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ARTIFICIAL NEURAL NETWORK-BASED ESTIMATION OF PEAK GROUND ACCELERATION

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ABSTRACT

This paper presents the application of artificial neural networks (ANNs) for the estimation of peak ground acceleration (PGA) for the earthquakes of magnitudes more than 5.0 and hypocentral distances less than 50 km. Earthquake magnitude, hypocentral distance, and average values of four geophysical properties of the site, i.e., standard penetration test (SPT) blow count, primary wave velocity, shear wave velocity, and density of soil, have been used as six input variables to train the neural network. An attempt has also been made to train the neural network with magnitude, hypocentral distance and average shear wave velocity as three input variables. This study shows that ANN is a valuable tool for the prediction of peak ground acceleration at a site, given the magnitude and location of earthquake, and local soil conditions. It has also been observed that the prediction using the trained network with six inputs is better than that with three inputs.

KEYWORDS: Artificial Neural Networks, Peak Ground Acceleration, Hypocentral Distance, Shear Wave Velocity

INTRODUCTION

Historically, peak ground acceleration has been considered as a parameter representing the severity of shaking at a site. Traditionally, engineers have been interested in the acceleration, which can be related to force. Peak ground acceleration (PGA), also termed as zero-period acceleration (ZPA), is defined as the absolute maximum amplitude of recorded acceleration. In the past, more than 120 equations have been derived to predict PGA (Douglas, 2003). A majority of the published ground motion estimation relations involves assumption of a model (i.e., a mathematical function) that relates a given strong-motion parameter to one or more parameters comprising magnitude, distance, and local site conditions. Subsequently, by using a strong ground motion dataset, ground motion relations are developed from the statistical regression analyses. Regression analysis is used to determine the best estimates of various constants in the mathematical function. The emergence of artificial neural networks (ANNs) as efficient computing models has provided an alternative tool for the estimation of PGA by using the actual seismic data without any simplification and assumptions. This paper presents the application of multi-layer perceptron in estimating PGA, and is based on the M.Tech. thesis of the first author (Arjun, 2008).

In the following sections of the paper, the compilation and processing of strong ground motion data for the Japanese earthquake records from Kyoshin-Net database is reviewed and a brief conceptualization of neural networks is presented. In addition, the application of ANN for the estimation of PGA along with the simulation results is presented.

COMPILATION OF STRONG GROUND MOTION DATA

The database used in the study is taken from Kyoshin Net (K-NET) database. Kyoshin Net is a dense strong-motion network consisting of over 1,000 observatories deployed all over Japan at the interval of approximately 25 km. The instruments in these observatories are located on the ground surface. Each station has a digital strong-motion seismograph (i.e., accelerograph) with a wide frequency-band and wide dynamic range. In this study, a total of 84,456 horizontal components of earthquake records from 609 earthquakes of Japan with the magnitude of 5 and above have been downloaded from the internet

(Kyoshin Network[1]). The magnitude scale used by Kyoshin Net is the JMA magnitude M_{JMA} estimated by the Japan Meteorological Agency (JMA). Almost all the sites have the data on soil conditions, e.g., standard penetration value, density, while including the P- and S-wave velocities recorded, except for a few stations where this soil data is not available.

All stations operated by K-NET have K-NET95 accelerometers, with 108 dB dynamic range having a maximum measurable acceleration of 20 m/s^2 (i.e., 2000 Gals). The resolution of A/D converter is 18 bits with a sampling frequency of 100 Hz. The resolution of accelerometer is 1.5 m/s^2. For processing the strong-motion data, a computer program developed by the second author has been used. In this program, the raw data available in terms of counts in the data format of K-NET has been converted into acceleration values by using the scale factor given in the header of data. As the natural frequencies of all accelerographs were very high (i.e., about 200 Hz), there was no need of the instrument response correction.

A baseline correction of all acceleration time histories has been performed by using the least square line of the time history. Corrections have also been applied in frequency domain by filtering the high- and low-frequency components of the accelerograms. All accelerograms were bandpass filtered by removing the frequencies below 0.1 Hz and above 30 Hz. A sixth-order Butterworth bandpass filter was used for this filtering operation.

