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Neural network-based generation of artificial spatially variable earthquakes ground motions

Hossein Ghaffarzadeh*, Mohammad Mahdi Izadi and Nima Talebian

Department of Structural Engineering, University of Tabriz, Tabriz, Iran

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Abstract. In this paper, learning capabilities of two types of Arterial Neural Networks, namely hierarchical neural networks and Generalized Regression Neural Network were used in a two-stage approach to develop a method for generating spatial varying accelerograms from acceleration response spectra and a distance parameter in which generated accelerogram is desired. Data collected from closely spaced arrays of seismographs in SMART-1 array were used to train neural networks. The generated accelerograms from the proposed method can be used for multiple support excitations analysis of structures that their supports undergo different motions during an earthquake.

Keywords: generation of artificial earthquake; neural networks; spatially varying earthquakes; response spectrum; SMART-1 array

1. Introduction

The appropriate ground motions are required to assess the seismic response of a structure. It is usual to assume that the ground motion which is experienced by all supports of structure is considered the same during the seismic response analysis. This assumption is not justifiable for extended structures or structures placed on several foundations such as dams and bridges, since earthquake waves passing through the ground can vary considerably within small distances. This is due to the change in amplitude and frequency of earthquake waves away from their source that leads to non-uniform support movements which can cause significant effect on the seismic response. Therefore, an important aspect of earthquake waves is the spatial variability of the seismic motion.

A great deal of research has been carried out in the field of spatial variation of ground motion. (Harichandran *et al.* 1986, Zerva *et al.* 2002). The main studies have been focused on defining an appropriate ground motion model which considers spatially varying effects and key parameters in modeling and simulation techniques for the generation of artificial spatially variable seismic ground motions to obtain optimized model. Harichandran and Vanmark (1986) carried out a preliminary study on the recurrence of earthquakes in SMART-1 array. They considered the ground motion during a specific earthquake event as a space-time random field. Following a description of spectral estimators and examination of accelerograms to determine the

*Corresponding author, Professor, E-mail: ghaffar@tabrizu.ac.ir

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frequency-dependent spatial correlation of earthquake ground motions, they obtained a spectral equation to be used in spectral analysis of multi-support excitation cases. As a practical example, Harichandran and Wang (1988) investigated the effects of a wave passing through the supports of a simply supported beam. They used a semi-experimental random model and conducted probabilistic analyses.

Simulation techniques in random process generation have enabled researchers to generate seismic events. The theory of Gaussian random process was utilized by Shinozuka (1972) to generate simulated random process. He based his simulations on the spectral representation method in which simulations of zero mean, Gaussian random process, are obtained by adding up a large number of weighted trigonometric functions. However, the computational time required for simulation was too long. Yang (1972) studied efficient and practical methods of simulating random processes introducing the Fast Fourier Transform (FFT) technique. Using of FFT technique reduced computational time for simulation. Afterward, Shinozuka (1987) utilized Yang's FFT technique to further his work on simulation of multivariate and multi-dimensional random fields. However, the simulations generated by FFT are not ergodic in the mean and the value of the field spectrum at spectral representation method for the generation of simulated random processes by means of the Fast Fourier Transform algorithm. Shinozuka overcame that problem by combining Shinozuka's original approach of using trigonometric series with FFT. The new simulations are ergodic in the mean without any restricting assumptions at the origin of the spectra and leads to a faster convergence rate. Other researches by Zenardo *et al.* (2002), Liao and Li (2002), Dumanogluid and solyluk (2003), Bilici *et al.* (2009) have also studied the spatial variation based on stochastic methods.

Der Kuireghian and Neuenhofer (1992) presented a new spectral approach to analyze MDOF systems subjected to different support excitations. In their method, variations of the ground motion due to wave passage, loss of coherency with distance and local soil conditions were considered. Several other response spectrum methods that take into consideration the effect of correlated ground motion have been developed (Yamamura and Tanaka (1990), Berrah and Kausel (1992)). Kahan *et al.* (1996) extended the spectral analysis carried out by Der Kiureghian and Neuenhofer (1992) and studied the sensitivity of bridges to spatial variations of seismic ground motions and the effects of support distance on the response of bridges. Deodatis (1996a) proposed a method to generate nonstationary and response spectral compatible ground motions based on spectral representation methods. Liang *et al.* (2007) extended the spectral representation method to simulate nonstationary ground motions based on evolutionary spectral theory. Recently, Yongxin *et al.* (2011) have presented a new model to simulate spatially correlated earthquake ground motions.

The response of large structures to asynchronous support excitations have been investigated by several researchers. Harichandran and Wang (1990) examined the effect of the spatial variation of ground motion on the response of a two-span beam and concluded that the effect of the spatial variation of ground motion can be significant. The seismic behavior of large-size structures subjected to multiple-support excitation was studied by means of a random vibration approach by Perotti (1992). Nazmy and Abdel-ghaffar (1992) studied the effects of spatial variability of ground motion on the structural response of cable-stayed bridges. They applied differential ground motion records to the different piers of bridge. It revealed that response quantities may increase substantially due to the non-uniform input ground motion. In addition, seismic response of large structures such as bridge and dam subjected to asynchronous and non-uniform support excitation was investigated by Maheri and Ghaffarzadeh (1992). Their results showed that asynchrony and non-uniformity in ground motion may, in some cases, amplify the seismic response; therefore, it should be considered in the dynamic analysis. A random vibration methodology was formulated for the seismic analysis of multi-supported structures subjected to spatially varying ground motions by Zhang *et al.* (2008). They considered the wave passage, incoherence and site–response effects and investigated random seismic responses of a realistic long-span bridge. They concluded that all those effects have significant influence on the seismic response. Park *et al.* (2009) developed a new procedure for simulating the tunnel response under spatially varying ground motion. They showed that the spatially variable ground motion causes longitudinal bending of the tunnel and can induce substantial axial stress on the tunnel lining. Chopra and Wang (2010) examined the response of two arch dams to spatially varying ground motions based on linear analysis procedure and demonstrated that spatial variation in ground motions can have profound effect on the response of the dam. They showed that this effect could differ from one earthquake to the next, based on the epicenter location and the focal depth of the earthquake relative to the dam site.

