

 <p>ISSN NO. 2320-5407</p>	<p>Journal Homepage: - www.journalijar.com</p> <h2 style="text-align: center;">INTERNATIONAL JOURNAL OF ADVANCED RESEARCH (IJAR)</h2> <p style="text-align: center;">Article DOI: 10.21474/IJAR01/4508 DOI URL: http://dx.doi.org/10.21474/IJAR01/4508</p>	 <p>INTERNATIONAL JOURNAL OF ADVANCED RESEARCH (IJAR) ISSN 2320-5407 Journal Homepage: http://www.journalijar.com Journal DOI: 10.21474/IJAR01</p>
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RESEARCH ARTICLE

APPLICATION OF NEURAL NETWORK TO PREDICT STRONG GROUND MOTION FOR HIMALAYAN REGION.

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Manuscript Info

Manuscript History

Received: 17 April 2017

Final Accepted: 19 May 2017

Published: June 2017

Key words:-

neural, ground motion, regression,
Himalaya, India.

Abstract

To design engineering structures at a particular region, it requires the information about the characteristics of strong ground motion. Peak Ground Acceleration (PGA) is most frequently used parameter to characterize such ground motions. Ground motion predictions using regression analysis are commonly used for estimating these loading conditions by using strong ground motion data from previous recorded earthquakes. Artificial Neural Networks (ANNs) are efficient computing models which have shown their strengths in solving many complex problems in numerous fields. A data set of 398 strong ground motion records from 69 earthquakes ($3.0 \leq M \leq 6.8$) occurred in Himalayan region is used in this study. Multi-layer perceptron architecture with the error back-propagation learning algorithm has been adopted to estimate peak ground accelerations for the Himalayan earthquakes. The PGAs predicted by the ANN have been compared with PGAs obtained by regression analysis. From these observations it has been concluded that the perceptron model is quite promising for the estimation of peak ground acceleration. Results of the predicted PGA have indicated that ANN is a promising tool for the estimation of peak ground acceleration at a site.

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Introduction:-

Strong Ground Motion (SGM) record at a particular site during an occurrence of earthquake is a result of complex – non linear combination of many factors (Sachdeva, 2014). Ground motion associated with a peak ground acceleration of 0.05g or higher is considered as strong ground motion (Chen and Scawthorn, 2003). For design of engineering structures for a specified region the information about the characteristics of strong ground motion is of paramount importance. Peak Ground Acceleration (PGA) is most frequently used parameter to characterize such ground motions. Ground Motion Prediction Equations (GMPE's) are commonly used for estimating these loading conditions by using strong ground motion data from previous recorded earthquakes. A very little agreement has been reached in the past 30 years of ground motion estimation relation studies and the scatter could not be reduced to requisite level. This is more because the relations not only depends upon data selection, characterization of source, path or site or the regression technique employed but also on the purpose for which equation is intended to be used.

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So the process of determining the regression relation much depends upon the appropriate judgment of scholar (Sachdeva, 2014).

Artificial Neural Networks (ANNs) are efficient computing models which have shown their strengths in solving many complex problems in numerous fields. They have the versatility to approximate a wide range of complex functional relationships between sets of input and output data. The purpose of this study is to predict strong ground motion parameters using ANN that are of primary significance in earthquake engineering. In this study, sets of Multilayer Perception (MLP) neural network model are trained to predict the PGA. Neuro Intelligence (Neural Network Simulator) software has been used to model ANN and the standard back-propagation supervised training scheme is used to train all networks. A data set of 398 strong ground motion records from 69 earthquakes ($3.0 \leq M \leq 6.8$) occurred in Himalayan region are used in this study. A comparison of PGA values obtained from neural network and regression analysis have made.

Acceleration Data:-

Two types of data sets collected from the Himalaya region have been used in the study. The first data set of 144 records from 10 earthquakes ($5.2 \leq M \leq 6.8$) as shown in Figure 1 became available from strong motion array comprised of strong motion accelerographs (SMA-1 of Kinematrics) in the Himalaya region. The purpose of deploy these instruments is to record the strong ground motion due to moderate and large-sized earthquakes occurring in the Himalayan region (Chandrasekharan, 1991). At each station the threshold level (trigger level) to sense the ground motion was set about 0.01 g. The analog recordings of these earthquakes were manually digitized using a semi automatic digitizer and digital data was processed adopting standard processing procedures (Trifunac, 1976). The data was converted to a uniform sampling rate of 0.02 seconds and band-pass filtered (0.17–0.20 Hz; 25–27 Hz) using an Ormsby filter (Chandrasekharan and Das, 1992).