All the 84,456 horizontal components of the earthquake records were manually viewed by plotting the acceleration time histories, and it was observed that in some of the time histories, two or more events had taken place. All such records with multiple events have been considered only up to the end of the first event by changing the duration of the motion in the header of the data format.

The average values of shear wave velocity, primary wave velocity, standard penetration test (SPT) blow count, and the density of soil have been used. The averaging of these parameters has been done as per FEMA-356 (FEMA, 2000). These values were calculated as shown below:

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

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.

ARTIFICIAL NEURAL NETWORKS

Artificial neural networks are among the most powerful learning models that are capable of establishing a mapping relationship between the given sets of inputs and outputs. The theoretical background on neural networks (NN) can be found in a large volume of literature (e.g., Zurada, 1992; Hagan et al., 1996; Bishop, 1995; Mehrotra et al., 1996; Haykin, 1994; Demuth et al., 2006). Here, only a brief conceptualization of neural networks is given.

There is no universally accepted definition of an artificial neural network. It is a massively parallel-distributed information processing system that has certain performance characteristics resembling the biological neural networks of the human brain (Haykin, 1994).

Neural networks have been inspired by the neuronal architecture of the brain. A neuron is the information-processing unit of the neural network, much like the brain in human beings (Haykin, 1994). Figure 1 shows the block diagram of a neuron.

A neuron consists of three main parts: a set of synapses, which connect the input signal x_j to the neuron via a set of weights, w_{kj}; an adder u_k which sums up the input signals, weighted by the respective

[1] Website of Kyoshin Network, http://www.k-net.bosai.go.jp

synapses of the neuron; and an activation function $\phi(.)$ for limiting the amplitude of the output of the neuron. At times, a bias b_k is added to the neuron to increase or decrease the net output of the neuron.

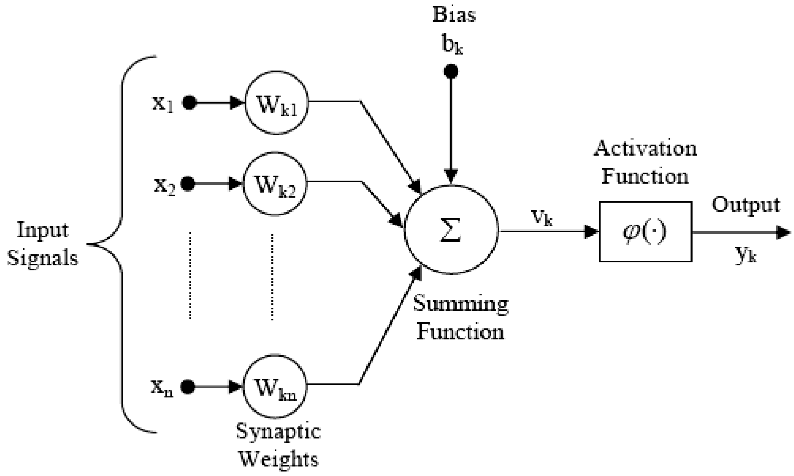

Fig. 1 The block diagram of a neuron (Haykin, 1994)

Mathematically, a neuron k is described as (Haykin, 1994)

$$u_k = \sum_{j=1}^{n} w_{kj} x_j \tag{2}$$

$$y_k = \phi(u_k + b_k) \tag{3}$$

where $x_1, x_2, x_3, \ldots, x_n$ are the input signals; $w_{k1}, w_{k2}, \ldots, w_{kn}$ are the weights for the neuron k; b_k is the bias; u_k is the adder or the linear combiner; $\phi(.)$ is the activation function; and y_k is the output signal of the neuron.

The output range of the neuron depends on the type of activation function used. There are four types of activation functions, which are in common use (Demuth et al., 2006), namely, the hard-limit activation function, the log-sigmoid activation function, the tan-sigmoid activation function, and the linear activation function.

1. Multilayer Perceptron

Network architecture refers to the manner in which the neurons are structured and connected to each other. There are a wide variety of networks depending on the nature of the information processing carried out at the individual neurons, the topology of the links, and the algorithm for the adaptation of link weights. Network architectures can generally be classified as (1) single-layer feedforward, (2) multi-layer feedforward, (3) recurrent, and (4) lattice structure (Haykin, 1994). Furthermore, the networks can be fully or partially connected, meaning that neurons in a given layer might not be connected to all the neurons in the preceding or the following layers.