Artificial neural network models have been widely applied to various relevant engineering areas. Several researchers have used ANN in the field of earthquake engineering. Ghaboussi and Lin (1998) proposed a new method of generating artificial earthquake accelerograms from response spectra using neural networks. Furthermore, Lee and Han (2002) developed efficient neural-network-based models for the generation of artificial earthquake and response spectra. Additionally, several neural-network-based models have been proposed for replacing traditional processes to predict earthquake parameters of an area. Lin and Ghaboussi (2002) improved their previous method by presenting a new stochastic neural network that was capable of generating multiple earthquake accelerograms from a single-response spectrum. A simulation technique for the generation of artificial spatially variable seismic ground motions was presented using neural networks by Ghaffarzadeh and Izadi (2008). Ghodrati and Bagheri (2008) investigated the use of wavelet multi resolution analysis and neural network for simulation of artificial earthquake accelerograms from target response. Moreover, Asadi *et al.* (2011) developed a numerical approach based on artificial neural network and wavelet packet transform method for the decomposition of artificial earthquake records consistent with any arbitrarily specified target response spectra requirements. They modeled ground motion as a non-stationary process using wavelet packet.

According to powerful ability of the artificial neural networks to model engineering cases, an ANN based method was proposed in this paper to generate artificial spatially varying earthquake accelerograms. Pseudo acceleration response spectra of earthquake events in SMART-1 array were used to simulate accelerograms. The validity of the presented neural network was evaluated by Fourier amplitude spectra and coherency spectra. The generated acceloragrams can be utilized in dynamic analysis of extended structures such as bridges and dams.

2. Dense strong motion arrays

To investigate the spatial variability phenomenon in seismic ground motions, a large number of strong motion records from dense accelerometer arrays are required. Nowadays, there are more than 59 dense strong motion arrays in the highly seismic regions of the world. One of the most important arrays, SMART-1 (Strong Motion Array in Taiwan), became operational in September 1980 in a highly seismic region in Loting of Taiwan. Data collected from closely spaced arrays of seismographs such as SMART-1 array has provided an excellent opportunity for researchers and

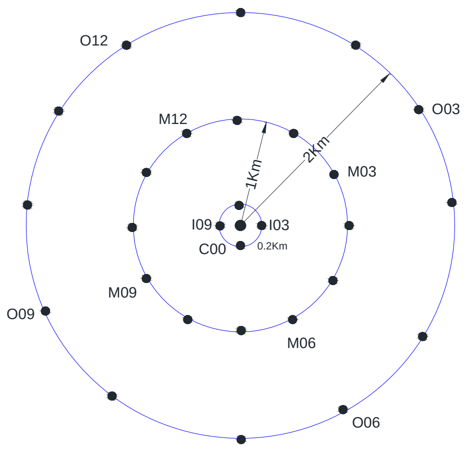

Fig. 1 The layout of stations on SMART-1 array

Table 1 Earthquake accelerograms used in training and testing neural networks

Event. No.	Origin time	Epicenter		Depth	Mag.	PGA (gals)	PGA (gals)	t^*	Accelerogram	
	(UT)	Lat.(N)	Lon.(E)	(km)	(M_L)	EW	NS		Direction	
5	1981-01-29	24.2575	121.53.78	11.1	5.9	158.24	244.3	36	EW	NS
20	1982-12-17	24.2284	122.52.44	29.2	6	62.82	86.12	31	EW	NS
24	1983-06-24	23.5889	122.3680	25	6.6	51.06	64.9	35	EW	NS
25	1983-09-21	23.5629	122.1900	18	6.5	35.57	38.45	36	EW	NS
33	1985-06-12	24.3438	122.1168	3.3	6.1	148.63	97.16	36	EW	NS
39	1986-01-16	24.4577	121.5767	10.2	6.1	375.34	307.71	37	EW	NS
40	1986-05-20	24.0490	121.3549	15.8	6.2	210.47	251.07	39	EW	NS
43	1986-07-30	24.3773	121.4765	1.5	5.8	230.94	283.4	36	EW	NS
45	1986-11-14	23.5951	121.4999	15	6.5	168.25	237.73	27	EW	NS

*Number of stations in each event

have enabled them to study spatial variability phenomenon (Zerva 2002, Kawakami *et al*. 1999, Shama 2007). The SMART-1 array consisted of 37 force-balanced triaxial accelerometers arranged on three concentric circles (the inner denoted by *I*, the middle by *M*, and the outer by *O*) with radii of 200 m, 1 km and 2 km, respectively. Twelve equi-spaced stations, numbered 1-12, were located on each ring, and station C00 was located at the center of the array (Fig. 1).

Data collected from 1980 to 1991 in the SMART-1 array, consist of 60 earthquakes, with different magnitude, depth and epicenter, which include 987 accelerograms totally. The earthquake accelerograms of SMART-1 array related to both EW and NS directions were used for training and testing of neural networks. In this study, they include events number 5, 20, 24, 25, 33, 39, 40, 43, 45 that are listed in Table 1.