The second data set of 254 records from 59 earthquakes of magnitude range ($3.0 \leq M \leq 6.8$) was recorded by recently installed digital accelerographs in the Himalayan region (Figure 2). These accelerograph installations form part of the National Strong Motion Network of 300 strong motion stations deployed under Mission Mode project to cover seismic zones V, IV and some thickly populated cities falling in seismic zone III (Kumar et al., 2012; Mittal et al., 2012). The digital accelerographs are of GSR-18 type (Geosig, model GSR-18) and data is acquired at a sampling rate of 200 Hz. About 260 digital accelerographs, networked using NIC-net allows monitoring the health of accelerographs as well as downloading of the strong motion data at IIT Roorkee campus.

The earthquakes considered for training neural network are shown in Table 1. The magnitude distance distribution of these earthquakes is shown in Figure 4.

Artificial Neural Network:-

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; Arjun and Kumar, 2009).

In this study, multi-layer feedforward neural networks, commonly referred to as multilayer perceptrons (MLPs) have been used. 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 3 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 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.

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 error criterion used is the 2 L -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:-

A data set of 398 strong ground motion records from 69 earthquakes ($3.0 \leq M \leq 6.8$) occurred in Himalayan region is used in this study. Figure 4 gives the scatter plot of magnitude versus hypocentral distance of the data used. The neural network is trained and tested using the data.

The total set of 398 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.

A [2-2-1] architecture with 9 weights have been selected which have 3.25 fitness. The training error is 0.35; validation error is 0.27 and testing error is 0.31 for this architecture. A correlation of 0.73 is obtained between the actual PGA and predicted PGA (Figure 5). Then estimated PGAs for magnitude 6.8 were compared with actual and that obtained from regression analysis.

$$\log(A) = -1.497 + 0.3882M - 1.19(X + e^{0.2876M}) \quad (\text{Kumar et al., 2017})$$

A good correlation has been observed between predicted by ANN and that obtained from regression analysis.

Table 1: The earthquakes considered for attenuation regression analysis:

Earthquake	Date	Time	Latitude (°N)	Longitude (°E)	Depth (Km)	Magnitude	Records
1	19860426	13:05	32.18	76.29	07.0	5.5	9
2	19860910	13:20	25.43	92.08	43.0	5.2	12
3	19870518	07:24	25.27	94.20	50.0	5.7	14
4	19880206	20:21	24.65	91.52	15.0	5.8	18
5	19880806	06:07	25.15	95.13	91.0	6.8	33
6	19900110	00:21	24.75	95.24	119.0	6.1	14
7	19911020	02:30	30.74	78.79	12.0	6.6	13
8	19950506	07:29	25.01	95.34	122.0	6.4	9
9	19970805	08:23	24.89	92.25	35.0	5.6	11
10	19990329	00:35	30.41	79.42	20.0	6.8	11
11	20050406	08:10	31.20	91.10	10.0	4.3	1
12	20051214	07:09	30.90	79.30	25.3	5.2	8
13	20070722	23:02	31.20	78.20	33.0	5.0	2
14	20080819	10:54	30.10	80.10	15.0	4.3	4
15	20080904	12:53	30.10	80.40	10.0	5.1	7
16	20090215	07:35	26.00	90.20	39.3	4.4	5
17	20090224	17:46	25.90	94.30	10.0	4.8	5
18	20090225	04:04	30.60	79.30	10.0	3.7	1