In this study, multi-layer feedforward neural networks, commonly referred to as multilayer perceptrons (MLPs), have been used. Multilayer perceptrons have been applied successfully to solve some of the difficult and diverse problems in several domains including the structural engineering applications. It has a layered architecture consisting of input, hidden, and output layers. The input signal propagates through the network in a forward direction on a layer-by-layer basis. The output of each layer is transmitted to the input of neurons in the next layer through weighted links. The hidden layer aids in performing useful complex computations by extracting progressively more meaningful features from the input layer. Figure 2 shows a one-hidden-layer MLP with *D* inputs, *K* hidden processing elements and *M* outputs (i.e., MLP (*D-K-M*)).

Training and weight adaptation is done in MLPs in a supervised manner with a highly popular algorithm known as the error back-propagation algorithm. Back-propagation is a very powerful and computationally efficient algorithm. Back-propagation learning consists of two phases. During the first phase, inputs presented to the input layer propagate through the network, layer by layer, to the output layer, where the error between the desired output and the network output is calculated. During this phase, the weights are not modified, and they remain constant. During the second phase, the error signal is propagated backwards from the output layer through the network to the input layer. During this stage, the weights are adjusted in such a way that the actual output moves closer to the desired output. The following equation is used for the adjustment of connection weights:

$$\Delta w_{ij}(n) = \eta(\partial E / \partial w_{ij}) + \alpha \Delta w_{ij}(n-1) j \qquad (4)$$

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 epoch; η is the learning rate; and α is the momentum.

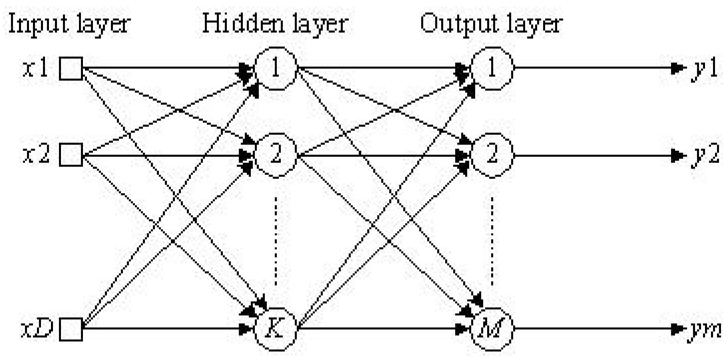

Fig. 2 Multilayer perceptron, MLP (*D-K-M*), with one hidden layer

The momentum factor can speed up training in the very flat regions of the error surface and help prevent oscillations in the weights. A learning rate is used to increase the chance of avoiding the training process being trapped in the local minima instead of global minima. The derivation of the back-propagation algorithm can be found in the literature (Haykin, 1994).

2. Implementation of Back-Propagation Algorithm

Networks have been 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, Inc.[2]) was used for the simulation of neural network models. The 'Error Criteria' family in NeuroSolutions computes different error measures that can be used to train the network. In this study, the criterion used is the L_2-norm or mean squared error (MSE) criterion. It simply computes the difference between the system output and the desired signal and squares it.

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

APPLICATION OF ANN FOR ESTIMATING PGA

In this study, the earthquake records from Kyoshin Net database have been used for training the neural networks. A total of 1,850 horizontal components of earthquake records from the 145 earthquakes of magnitudes more than 5.0, and with hypocentral distances of less than 50 km, have been used for training the networks. Figure 3 gives the scatter plot of magnitude versus hypocentral distance of the data used.

An average of the two horizontal components has been used for the computation of peak ground acceleration. The so-obtained set of 925 values from the 145 earthquakes has been used for training and testing the neural networks.