3. Artificial neural networks

An artificial neural network is a computational model that is loosely based on the neuron cell structure of the biological nervous system. The biological brain consists of billions of highly interconnected neurons forming a neural network. Human information processing depends on this connection system of nervous cells. Based on this advantage of information processing, neural networks can easily exploit the massively parallel local processing and distributed storage properties in the brain. ANN attempts to simulate the architecture and internal operational features of the human brain and nervous system. The interest in neural networks comes from the networks' ability to mimic human brain as well as its ability to learn and respond. As a result, neural networks have been used in a large number of applications and have been proven to be effective in performing complex functions in a variety of fields. In addition to their pattern matching capability makes them very suitable to be employed as a tool for different purposes. The origin of neural networks dates back to 1940s which McCulloch, Pitts and Hebb (Haykin 1994) studied networks of simple computing devices which could model neurological activity and learning process within these networks, respectively. ANN architectures are formed by input layer, output layer and a number of hidden layers in which neurons are connected to each other with modifiable weighted interconnections. Information propagates through connection and the strength of the transmitted information depends on the numerical weights which are assigned to the connections. Each neuron receives information along the incoming connection and performs some simple operations, such as calculating weighted sum of the incoming information, assessing an activation function and sending information along its outgoing connections. The number of neurons in each layer may vary depending on the problem. The knowledge learned by a neural network is stored in its connection weights. Learning takes place, when a learning method is used to modify the connection weights in a way that a given input pattern produces a given output pattern. The patterns used in the training process are called the training set. During the training, a neural network acquires the knowledge from the input-output pairs in the training set, and stores that knowledge in its connection weights.

In this study, the Generalized Regression Neural Network (GRNN) along with hierarchical neural network that is a kind of back propagation neural networks was adopted. Main characteristics of these two neural networks make them to be applied as appropriate networks. According to complexity of accelerograms, neural networks with radial basic functions result in better simulations rather than back propagation neural networks. GRNN is a three layer network with radial basic function in which the impressibility of outputs from inputs is markedly more than other networks. Hierarchical neural networks have capability of memorizing that promotes the learning process and generalization of network.

4. The proposed method for generating spatial earthquake

In this research, ANN is used to produce artificial earthquake accelerograms which vary spatially through supports of large structures such as bridges and dams. The generated accelerograms can be used for the analysis of structures which will experience multiple support excitations, probably. The proposed method is based on producing earthquake accelerograms from a specified response spectrum. An ANN is constructed using accelerorams as output data set and corresponding response spectra and distance parameter as input information. Such neural network will be trained with discrete response spectra and earthquakes' accelegrams selected from SMART-1 array (Table 1). Earthquake response spectra have been discretized with a large number of discrete values to keep reasonable accuracy. On the other hand, the output networks will be large and complicated to train since there are large amount of complex discrete data. To avoid this problem, another lossless preprocessing neural network is used to diminish neural network dimension. Actually, two neural networks were constructed based on two strategies. Using main records as input data was the first strategy, and the second was compressing of data in order to decrease network dimension. Direct use of accelerograms leads to large dimension of the main network and its ability of simulation reduces. There are different methods of lossless data compression such as Fast Fourier Transform technique (FFT), principle component analysis, vector quantization, self-organization networks and hierarchical neural networks which the latter has been used for data compression of accelerograms in current research.

4.1 Artificial neural network for generation of accelerograms with lossless data compression

4.1.1 Hierarchical neural networks

The hierarchical neural network is a multilayer neural network composed of a large input layer feeding into a small hidden layer, which then feeds into a large output layer (Mavrovouniotis *et al.* 1992). Due to replicating of input vector in the output layer of the neural network, it can refer to replicator neural network. The advantage of a hierarchical neural network structure is that the functionally specialized neurons of each layer process only a limited amount of information from the previous layer. The total situation is then pieced together as one ascends from one hierarchical layer to the next. These neural networks are trained to replicate given input vector into their output layer. Actually, they are able to form a compressed representation for the input data and provide a hierarchical solution to overcome the complicated approximation function. This approach can be very useful in the case of complicated approximation function involving with a large training data set. Moreover, they can minimize high-dimensional input data into smaller and manageable ones. The first serious studies of hierarchical neural networks were carried out by Kohenon (1976). Later Ackley (1985) studied these networks in field of encoder problems and Cottrell (1987) developed hierarchical version of multilayer perceptron neural network. Then, Hetch-Nielsen (1995, 1996) studied the operation of these networks theoretically and found that producing optimal source codes takes place in the middle hidden layer. They showed that a mapping from the n-dimensional input vector space to a unit cube in the k-dimensional vector space of middle hidden layer, is performed by hierarchical neural network, where k is much smaller than n. Many version of hierarchical neural network have been introduced and applied in various fields like image processing and visualization, computer sciences, electrical engineering, etc (Srivastavaa *et al.* 1999, Lai *et al.* 2000). Use of hierarchical neural network for data compression of accelerograms was first studied by Ghaboussi and Lin (1998). As noted earlier, they proposed a new method for generating artificial earthquake accelerograms from response spectra.

A suitable neural net architecture to solve the data compression problem is shown in Fig. 2. As it is clear in the Figure, a replicator neural network can be thought of as being composed of two neural networks. Data compression happens in the first half including input layer up to middle hidden layer and data decompression is done in the second half, including middle hidden layer up to output layer.

