ESTIMATION OF PEAK GROUND ACCELERATION USING ARTIFICIAL NEURAL NETWORK

Rajiv Sachdeva, Ashok Kumar, M.L. Sharma
Department of Earthquake Engineering, Indian Institute of Technology, Roorkee, India

SUMMARY
This paper presents a study to estimate the averaged horizontal peak ground acceleration (PGA) of strong motion data from Japan using Artificial Neural Network (ANNs), as a tool to remove uncertainties in attenuation equations. The input variables used in construction of ANNs model were magnitude, hypo-central distance, fault type, average shear wave velocity and output parameter was PGA. By using Back Propagation (BP) algorithm, 75 % of respective dataset was used to train the ANNs model and remaining 25 % data were used for validation and testing purpose. Data set kept for testing is then used to check the performance of neural network by making appropriate statistics. The result showed that the graph between predicted PGA values by network and observed PGA values give high correlation coefficient value (i.e. R). To show the authenticity of this approach, estimated value of PGA by ANNs model was compared with one of the regression model, and results show that ANNs is a valuable approach for prediction of PGA at a site.

Keywords: Peak Ground Acceleration, Artificial Neural Network and Back Propagation Algorithm

1. INTRODUCTION

Earthquake ground motions are affected by several factors including source, path, and local site conditions. These factors are considered in engineering design practice through seismic hazard analyses that normally use attenuation relations derived from strong motion recordings to define the occurrence of an earthquake with a specific magnitude at a particular distance from the site. Knowing the characteristics of ground motions in a specified region is vital for the design of engineering structures. Loading conditions appropriate for a particular type of structure are expressed in terms of ground motion. Peak ground acceleration (PGA) is commonly used to define the ground motions, most of the times it is estimated by the attenuation relationships which are developed using regression analysis of strong ground motion recorded during previous earthquakes. In the regression analyses, the PGA is generally calculated as a function of independent variables like magnitude, source to site distance, local site conditions, type of faulting and wave propagation (Kramer, 1996; Douglas, 2003). However, these independent variables generally present uncertainties in the construction of database for the recording station, because they often oversimplify reality. Beside these uncertainties, the shortcoming of the modelling and the analysis technique of regression used strongly effect the predictive equations such that different coefficients of independent variables may be obtained. These uncertainties due to both physical aspects as well as computational aspects lead to significant residuals between the estimated PGA from the predictive equations and the observed value measured at particular site. Therefore, these predictive equations had limited ability to predict the observed PGA value.

On the other hand a soft computing technique known as Artificial Neural Networks (ANNs) can be used to remove uncertainties in predictive equations. Since ANNs are not defined as a specific equation form, they can infer solutions to problems having nonlinear and complex interaction among the variables and find functional relationship between the input and output of dataset. In recent years many authors used ANNs as a tool to predict the characteristics of strong ground motions. Ghaboussi and Lin (1998) used ANNs as a tool to generate spectrum compatible accelerograms from response spectra. Lin and Ghaboussi (2001) applied stochastic Neural Networks to generate multiple spectrum accelerogram from response spectra or design spectra. Pandya et al. (2002) have used ANN to predict site-specific response spectra. Lin et al. (2002) used Neural Network to estimate the damage in bridges after major earthquake in Taiwan. Tehranizadeh and Safi (2004) used ANN model based on back propagation as a tool to obtain appropriate design spectra for different site conditions using more than 2000 ground motion records of Iran. Güllü and Ercelebi (2007) used ANN to predict PGA using strong motion data from using Fletcher Reeves conjugate back propagation. Günaydin et al. (2008) used feed forward back propagation algorithm to predict PGA using moment magnitude, hypocentral distance, focal depth and site condition as inputs parameter for north western Turkey. Arjun and Kumar (2009) have used ANN to predict PGA using six input variable as magnitude, Hypocentral, average SPT blow count, average primary wave velocity, average shear wave velocity and average density of soil. So we have found that many researcher in the past used ANN as tool to predict site specific response spectra, and PGA.

In present study, an attempt has been made to estimate the averaged horizontal peak ground acceleration of strong motion as a function of earthquake magnitude, source to site distance, fault type and averaged shear wave velocity using Artificial Neural Network (ANNs). The database used in present study is taken from Kyoshin net (K-NET) database of Japan The input variables used in construction of ANNs model were magnitude, hypo-central distance, average shear wave velocity (Vs), fault type (i.e. Normal, Reverse and Strike slip) and output parameter was PGA. By using back propagation algorithm (BP), 75% of respective dataset was used to train the ANNs model and remaining 25 % data were used for validation and testing purpose. Data set kept for testing is then used to check the performance of each neural network by making appropriate statistics. The result showed that the graph between predicted PGA values by network and observed PGA values give high correlation coefficient value (R). To show the authenticity of this approach, estimated value of PGA by ANNs model was compared with one of the regression model, and results show that ANNs In valuable approach for prediction of PGA at a site.

