S is the maximum stress in each element group for all loading cases, S_a is the allowable stress.
Similarly, the displacement constraints can be written as

$$|D| \le |D_a| \tag{3}$$

where D is the displacement at a certain node and D_a is the limiting value of the displacement at a certain node, or the maximum nodal displacement.

Structural Analysis for Earthquake Loading

The dynamic analysis considered here is the time history method. The procedure involves a step-by-step solution through a time domain to yield the dynamic response of a structure to a given earthquake. The equations of equilibrium for a finite element system subjected to the earthquake may be written in the usual form:

$$[\boldsymbol{M}]\{\ddot{U}(t)\} + [\boldsymbol{C}]\{\dot{U}(t)\} + [\boldsymbol{K}]\{U(t)\} = -[\boldsymbol{M}]\{I\}\ddot{U}_g(t) \tag{4}$$

where $[\boldsymbol{M}]$, $[\boldsymbol{C}]$ and $[\boldsymbol{K}]$ are the mass, damping and stiffness matrices; $\{\ddot{U}(t)\}$, $\{\dot{U}(t)\}$, $\{U(t)\}$ and $\{I\}$ are the accelerations, velocities, displacements and unit vector (with all elements equal to 1), respectively. The ground acceleration is expressed by $\ddot{U}_g(t)$.
For analysis of the structures subjected to earthquake loading, ANSYS computer program is used. The theory and solution procedures are based on the finite-element formulation of the displacement method with the nodal displacements as the unknown variables. It uses a step-by-step implicit numerical integration procedure based on Newmark's method to solve the resulting equations.

Dynamic Constraint Treatment

All of the stress and displacement constraints are time dependent. These constraints need to be imposed at each point in the desired time interval. The consideration of all the constraints requires an enormous amount of computational effort and, therefore, treatment with a vast number of time history responses is a

challenging problem for most numerical optimisation algorithms (Zou and Chan, 2005). Various numerical techniques exist for treating such time-dependent constraints (Arora, 1999). The basic idea of these methods is to eliminate somehow the time parameter from the optimisation problem. In other words, a time-dependent problem is transformed into a time-independent one. In the present study, the conventional method (Arora, 1999) is employed. The conventional method is quite simple and convenient to implement where the time interval is divided into n subintervals and the time-dependent constraints are imposed at each time grid point. Let
the ith time-dependent constraint (stress or displacement) be written as:

$$g_i(X,t) \leq 0, \quad 0 \leq t \leq T \tag{5}$$

where *T* is time interval over which the constraints need to be imposed.
Because the total time interval is divided into *n* subintervals, the constraint (5) is replaced by the constraints at the *n*+1 time grid points as:

$$g_i(X,t_j) \leq 0, \quad j = 0,1,\cdots,n \tag{6}$$

The constraint function $g_i(X,t)$ can be evaluated at each time grid point after the structure has been analyzed and stresses and displacements have been evaluated at each time point. If fewer grid points are used, the time-dependent constraints may be violated between the grid points. Use of a finer grid can capture these points.

Optimisation Method

There are two major steps in computer implementation of the optimal design process: the analysis step and the optimisation step. As previously mentioned, the time history analysis is performed using ANSYS. The optimisation method employed here is genetic algorithm (GA). GA has been quite popular and has been applied to a variety of engineering problems (Mathias *et al.*, 2006; Govindaraj and Ramasamy, 2005; Gazonas *et al.*, 2006; Hwang and He, 2006; Madeira *et al.*, 2005; Togan and Daloglu, 2006). The stochastic nature of GA makes the convergence of the method slow. Specially, employing GA to optimal design of structures with many degrees of freedom requires time consuming cycles. In this paper, to reduce the computational burden of the optimisation process the VSP method is employed. As shown in (Salajegheh and Gholizadeh, 2005) the computational work by VSP is less than that of the standard GA.
Despite utilizing of the VSP to search the optimum design, the computational burden of the process due to implementing the time history analysis is still high. Therefore, using neural networks to reduce the computer effort can be very effective.