19	20090318	11:22	30.20	78.90	10.0	3.3	1
20	20090425	04:04	30.60	79.30	10.0	4.0	2
21	20090501	10:11	30.20	78.10	10.0	4.6	7
22	20090615	11:17	30.90	78.10	10.0	3.4	2
23	20090615	12:12	27.40	79.20	05.0	3.0	1
24	20090615	08:19	30.50	78.30	15.0	4.1	1
25	20090819	10:45	26.60	92.50	20.0	4.9	2
26	20090827	16:54	30.00	80.00	14.0	3.9	3
27	20090830	19:27	25.40	94.80	85.0	5.3	5
28	20090903	19:51	24.30	94.60	100.0	5.9	9
29	20090921	08:53	27.30	91.50	08.0	6.2	14
30	20090921	09:43	30.90	79.10	13.0	4.7	12
31	20091003	05:20	30.00	79.90	15.0	4.3	3
32	20091029	17:00	27.30	91.40	10.0	4.2	5
33	20091029	19:56	26.60	90.00	05.0	5.2	5
34	20091108	21:43	24.40	94.80	22.0	5.6	12
35	20091229	09:01	24.50	94.80	80.0	5.5	6
36	20091231	09:57	27.30	91.40	07.0	5.5	5
37	20100111	05:15	29.70	80.00	15.0	3.9	3
38	20100222	17:23	30.00	80.10	02.0	4.7	6
39	20100226	04:42	28.50	86.70	28.0	5.4	7
40	20100503	17:15	30.40	78.40	08.0	3.5	4
41	20100531	11:37	30.00	79.80	10.0	3.6	2
42	20100706	19:08	29.80	80.40	10.0	5.1	2
43	20100710	03:16	29.90	79.60	10.0	4.1	4
44	20100911	07:02	25.90	90.20	20.0	5.0	3
45	20101212	01:40	25.00	93.30	15.0	4.8	2
46	20110204	13:53	28.40	94.60	30.0	6.4	7
47	20110209	11:23	27.45	92.24	10.0	5.0	6
48	20110314	09:01	30.50	79.10	08.0	3.3	1
49	20110404	11:31	29.60	80.80	10.0	5.7	22
50	20110504	2057	30.20	80.40	10.0	5.0	1
51	20110620	06:27	30.50	79.40	12.0	4.6	13
52	20110623	22:13	30.00	80.50	05.0	3.2	1
53	20110918	12:40	27.70	88.20	10.0	6.8	13
54	20110921	02:24	30.90	78.30	10.0	3.1	1
55	20110924	14:32	30.90	78.30	10.0	3.0	1
56	20120116	05:01	29.70	78.90	10.0	3.6	1
57	20120226	23:08	29.60	80.80	10.0	4.3	2
58	20120510	22:00	30.20	79.40	05.0	3.9	1
59	20120728	05:48	29.70	80.70	10.0	4.5	2
60	20120823	16:30	28.40	82.70	10.0	5.0	3
61	20121111	18:39	29.20	81.50	10.0	5.0	3
62	20121127	12:15	30.90	78.40	12.0	4.8	4
63	20130102	17:42	29.40	81.10	10.0	4.8	2
64	20130109	07:44	29.70	81.70	34.0	5.0	4
65	20130110	15:16	30.10	80.40	05.0	3.2	1
66	20130129	19:42	30.00	81.60	07.0	4.0	1
67	20130211	10:48	30.00	78.40	05.0	4.3	3
68	20130217	16:27	30.90	78.40	10.0	3.2	1
69	20130905	18:35	30.90	78.50	11.0	3.5	1