EW and NS components of events 5, 20, 24, 25, 39, 40, 43 and 45 were used for training and testing of the hierarchical neural network (records duration = 30 s). Training and testing data set consists of eight events of SMART-1 array including 180 earthquake accelerograms with various magnitude and distance from epicenter. These accelerograms include earthquakes with magnitudes ranging from 5.9 to 6.5. Peak ground accelerations of EW components vary from 35.57 gals to 210.47 gals and peak ground accelerations of NS component vary from 38.45 gals to 251.07. The durations of the strong shaking vary from 20 to 35 s. Therefore, an arbitrary duration of 30 s was considered for all the accelerograms and adequate points with zero amplitude were added at the end of accelerograms with shorter duration to bring the total durations of them to 30 s. Total durations of longer ground motions were considered to 30 s. To determine a hierarchical neural network with optimum algorithm for data compressing and decompressing, different back propagation algorithms were evaluated and effect of number of layers on simulation and convergence speed was investigated. Eventually, three layer back propagation neural network with scaled conjugated gradient algorithm was employed to train the neural network including 1500 neurons in input and output layers and 80 neurons in middle hidden layer (Fig. 2).

The trained hierarchical neural network was then tested by presenting new accelerograms of SMART-1 array as input. The new accelerograms were compared with replicated accelerograms. These comparisons were first performed for the accelerograms in the training set and then for novel accelerograms which were not included in the training data set. A typical comparison for one of the accelerograms from the training set is shown in Fig. 3. It shows that the trained replicator neural network has learnt the training cases very well. Fig. 4 shows a similar comparison for a novel accelerogram. It can be seen that the replicator neural network has learnt to compress and then decompress an accelerogram which is very close to the input accelerogram.

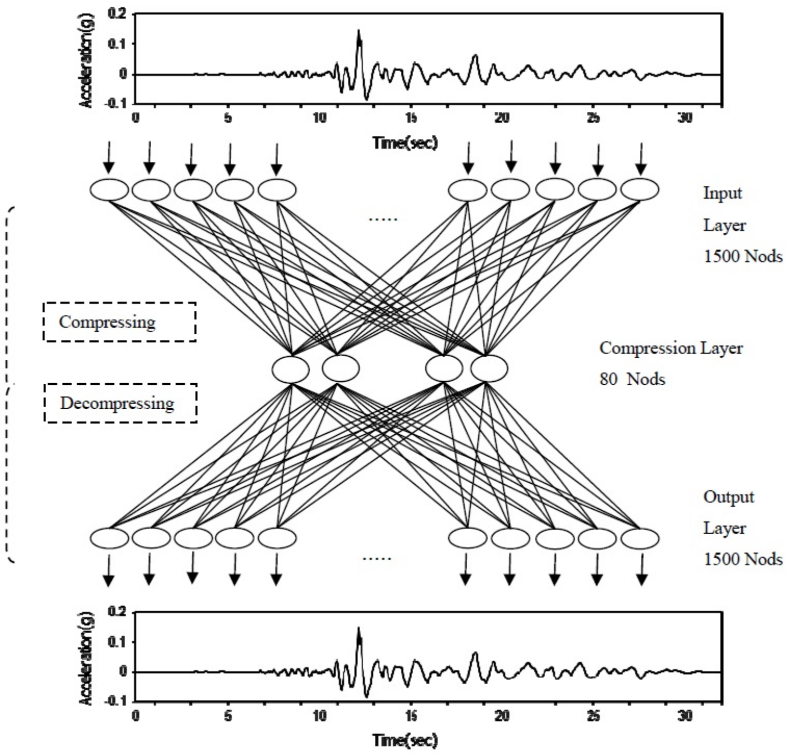

Fig. 2 Demonstration of hierarchical neural network architecture

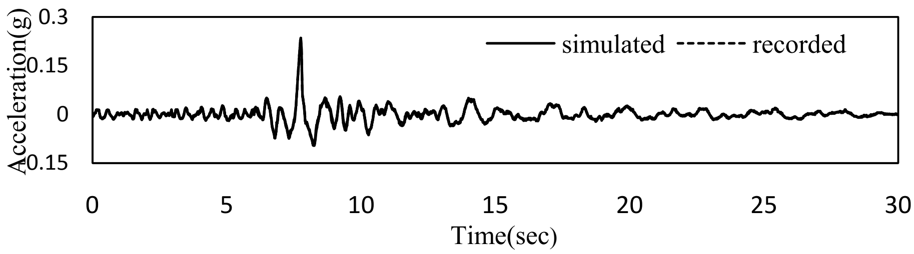

Fig. 3 Test of the trained hierarchical neural network with training data set, NS component of event 40, station C00

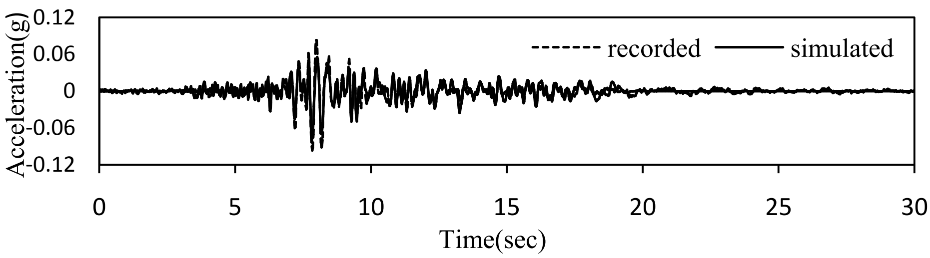

Fig. 4 Test of the trained hierarchical neural network with test data set, EW component of event 5, station C00

4.1.2 Main neural network for spatially varying accelerograms generation

Having compressed the accelerograms in a lossless way, a new GRNN neural network was combined with two part hierarchical neural network to improve generalization power of the network. After successful training of hierarchical neural network, the connection weights were saved to use them to compress and decompress of the presenting accelerograms of the main neural network in coming stage. For this purpose the replicator neural network was split into compressing and decompressing half parts in which by propagating a accelerogram vector in the first half, it compresses and vice versa.