[2] Website of NeuroDimension, Inc., http://www.nd.com

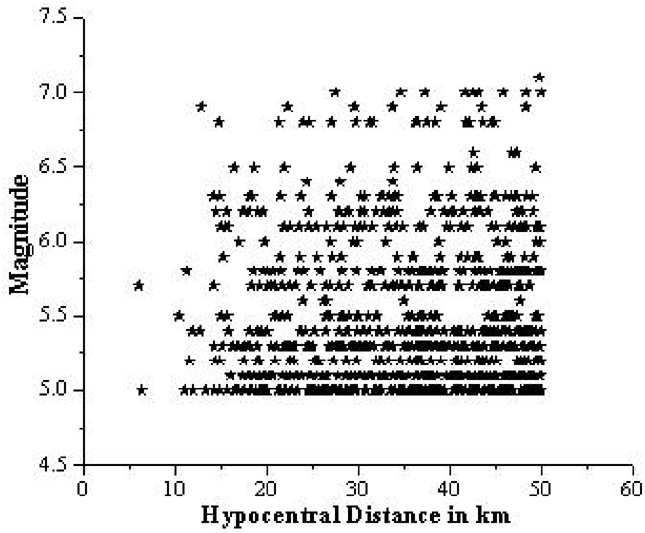

Fig. 3 Scatter plot of magnitude versus hypocentral distance

The prediction of PGA using ANN has been taken up in two stages. In the first stage, earthquake magnitude M, hypocentral distance H, average SPT blow count $\bar{N}$, average primary wave velocity $\bar{v}_p$, average shear wave velocity $\bar{v}_s$, and average density $\bar{\rho}$ of soil have been used as the input variables, and peak ground acceleration has been considered as the output variable. In the second stage, the neural network with three nodes on the input layer representing earthquake magnitude M, hypocentral distance H, and the average shear wave velocity $\bar{v}_s$ has been created, and PGA has been considered as the output. The database has the values of H ranging from 0 to 50 km, $\bar{N}$ ranging from 1 to 99, $\bar{v}_p$ ranging from 450 to 3590 m/s, $\bar{v}_s$ ranging from 85 to 1676 m/s and $\bar{\rho}$ ranging from 1125 to 2425 kg/m^3.

The total set of 925 values has been divided into three sets:

1. training set,
2. validation set, and
3. testing set.

The training set, which is about 80% of the complete dataset, has been used to train the network; the validation set, which is about 10%, has been used for the purpose of monitoring the training process, and to guard against overtraining; and the testing set, which is about 10%, has been used to judge the performance of the trained network. The training was stopped when the cross-validation error began to increase, i.e., when the cross-validation error was minimum.

1. Six Inputs-Based Network

The ANN model with six nodes on the input layer has been created. The six nodes represent the earthquake magnitude M, hypocentral distance H, average SPT blow count $\bar{N}$, average primary wave velocity $\bar{v}_p$, average shear wave velocity $\bar{v}_s$, and average density $\bar{\rho}$ of soil. A set of 825 values was selected randomly from the total set of 925 values for training and cross-validation, and the remaining set of 100 values was used to test the performance of the trained networks. Four different datasets of 825 values were created and randomized. The four datasets were trained independently, and the dataset, which gave the minimum mean square error (MSE), was considered for testing the network. Parametric studies have been carried out in order to evaluate the optimum values of the hidden nodes and learning parameters. Various parameters used for training the network are given in Table 1. Figure 4 shows one hidden layer network model, with 15 hidden neurons, six input neurons and one output neuron.

Typical trained patterns have been presented in Table 2 for the six inputs-based network. In this table, MSET represents the mean square error of the training set, and MSECV represents the mean square error of the validation set. The network with 15 hidden neurons in the hidden layer (i.e., 6-15-1) showed the best performance with minimum MSE.

