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NEURAL-NETWORK BASED ESTIMATION OF NORMALIZED RESPONSE SPECTRA

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ABSTRACT

This paper focuses on the application of neural networks as an alternative computational tool for the estimation of normalized response spectra for the horizontal ground motions with magnitudes $M_{\mathrm{JMA}} \geq 5$ and hypocentral distances less than 50 km. The feasibility of using the perceptron neural networks in estimating site-specific response spectra and the effects of the geophysical properties of the site is examined. Two neural-network models are proposed for generating normalized response spectra, such that those consider the effects of local site conditions. Model 1 is developed with six inputs (i.e., magnitude, hypocentral distance, primary wave velocity, shear wave velocity, N-values obtained by the standard penetration test (SPT), and density of soil), whereas Model 2 is developed with three inputs (i.e., magnitude, hypocentral distance, and shear wave velocity). As expected, a better performance is obtained from (neural-network) Model 1 in terms of accuracy and efficiency. The results obtained from this study are very encouraging and have a potential to replace the commonly used regression approach.

KEYWORDS: Neural Networks, Response Spectra, Hypocentral Distance, Shear Wave Velocity, Regression Approach

INTRODUCTION

Response spectrum is a fundamental engineering tool in the dynamic analysis and design of structures. The concept of response spectrum, introduced originally by Biot (1941) and later popularized by Housner (1941), describes the maximum response of a series of damped, linear elastic, single-degree-of-freedom oscillators to a particular ground motion as a function of the natural period of vibration or the circular frequency of the oscillator. A response spectrum forms the basis for the structural engineers interested to know the response of structures subjected to a ground motion resulting from an earthquake. For design purposes, seismic codes provide a design spectrum that describes the level of seismic resistance required for design, based on the statistical analysis of the response spectra for an ensemble of ground motions. The design spectrum contains all the information on ground motion amplitudes and frequencies and hence can be directly used to design a structure for earthquake loads (Gupta, 1990). In the past, over 80 studies have been carried out for the estimation of (design) response spectral ordinates (Douglas, 2001, 2002). A majority of the published prediction models for the generation of acceleration response spectra are based on regression analysis.

One of the ways of evaluating site-dependent spectra is by describing the site itself. The most commonly used method to classify sites is according to the shear wave velocity recorded at the recording stations. The literature on the site-dependent spectra is voluminous (e.g., Kuribayashi et al., 1972; Mohraz et al., 1973; Seed et al., 1976; Mohraz, 1976; Trifunac, 1976; Iwasaki et al., 1980; Trifunac, 1990; Lee and Trifunac, 1995; Borcherdt, 1994) and hence a review of this literature is not covered in this paper. In this work, an attempt is made to incorporate all the reported site effects at the Kyoshin Net recording stations. Neural networks are used as an alternative tool for generating the response spectral ordinates by using the actual seismic data without any simplifications and assumptions, instead of the commonly used regression approach. To the best of the knowledge of the authors, this is the first time that neural networks are used for estimating normalized response spectra by using the detailed soil properties and site characteristics at the recording stations.

This paper provides a neural-network based approach for estimating the site-dependent response spectra based on earthquake records and site characteristics. The first part of the paper is concerned with the compilation and processing of strong-motion data for the Japanese earthquake records from the

Kyoshin Net database. The second part of the paper presents the application of artificial neural networks to predict response spectral ordinates with six inputs as well as with three inputs, along with the simulation results for each model. Finally, the trained network with three inputs is tested for a few significant US earthquakes and the results are presented. In an earlier work (Arjun and Kumar, 2009) the authors of the present paper have developed an artificial neural network in the form of a multilayer perceptron model to predict peak ground accelerations with different training parameters. Also, the first author (Arjun, 2008) has used artificial neural networks for predicting the strong ground motion parameters that are of primary significance in earthquake engineering.

INFORMATION ON RECORDING STATIONS AND DATA PROCESSING TECHNIQUE

Japanese ground motion records from the Kyoshin Net (K-NET) database are selected for this study, as K-NET provides detailed soil properties and site characteristics at almost all the recording stations. K-NET is a dense strong-motion network, consisting of over 1,000 recording stations deployed all over Japan at free-field sites at the interval of approximately 25 km. Each station has a digital strong-motion accelerometer with a wide frequency band and a wide dynamic range. The K-NET data is openly available on registration through their web-site[1]. Almost all the sites in this database have the soil conditions (e.g., standard penetration value (SPT), density) available, including the P- and S-wave velocity structures obtained from the downhole measurements. A majority of the K-NET stations are located on thick sedimentary sites in the urban areas. The accelerometer at a station is placed on a concrete base and its housing is made of fiber reinforced plastic (FRP). The layout of a typical observatory is shown in Figure 1.

All stations operated by K-NET have K-NET95 accelerometers, with 108 dB dynamic range and the maximum measurable acceleration of 2000 Gal (20 m/s^2). Each accelerometer is a triaxial, force balance accelerometer (i.e., V403BT model by Akashi Co.) with a natural frequency of 450 Hz and critical damping ratio of 0.707. The resolution of the A/D converter is 18 bits with the sampling frequency of 100 Hz. The resolution of the accelerometer is 15 mGal (0.15 mm/s^2). The response characteristic curves of the accelerograph, which include the effect of anti-aliasing filter in digitization, are shown in Figure 2. The cutoff frequency of the filter is 30 Hz.