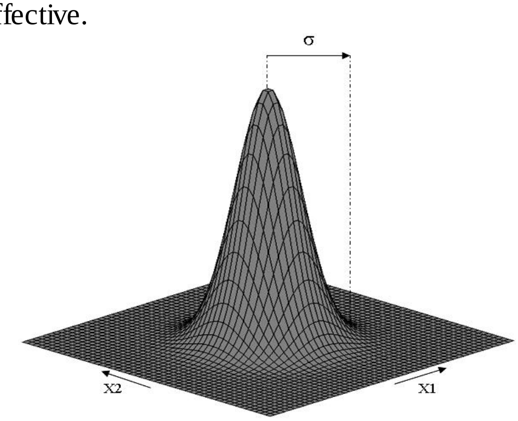


Figure 1: Receptive field of the RBF neuron with two inputs

Neural Networks

Neural networks have recently emerged as a powerful tool that may be widely used to replace time consuming procedures in many scientific and engineering applications. The interest shown to neural networks is mainly due to their ability to process external data and information based on past experiences. As in the present study the combination of CNN and RBF is employed to predict the time history response of structures, the two neural network models are focused in the next sections.

Radial Basis Function Neural Network (RBF)

RBF is widely used in the field of structural engineering due to their fast training, generality and simplicity. The hidden layer consists of RBF neurons with Gaussian activation functions. The outputs of RBF neurons have significant responses to the inputs only over a range of values of inputs called the receptive field. Receptive field of the simplified single RBF neuron with two inputs is shown in Figure 1. During the training, the σ value of RBF neurons is such determined as the neurons could properly cover the input space.

The numerical results of many engineering applications (Rafiq *et al.*, 2001; Zhang and Zhang, 2004; Deng, 2006; Roy and Ganguli, 2006) indicate that RBF networks are very good tools for interpolating and their training is very fast.

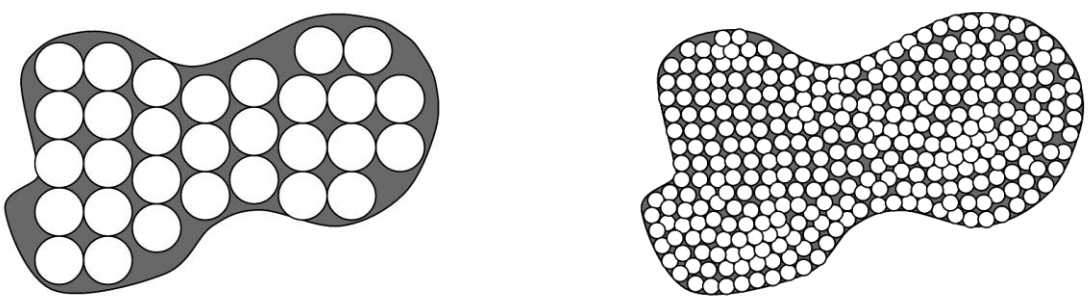
Competitive Neural Network (CNN)

Some applications need to group data that may, or may not be, clearly definable.

CNN can learn to detect regularities and correlations in their input and adapt their future responses to that input accordingly. The neurons of CNN learn to recognize groups of similar input vectors. A CNN automatically learns to classify input vectors. If two input vectors are very similar, the CNN probably will put them in the same class. A key difference between this network and many other networks is that the CNN learns without supervision.

Intelligent Neural System (INS)

In a single RBF all hidden layer neurons have equal σ. In other words, by employing a single RBF the input space is covered by the RBF neurons which have equal radius of receptive field. A simple two dimensional schematic example is shown in Fig. 2a. As shown in this Figure, some parts of the input space are not properly covered by the RBF neurons. Therefore, performance generality of the RBF network over these parts of the input space is low. In order to improve performance generality of the RBF network, more RBF neurons with smaller σ may be assigned to the hidden layer. In this case, as shown in Figure 2b, the input space is smoothly covered by the RBF neurons.



(a) **(b)**

Figure 2: (a) Input space covering by RBF neurons of a single network with large σ
(b) Input space covering by RBF neurons of a single network with small σ

It should be noted that, due to employing many RBF neurons the computational burden of the network training is high.

In order to attain the appropriate performance generality spending low computer effort an intelligent neural system (INS) is employed. Details of INS training are summarized as follows:

In the beginning, the generated input-target training pairs are classified based on a specific criterion. In other words, the input and target spaces are divided into some subspaces so that the data located in each subspace have the same properties. Classification of input space is implemented by using a CNN. Now it is possible to train an RBF network for each subspace using its training data. By involving the mentioned strategy, the single RBF network trained to cover all the input space is substituted by a set of RBF networks as each of them is trained to cover one specific part of the classified input space. A simple scheme of INS is shown in Figure 3. Further information about INS can be found in (Fang *et al.*, 2005).