2. ARTIFICIAL NEURAL NETWORK

Artificial Neural Networks (ANNs) are computational models derived from the biological structure of neurons which imitate the operation of human brain. Artificial Neural Networks are nonlinear information (signal) processing devices, which are built from interconnected elementary processing devices called neurons. ANNs like people learns by data examples presented to them in order to capture the fine functional relationship among the data even if underlying relationships are unknown or the physical meaning is difficult to explain. It has advantaged over the most traditional empirical and statistical model, which require prior information about the nature of the relationships among the data.

Back propagation algorithm (Hertz et al., 1991; Zurada, 1992; Haykin, 1999) is the most popular Neural Networks used particularly for prediction applications and data modelling. GE Hinton, Rumelhart and R.O. Williams first introduced Back propagation network (BPN) in 1986. Back propagation is a systematic method for training multi-layer artificial Neural Networks. It is a multilayer forward network using extend gradient-descent based delta-learning rule, commonly known as back propagation (of errors) rule. Back propagation provides a computationally efficient method for changing the weights in a feed forward network, with differentiable activation function units, to learn a training set of input-output examples. Being a gradient descent method it minimizes the total squared error of the output computed by the net. The network is trained by supervised learning method. A typical structure and operation of multilayer Feed Forward Neural Network with back propagation algorithm as shown in Fig. 1. For Feed Forward Neural Network (FFNN), which is the most commonly used ANN; processing units are usually arranged in layers. Each network has an input layer, an output layer and one or two hidden layer. Each processing unit in a specific layer is fully or partially connected to many other processing units in different layer via weighted connections. No

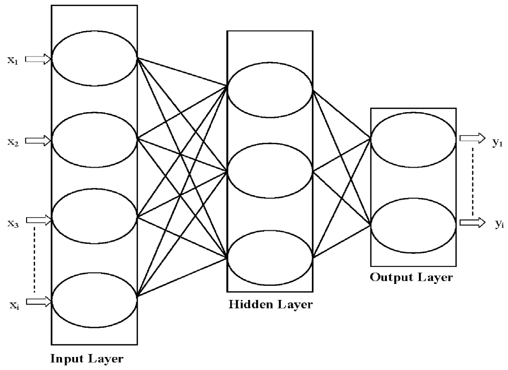

Figure 1. Typical structure of ANN (Shahin et al., 2001)

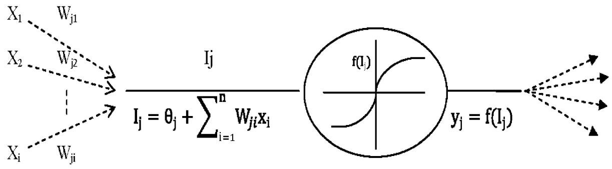

Figure 2. Processing unit of ANN (Shahin et al., 2001)

connection is allowed between the processing units within a same layer. The scalar weights determine the strength of the connections between interconnected neurons. A zero weight refers to no connection between two neurons and a negative weight refers to a prohibitive relationship. From many other processing units, an individual processing element receives its weighted inputs, which are summed and a bias unit or threshold is added or subtracted. The bias unit is used to scale the input to a useful range to improve the convergence properties of the Neural Network. The result of this combined summation is passed through a transfer function (like logistic sigmoid or hyperbolic tangent) to produce the output of the processing unit. For node j, this process is summarized in Eqs. 1and 2 (Shahin et al., 2001) and illustrated in Fig. 2.

$$I_j = \theta_j + \sum_{i=1}^{n} W_{ji} x_i \qquad (1)$$

$$y_i = f(I_j) \qquad (2)$$

where I_j = the activation level of node j ; W_{ji} = the connection weight between nodes j and i; x_i = the input from node I, i=0,1,…..,n ; θ_j = the bias or threshold for node j ; y_j = the output node j ; and $f(I_j)$= the transfer function. The propagation of information in FFNN starts at the input layer where the input data are presented. The inputs are weighted and received by each node in the next layer. The weighted inputs are then summed and passed through a transfer function to produce the nodal output, which is weighted and passed to processing units in the next layer. The network adjusts its weights on presentation of a set of training data and uses a learning rule until it can find a set of weights that will produce the input-output mapping that has the smallest possible error. The above process is known as 'learning' or 'training'.

