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RESPONSE PREDICTION OF STRUCTURAL SYSTEM SUBJECT TO EARTHQUAKE MOTIONS USING ARTIFICIAL NEURAL NETWORK

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ABSTRACT

This paper uses Artificial Neural Network (ANN) models to compute structural response of a structural system by training the model for a particular earthquake. Here, the earthquakes in India viz. at Chamoli and Uttarkashi ground motion data have been considered for the analysis. The neural network is first trained here for a single real earthquake data on a single degree of freedom structural system. The trained ANN architecture is then used to simulate earthquakes by feeding various intensities as well as other earthquake data and it is found that the predicted responses given by ANN model are good for practical purposes. If the ANN is trained by a part of the ground motion data then it can also identify the responses of the structural system well for the total period. The safety of the structural systems may be predicted in case of future earthquakes without having to wait for the earthquake to occur for the lessons.

Keywords: Earthquake, chamoli, uttarkashi, neural network, back-propagation, structure

1. INTRODUCTION

Real earthquake ground motion at a particular building site is very complicated. This earthquake ground motion, when it is strong enough sets the building in motion, starting with the foundation and transfers the motion throughout the rest of the building in a very complex way. Powerful technique of Artificial Neural Network (ANN) is used to model the problem of one storey structure. Dynamic response of a structure to strong earthquake ground motion may be investigated by different methods. One of these methods consists of constructing a good theoretical model of a structure and calculating the exact dynamic response for an assumed known motion of the foundation. This approach is relatively time-consuming and costly, has recently been used frequently for the final design of important

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structures. The other method, that has been used here, may be to create a trained black box containing the characteristics of the structure and of the earthquake motion which can predict the dynamic response for any other earthquake for a particular structure.

Artificial Neural Network have gradually been established as a powerful tool in various fields because of their excellent learning capacity and their high tolerance to partially inaccurate data. ANN has, recently been applied to assess damage in structures. Wu et al.[1] used a back-propagation neural network (BPN) to elucidate damage states in a three-storey frame by numerical simulation. Elkordy et al.[2] used a back-propagation neural network with mode shapes in the input layer, to detect simulated damage of structures. Pandey and Barai [3] detected damage in a bridge truss by applying ANN of multilayer perceptron architectures to numerically simulated data. Zhao et al.[4] applied a counter-propagation Neural Network (NN) to locate damage in beams and frames. Masri et al. [5] used back propagation neural network for detecting damage, based on non-linear system identification. Among the different types of ANN, the feedforward, multilayer, supervised neural network with Error Back Propagation Algorithm [6] is the most frequently applied NN model. [7, 8]

In the present work, the Chamoli earthquake and Uttarkashi earthquake ground acceleration, recorded at Barkot in NE (North-East) direction has been considered. From their ground acceleration the responses are computed using the usual procedure. Then the ground acceleration and the corresponding response are trained using ANN with damping and frequency parameter. After training the network with one earthquake the converged weight matrices are stored. In order to show the power of these converged (trained) networks other earthquakes are used as input to predict the direct response of the structure without using any mathematical analysis of the response prediction. Similarly, various other results related to the use of these trained networks are discussed for future / other earthquakes.

2. ARTIFICIAL NEURAL NETWORK

A neural network is a parallel, distributed information processing structure that consists of processing elements called neurons, which are interconnected and unidirectional signal channels called connections. Each processing element branches into as many output connections as desired and carry signals known as neuron output signal. The neuron output signal can be of any mathematical type desired. In ANN, the first layer is considered to be input layer and the last layer is the output layer. Between the input and output layer, there may be more than one hidden layer. Each layer will contain a number of neurons or nodes (processing elements) depending upon the problem. These processing elements operate in parallel and are arranged in patterns similar to the patterns found in biological neural nets. The processing elements are connected to each other by adjustable weights. The input/output behaviour of the network changes if the weights are changed. So, the weights of the net may be chosen in such a way so as to achieve a desired output. To satisfy this goal, systematic ways of adjusting the weights have to be developed, which are known as training or learning algorithm. Neural network basically depends upon the type of processing elements or nodes, the network topology and the learning algorithm. The typical network may be understood from the Figure 1.