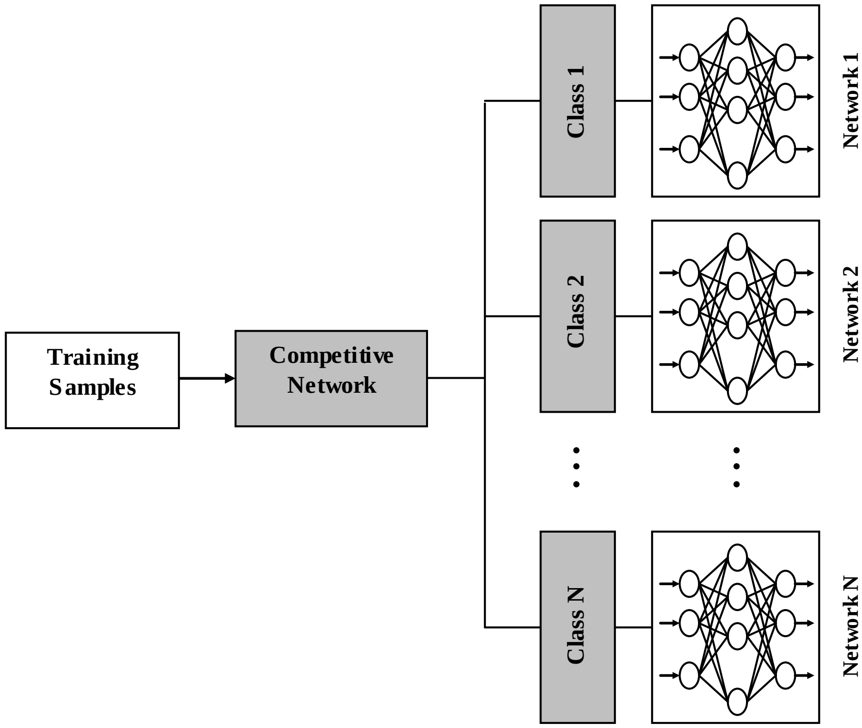


Figure 3: Scheme of the intelligent neural system (INS)

Error Estimation

In order to determine the error between exact and approximate results, the relative root mean squared error (*rrmse*) is calculated. A value closer to 0 indicates a better accuracy.

$$rmse = \sqrt{\frac{\frac{1}{d\text{-}1}\sum_{i=1}^{d}(E_i - A_i)^2}{\frac{1}{d}\sum_{i=1}^{d}(E_i)^2}} \tag{7}$$

where, E_i and A_i are the ith component of the exact and approximate vectors, respectively. The vectors dimension is expressed by d.

To measure how successful fitting is achieved between exact and approximate time history responses, the rsquare statistic measurement is employed. A value closer to 1 indicates a better fit.

$$rsquare = 1 - \frac{\sum_{i=1}^{d}(E_i - A_i)^2}{\sum_{i=1}^{d}(E_i - \overline{E})^2} \tag{8}$$

where, $\overline{E}$ is the mean of exact vectors component.

Approximation of time History Responses By INS

The input space consists of some higher natural periods of the selected structures and the corresponding time history responses of nodal displacements and element internal stresses against earthquake are considered as the target space components. As the first step in training of the INS, a CNN is trained to classify the input space based on the natural periods. Then a distinct RBF network is trained to approximate the time history responses of structures located in each subspaces using its assigned data. Figure 4 gives an overview of the training process of INS.