Table 1: 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	0.9	0.9

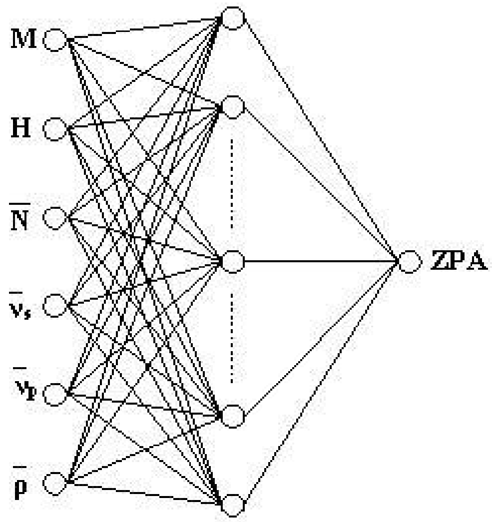

Fig. 4 Neural network architecture with six inputs for the prediction of PGA

Table 2: MSE of Six Inputs-Based Network

Dataset	Network	Epochs	MSET	MSECV	Time Taken (h:min:s)
Dataset 3	6-10-1	10000	1.36×10^{-3}	1.43×10^{-3}	0:02:00
	6-7-1	10000	1.42×10^{-3}	1.50×10^{-3}	0:01:57
	6-14-1	10000	1.35×10^{-3}	1.45×10^{-3}	0:02:25
	6-15-1	10000	1.31×10^{-3}	1.40×10^{-3}	0:02:28
	6-16-1	10000	1.36×10^{-3}	1.44×10^{-3}	0:02:32
	6-18-1	10000	1.34×10^{-3}	1.49×10^{-3}	0:02:39
	6-19-1	10000	1.35×10^{-3}	1.45×10^{-3}	0:02:41
	6-10-1	20000	1.17×10^{-3}	1.32×10^{-3}	0:04:03
	6-18-1	20000	1.16×10^{-3}	1.28×10^{-3}	0:05:41
	6-15-1	20000	1.14×10^{-3}	1.28×10^{-3}	0:05:16
	6-15-1	30000	1.11×10^{-3}	1.19×10^{-3}	0:08:11
	6-15-1	50000	9.33×10^{-4}	1.12×10^{-3}	0:13:50

2. Observations of Six Inputs-Based Network

The results obtained after testing the six inputs-based network were quite promising. These results have been compared by calculating the percentage error between the actual and predicted values of peak ground acceleration. The efficiency of results obtained from the tested network has been categorized as follows:

1. the results with percentage error less than 3% as accurate,
2. the results with percentage error in the range of 3–5% as substantially accurate,
3. the results with percentage error in the range of 5–10% as moderately accurate, and
4. the results with percentage error more than 10% as incorrect.

The efficiency of results, which have been categorized as above, is tabulated in Table 3. The comparison between the desired PGA and the ANN output with six inputs is shown in Figure 5.

Table 3: Efficiency of the Six Inputs-Based Network

Serial No.	Efficiency	Percentage
1	Accurate	65
2	Substantially Accurate	10
3	Moderately Accurate	5
4	Incorrect	20

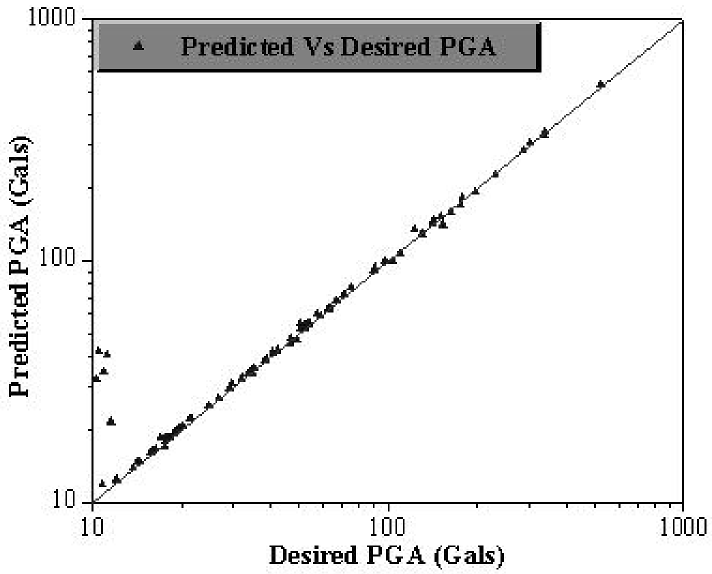

Fig. 5 Scatter plot of predicted PGA versus desired PGA (with six inputs)

From the results, it is seen that the ANN with six inputs has predicted 65% accurate results on PGA along with some inaccurate results. It is also observed that the incorrect results are for the PGAs less than 0.1 m/s^2 (i.e., 10 Gals). It can therefore be concluded that ANN cannot predict lower peak ground accelerations correctly with the above trained network. This could be either due to the reason of overgeneralization during the training or because the training space contained very little data pertaining to the PGA less than 0.1 m/s^2 (i.e., 10 Gals).