3. STRONG MOTION DATA (JAPANESE DATA)

In this study, the strong ground motion data of Japan was utilized for the ANN application to predict PGA. Kyoshin Net (K-NET) database of Japan provides one of the most extensive records of various features of strong ground. Kyoshin Net is a dense strong-motion networking consisting of over 1,000 observatories deployed all over Japan at free-field sites at intervals of approximately 25 km covering the country with instruments located on ground surface. Each station has a digital strong-motion seismograph (accelerometer) with a wide frequency-band and wide dynamic range, having a maximum measurable acceleration of 2000 Gals. We started working with 2, 19,050 (only horizontal component) time histories from 3471 earthquakes recorded at different locations in Japan. All K-NET data is openly available on registration through their Web-site (http://www.k-net.bosai.go.jp,). Out of above we obtained 1355 averaged horizontal components of records having magnitude varying between 5 to 8, hypocentral distance of 200 Km or less, focal depth of 35 km or less , PGA of 5 gals or more and recorded at stations having average shear wave velocity (V_{s20}) between 180 and 1200 m/sec.

The average values of shear wave velocity of soil have been done as per FEMA 356, 2000. This value was calculated using eq. (3):

$$\overline{V}_s = \frac{\sum_{i=1}^{n} d_i}{\sum_{i=1}^{n} \frac{d_i}{V_{si}}} \qquad (3)$$

Where V_{si} = Shear wave velocity of i^{th} layer; d_i = Depth of the i^{th} layer; n = Number of layers of similar soil materials for which data is available.
Source mechanisms of these earthquakes are taken from (http://www.fnet.bosai.go.jp) and type of faulting (i.e. Normal, Reverse and Strike Slip) is assign to each earthquake using tectonic map of Japan. Distributions of JMA magnitude of the data used with (a) Hypocentral distance and (b) PGA are shown in Fig. 3 and Fig. 4 respectively.

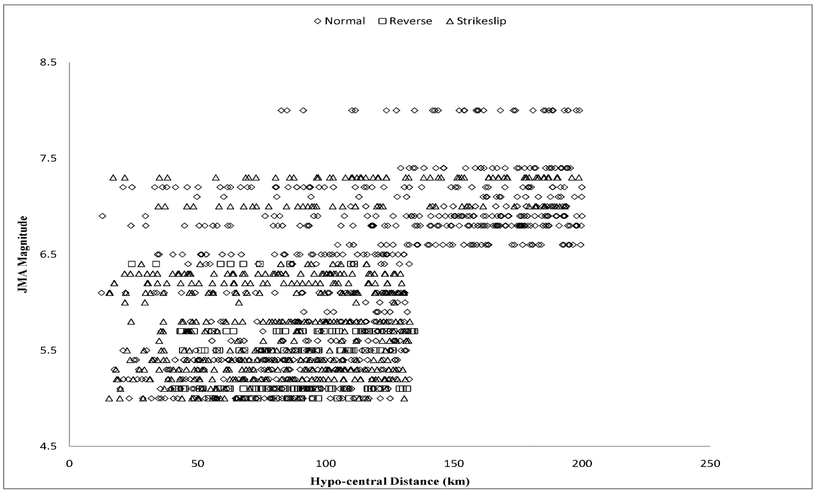

Figure 3. Distribution of JMA Magnitude with respect to Hypo-central Distance.

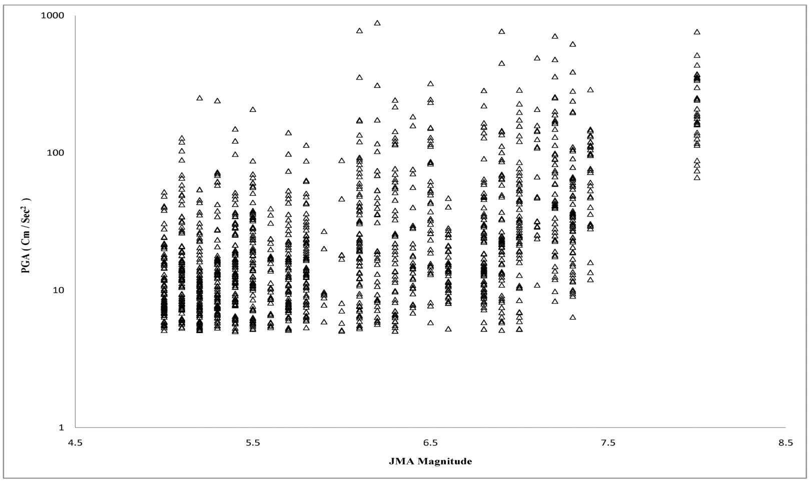

Figure 4. Distribution of PGA w.r.t JMA Magnitude.