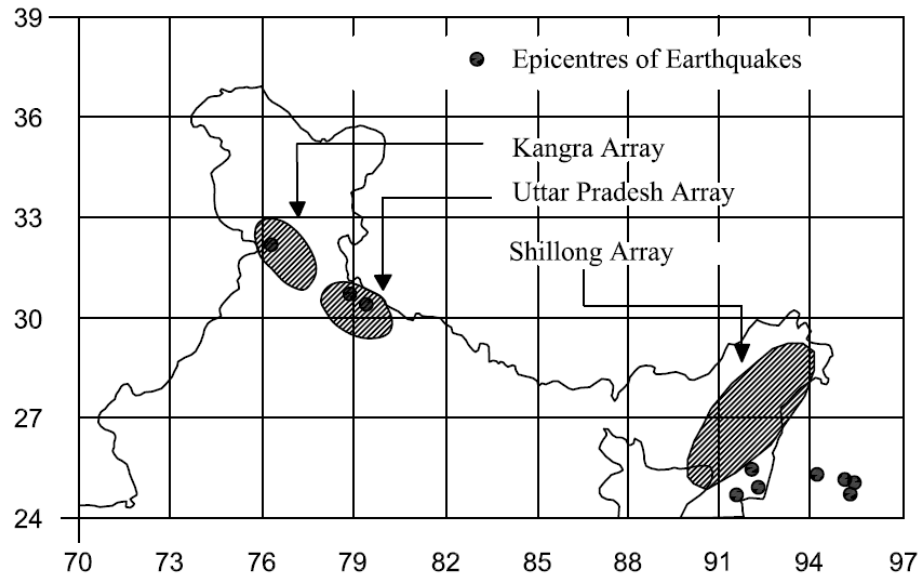


Figure 1:- Map showing the strong motion arrays and locations of earthquakes (Sharma, 2005).

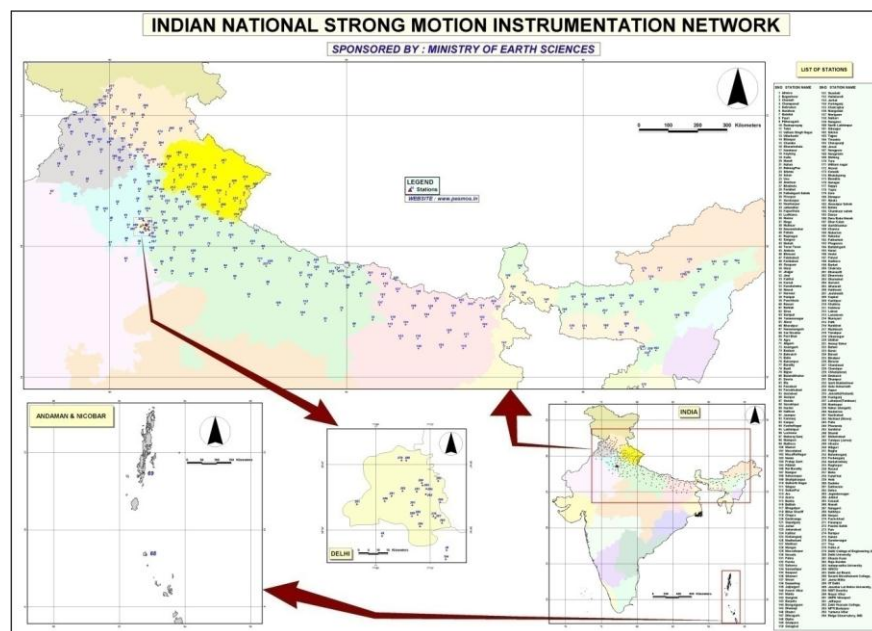


Figure 2:- Indian nation strong motion instrumentation network (Kumar et al., 2012).

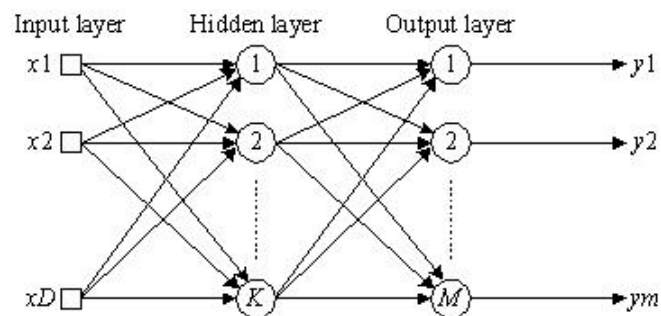


Figure 3:- Multilayer perceptron, MLP (D - K - M), with one hidden layer.