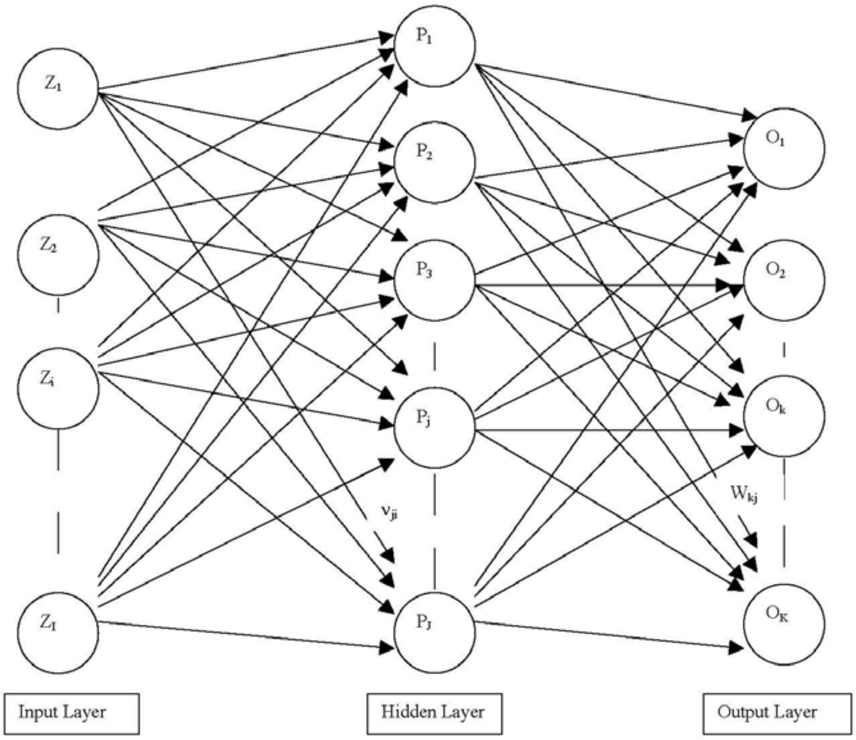

Figure 1. Layered feed forward neural network

3. ERROR BACK PROPAGATION TRAINING ALGORITHM (EBPTA)

Here, Error Back Propagation Training algorithm and feed-forward recall with one hidden layer have been used. In Figure 1, Z_i, P_j and O_k are input, hidden and output layer, respectively. The weights between input and hidden layers are denoted by ν_{ji} and the weights between hidden and output layers are denoted by W_{kj}. The procedure may easily be written down for the processing of this algorithm.

Given R training pairs

$$\{Z_1, d_1; Z_2, d_2; \ldots\ldots\ldots Z_R, d_R\}$$

where Z_i (Ix1) are input and d_i (Kx1) are desired values for the given inputs, the error value is computed as

$$E = \frac{1}{2}(d_k - O_k)^2, \qquad k = 1,2,\ldots\ldots K \tag{1}$$

for the present neural network as shown in Figure 2.

The error signal terms of the output (δ_{Ok}) and hidden layers (δ_{Pj}) are written respectively as,

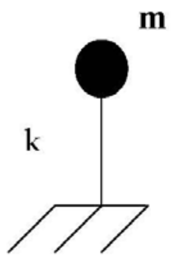

Figure 2. Generalized one storey structure

Consequently, output layer weights (W_{kj}) and hidden layer weights (δ_{ji}) are adjusted as,

$$\delta_{Ok} = 0.5 * (d_k - O_k)(1 - O_k^{\,2}),\ k = 1,2,........K \tag{2}$$

$$\delta_{Pj} = 0.5 * (1 - P_j^{\,2}) \sum_{k=1}^{K} \delta_{Ok}\, W_{Pj},\ j = 1,2,....J \tag{3}$$

$$\nu_{ji}^{(New)} = \nu_{ji}^{(Old)} + \beta \delta_{Pj}\, Z_i,\ j = 1,2.......J \text{ and } i = 1,2,.......I \tag{4}$$

$$W_{kj}^{(New)} = W_{kj}^{(Old)} + \beta \delta_{Ok}\, P_j,\ k = 1,2.....K \text{ and } j = 1,2,.....J \tag{5}$$

Where, β is the learning constant.