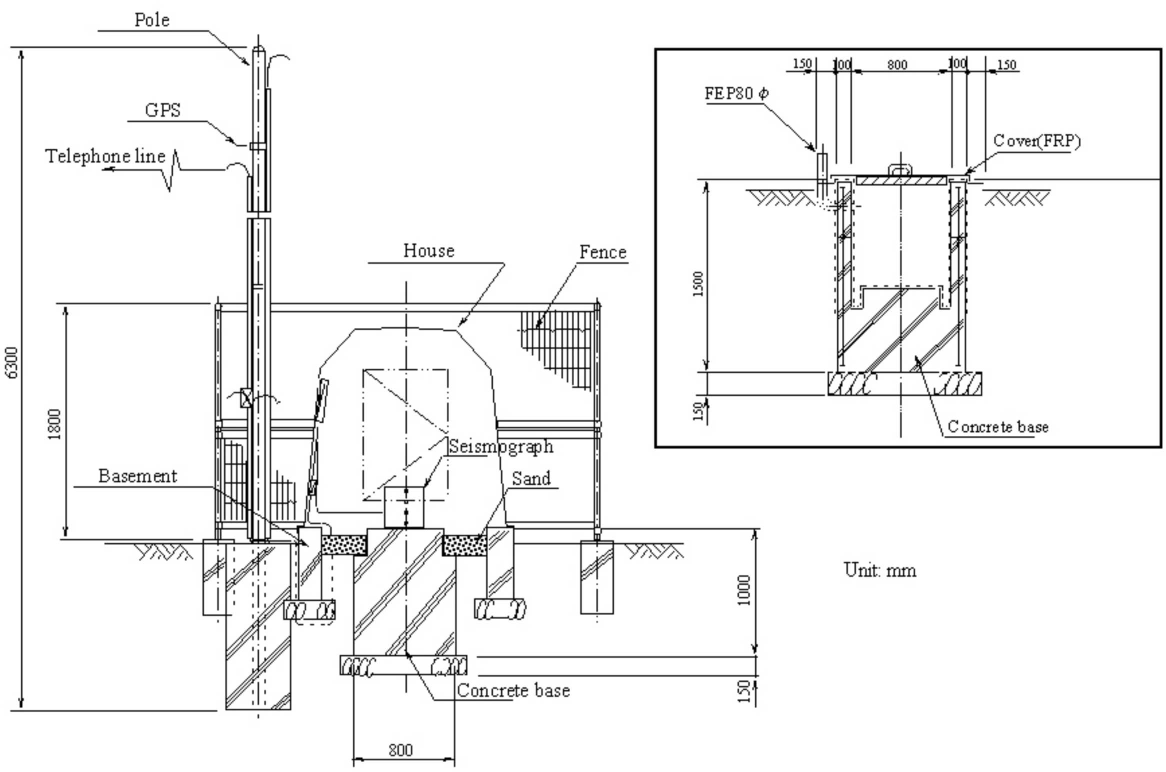


Fig. 1 The layout of typical observatory[1]

[1] http://www.k-net.bosai.go.jp

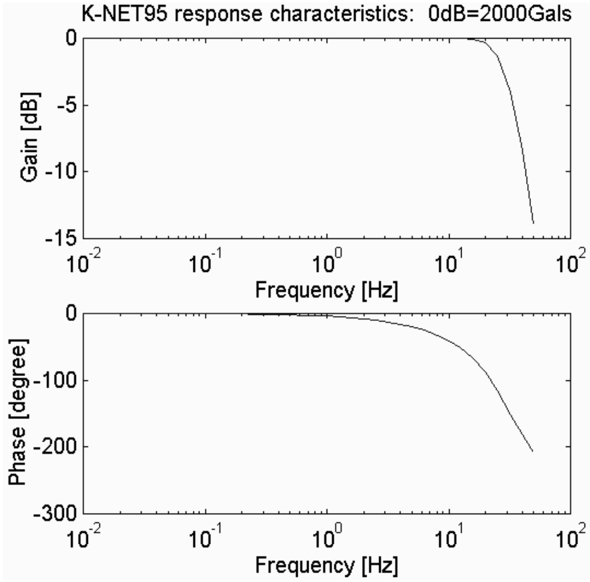


Fig. 2 Response characteristic curves of K-NET95 accelerographs[1]

Baseline correction is an important part of the data processing procedure and is essentially required for the correction of errors due to noise. A baseline correction of all uncorrected acceleration time histories is performed by using the least-square line of the time history. Corrections are also applied in frequency domain by filtering the high- and low-frequency components of the accelerograms. All accelerograms are band-pass filtered by removing the frequencies below 0.1 Hz and the frequencies above 30 Hz. A sixth-order Butterworth band-pass function in frequency domain (commonly called as frequency filter) is used for the above filtering operation. For the dynamic analysis of structures, the frequency range of interest is usually below 30 Hz, and hence a frequency limit of 30 Hz is acceptable. The low value of the frequency limit is critical only when the recorded event is in the near-field of a large earthquake. The objective of this study is to use the K-NET database as input to a neural network, and not to study the noise characteristics of the database. Hence, a filter with the band limit of 0.1–30 Hz is applied. As the natural frequency of all accelerographs is very high, there is no need of any instrument response correction.