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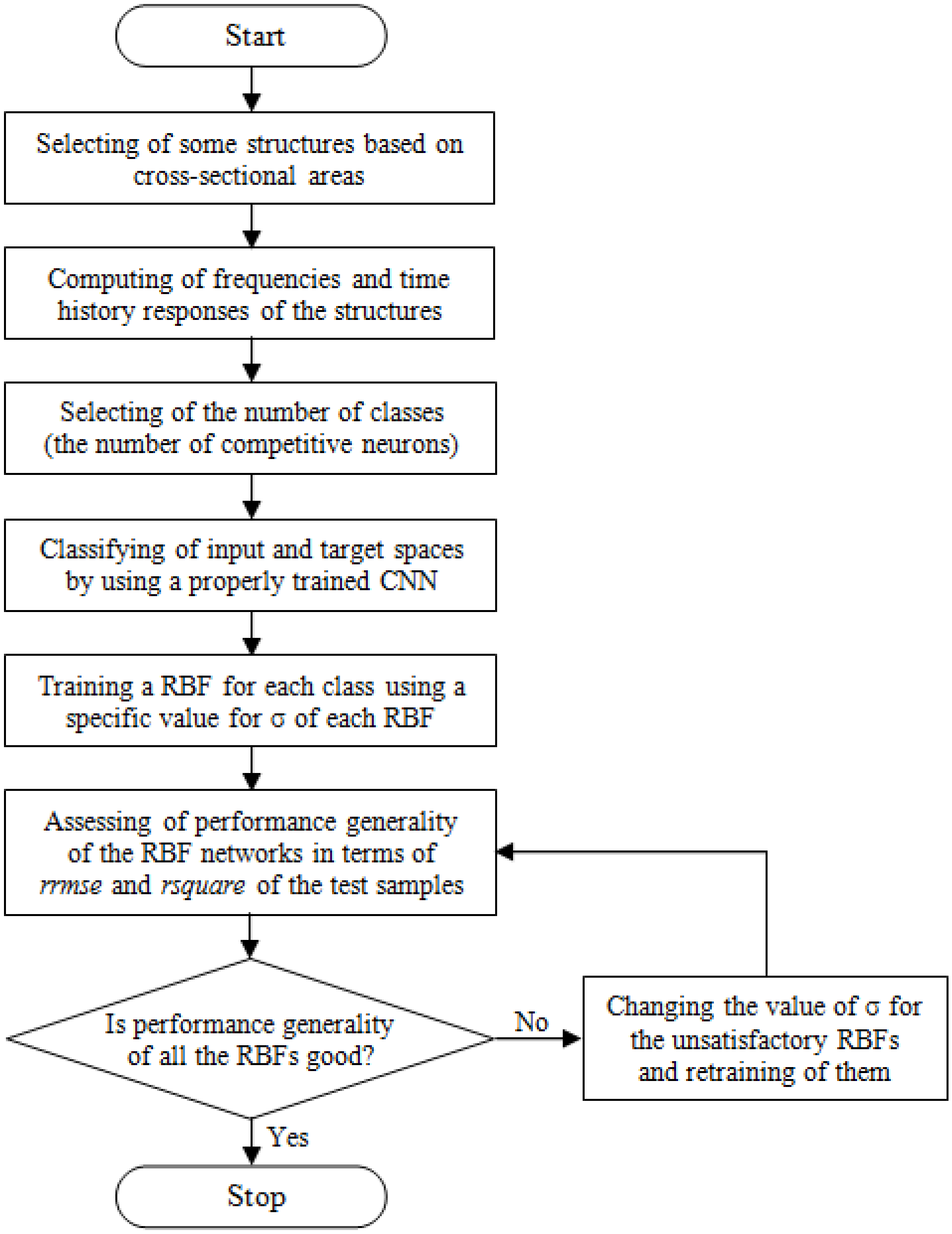

Figure 4: Flowchart of INS training

Main Steps of Optimisation Process By VSP Using INS

The fundamental steps in the optimisation process by VSP using INS for earthquake loading are as follows:

(a) Selecting some parent vectors from the design variables space.
(b) Evaluating the time history responses of the structure employing trained INS.
(c) Evaluating the objective function.
(d) Checking the constraints at grid points for feasibility of parent vectors.
(e) Generating offspring vectors using selection, crossover, mutation and reproduction operators.
(f) Predicting the structural time history responses for the offspring population using trained INS.
(g) Evaluating the objective function.

(h) Checking the constraints at grid points; if satisfied continue, else change the vector and go to step (f).
(i) Checking convergence; if satisfied stop, else go to step (e).
(j) Selecting the majority parent vectors from the previous solution and some random design variables as a VSP.
(k) Repeating steps (e) to (k) until the proper solution is met.

As the size of populations in VSP is small the method is rapidly converged. It can be observed that during the optimisation, the dynamic analysis of the structures is not needed. In fact, the necessary responses are found by the trained INS.

Numerical Examples

Two illustrative examples are optimised for minimum weight subject to the El Centro (S-E 1940) and Naghan (1977 Iran) earthquakes, respectively. The earthquakes are shown in Figure 5. The time of optimisation is computed in clock time by a personal Pentium IV 3000MHz. The earthquake records are applied in x direction. Young's modulus is 2.1×10^{11} N/m^2, mass density is 7850 kg/m^3. Cross sections of the members are selected from the pipe, with the ratio of radius to thickness less than 50, sections available in European profile list.