4. STRATEGY FOR RESPONSE PREDICTION

The basic concept behind the proposed methodology is to predict the structural response of single degree of freedom system viz. single storey building subjected to various earthquake forces by training the same for one particular earthquake data.

Let M be the mass of the generalized one storey structure (as shown in Figure 2), K the stiffness of the structure, C the damping and x be the displacement relative to the ground then the equation of motion may be written as:

$$M\ddot{x} + C\dot{x} + Kx = -M\ddot{a} \tag{6}$$

where,

$\ddot{x}$ = Response acceleration,
$\dot{x}$ = Response velocity
$\ddot{a}$ = Ground acceleration,
x = Displacement

Equation (6) may be written as,

$$\ddot{x} + 2\xi\omega\dot{x} + \omega^2 x = -\ddot{a} \tag{7}$$

where $\xi\omega$ = C/2M and ω^2=K/M, is the natural frequency parameter of the undamped structure.

The solution of equation (3) [Ref.8] is given by

$$x(t) = -\frac{1}{\omega}\int_0^t \ddot{a}(\tau)\exp[-\xi\,\omega(t-\tau)]\sin[\omega(t-\tau)]d\tau \tag{8}$$

From this solution the response of the structure viz. acceleration is obtained. Hence, the neural network architecture is constructed, taking ground acceleration as input and the response obtained from the above solution is taken as output for each time step. Therefore, the whole network consists of one input layer, one hidden layer with varying nodes and one output layer as shown in Figure 1.

5. NUMERICAL RESULTS AND DISCUSSIONS

For the present study two Indian earthquakes viz. the Chamoli Earthquake (max. ground acceleration=0.16885 m/sec/sec) at Barkot in NE (north–east) direction shown in Figure 3(a) and the Uttarkashi earthquake (maximum ground acceleration=0.931 m/sec/sec) at Barkot in NE (north–east) direction as given in Figure 3(b) have been considered for training. First the ground acceleration of Chamoli earthquake was used to compute the response for single storey structure using the usual procedure. The obtained responses and the ground acceleration are trained by the said ANN model for a structural system with frequency parameter ω=0.68981 and damping=1.58033. This training was done for the total time range 0 to 14.92 seconds (748 points, earthquake period) taking the continuous activation function with accuracy 0.0005. When the network is trained then by direct use of the converged weight matrix gives the structural response. Accordingly a plot of 100% response comparison between neural network results and desired response for Chamoli earthquake at barkot (NE) is shown in Figure 3(c). After training ground acceleration and response data for Chamoli earthquake for various nodes in the hidden layer it was confirmed that 10 nodes are sufficient for the prediction. So, the weights corresponding to 10 hidden nodes are stored and they are used to predict responses for various intensity earthquakes. It is worth mentioning here that the response for any other earthquake can be predicted using the converged weights after the training with Chamoli earthquake (or any particular earthquake). Here, the response for Uttarkashi earthquake at Barkot in NE direction is predicted using the trained network by Chamoli earthquake (at the same place) for the considered structure. The Uttarkashi earthquake occurred on October 20, 1991 is more stronger (maximum response=0.9317 m/sec/sec) than the Chamoli earthquake (maximum response=0.16885 m/sec/sec), which occurred on March 29, 1999. Here, first the network is trained for a suitable high percentage of Chamoli earthquake and then the converged weights from this training is used to predict the response for Uttarkashi earthquake at Barkot (NE), Tehri (in NE directions) and for the Chamoli Earthquake at Barkot (NW). The response comparisons between the neural (using the trained weights from Chamoli earthquake) and desired of Uttarkashi earthquake at Barkot (NE) and Tehri (NE) are shown in Figs. 4(a) and 4(b) respectively. Similarly, the response comparison between the neural and desired of Chamoli earthquake at Tehri (NW) is also shown in Figure 4(c).