SITE INFORMATION

The most commonly used parameter to classify the sites is the average shear wave velocity in the top 30 m of the earth, $Vs30$. The National Earthquake Hazards Reduction Program (NEHRP) in USA also uses $Vs30$ to define various site categories. K-NET provides the velocity structures beneath the site basically to a depth of 10–20 m by using the downhole measurement method. Apart from the P- and S-wave velocity structures, at each station the N-values of SPT, the bulk density values of soil, and soil profiles are reported. A typical soil data at the recording stations is given in Figure 3. The average values of the shear wave velocity, primary wave velocity, SPT blow count and the density of soil, i.e., $\overline{v}_s$, $\overline{v}_p$, $\overline{N}$, $\overline{\rho}$, respectively, are used as the inputs to a neural network. The averaging is done in accordance with Section 3.5.1 of the NEHRP recommended provisions for seismic regulations for new buildings and other structures (FEMA, 2003):

$$\overline{v}_s, \overline{v}_p, \overline{N}, \overline{\rho} = \frac{\sum_{i=1}^{n} d_i}{\sum_{i=1}^{n} \frac{d_i}{v_{si}}, \frac{d_i}{v_{pi}}, \frac{d_i}{N_i}, \frac{d_i}{\rho_i}} \tag{1}$$

where v_{si} denotes the shear-wave velocity of soil, v_{pi} the primary-wave velocity of soil, N_i the SPT blow count, and ρ_i the density of soil, in the layer i; d_i denotes the depth of the layer i; and n denotes the number of layers of the similar soil materials, for which data is available.

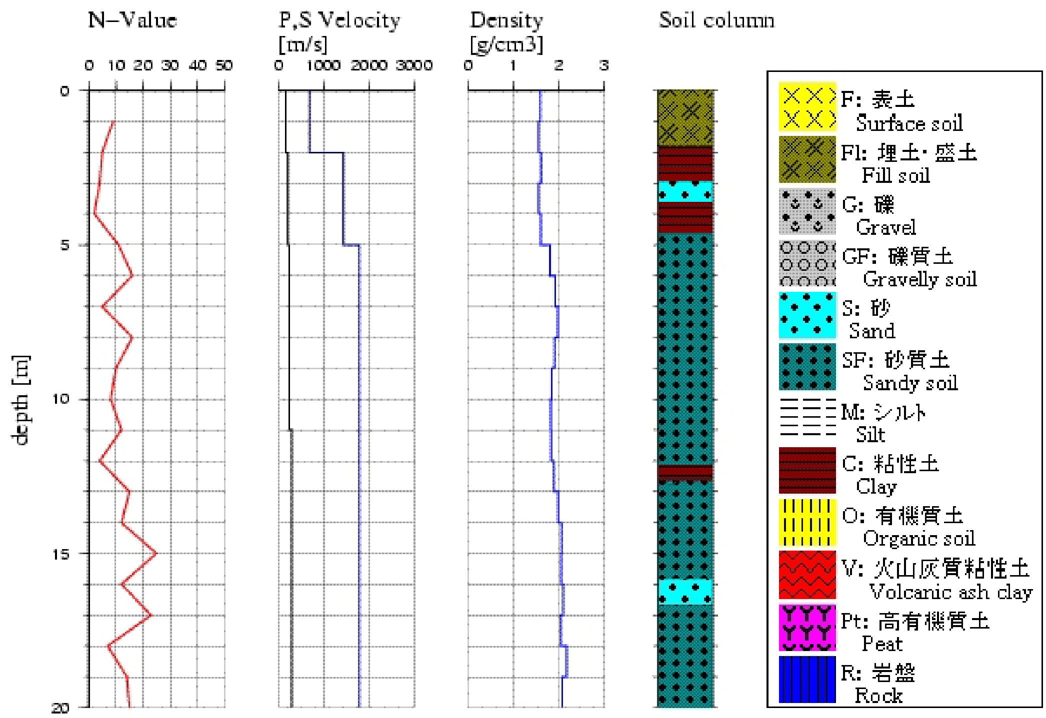


Fig. 3 Site information at FURUDONO site[1]

PREDICTIVE MODELS FOR GENERATING RESPONSE SPECTRA USING NEURAL NETWORKS

Artificial neural networks are efficient computing models wherein the solution to a problem is learned from a set of examples. One of the major shortcomings of neural networks is that those are considered as a black box, since there is no satisfactory explanation of their behavior for finding a solution (Benitez et al., 1997). There are many definitions of an artificial neural network (ANN). It is a massively parallel-distributed processor made up of simple processing units, which have a natural tendency of storing experiential knowledge and making it available for use (Haykin, 1994).

The most powerful feature of a neural network involving supervised learning is the input-output mapping. In a supervised learning algorithm the output is known and given to the neural network during the training process so that the neural network can adjust weights in such a way that the actual output moves closer to the desired output. After the training, the neural network is tested by giving only the input values, to see how close its output is to the desired values. Backpropagation is one of the most commonly used algorithms for training the multilayer ANNs. Many researchers have used the multilayer feedforward neural networks in structural dynamics, especially in the field of earthquake strong ground motion problems (e.g., Lee and Han, 2002; Tehranizadeh and Safi, 2004; Ghaboussi and Lin, 1998; Kerh and Chu, 2002; Kerh and Ting, 2005; Kerh et al., 2011). A multilayer neural network consists of an input layer, one or more hidden layers, and an output layer. The relationship between the input and output of a neural network can be linear as well as non-linear. This relationship in any network requires a function, known as the activation function or the transfer function. There are several activation functions, such as step function, linear function, hyperbolic tangent function, and sigmoid function. The transfer functions used in this study are described below.