Generalized Regression Neural Network (GRNN) was employed to generate artificial accelerograms based on seismic response spectra. It was combined with the hierarchical neural network to perform the generation in two stages. Actually, two neural networks were constructed to generate accelerograms. The first neural network is GRNN and the second one is the second half part of the hierarchical neural network as trained previously.

GRNN is a probabilistic neural network has been proposed by Specht (1991). The concept of the GRNN is based on nonparametric estimation commonly used in statistics. The GRNN has been applied to solve a variety of problems like prediction, control, modeling or general mapping problems. Main advantage of GRNN over other techniques is that, unlike the methods which need a large number of iterations to be performed during the training and converge to a desired solution, the GRNN needs only a single pass of learning to achieve an optimal performance in classification (Buendia *et al.* 2004). Our preliminary study shows that among many types of back-propagation neural networks and radial basic functions (RBF) neural networks, the GRNN which is a type of RBF neural networks, has less training time and more learning capability of simulating accelerograms.

Fig. 5 shows the schematic architecture of a GRNN. The GRNN consists of four layers: input layer, a radial basis layer, a special linear layer and an output layer. Radial basis layer and special linear layer power it for functional approximation and mapping problems. It approximates any arbitrary function between input and output vectors without any iterative training procedure as in back propagation method. There is a factor that influences the approximation function and is referred to as the spread factor whose optimal value is often determined experimentally (Hornik *et al.* 1989). A large spread, corresponds to a smooth approximation function. Too large a spread means a lot of neurons will be required to fit a fast changing function. Too small a spread means many neurons will be required to fit a smooth function, and the network may not generalize well. In this study, spread constants were examined with a simple trial and error method. The accelerogram generator neural network was developed to learn to generate the accelerogram from the vector of the pseudo-acceleratoin response spectrum at discrete periods. The architecture of main neural network is shown in Fig. 6. Input vector of GRNN was composed of descritized pseudo-acceleration response spectrum and distance parameter in which the varying spatial accelerogarm is generated. The compressed representation of accelegorams which obtained from the first half part of hierarchical neural network was considered as output vector of the GRNN. The output vector of the GRNN was propagated to the second half part of the trained hierarchical neural network. 240 earthquake accelerogarms recorded from event 5, 20, 24, 25, 43 and 45 at specified distances of SMART-1 Array, according to the distance of the rings, *I*, *M* and *O*, were used to train the main neural network. Accelerograms of events 33, 39, 40 were used for testing of the trained neural network. Each accelerogarm vector was compressed to a vector with the size of 80, using the heirarchical neural network as described, previously. Pseudo-acceleration response spectrum of each acceleroram was also descritized at 100 sample period. Input layer of the first neural network (GRNN) consists of 101 neurons, 100 neurons for presenting pseudo-acceleration response spectrum and one neuron for distance in which the spatially varying accelerogarm is generated. Output layer also consists of 80 neurons to present compressed accelerogram vectors.

The main neural network was trained by compressed accelerograms and their corresponding pseudo response spectra. All the simulated accelerograms with 80 acceleration points were decompressed and developed to accelerograms with 1500 points. Using trial and error method and testing spread values from 0.01 to 5, appropriate spread factor for the GRNN neural network was obtained equal to 0.2.

4.1.3 Testing of the main neural network

All the pseudo-acceleration response spectra were computed by using the Newmark Method with $\beta = 0.25$ and $\gamma = 0.5$, 5 % damping, $\Delta t = 0.04$ s, for periods between 0 and 4 s. Therefore, all the pseudo-acceleration response spectra included 100 discrete pseudo-acceleratoin points.

The input layer includes pseudo-acceleratoion response spectra and distance parameter between stations (km) which determines the spatially variation of seismic ground motions. Input and output data were normalized by scaling them between -1 and 1, in order to increase ability of training and generalization of network.

In order to verify the developed model, the main neural network was first tested for the accelerograms in the training data set and then for novel accelerograms which were not included in the training data set. For example, the recorded accelerograms of event 24 in station I06 from training data set and its pseudo acceleration spectrum of NS component with various distances of 0, 0.2 and 1 km are illustrated in Fig. 7. The lower portion of Fig. 7 shows the generated accelerograms. Comparison of the input and output accelerograms and their response spectra clearly indicates that the trained neural network has learnt the training cases very well.