4. DEVELOPMENT OF ANN MODEL

Steps shown in Fig. 5 are used for the development of ANN model to predict PGA by implementing multilayer feed forward Neural Network with BPN learning scheme using Japanese earthquake.

4.1. Forming inputs and outputs

The most important step in ANN modelling problem before training any network particularly for the back propagation is the selection of inputs and outputs since it has significant impact on model performance (Kaastra and Boyd, 1995). In present study ANN algorithms were composed of 4 inputs parameters (magnitude, hypo-central distance, type of faulting and averaged shear wave velocity) in the input layer and one output parameter (PGA) in the output layer. Here we assign the numbers to type of faulting for Normal-1, Reverse-2 and Strike Slip-3. Entire dataset comprised of 1355 averaged horizontal components of earthquake records is classified into three categories (Stone, 1974):- (1) The training set, (2) The validation set, and (3) The testing set. The training set, which consisted of about 75 % of the data set, is used to train the network by adjusting the connection weights; the validation set, which is about 10 % of the data set, is used for the purpose of monitoring the training process at various stages and to guard against overtraining. The testing set, which is taken about 15 % of the data set, is used to judge the performance of the trained network.

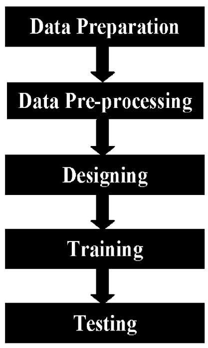

Figure 5. Steps used for development of ANN model

4.2. Pre-processing of data

Neural Networks works only with numeric data and numeric values should be scaled before feeding them to the network input, because artificial neurons have a limited range of operating value. Therefore we modify the data before it is fed to a Neural Network which is known as preprocessing of data. The objective of preprocessing the input data is to reduce its dimensionality and simplify the patterns to be recognized in order to avoid a huge amount of computation and to improve the network's generalization ability. In preprocessing the whole inputs parameters is converted in the scaling range of -1 to 1 and output parameter is converted in the scaling range of 0 to 1.

4.3. Search for the Finest Network

To search for finest network hit and trial method is used. Initially a large numbers of architecture were taken on trial. Criteria used to filter out the best architectures were correlation coefficient and network error. For given dataset, the search for finest network was performed in various steps. In the first step, an exhaustive search has been made among a large array of networks with a single and double hidden layer with different number of hidden neurons. From that search, the best performing five architectures were chosen on the basis of correlation coefficient. In the second step, the chosen architecture is then trained for higher number of epochs with different momentum and learning rate. In the third step the best performing network in terms of correlation coefficient and network error from the chosen architecture are once again trained for increasing number of epochs, the training is stopped when the validation error is minimum in order to obtain the suitable network model. The correlation coefficients (R) and the network error used to evaluate the accuracy of each model are defined as

$$R = \frac{\sum_{i=1}^{n}(X_i - \overline{X}) - (Y_i - \overline{Y})}{\sqrt{\sum_{i=1}^{n}(X_i - \overline{X})^2 \sum_{i=1}^{n}(Y_i - \overline{Y})^2}} \tag{4}$$

where X_i is observed PGA value at i^{th} record, Y_i is predicted PGA value at i^{th} record, n is total number of testing data, $\bar{X}$ and $\bar{Y}$ is the mean of X_i and Y_i respectively. The correlation coefficient (R) is a statistical measure of strength of the relationship between the actual values and network outputs. The R can range from -1 to +1. The closer R is to 1, the stronger the positive linear relationship, and the closer R is to -1, the stronger the negative linear relationship. When R is near 0 there is no linear relationship. Network error is a value in terms of Sum of Squares, it is used to rate the quality of the Neural Network training process. The smaller the network's error is, the better the network has been trained. Minimization of the error is the main objective of Neural Network training. *Sum-of-Squares* is the most common error function and is the sum of the squared differences between the actual value (target column value) and Neural Network output.

4.4. Training and Testing of ANN models

ANN model with four nodes in the input layer and one node in the output layer has been created. The four nodes of the input layer represent the earthquake magnitude (M), hypo-central distance (H), type of faulting and Averaged shear wave velocity (Vs). A set of 1152 was selected randomly from the total set of 1355 for training and cross validation and the remaining 203 was used to test the performance of the trained networks. An exhaustive search has been done for the single hidden layer and the double hidden layer, and then the best five architectures based on correlation are selected for training as shown in Table 1.