Hyperbolic Tangent Transfer Function: The hyperbolic tangent transfer function, shown in Figure 4 and used for the hidden units of the multilayer perceptron neural network, has the form $F(x) = \tanh(\alpha x)$, where α is the slope parameter. This function takes the input in form of any value between minus and plus infinity and limits the output to the range (−1, 1).

Sigmoid Transfer Function: The sigmoid transfer function has the form $F(x) = 1/(1+e^{-\alpha x})$. This transfer function takes the input in form of any value between minus and plus infinity and limits the output to the range (0, 1). This transfer function is used in this study for the output layer and is shown in Figure 5.

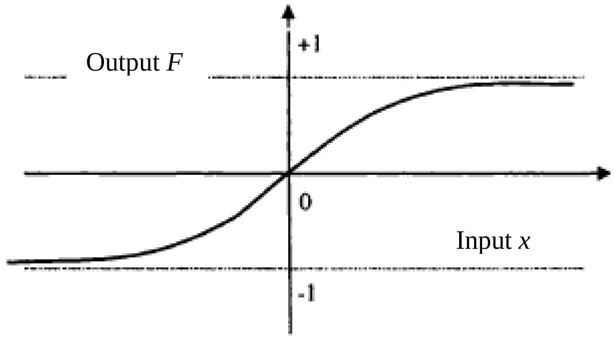


Fig. 4 Hyperbolic tangent transfer function

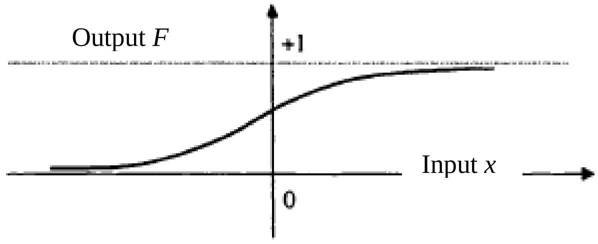


Fig. 5 Sigmoid transfer function

The backpropagation algorithm provides a prescription for changing the weights. The input signal propagates through the neural network in a forward direction, layer by layer. During the forward phase, an input vector is presented to the network, resulting in an output at the output layer. During this phase, the weights are not modified and they are all fixed. In the backpropagation phase the weights are adjusted based on the error between the actual and desired outputs. The hidden layer aids in extracting the higher-order statistics, which tends to be useful when the input layer is large. Also, the use of hidden layer implies that the information needed to compute the output is filtered before passing it on to the next layer. The size of hidden layer is one of the most important considerations, while solving the multilayer feedforward neural networks. Choosing the number of neurons in the hidden layer is an art and is dependent on the complexity of the desired input-output mapping. The following equation is used for the adjustment of connection weights:

$$\Delta w_{ij}(n) = \eta\left(\partial E/\partial w_{ij}\right) + \alpha \Delta w_{ij}(n-1)\, j \tag{2}$$

where $\Delta w_{ij}(n)$ and $\Delta w_{ij}(n-1)$ are the weight increments between the nodes i and j during the nth and $(n-1)$th epochs (or iterations), respectively, η is the learning rate, and α is the momentum.

The momentum factor and learning rate are used to accelerate the speed of learning without leading to oscillations. The theory of backpropagation algorithm is described in the neural-network related books (e.g., Haykin, 1994; Hagan et al., 1996).

The objective of the training algorithm is to adjust the weights, such that the network performs well, i.e., the quantitative measurement of the network performance decreases. Networks are trained in this study by using the gradient descent with momentum learning scheme, which focuses on using the error between the network output and the desired output. The learning algorithm adapts the weights of the system based on the error until the system produces the desired output. The software NeuroSolutions, Version 5.0 (NeuroDimension, 2003) is used here for the simulation of neural network models. The error criteria family in NeuroSolutions computes the different error measures that can be used to train the network. In this study the criterion used is the L2 norm or the mean squared error (MSE) criterion defined below. In this criterion the squared difference between the system output and the desired signal is simply averaged as

$$\mathrm{MSE} = \frac{1}{2N}\sum_{i=1}^{N}\left(x_i - y_i\right)^2 \tag{3}$$

where x_i and y_i are the actual and predicted values, and N denotes the number of data points in the analysis.

The stopping criterion should be such that it addresses the problem of generalization. This is done by stopping the training at the point of maximum generalization. The training set is usually divided into two sets: the training set and the cross-validation set. The training is stopped when the error in the cross-validation set is smallest. This will be the point of maximum generalization.

A total of 1,850 horizontal components of earthquake records from the Kyoshin Net database of 145 earthquakes, having magnitude M_{JMA} values more than 5.0 and hypocentral distances less than 50 km, are considered in this study. The geometric mean of the two horizontal components at each recording station is considered for the computation of response spectral ordinates. This leads to a set of 925 spectra that will be used for training and testing the neural networks.