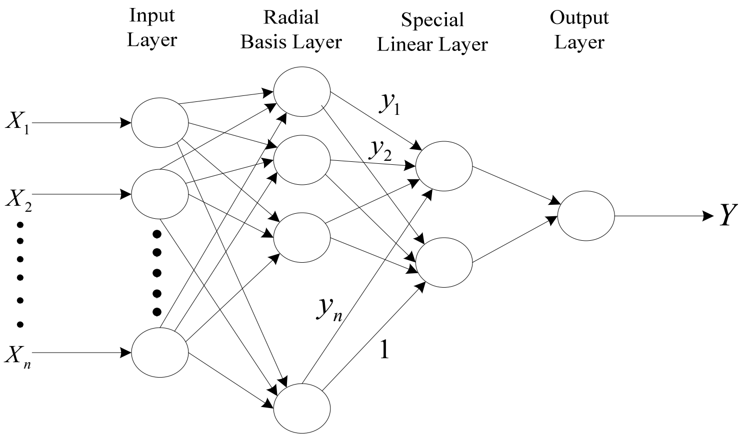

Fig. 5 Schematic diagram of a GRNN architecture

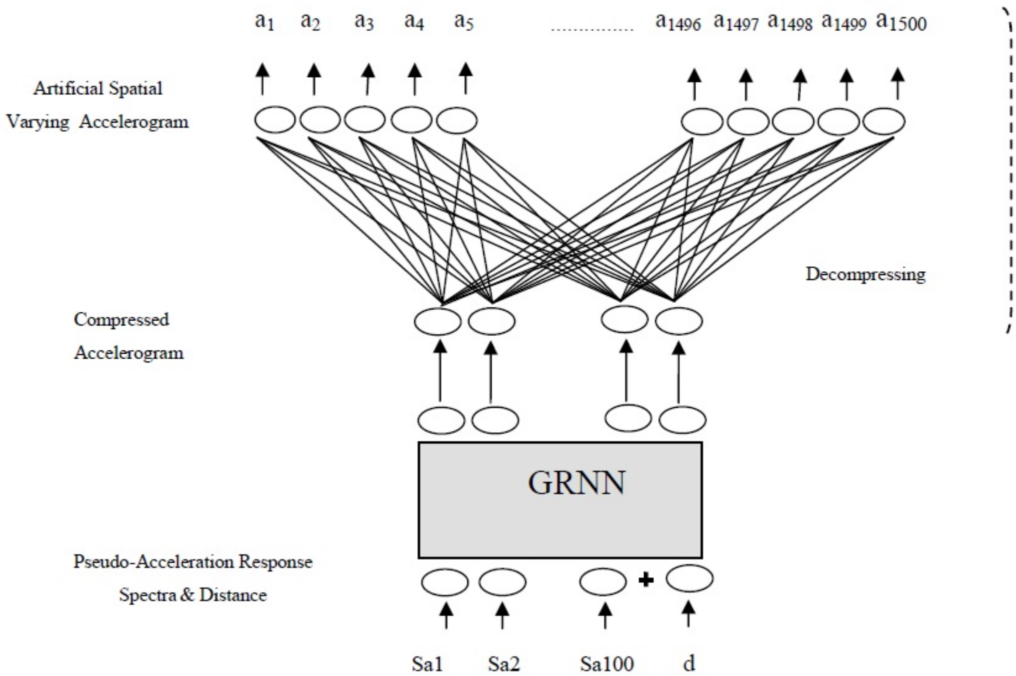

Fig. 6 Artificial spatial varying accelerogram procedure

The trained neural network is then evaluated with novel response spectrum and a novel distance parameter in which generated accelerogram is desired. Pseudo-acceleration spectrum of EW component of event 43 recorded in the station C00 was considered with various distances of 0, 1 and 2 as testing data set. Comparisons between recorded accelerograms and simulated accelerograms are shown in Fig. 8. Fig. 9 also shows the results of testing the main neural network for the novel cases from the test set related to EW component of event 39 with various distance of 0, 1 and 2 km in the station C00. As can be observed, the neural network is satisfactorily capable

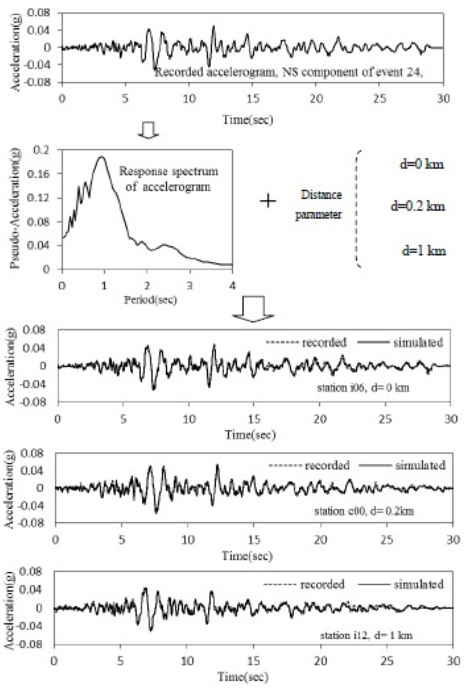

Fig. 7 Test of the trained main neural network with inputs from the training set

of generating spatially varying earthquakes compared to recorded ground motions. It can be seen that as distance increases from the center of the SMART-1 array, accelerograms are modified and acceleration values tend to diminish. The time shifting of peak acceleration in the accelerograms can be also observed in the results. The major objective of simulation is envelope value of records and modeling of spatial variation which has been well provided. Some minor differences between recorded and simulated accelerograms are due to irregular variation of the records (PGA value and its occurring time) and can be ignored.

5. Verification of the simulated ground motions based on fourier amplitude spectra and correlation test

In order to evaluate the validity of the presented neural network, a typical comparison of Fourier amplitude spectrum relating to recorded and simulated accelerograms of Fig. 9 is conducted.