Table 1. Architecture exhaustive search results

Architecture	Epochs	Correlation
4-40-17-1	5000	0.956885
4-29-25-1	5000	0.95121
18-33-25-1	5000	0.950632
18-21-40-1	5000	0.939185
18-31-13-1	5000	0.938564

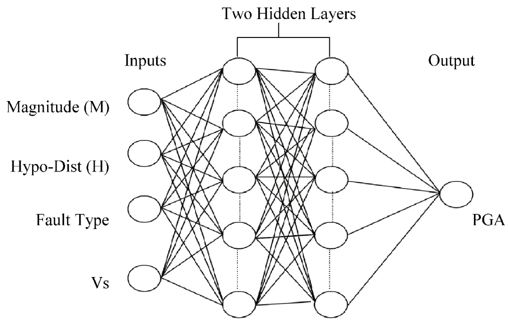

Figure 6. ANN architecture (4-40-17-1).

Architectures shown in Table 1 are further trained with different momentum, learning rate and for different number of epochs. It has been found that the network with 40, 17 hidden neurons in the first, second hidden layer (4-40-17-1) shown in Fig. 6 had the best performance with better correlation and minimum network error. The various parameters used for training this network are shown in Table 2.

The network was then further trained for 15500 epochs and finally test dataset was used to check the performance of the trained network. Network result for 15500 epochs is shown in Table 3. Comparison between the predicted PGA and true PGA is shown in Fig. 7. The percentage error is given by **Percentage Error = [| (Network $\overline{V}_s$ - Actual $\overline{V}_s$)| / | Actual $\overline{V}_s$ |] x 100(%).**

Table 2. Parameters for Neural Network.

Description	Hidden Layer	Output Layer
Transfer Function	TanhAxon	SigmoidAxon
Learning Rate	0.15	0.15
Step Size	1.0	1.0
Momentum	0.9	0.9

Table 3. Network results for the given dataset.

Architecture	Epochs	Correlation	Network error
18-38-23-1	15500	0.944317	0.000369

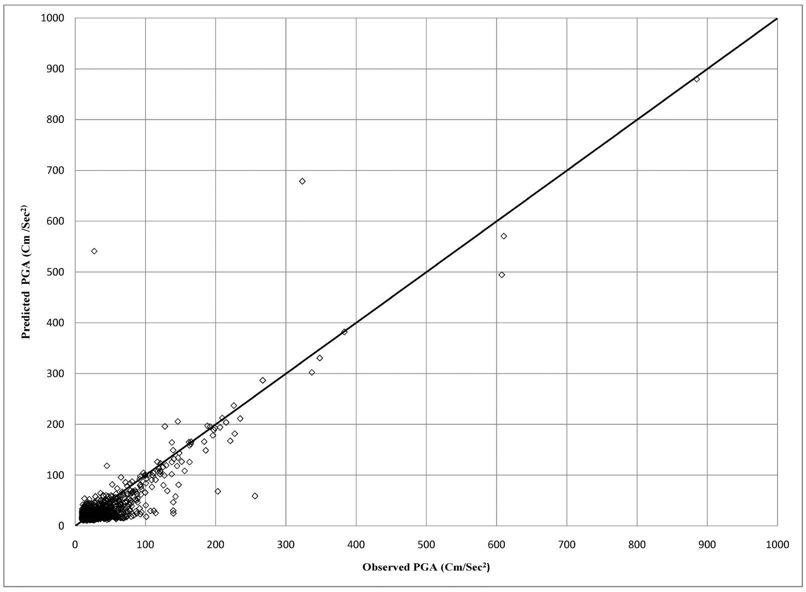

Figure 7. Scatter Plot of Predicted PGA Vs Observed PGA.

To evaluate the efficiency of the model, the results obtained from the entire dataset is categorized as: - **Accurate**: Results with percentage error less than 5%; **Substantially Accurate:** Results with percentage error in the range of 5 to 10 % ; **Moderately Accurate:** Results with percentage error in the range of 10 % to 20 % ; **Incorrect**: Results with percentage error more than 20 %. The efficiency of the results have been described in form of statistics are shown in Fig. 8,

From the results presented above the following observations are made:

1. The PGA predicted by ANN for given dataset has is high as about 40 % Substantially Accurate.
2. It is seen from the test results that major of the incorrect results are for a PGA of less than 20 Gals.
3. It can therefore be concluded that ANN cannot predict lower peak ground accelerations correctly from the above trained network.
4. Careful selection of data may significantly improve the performance of the trained network.