1. Implementation Details of Individual Models

For generating a response spectrum by using ANN, neural network models are created in two phases. In the first phase, the magnitude of earthquake, M_{JMA}, hypocentral distance H, average SPT blow count $\overline{N}$, average primary wave velocity $\overline{v}_p$, average shear wave velocity $\overline{v}_s$, and average density of soil, $\overline{\rho}$ are used as the six input variables. In the second phase, a neural network with three nodes on the input layer is created, such that this represents the magnitude of earthquake, M_{JMA}, hypocentral distance H, and the average shear wave velocity $\overline{v}_s$. In both the phases, the output layer consists of 55 response spectrum ordinates with 5 percent critical damping ratio. Table 1 shows the 55 time periods selected from 0.03 to 10 s for these ordinates. It may be mentioned that in the database considered, the values of M_{JMA} range from 5 to 7.1, H from 0 to 50 km, $\overline{N}$ from 1 to 99, $\overline{v}_p$ from 450 to 3590 m/s, $\overline{v}_s$ from 85 to 1676 m/s and $\overline{\rho}$ from 1125 to 2425 kg/m^3.

Table 1: Time Periods Selected for Response Spectrum Ordinates

Period (s)	Ordinate	Period (s)	Ordinate	Period (s)	Ordinate
0.030	RS(1)	0.140	RS(20)	0.900	RS(39)
0.035	RS(2)	0.150	RS(21)	1.000	RS(40)
0.040	RS(3)	0.160	RS(22)	1.200	RS(41)
0.045	RS(4)	0.170	RS(23)	1.400	RS(42)
0.050	RS(5)	0.180	RS(24)	1.600	RS(43)
0.055	RS(6)	0.190	RS(25)	1.800	RS(44)
0.060	RS(7)	0.200	RS(26)	2.000	RS(45)
0.065	RS(8)	0.220	RS(27)	2.500	RS(46)
0.070	RS(9)	0.240	RS(28)	3.000	RS(47)
0.075	RS(10)	0.260	RS(29)	3.500	RS(48)
0.080	RS(11)	0.280	RS(30)	4.000	RS(49)
0.085	RS(12)	0.300	RS(31)	5.000	RS(50)
0.090	RS(13)	0.350	RS(32)	6.000	RS(51)
0.095	RS(14)	0.400	RS(33)	7.000	RS(52)
0.100	RS(15)	0.450	RS(34)	8.000	RS(53)
0.108	RS(16)	0.500	RS(35)	9.000	RS(54)
0.116	RS(17)	0.550	RS(36)	10.000	RS(55)
0.124	RS(18)	0.670	RS(37)		
0.132	RS(19)	0.800	RS(38)		

The total set of 925 spectra is divided into three sets: (1) training set, (2) validation set, and (3) testing set. The training set, consisting of about 80% of the data set, is used to train the network; the validation set, consisting of about 10% of the data set, is used for the purpose of monitoring the training process and to guard against overtraining; and the testing set, consisting of about 10% of the data set and not used in the training process, is used to judge the performance of the trained network. The training is stopped when the cross-validation error begins to increase, i.e., when the cross-validation error becomes minimum.

2. Neural Network Model 1

The ANN model with six nodes on the input layer as described in the previous section is created. A set of 825 spectra is selected randomly from the total set of 925 spectra for training and cross validation, and the remaining spectra are used to test the performance of the trained networks. Four different data sets of 825 spectra are created and randomized. These data sets are trained independently and the data set, which gives the minimum mean-square error (MSE), is considered for testing the network. Parametric studies are carried out in order to evaluate the optimum values of the hidden nodes and learning parameters. The various parameters used for training the network are given in Table 2. Figure 6 shows one hidden layer network model, with 51 hidden neurons, six input neurons and 55 output neurons.

Table 2: Parameters for Neural Network with One Hidden Layer for Six Inputs

Description	Hidden layer	Output layer
Transfer Function	TanhAxon	SigmoidAxon
Learning Rule	Momentum	Momentum
Step Size	1.0	0.1
Momentum	0.7	0.7

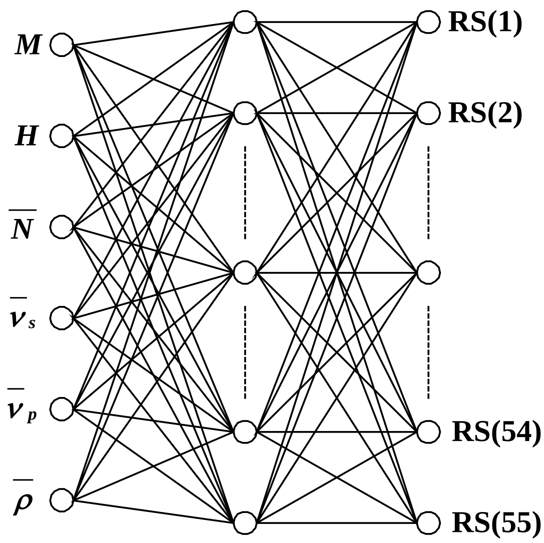


Fig. 6 Neural network architecture with six inputs

The network with 51 hidden nodes in the hidden layer shows the best performance (with minimum MSE). The results obtained after testing the network are compared by plotting the actual and predicted values of the response spectral ordinates. A typical set of results are shown graphically in Figure 7.

The efficiency of results obtained from the tested network is categorized as (a) excellent matching for MSE less than 0.1, (b) very good matching for MSE less than 0.2 and more than 0.1, (c) good matching for MSE less than 0.3 and more than 0.2, and (d) incorrect matching for MSE more than 0.3. The efficiency of results so categorized is tabulated in Table 3. It is observed from this table that the prediction of the trained neural network is quite satisfactory and therefore Model 1 has the potential to fully replace the empirical regression technique. It may be noted that 71% excellent matching is shown by the normalized response spectra predicted by an ANN with six inputs.