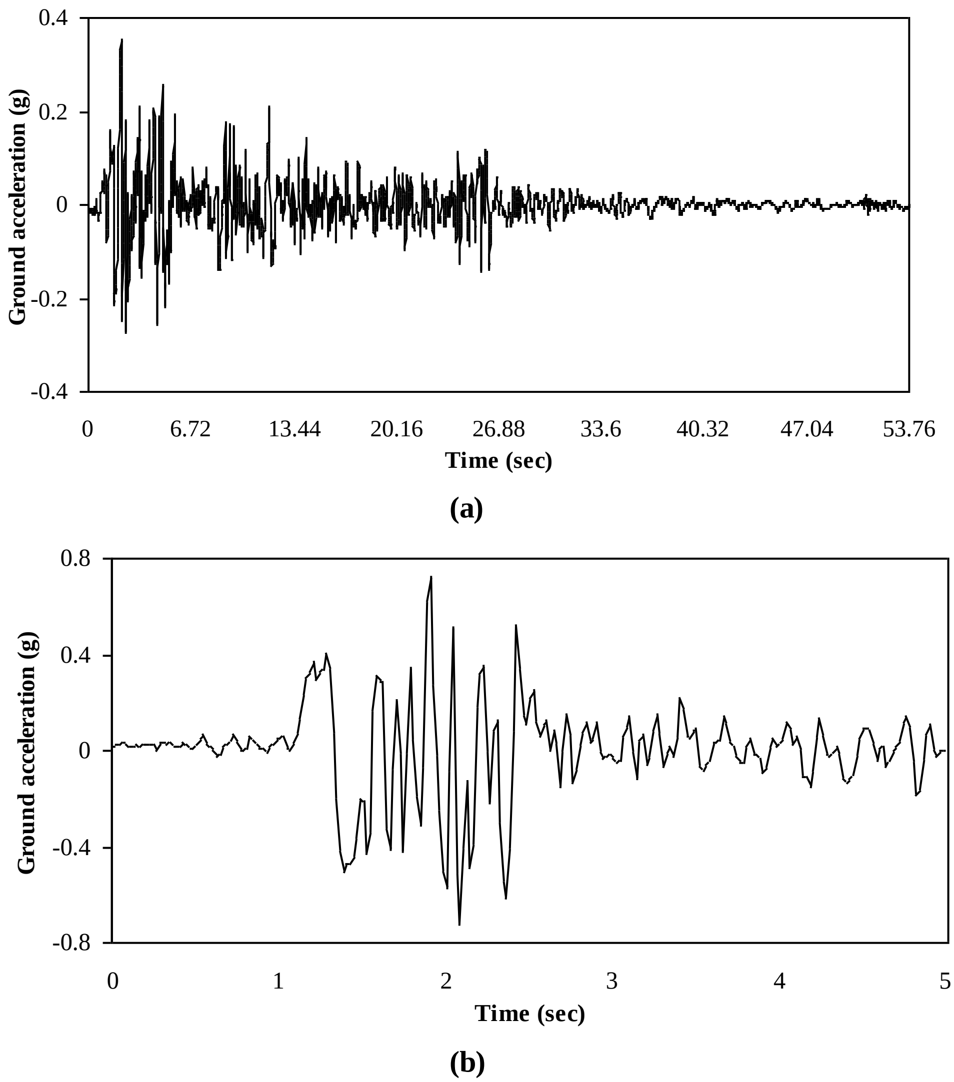

Figure 5: (a) The El Centro (S-E 1940) earthquake records
(b) The Naghan (1977 Iran) earthquake record

The optimisation is carried out by the following methods:
(a) GA using exact analysis.
(b) GA using approximate analysis by a single RBF network.
(c) GA using approximate analysis by INS.
(d) VSP using exact analysis.
(e) VSP using approximate analysis by a single RBF network.
(f) VSP using approximate analysis by INS.
The specifications of GA and VSP are shown in Tables 1 and 2, respectively.

Table 1: Specifications of GA method

Population size	50
Crossover method	One, two and three points crossover
Crossover rate	0.9
Mutation rate	0.001
Maximum generation	150

Table 2: Specifications of VSP method

Population size	30
Crossover method	One, two and three points crossover
Crossover rate	0.9
Mutation rate	0.001
Maximum generation	30

Example 1: 10 - Bar Steel Truss

The 10-bar steel truss is shown in Fig. 6. The truss is subjected to the El Centro earthquake records. Span in x direction and height of the truss is 3 m and 6 m, respectively. The mass of 5000 kg is lumped at each free node. Due to simplicity and practical demands, the truss members are divided into 6 groups based on cross-sections, shown in Table 3.