3. Three Inputs-Based Network

Except the K-Net strong motion database of Japan, no other database provides the detailed soil condition data at the recording stations. Only few databases provide the average shear wave velocity $\overline{V}_s$ recorded at the stations. Therefore, for the use of trained networks based on the Japanese strong motion data in other countries, it is essential to train the networks for three inputs.

An ANN model with three nodes on the input layer has been created. The three nodes represent the earthquake magnitude M , hypocentral distance H , and average shear wave velocity $\overline{V}_s$. Similar to the six inputs-based network, a set of 825 values was selected randomly from the total set of 925 values for the purpose of training and cross-validation, and the remaining 100 values were used to test the performance of the trained networks. Four different datasets of 825 were created and randomized. The four data sets were trained independently, and the dataset, which gave the minimum mean square error (MSE), was considered for testing the network. The parameters used for training the network are given in Table 4. Figure 6 shows a hidden layer network model, with 18 hidden neurons, three input neurons and one output neuron.

Typical trained patterns have been presented in Table 5 for the three inputs-based network. In this table, MSET represents the mean square error of the training set, and MSECV represents the mean square error of the validation set. The network with 18 hidden neurons in the hidden layer (i.e., 3-18-1) showed the best performance with minimum MSE.

Table 4: Parameters for Neural Network with One Hidden Layer for Three Inputs

Description	Hidden Layer	Output Layer
Transfer Function	TanhAxon	SigmoidAxon
Learning Rule	Momentum	Momentum
Step Size	1.0	0.1
Momentum	0.9	0.9

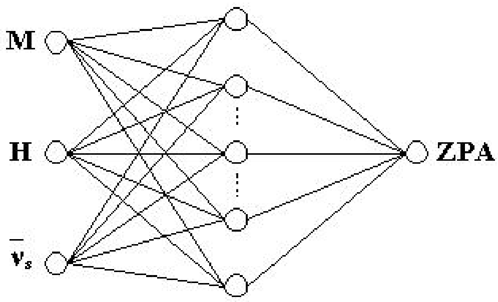

Fig. 6 Neural network architecture with three inputs for the prediction of PGA

Table 5: MSE of Three Inputs-Based Network

Dataset	Network	Epochs	MSET	MSECV	Time Taken (h:min:s)
Dataset 4	3-4-1	10000	1.56×10^{-3}	1.93×10^{-3}	0:01:39
	3-10-1	10000	1.55×10^{-3}	1.85×10^{-3}	0:01:57
	3-15-1	10000	1.49×10^{-3}	1.71×10^{-3}	0:02:18
	3-15-1	20000	1.48×10^{-3}	1.67×10^{-3}	0:05:07
	3-18-1	10000	1.43×10^{-3}	1.62×10^{-3}	0:02:22
	3-18-1	20000	1.41×10^{-3}	1.59×10^{-3}	0:05:49
	3-18-1	30000	1.39×10^{-3}	1.53×10^{-3}	0:07:41
	3-18-1	40000	1.38×10^{-3}	1.52×10^{-3}	0:10:39
	3-18-1	50000	1.37×10^{-3}	1.51×10^{-3}	0:13:10

The efficiency of results obtained from the tested network has been categorized in a similar manner as that of the results from the six inputs-based network. The efficiency of results has been presented in Table 6. Figure 7 shows the scattered plot of desired PGA versus predicted PGA.

4. Observations of Three Inputs-Based Network

From the results presented, it is observed that the percentage of accurate results with three inputs is less when compared with that with six inputs. Further, it is observed that the trained networks are not capable of mapping peak ground accelerations less than about 0.2 m/s^2.

5. Testing of Trained Network for Few Significant U.S. Earthquakes

Only few organizations provide information on the average shear wave velocity $\bar{v}_s$ recorded at the stations. One such organization that provides the average shear wave velocity $\bar{v}_s$ recorded at the stations is the California Strong Motion Instrumentation Program (CSMIP). In this study, the processed data from the CSMIP database has been taken. The data consists of the ground motion recorded at a particular station for a particular event. In addition, for each recording station the average shear wave velocity $\bar{v}_s$, as recorded, is also available. The earthquake magnitude M, the hypocentral distance H, and the average shear wave velocity $\overline{v}_s$ are considered as the inputs, and the PGA is considered as the output. An average of the two horizontal components has been used for the computing the PGA. 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 from 5 to 7. The networks trained with three inputs for the K-Net records were tested for a few significant CSMIP records. The testing has been done for the following records:

1. Loma Prieta Earthquake record (M_w = 7.0; October 17, 1989; Eureka Canyon Road, Corralitos station),
2. Big Bear Earthquake record (M_w = 6.4; June 28, 1992; Civic Center Grounds, Big Bear Lake station),
3. Northridge Earthquake record (M_w = 6.7; January 17, 1994; Cedar Hill Nursery A, Tarzana station), and
4. Parkfield Earthquake record (M_w = 6.0; September 28, 2004; Gold Hill 3W, Parkfield station).