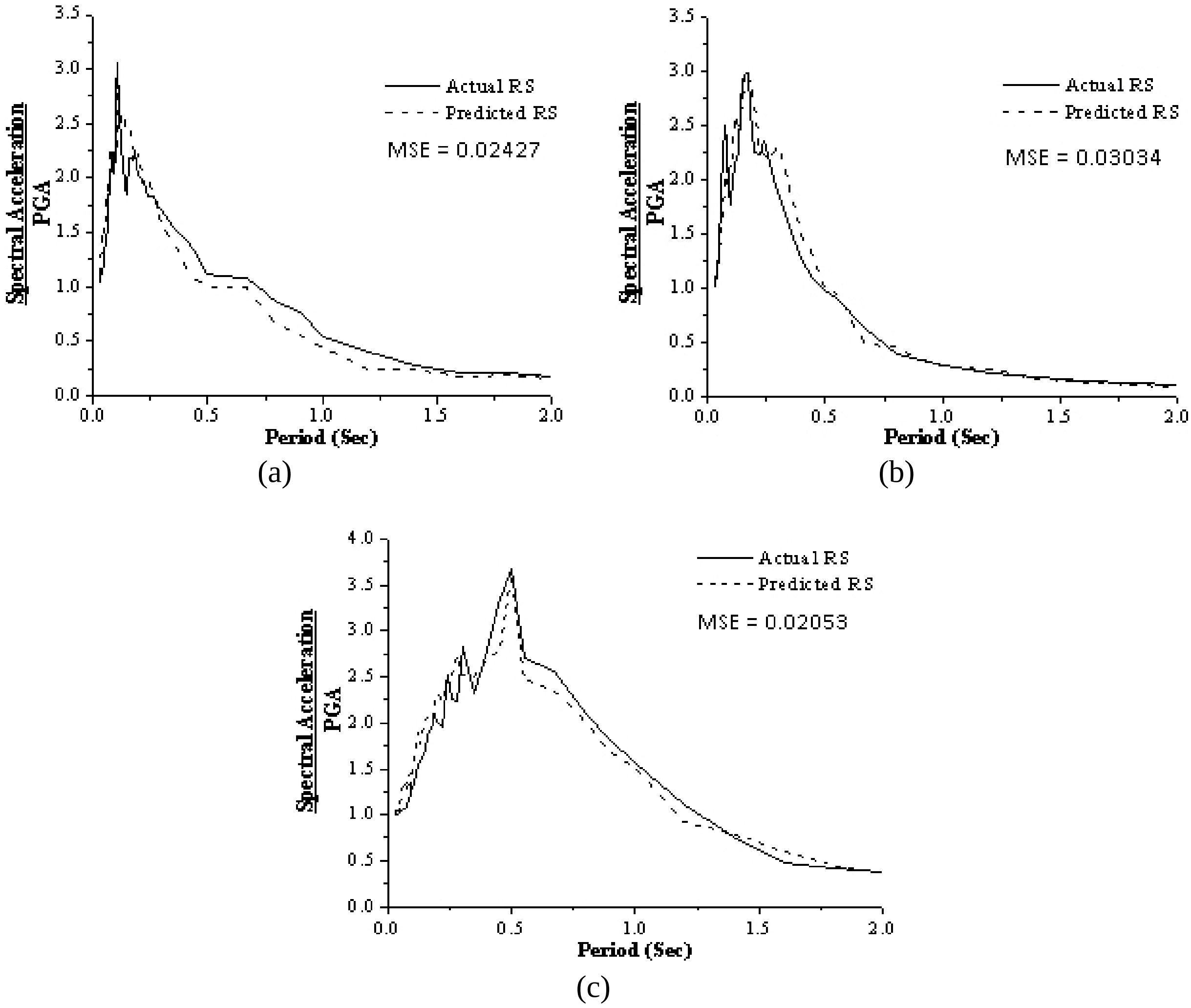


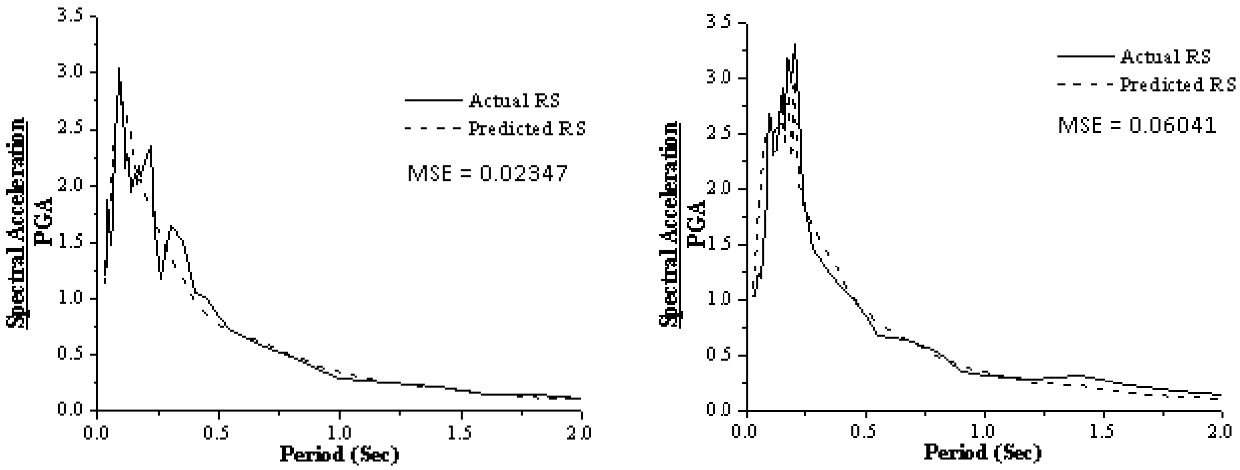
Fig. 7 Typical plots of acceleration response spectra predicted by ANN with six inputs for (a) M = 5.3, H = 30 km, $\bar{N}$ = 99, $\bar{v}_p$ = 1730 m/s, $\bar{v}_s$ = 559.2 m/s, $\bar{\rho}$ = 2.1 g/cm^3, (b) M = 5.0, H = 18.3 km, $\bar{N}$ = 80, $\bar{v}_p$ = 1374 m/s, $\bar{v}_s$ = 334 m/s, $\bar{\rho}$ = 2.1 g/cm^3 and (c) M = 5.1, H = 31.4 km, $\bar{N}$ = 7, $\bar{v}_p$ = 930 m/s, $\bar{v}_s$ = 124.5 m/s, $\bar{\rho}$ = 1.6 g/cm^3

Table 3: Efficiency of Six-Inputs Based Network

S. No.	Efficiency	Percentage
1	Excellent Matching	71
2	Very Good Matching	17
3	Good Matching	8
4	Incorrect Matching	4

3. Neural Network Model 2

Except the K-Net database of Japan, no other country provides detailed soil-condition data at the recording stations. Only few countries provide the values of average shear wave velocity recorded at their recording stations. For the use of trained networks based on the Japanese strong-motion data in other countries, it is essential to train the network with average shear wave velocity representing the site as one of the inputs. Model 2 is developed in a manner simlar to that of Model 1, but with only three inputs, i.e., M_{JMA}, H and $\bar{v}_s$. The network is designed with 3 input nodes, 55 output nodes and 58 hidden nodes (i.e., with the 3–58–55 scheme). The training parameters in Model 2 are similar to those of Model 1. A typical set of results are shown graphically in Figure 8.



(a) (b)

Fig. 8 Typical plots of acceleration response spectra predicted by ANN with three inputs for (a) M = 5.2, H = 42 km, $\overline{v}_s$ = 455.5 m/s and (b) M = 5.1, H = 39.6 km, $\overline{v}_s$ = 345.8 m/s

The efficiency of results obtained from the tested network is categorized in a similar manner as that for the six inputs and is tabulated in Table 4. It may be observed that with three inputs, 60% of the response spectra predicted show excellent matching. However, the ANN with three inputs is not able to predict sharp variations at the response spectrum peaks.

Table 4: Efficiency of Three-Inputs Based Network

S. No.	Efficiency	Percentage
1	Excellent Matching	60
2	Very Good Matching	20
3	Good Matching	14
4	Incorrect Matching	6

4. Testing of Trained Neural Network Model 2 for Few Significant US Earthquake Motions

As described in the previous section, only few countries provide the values of average shear wave velocity $\overline{v}_s$ recorded at their stations. One such organization is California Strong Motion Instrumentation Program (CSMIP). In this study, processed data from the CSMIP database is considered. It has been found by Katsumata (1996) that the average difference between M_{JMA} and moment magnitude M_w is not significant for the earthquakes in the magnitude range of 5 to 7. The strong-motion records considered from the CSMIP database are (a) Loma Prieta earthquake (with M_w = 7.0) of