As shown in Fig. 10, comparisons of Fourier amplitude spectra also show that the model has reasonable accuracy and is capable of generating spatially varying ground motions. Additionally, technique of magnitude squared coherence spectrum is employed to scrutinize the accuracy of the developed neural network. The coherence spectrum is a prominent measure of the linear statistical correlation between two time series. This approach provides a frequency-dependent measure of the linear relationship between two stationary random processes. In other words, it is explained as a correlation coefficient in the frequency domain (Stoica and Moses 2005). The magnitude squared

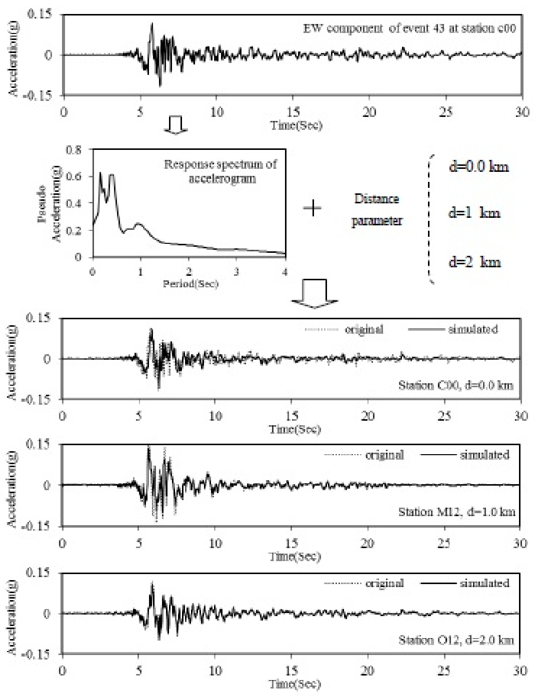

Fig. 8 Test of the trained main neural network with inputs from the test data set

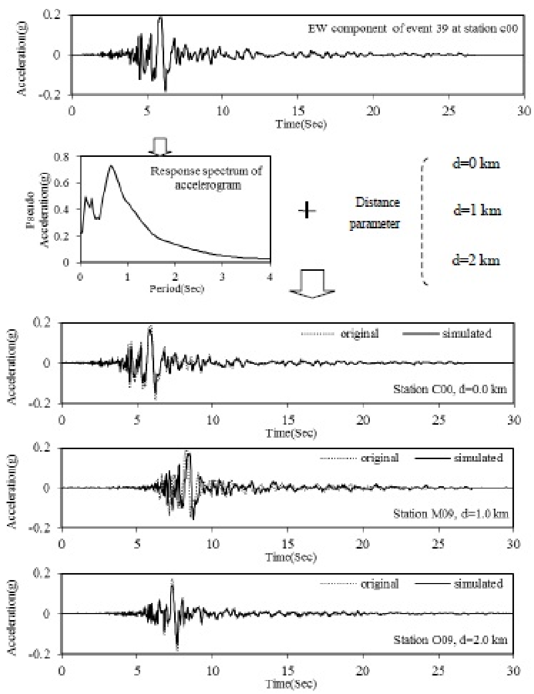

Fig. 9 Test of the trained main neural network with inputs from the test data set

coherence estimate with values between 0 and 1 indicates how well x (recorded earthquake) corresponds to y (simulated earthquakes) at each frequency and is given by

$$C_{xy}(f) = \frac{\left|P_{xy}(f)\right|^2}{P_{xx}(f)P_{yy}(f)} \tag{1}$$

where P_{xx} and P_{yy} are the power spectral density of x and y, and P_{xy} is the cross power spectral density of x and y. The coherence estimate between the recorded and simulated ground motions are developed and compared. Fig. 11 shows the coherence between recorded and simulated earthquakes relating to EW component of event 39 at stations C00, M09 and O09. As it is clear, the coherence estimation reveals convincingly the accuracy of the presented algorithm and the validity of the neural network to produce spatially varying acceloragrams is well evaluated.