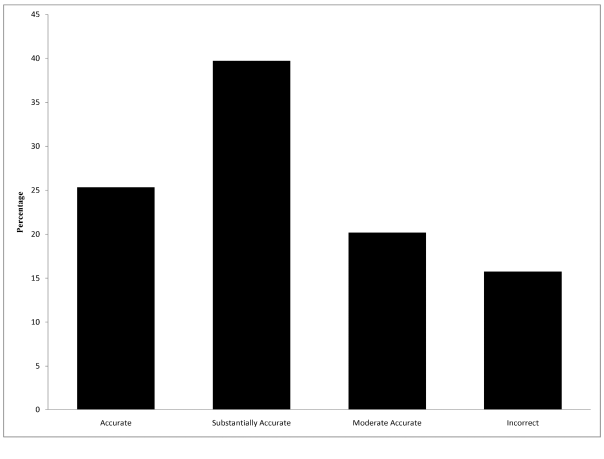

Figure 8. Efficiency of 4 input based network for prediction of PGA.

5. ESTIMATION OF PGA USING ATTENUATION RELATIONSHIPS.

In this section of work PGA is estimated by the previously developed attenuation relationships, to compare the results obtained from the above ANN network and attenuation models considered are based on the independent parameters used. The attenuation models considered for the estimation of PGA are (1) Boore and Atkinson (2008) and (2) Fukushima & Tanaka (1990). The independent parameters in Boore and Atkinson (2008) model are Magnitude, Joyner Boore distance R_{JB}, Average shear wave velocity, and Fault type. Where as in Fukushima & Tanaka (1990) only Magnitude and Hypocentral distance are considered.

Ground motion model considered by Fukushima & Tanaka (1990) is:

$$\log A = aM - \log(R + c10^{aM}) - bR + d \qquad (5)$$

where A is in cms^{-2}, a = 0.41, b = 0.0034, c = 0.032, d = 1.30 and σ = 0.21. Fig. 9 shows the Estimated PGA for the varying distance using Fukushima Attenuation Model.

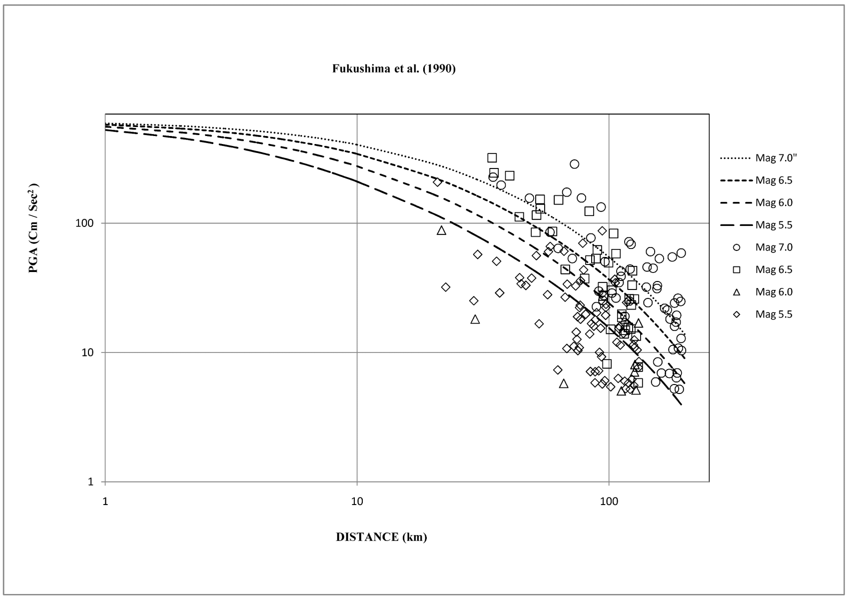

FIGURE 9. Estimated PGA with distance.

Equation for predicting ground motions using Boore and Gail Atkinson(2008) is:

$$\ln Y = F_M(\mathbf{M}) + F_D(R_{JB},\mathbf{M}) + F_S(V_{S30},R_{JB},\mathbf{M}) + \varepsilon\sigma_T, \qquad (6)$$

In this equation, F_M, F_D, and F_S represent the magnitude scaling, distance function, and site amplification, respectively. **M** is moment magnitude, R_{JB}, Joyner-Boore distance (defined as the closest distance to the surface projection of the fault), and the velocity V_{S30} is the inverse of the average shear-wave slowness from the surface to a depth of 30 m. The predictive variables are **M**, R_{JB}, and V_{S30}; the fault type is an optional predictive variable that enters into the magnitude scaling term. Fig. 10 shows the Estimated PGA for the varying distance using Boore and Atkinson Model. Table 4 shows the value of correlation coefficient find for ANN network and regression models. The efficiency of Fukushima et al. (1990) as well as Boore et al. (1990) attenuation model to predict PGA have been calculated and shown in the form of statistics in Fig. 11.