October 17, 1989, recorded at Eureka Canyon road, Corralitos, (b) Big Bear earthquake (with M_w = 6.4) of June 28, 1992, recorded at Civic Center grounds, Big Bear lake, (c) Northridge earthquake (with M_w = 6.7) of January 17, 1994, recorded at Cedar Hill Nursery A, Tarzana, and (d) Parkfield earthquake (with M_w = 6.0) of September 28, 2004, recorded at Gold Hill 3W, Parkfield. The acceleration response spectra predicted by Model 2 for the horizontal motions in these cases are presented in Figure 9. It is observed that the response spectra predicted for these motions (recorded in USA) are quite close to the actual spectra and that MSE is less than 0.1 for the Big Bear, Northridge, and Parkfield earthquake motions and less than 0.2 for the Loma Prieta earthquake motion.

SUMMARY AND CONCLUSIONS

The usefulness of considering the site effects reported by the Kyoshin Net database has been illustrated by implementing neural networks as an alternative predictive tool. Two multilayer perceptron neural network models with back-propagation learning scheme have been generated with variable hidden layer sizes to predict the 5%-damped normalized response spectra. The prediction abilities of both the neural network models have been tested by using mean-square error as a statistical measure. For Model 1 71% of the predicted normalized response spectra have shown excellent matching (i.e., MSE < 0.1), whereas Model 2 has shown excellent matching in 60% cases. Although the neural network models in this study have made acceptable predictions, the accuracy of neural network estimation may need further improvement with the availability of more data sets from different locations and by considering reasonably uniform distribution of records with respect to local site effects while training the network. The models developed here may still serve as a useful guide for evaluating the site-specific response spectra, if detailed information of the local site conditions and potential fault sources are available within a hypocentral distance of 50 km. At the present stage of this study, the effectiveness of perceptron neural network has been demonstrated to predict the 5%-damped normalized response spectra. However, it will be useful to also investigate the applications of the other types of artificial neural networks. Further, in the present study the velocity structure, N -values of SPT and bulk density of soil have been considered over a maximum depth of 20 m and have not been extended to the top 30 m of the earth. However, in future studies it is proposed that these site effects may be extrapolated to at least 30-m depth (Boore, 2004). Also, this study has been limited to the 5%-damped normalized response spectra and therefore it could be extended to include the other values of damping. Another important aspect that could be looked into is the inclusion of fault mechanism as one more additional input to the neural network.