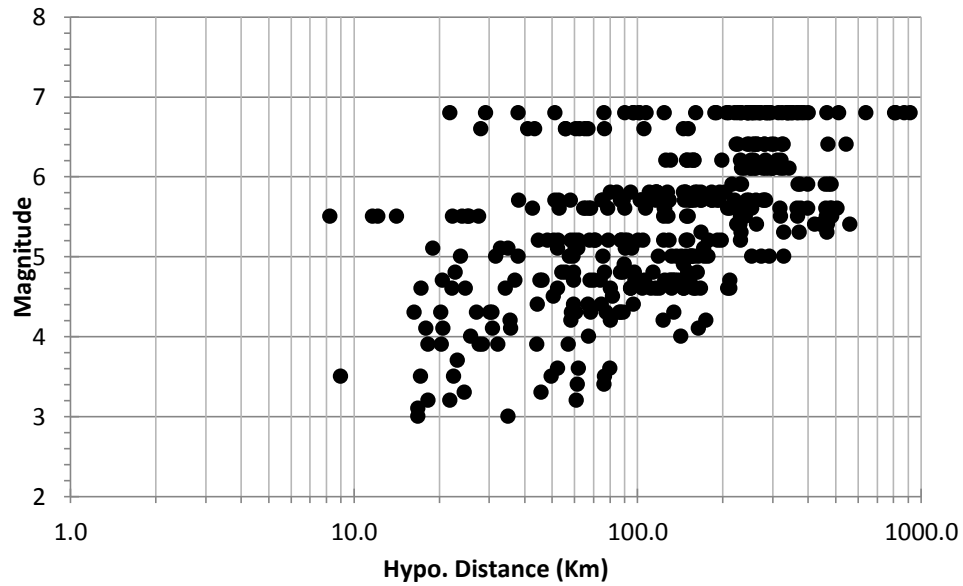


Figure 4:- The magnitude-distance distribution of peak ground horizontal accelerations.

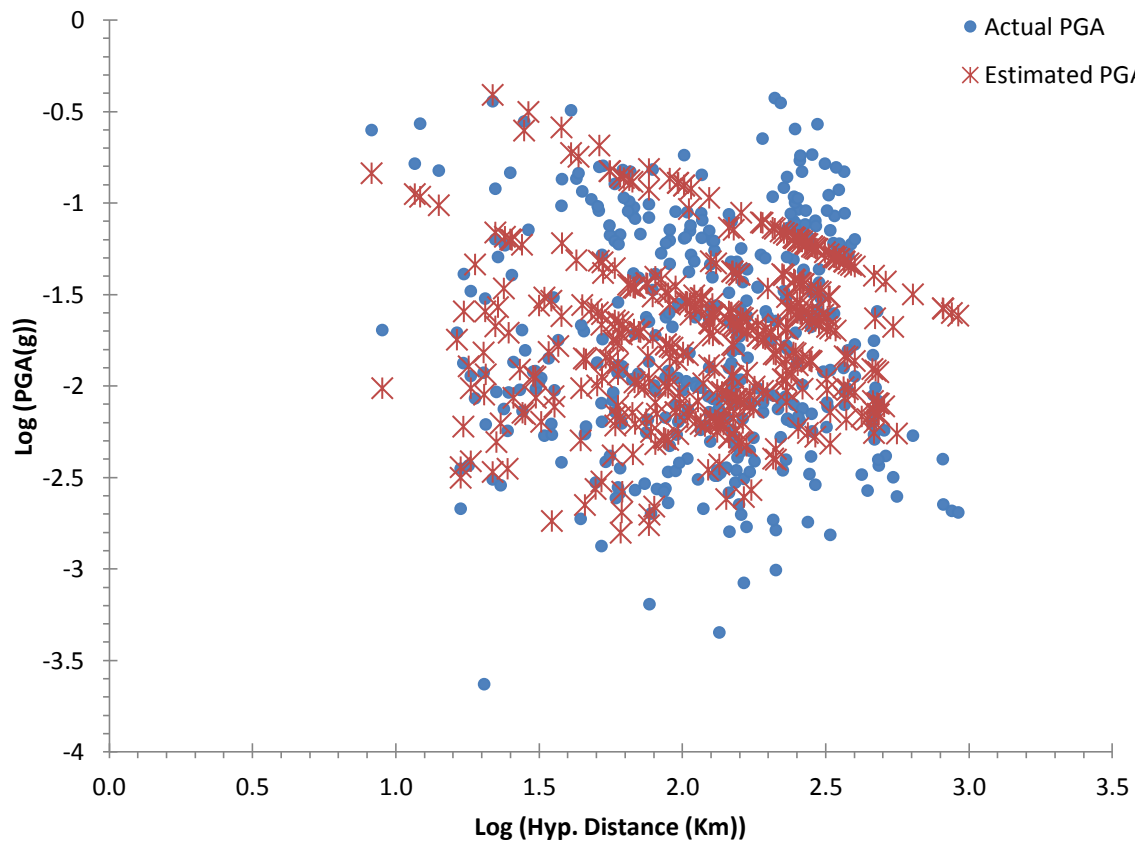


Figure 5:- Scatter plot showing actual PGA vs estimated PGA.