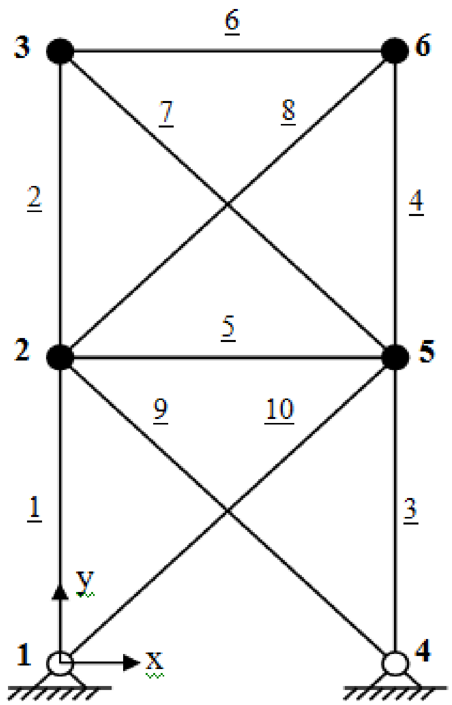

Figure 6: 10-bar steel truss

Table 3: Groups of the 10-bar steel truss members

Group	**1**	**2**	**3**	**4**	**5**	**6**
Members	1	2	3	4	7 8	9 10

In order to practical demands, 8 types of cross sections are considered for the truss elements which are displayed in Table 4.

Table 4: Available pipe profiles

No.	**Area (10^{-4} m^2)**
1	12.5
2	13.7
3	17.2
4	25.1
5	27.2
6	31.1
7	50.0
8	52.7

Because of the zero internal stresses of elements 5 and 6 under the earthquake excitation, a minimum cross sectional area of 0.51×10^{-4} m^2 is assigned to them.

As a single constraint, the horizontal displacement at joint 6 is considered to be less than 0.05 m in the earthquake duration.

Constraints are checked at 2688 time grid point whit the time interval of 0.02 s. To train and to test the parallel RBF networks of INS, the total number of 244 structures is generated.

From which 204 samples are used for training and 40 ones are employed for testing the networks performance generality. The spending time in this stage is 152 minutes. In this example INS contains five parallel RBF networks with 30, 42, 39, 40 and 53 RBF neurons. The results of performance generality assessing of the RBF networks are displayed in Table 5.

Table 5: Average of *rrmse* and *rsquare* of the five data classes

Class	**1**	**2**	**3**	**4**	**5**
Average of *rrmse*	0.0422	0.0571	0.0659	0.0473	0.0608
Average of *rsquare*	0.9902	0.9892	0.9806	0.9893	0.9867

As shown in Table 5 all the RBF networks have good performance generality. Results of optimisation of the 10-bar truss are shown in Table 6.

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2014 Vol. 4 (S4), pp. 3295-3308/Hosseinpoor and Mikaili
Research Article

Table 6: Optimum design of the 10-bar steel truss by various methods

No.	**Optimum Areas (10^{-4} m^2)**					
	GA			**VSP**		
	Exact	**RBF**	**INS**	**Exact**	**RBF**	**INS**
1	52.70	50.00	31.10	50.00	50.00	31.10
2	13.70	12.50	13.70	12.50	12.50	12.50
3	17.20	27.20	52.70	27.20	50.00	27.20
4	27.20	12.50	12.50	12.50	12.50	12.50
5	0.51	0.51	0.51	0.51	0.51	0.51
6	0.51	0.51	0.51	0.51	0.51	0.51
7	12.50	12.50	12.50	13.70	13.70	17.20
8	12.50	12.50	12.50	13.70	13.70	17.20
9	27.20	31.10	27.20	25.10	17.20	25.10
10	27.20	31.10	27.20	25.10	17.20	25.10
Weight (N)	5277.9	5335.2	5259.1	5015.5	5026.2	4803.5
Generations	92	64	78	105	93	88
Analyses	4600	3200	3900	3150	2790	2640
Time (min)	1075	0.5	0.7	735	1.1	1.0
rrmse	-	0.1427	0.0714	-	0.1263	0.0629
rsquare	-	0.8954	0.9673	-	0.9125	0.9871