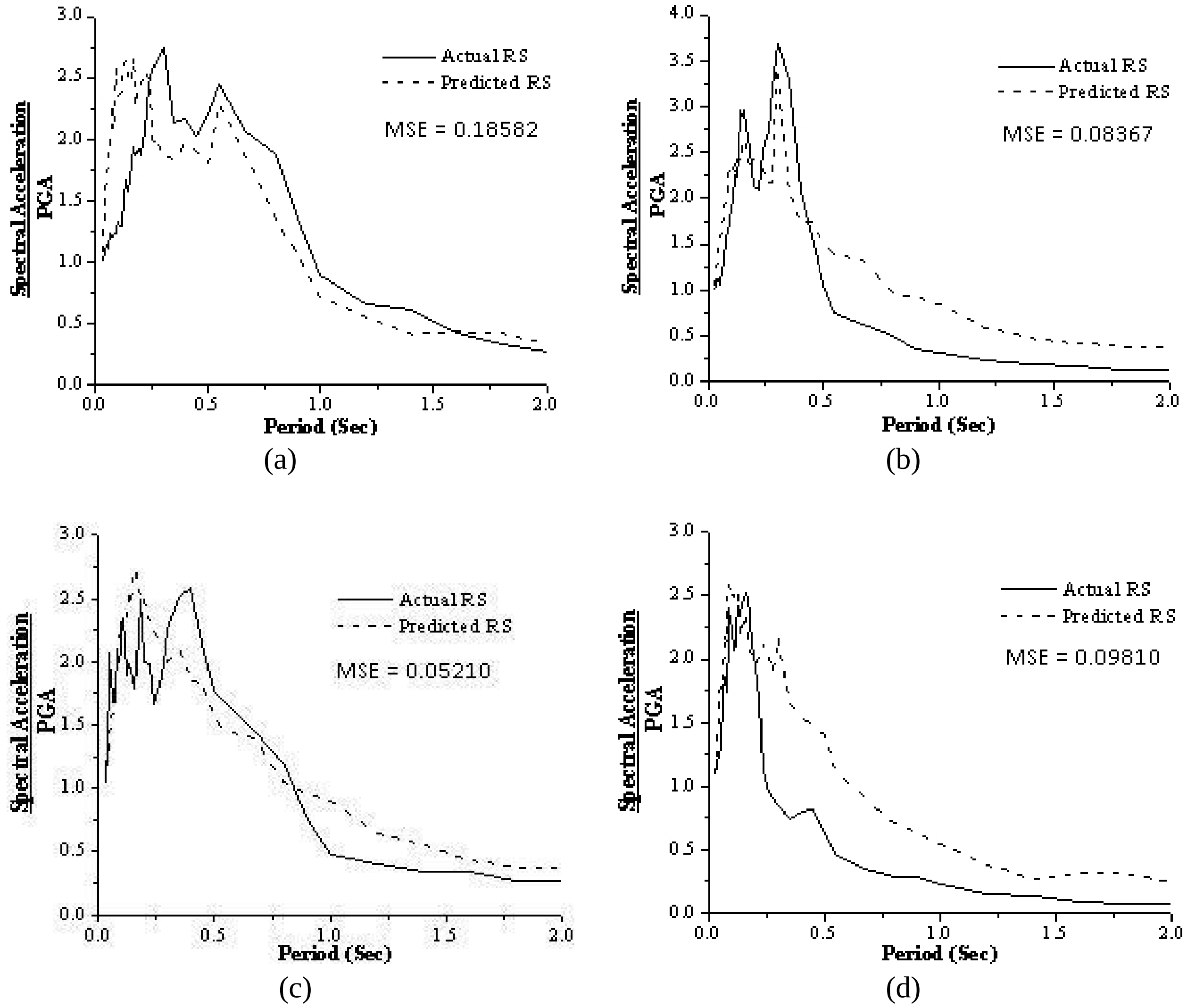


Fig. 9 Acceleration response spectra predicted by Model 2 for (a) Loma Prieta earthquake, (b) Big Bear earthquake, (c) Northridge earthquake and (d) Parkfield earthquake motions

The traditional regression approach models, to predict peak ground acceleration (PGA) and spectral acceleration (SA), have concentrated on finding the standard deviation, which is really a measure of the goodness of fit of the derived relationship with the data used and thus does not provide an insight for the records not used in the regression analysis. However, the proposed neural network models with backpropagation learning have been tested also for some of the records not used for the development of these models. The statistics of the results presented in this work are only for 10% of the data used for testing. Hence, the neural network methodology can be a better alternative and can provide excellent results compared to the conventional regression approach for predicting PGA and SA.

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