Table 4. Comparison of Correlation using ANN and Regressions Models

Correlation	ANN	Fukushima et al. (1990)	Boore & Atkinson (2008)
R	0.944317	0.5391	0.6517

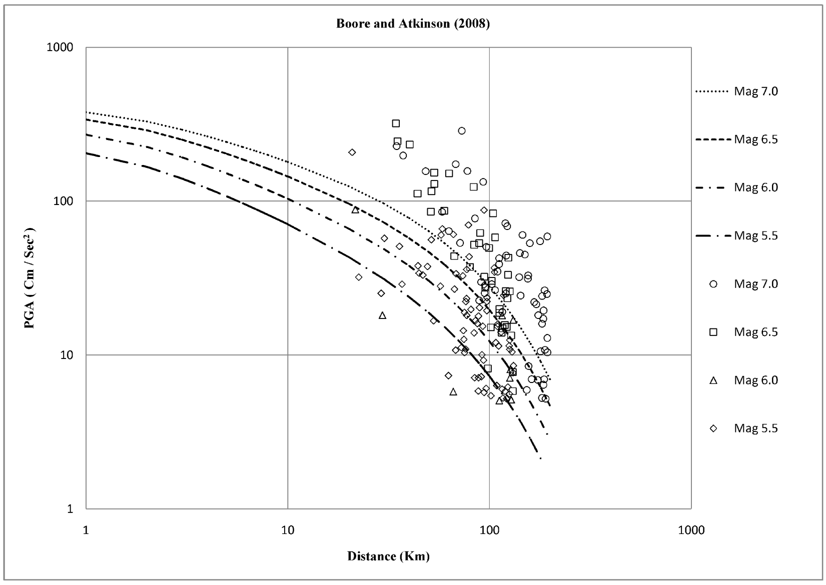

Figure 10. Estimated PGA with distance.

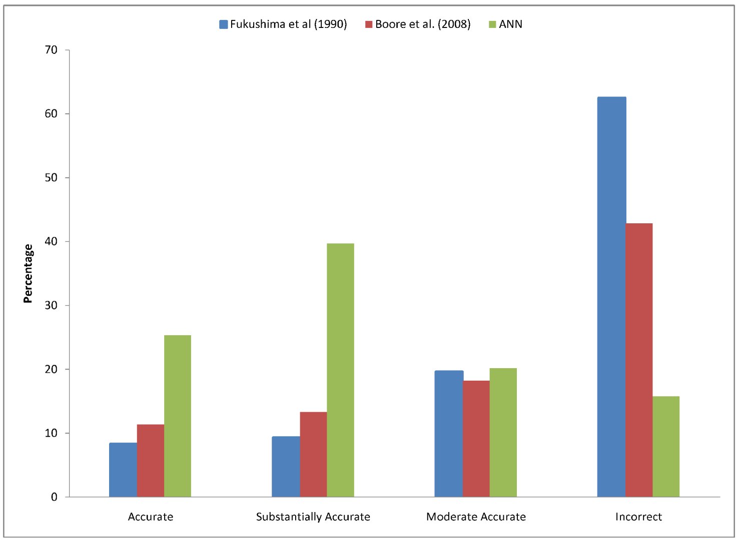

Figure 11. Comparison of Statistics for ANN and Regression Model.

It is clear from Fig. 11 , the ANN predict PGA value is high as about 40 % substantially accurate where as Fukushima et al.(1990) model predict incorrect PGA value is high as about 64 %.It may be noted that Fukushima et al.(1990) attenuation relationship do not consider the effects of fault types and site characteristics, Where as Boore et al. (2008) consider all for four independent parameters (magnitude, distance, fault type and shear velocity) to estimated the PGA which we used as inputs in ANN Network ,still it's predict inaccurate PGA value is high as about 40 %.

CONCLUSIONS

ANN can successfully predict the PGA vales with a margin of error within acceptable limits. Its seems that from the test results that major of the incorrect ANN results are for PGA of less than 20 gals or of lower cut off values. Therefore careful selection of data may significantly improve the performance of the trained network. The correlation obtained from Attenuation models are compared with ANN developed models, correlation for ANN models is as high as 0.944317, whereas correlation coefficients for Boore et al. (2008), and Fukushima et al. (1990) are found as 0.6517 and 0.5391, respectively.

ACKNOWLEDGEMENT

The authors wish to thank Kyoshin Net, strong-motion network of Japan for providing us with an excellent strong motion database for carrying our studies and Alyuda Research Company for providing us NeuroIntelligence 2.2 software for our studies.