The PGAs predicted by the neural network (trained for three inputs) for these ground motions are tabulated in Table 7.

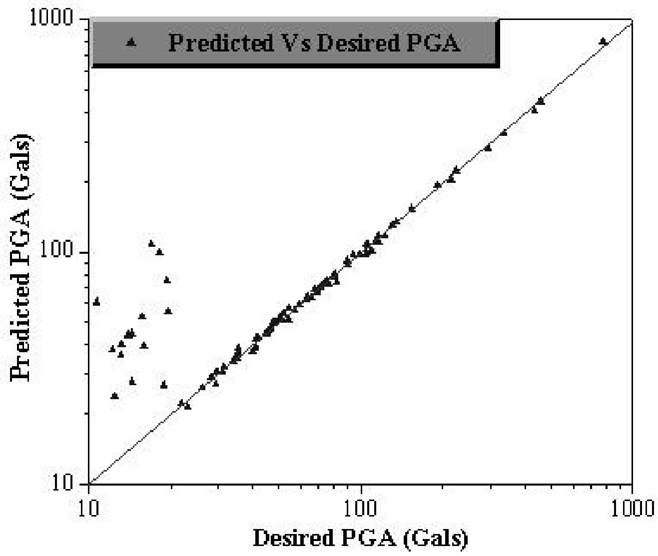

Fig. 7 Scatter plot of predicted PGA versus desired PGA (with three inputs)

Table 6: Efficiency of the Three Inputs-Based Network

Serial No.	Efficiency	Percentage
1	Accurate	44
2	Substantially Accurate	20
3	Moderately Accurate	12
4	Incorrect	24

CONCLUSIONS

A multi-layer perceptron architecture with the error back-propagation learning algorithm has been adopted to estimate peak ground accelerations for the Japanese earthquake records with earthquake magnitudes more than 5.0 and hypocentral distances less than 50 km. The PGAs predicted by the ANN with six inputs have been found to be more accurate in comparison with the three-inputs case. From these observations it has been concluded that the perceptron model is quite promising for the estimation of peak ground acceleration and that the obtained results might be of significant importance for future project sites coming up near the active faults with expected hypocentral distances less than 50 km. The PGAs predicted with six inputs showed accurate results (with percentage errors less than 3%) for 65% cases, whereas, in the case of three inputs, 44% of the predicted PGAs showed accurate results. It has been also seen that a majority of the incorrect results (with percentage errors more than 10%) are for the lower peak ground accelerations. A careful selection of the data may enhance the predictions, especially in the case of PGAs more than 0.1 m/s^2 (i.e., 10 Gals). The PGAs predicted by the three inputs-based network for a few significant U.S. earthquakes were found to be quite close to the desired values and generally on the higher side.

Table 7: PGAs Predicted by the Three Inputs-Based Network

Earthquake	M	H (km)	$\overline{V}_s$ (m/s)	Desired PGA (m/s^2)	Network PGA (m/s^2)	Percentage Error
Loma Prieta	7.0	20.13	462	5.435	5.947	9.42
Big Bear	6.5	12.9	339	5.032	5.284	5.00
Northridge	6.4	18.7	257	13.576	11.786	13.18
Parkfield	6.0	9.5	438	5.372	5.685	5.82
Percentage Error = 100×|(Network PGA–Desired PGA)|/|Desired PGA|						

Results of the predicted PGA have indicated that ANN is a promising tool for the estimation of peak ground acceleration at a site. The performance of networks may be improved by carrying a detailed parametric study on the optimal network to be used for predicting the peak ground acceleration. Future work may also examine the application of hybrid artificial intelligence techniques.

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