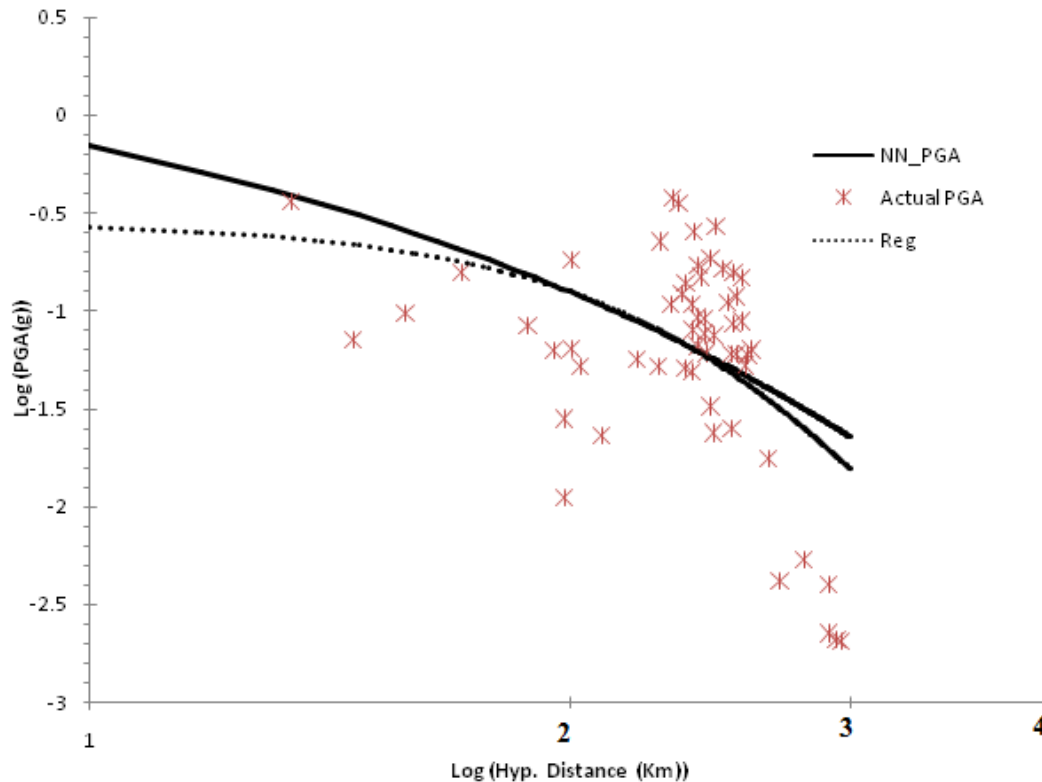


Figure 6:- Plot shows actual PGA; estimated by ANN and regression analysis.

Conclusions:-

A multi-layer perceptron architecture with the error back-propagation learning algorithm has been adopted to estimate peak ground accelerations for the Himalayan earthquakes. The PGAs predicted by the ANN have been compared with PGAs obtained by regression analysis. From these observations it has been concluded that the perceptron model is quite promising for the estimation of peak ground acceleration. 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.

Acknowledgments:-

The authors are thankful for the first data set of strong-motion provided by the research scheme "Strong Motion Arrays in India," sponsored by the Department of Science and Technology, Government of India. The authors are also thankful to Ministry of Earth Sciences (MoES) for funding the project under which the second data was collected. The author sincerely thanks Prof. Ashok Kumar and Prof. Ashwani Kumar for their helpful suggestions, advice, and critical comments at various stages of the study.

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