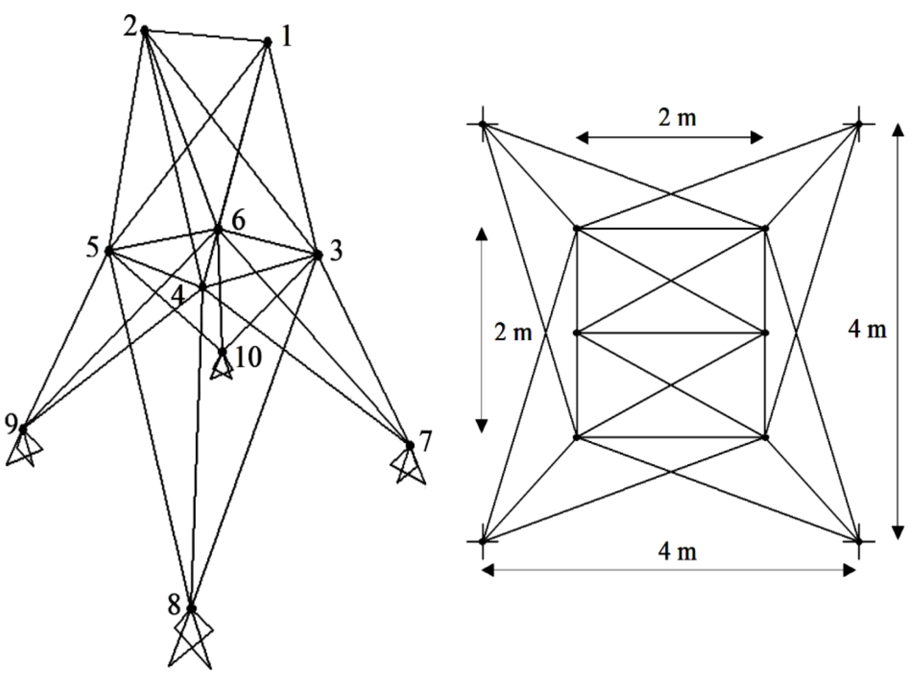

Figure 7: 25-bar space tower

As displayed in Table 6, the optimum designs obtained by VSP are better than that of obtained by GA in terms of structural weight, computational work and approximation errors. Also, it can be observed that by employing neural networks to predict the time history responses the overall time of optimisation, including training time, is 0.2 times of exact optimisation. In the case of both the GA and VSP, the solution obtained by using INS is better than that of obtained by employing RBF in terms of *rrmse* and *rsquare*. Finally, the optimum design obtained by VSP using INS is the best solution in comparison with the other ones.

Example 2: 25 - Bar Steel Space Tower

The 25-bar steel space tower with the height of 5 m is shown in Fig. 7. The positions of the tower elements are given in Table 7. The tower is subjected to the Naghan earthquake. The mass of 2000 kg is lumped at each free node. In order to practical demands, 8 types of cross sections are considered for the elements which are displayed in Table 8. In all the elements, allowable stress is 1.1×10^8 N/m^2. The horizontal displacement of joint 1 is limited to 0.007 m. constraints are checked at 250 grid points with the time interval of 0.02 s.

Table 7: Position of the 25-bar space truss elements

Element No.	1	2	3	4	5	6	7	8	9	10	11	12	13
Start joint	1	1	1	1	1	2	2	2	2	3	4	5	3
End joint	2	3	4	5	6	3	4	5	6	4	5	6	6
Element No.	14	15	16	17	18	19	20	21	22	23	24	25	
Start joint	3	3	3	4	4	4	5	5	5	6	6	6	
End joint	7	8	10	7	8	9	8	9	10	7	10	9	

Table 8: Available pipe profiles

No.	**Area (10^{-4} m^2)**
1	15.2
2	26.7
3	37.1
4	50.0
5	57.7
6	61.2
7	73.7
8	82.6

Because of the zero internal stresses of elements 1, 10 and 12 under the earthquake excitation, a minimum cross sectional area of 0.51×10^{-4} m^2 is assigned to them. Due to the practical demands the tower elements are grouped into 7 different types as shown in Table 9.

Table 9: Available pipe profiles

Group	**Elements**
1	11; 13
2	2; 4; 6; 8
3	3; 5; 7; 9
4	15; 17; 22; 25
5	16; 19; 20; 23
6	14; 18; 21; 24
7	1; 10; 12

To train and to test the parallel RBF networks of INS, a total number of 449 structures are generated. From which 360 and 89 samples are used for training and testing the performance generality of the networks, respectively. The spending time in this stage is 265 minutes. In this example, the INS includes five RBF networks with 71, 64, 75, 81 and 69 RBF neurons. The results of performance generality assessing of the RBF networks are displayed in Table 10.