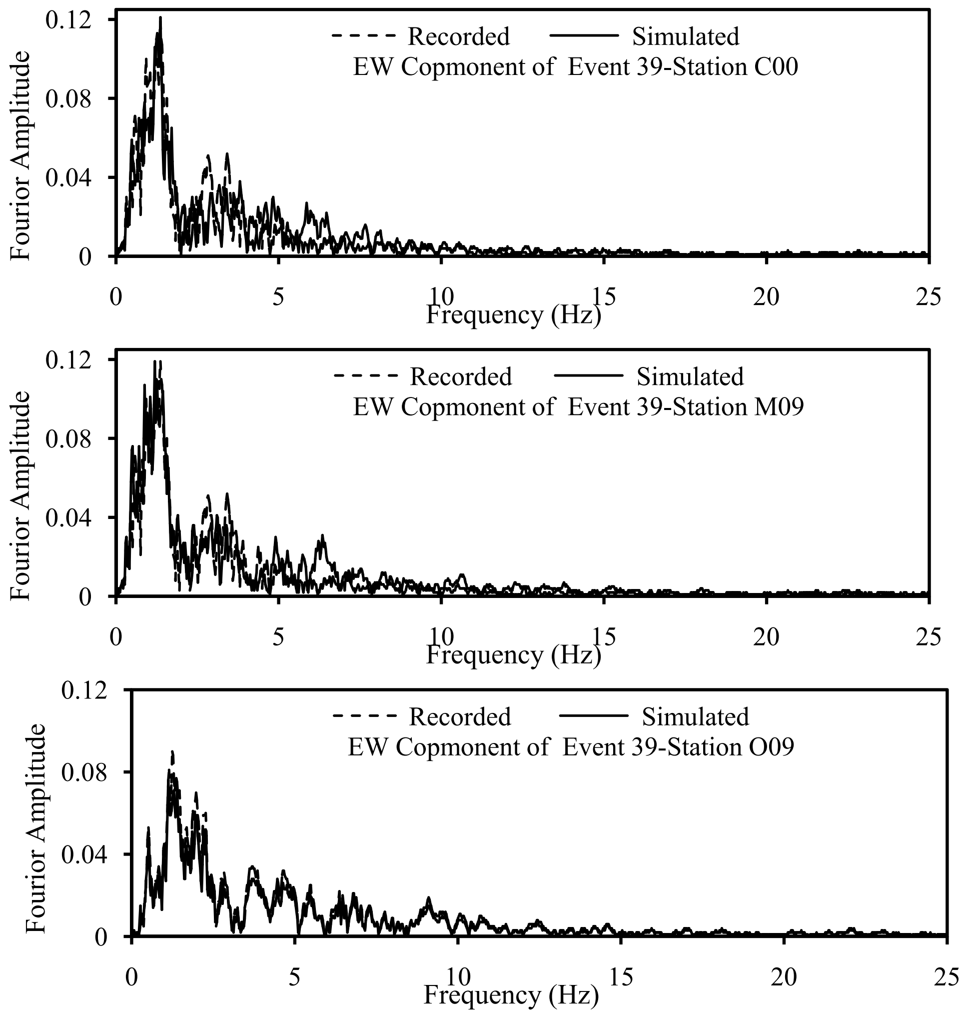

Fig. 10 Comparison of fourier amplitude spectrum

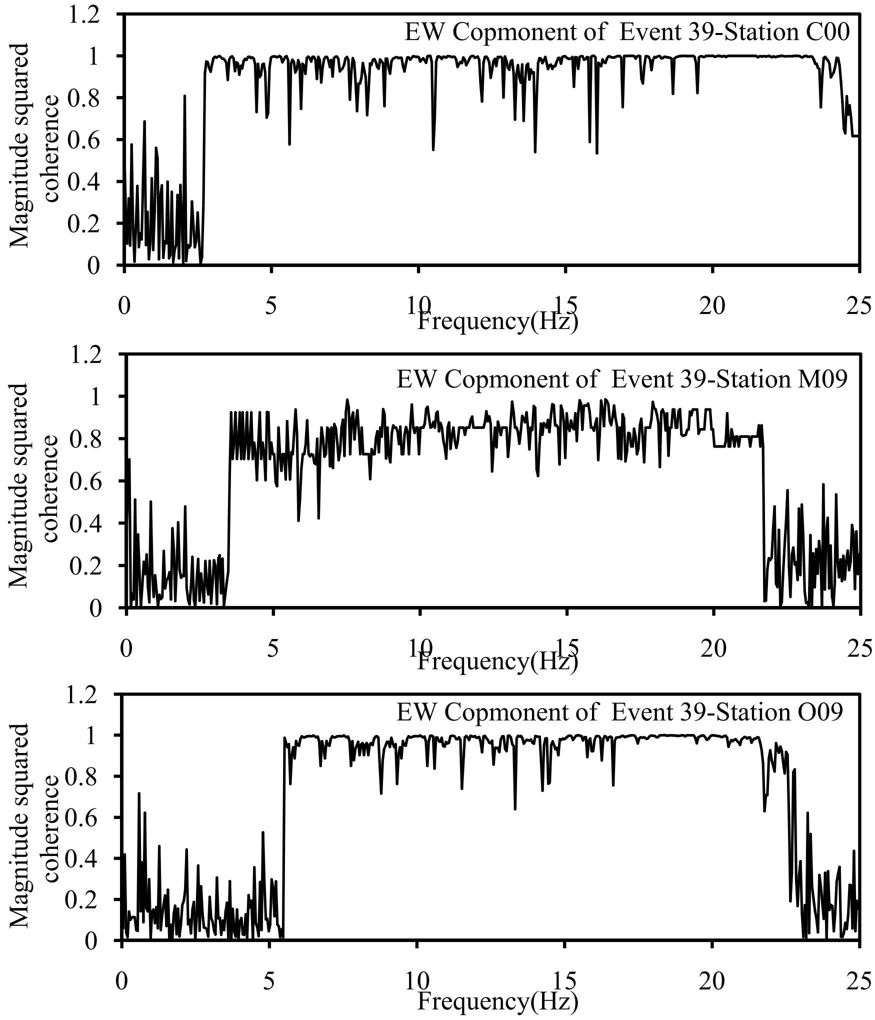

Fig. 11 Coherence estimate between the recorded and simulated accelerograms, EW component of event 39 at stations C00, M09 and O09

6. Conclusions

A new approach to generate artificial spatially varying accelerograms has been demonstrated. Spatial variation of seismic ground motion is an important characteristic of earthquakes that should be considered in dynamic analysis of large structures such as dams and bridges. To investigate the effect of this phenomenon on the seismic response of such structures, the spatially varying effect of earthquakes can be modeled by some proposed complicated models which exist in the literature.

In this study, a simplified ANN based method was proposed to generate spatially varying earthquake accelerograms. Comprehensive source of information obtained from SMART-1 array were utilized as the training and validation data set for the neural network. Preliminary investigation on feed-forward back propagation neural network and GRNN showed that the

GRNN is more efficient in training time and learning of the data than feed-forward back propagation neural network. They have high learning capability in simulation of seismic ground motions. First, a hierarchical neural network was trained to learn to compress the data. This pre-processing neural network was utilized to reduce the size of accelerogram vectors and enhance the efficiency of main neural network. The main neural network is then formed by combining the replicator neural network with GRNN which was trained to learn to associate the pseudo-acceleratoin response spectra with the compressed accelerograms. The ANN model was tested with the testing set which was not used in the training process. It was proven that the ANN-based model had good generalization results and can successfully provide accelerograms in which spatial variation of ground motions is quite noticeable. As distance from source increases, acceleration values in the accelerograms tend to decrease and a time shifting of peak acceleration is observed. The neural network is capable of simulating non-uniform accelerograms with desired response spectrum at any distance and the results of this network can be used in the analysis of extended structures. More research is needed to extend the developed neural networks to study other properties, such as duration, source characteristics, site characteristics and so on.

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