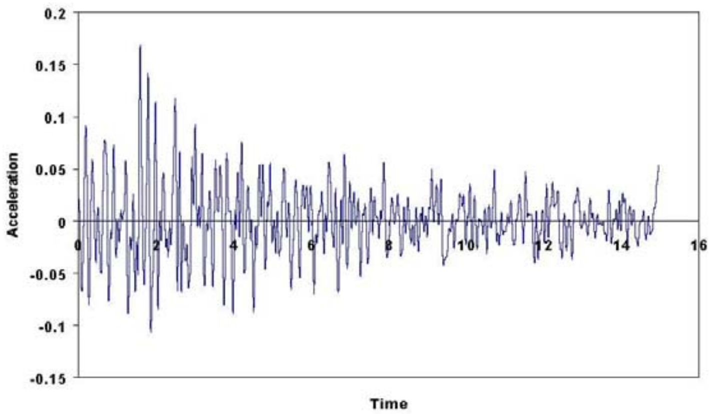

Figure 3a. Chamoli earthquake recorded at Barkot (NE direction)
peak acceleration = 0.16885m/sec/sec

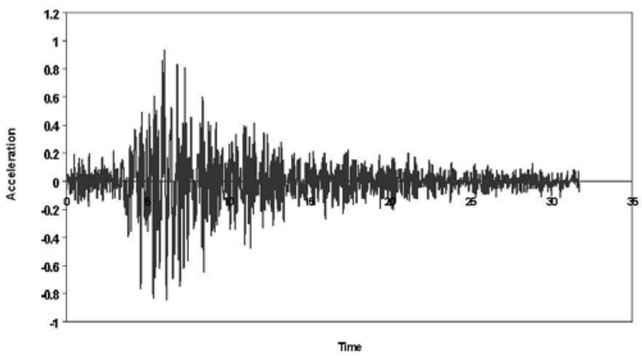

Figure 3b. Uttarkashi earthquake recorded at Barkot (NE direction)
peak acceleration = 0.9317 m/sec/sec

Next, the Uttarkashi earthquake at Barkot (NE) ground acceleration and the corresponding response of the structure are trained for another example with the same frequency parameter ω=0.68981 but with different damping=0.05. The weights obtained after training Uttarkashi earthquake at Barkot (NE) is used to predict the response for Chamoli earthquake at Barkot (NW), Tehri (NE) and for the Uttarkashi earthquake at Tehri (in NW direction). The response comparisons between the neural and desired of Chamoli earthquake at Barkot (NE) and Tehri (NE) are shown in Figures 5(a) and 5(b) respectively. Similarly, the response comparisons between the neural and desired of Uttarkashi earthquake at Tehri (NW) is shown in Figure 5(c).

Here, a part of the ground acceleration is also used for the training and it will be shown that the present ANN model can predict the whole period of the response using the trained ANN by the part of the data. So, the ground acceleration and response data with Chamoli earthquake at Barkot (NE) is trained without damping for an example with the time range 0 to 10.96 sec (550 data points) and its neural and desired response comparison is shown in Figure 6(a). Its weights are stored to find the response for the time range 0 to 14.92 seconds (748 data points, i.e. whole period). The 100% response comparison between neural and desired for ω=0.05 (maximum response=0.168849 m/sec/sec) from the time range 0 to 14.92 seconds (748 data points) is incorporated in Figure 6(b). These are obtained from the weights of the trained data for the time range 0 to 10.96 seconds (550 data points). A better representation of the results may be seen from Figure 7(a), which shows the maximum response comparison subject to Chamoli earthquake at Barkot, Tehri and Uttarkashi (NE) between neural and desired results. Similar results for Chamoli earthquake at Barkot, Tehri and Uttarkashi (NW) are given in Figure 7(b). The phase plane plots of neural and desired of Chamoli earthquake at Barkot in NE direction are given in Figures. 8(a) and 8(b). Using the weights of Chamoli training, the phase plane plots of neural and desired of Uttarkashi earthquake at Barkot (NE) are given in Figures 8(c) and 8(d). The phase plane plots given in Figures 8(a) to 8(d) very well depicts the efficacy of the neural network which shows the good comparisons between the neural and desired results.

6. CONCLUSIONS

This paper uses Artificial Neural Network to train the responses of structural systems for a particular earthquake. It is shown here that once the training is done then the trained architecture may be used to simulate for various intensity earthquakes as well as for any other earthquakes. Thereby showing the responses of the system which depend upon the structural properties (mass and stiffness) of the Structure. If the network is trained by a part of one earthquake data then also the model can predict the responses for any other earthquake data that had not been used during the training. In this way the safety of the structural systems may be predicted in case of future earthquakes.

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