Table 10: Average of *rrmse* and *rsquare* of the five data classes

Class	1	2	3	4	5
Average of *rrmse*	0.0961	0.1187	0.0906	0.1044	0.1208
Average of *rsquare*	0.9560	0.9385	0.9411	0.9436	0.9301

The results displayed in Table 5 indicate that all the RBF networks have good performance generality. Results of optimisation of the 25-bar space tower by standard GA and VSP methods using exact and approximate time history responses are shown in Table 11. As observed in this table, the optimum designs obtained by GA and VSP employing neural networks require much less time comparing with those of obtained by exact analysis.

Table 11: Optimum design of the 25-bar space tower by various methods

Element No.	**Optimum areas (10^{-4} m^2)**					
	GA			**VSP**		
	Exact	**RBF**	**INS**	**Exact**	**RBF**	**INS**
1	0.51	0.51	0.51	0.51	0.51	0.51
2	37.10	50.00	37.10	37.10	50.00	50.00
3	61.20	57.70	37.10	50.00	37.10	37.10
4	37.10	50.00	37.10	37.10	50.00	50.00
5	61.20	57.70	37.10	50.00	37.10	37.10
6	37.10	50.00	37.10	37.10	50.00	50.00
7	61.20	57.70	37.10	50.00	37.10	37.10
8	37.10	50.00	37.10	37.10	50.00	50.00
9	61.20	57.70	37.10	50.00	37.10	37.10
10	0.51	0.51	0.51	0.51	0.51	0.51
11	15.20	15.20	26.70	26.70	15.20	26.70
12	0.51	0.51	0.51	0.51	0.51	0.51
13	15.20	15.20	26.70	26.70	15.20	26.70
14	61.20	61.20	57.70	61.20	57.70	57.70
15	50.00	50.00	50.00	50.00	37.10	37.10
16	26.70	37.10	26.70	26.70	37.10	26.70
17	50.00	50.00	50.00	50.00	37.10	37.10
18	61.20	61.20	57.70	61.20	57.70	57.70
19	26.70	37.10	26.70	26.70	37.10	26.70
20	26.70	37.10	26.70	26.70	37.10	26.70
21	61.20	61.20	57.70	61.20	57.70	57.70
22	50.00	50.00	50.00	50.00	37.10	37.10
23	26.70	37.10	26.70	26.70	37.10	26.70
24	61.20	61.20	57.70	61.20	57.70	57.70
25	50.00	50.00	50.00	50.00	37.10	37.10
Weight (N)	25062.0	27270.0	22819.0	24359.0	23366.0	22411.0
Generations	74	50	58	63	70	62
Analyses	3700	2500	2900	1890	2100	1860
Time (min)	2158	1.5	1.8	1103	1.4	1.2
Avg. *rrmse*	-	0.1903	0.1364	-	0.1736	0.1121
Avg. *rsquare*	-	0.8444	0.9016	-	0.8691	0.9342

The results displayed in Table 11 indicate that the VSP converge to better solutions in comparison with GA. Incorporating neural networks in the optimisation process reduce the time of optimisation, significantly. In this case the time of optimisation including training time, is 0.2 times of exact optimisation. Also, it is obvious that performance generality of INS is better than that of the single RBF. Finally, the optimum design obtained by VSP using INS is the best solution in comparison with the other ones.

Conclusion

In this study, an efficient optimisation procedure has been developed for the optimal design of structures subject to earthquake using discrete design variables. In order to achieve this, a combination of the evolutionary algorithm and neural networks has been utilized. The employed evolutionary algorithm is virtual sub population (VSP) method. The VSP method has eliminated the shortcomings of the standard GA such as trapping into local optima and much computational effort in the phase of computer implementation. Moreover, performing the structural optimisation using the exact time history analysis imposes disproportionate computational burden to the procedure. That is, in each design point of the desired earthquake the structure should be analyzed to evaluate the necessary responses. To reduce the computer effort an intelligent neural system (INS) is employed. In the INS, a specific combination of competitive and radial basis function neural networks is employed to approximate the structural time history responses, more accurately. In the present paper, RBF neural network and INS is employed to approximate the necessary time history responses of structures. The numerical results of testing the networks performance generality, demonstrate the computational advantages of INS comparing with that of the single RBF network. A simple method is employed to treat with dynamic constraints. In the method the time interval is divided into some subintervals and the constraints are imposed at each time grid points. The numerical results of optimisation show that in the proposed methods, the time of optimisation including training time is reduced to about 0.2 of the time required for exact optimisation; however, the errors due to approximations is small. Finally, it is demonstrated that the best solution has been attained by VSP method using INS.

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