REFERENCES

Alyuda Neuro-Intelligence (2002). User manual version 2.2, Alyuda Research Company [http://www.alyuda.com/index.html]

Arjun, C.R. and Kumar, A. (2009). Artificial Neural Network Based Estimation of Peak Ground Acceleration. *Journal of Indian Society of Earthquake Engineering* **46:1**, Paper no. 501.

Boore , D.M. a nd Atkinson, G.M. (2008). Ground Motion Predictions Equations for the Average Horizontal Components of PGA, PGV, and 5 %-Damped PSA at spectral Periods between 0.01 s and 10.0 s. Special Issue on the Next generation Attenuation Project, *Earthquake Spectra*, **24:1**, 99-138

Douglas, J., (2003). Earthquake ground motion estimation using strong motion records: a review of equations for the estimation of peak ground acceleration and response and spectral ordinates*.* *Earth-Sci.* Rev. **61,** *43-104.*

FEMA, (356, 2000). Prestandard and Commentary for the Seismic Rehabilitation of Buildings, Federal Emergency Management Agency.

Fukushima, Y., and Tanaka, T. (1990). A new attenuation relation for peak horizontal acceleration of strong earthquake ground motion in Japan. *Bulletin of the Seismological Society of America*, **80:4**, 757–783.

Ghaboussi, J. and Lin, C-C.J. (1998). New method of generating spectrum compatible accelerograms using Neural Networks. *Earthquake Engineering and Structural Dynamics* **27:4**, 377-396.

Günaydin, K. and Günaydin, A. (2008). Peak Ground Acceleration Prediction by Artificial Neural Networks for Northwestern turkey. *Hindawi Publishing Corporation, Mathematical Problems in engineering*, **Vol 2008**: article ID 919420, 20 pp.

Gullu, H. and Ercelebi, E. (2007). A Neural Network approach for attenuation relationships: An application using strong ground motion data from Turkey. *Science Direct, Engineering Geology* **93**, 65-81.

Haykin, S. (1999). Neural Networks*:* A Comprehensive Foundation, Second Edition, Prentice-Hall. 842 pp.

Hertz, J., Krogh, A., and Palmer, R. G. (1991). Introduction to the Theory of Neural Computing, Addison-Wesley,

Kaastra, I. and Boyd, M.S. (1995). Forecasting futures trading volume using Neural Networks. *Journal of Futures markets* **15:8**, 953-970.

Kramer, S.L. (1996). Geotechnical Earthquake Engineering .Prentice-Hall. 653 pp.

Kyoshin Net (K-NET) Strong Motion Database, National Research Institute for Earth Science and Disaster Prevention, Ibaraki-kenn, Japan, (http://www.k-net.bosai.go.jp.).

Lin, C-C.J. and Ghaboussi, J. (2001). Generating multiple spectrum compatible accelerograms using stochastic Neural Networks. *Earthquake Engineering and Structural Dynamics* **30:7**, 1021-1042.

Lin,Tzu Kang; Lin, C.C.J., and Chang, K.C. (2002). A Neural Network based methodology for estimating bridge damage after major earthquakes. *Journal of Chinese Institute of Engineers* **25:4**, 415-424.

Pandya, B., Porwal, P., and Banerji, P. (2002). Application of artificial Neural Network in development of site-specific response spectra. *Proceedings of the Twelfth Symposium on Earthquake Engineering,* **Dec.16-18 (2002)**, 199-207.

Rumelhart, D.E., Hinton, G.E., and Williams, R.J. (1986) Learning internal representation by back propagation errors. Nature **323**, 533-536.

Rumelhart , , D.E. and McClelland, J.L. (1986). Parallel Distributed Processing, vol I and II. MIT, Cambridge.

Shahin, M.A., Jaska, M.B., and Maier, H.R. (2001). State of the Art of Artificial Neural Networks in Geotechanical Engineering. *Aust. Geomech.* ***36:1****, 49-62*.

Shivanandam, S.N., Sumathi, S., and Deepa, S.N. (2006). Introduction to Neural Networks using Matlab 6.0, Tata McGraw-Hill,

Stone, M. (1974). Cross-validatory choice and assessment of statistical prediction. *Journal of Royal Statistical Society* **B:36** , 111-147.

Tehranizadeh, M. and Safi, M. (2004). Application of artificial intelligence for construction of design spectra. *Science Direct. Engineering Structures* **26**, 707-720.

Zurada, J.M. (1992). Introduction to Artificial Neural Systems, West Publishing Company, 683 pp