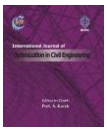
INTERNATIONAL JOURNAL OF OPTIMIZATION IN CIVIL ENGINEERING
Int. J. Optim. Civil Eng., 2016; 6(3):365-384



INTERVAL ARTIFICIAL NEURAL NETWORK BASED RESPONSE OF UNCERTAIN SYSTEM SUBJECT TO EARTHQUAKE MOTIONS

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ABSTRACT

Earthquakes are one of the most destructive natural phenomena which consist of rapid vibrations of rock near the earth's surface. Because of their unpredictable occurrence and enormous capacity of destruction, they have brought fear to mankind since ancient times. Usually the earthquake acceleration is noted from the equipment in crisp or exact form. But in actual practice those data may not be obtained exactly at each time step, rather those may be with error. So those records at each time step are assumed here as intervals. Then using those interval acceleration data, the structural responses are found. The primary background for the present study is to model Interval Artificial Neural Network (IANN) and to compute structural response of a structural system by training the model for Indian earthquakes at Chamoli and Uttarkashi using interval ground motion data. The neural network is first trained here for real interval earthquake data. The trained IANN architecture is then used to simulate earthquakes by feeding various intensities and it is found that the predicted responses given by IANN model are good for practical purposes. The above may give an idea about the safety of the structural system in case of future earthquakes. Present paper demonstrates the procedure for simple case of a simple shear structure but the procedure may easily be generalized for higher storey structures as well.

Keywords: earthquake; IANN; structure; building; Chamoli; Barkot.

Received: 20 November 2015; Accepted: 5 January 2016

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1. INTRODUCTION

One of the most frightening and destructive phenomena of nature is a severe earthquake and its terrible after effects. An earthquake is the sudden, rapid shaking of the earth caused by the breaking and shifting subterranean rock as it releases strain that has accumulated over a long time. Earthquakes are one of the most costly natural hazards faced by the world posing a significant risk to the public safety. The risks that earthquakes pose to society, including death, injury and economic loss, can be greatly reduced by better planning, construction, mitigation practices before earthquakes happen, providing critical and timely information to improve response after they occur. There is no way to stop these natural phenomena, but seismologists have several methods so that they can estimate approximately or predict for future earthquake to occur. By studying the amount of earthquakes and when they happen in a certain area, seismologist can then guess the probability of another one occurring in that area within a given time. This will certainly give an idea to the people about the time period of the occurrences of the next earthquake, so that they can prepare themselves for another possible quake. Real earthquake ground motion at a particular building site is very complicated. Earthquake usually occurs without warning.

The 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. 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 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.

System Identification (SI) techniques play an important role in investigating and reducing gaps between the structural systems and their structural design models. This is also true in structural health monitoring for damage detection. A great amount of research has been conducted in SI. SI techniques are also applied to determine vibration characteristics, modal shapes and damping ratios of complex structural systems so as to frame knowledge for modelling and assessing current design procedures. The result of such process identification is usually a mathematical model by which the dynamic behaviour can be estimated or predicted. As regards various methodologies for different type of problems in system identification were given by [1-7]. Studies related to structural damage detection have been done by various researchers. [8] used an efficient reparameterization of least-squares algorithm to identify parameters of linear models of buildings under orthogonal bi-dimensional seismic excitation in a 3 DOF system. Various methods viz. [9-13] were introduced for response estimation, structural control and for structural analysis using ANN. [14] presented an efficient procedure to determine the natural frequencies, modal damping ratios and mode shapes for torsionally coupled shear buildings using earthquake response records. An identification of dynamic models of a building structure using multiple earthquake records has been developed by [15].

Artificial Neural Network (ANN) has gradually been established as a powerful tool in

various fields. ANN has recently been applied to assess damage in structures. They have been successfully applied for identification and control of dynamic systems in various field of engineering because of its excellent learning capacity and high tolerance to partially inaccurate data. In this regards lots of works in structural health monitoring and damage detection using ANN have been done by various researchers. [16] used a back-propagation neural network with mode shapes in the input layer, to detect simulated damage of structures. [17] used probabilistic neural networks for seismic damage prediction. A nonparametric structural damage detection methodology based on nonlinear system identification approaches has been given by [18] for health monitoring of structure-unknown systems. [19] employed a structural parametric assessment approach involving neural networks to detect damage and thus monitor structural health using dynamic responses in time series. [20] gave two steps for structural damage detection. The first step involves system identification using Neural System Identification Networks (NSINs) to identify the undamaged and damaged states of a structural system and the second step involves structural damage detection using the aforementioned trained NSINs to generate free vibration responses with the same initial condition or impulsive force. A neural network approach for structural identification and diagnosis of a building from seismic response data has been presented by [21]. [22] predicted response of typical rural house subjected to earthquake motions using artificial neural networks. [23] used Artificial Neural Network model to compute structural response of structural system by training the model for a particular earthquake. A multistage identification scheme for structural damage detection with the use of modal data using a hybrid neural network strategy has been proposed by [24]. [25] presented an approach to detect structural damage using ANN method with progressive substructure zooming. This method also uses the substructure technique together with a multi-stage ANN models to detect the location and extent of the damage. To avoid the false positives of damages in the deterministic identification method induced by uncertainties in measurement noise, [26] proposed a probabilistic method to identify damages of the structures with uncertainties under unknown input. The proposed probabilistic method is developed from a deterministic simultaneous identification method of structural physical parameters and input based on dynamic response sensitivity. A probabilistic approach for damage identification considering measurement noise uncertainties has been given by [27]. The probability of identified structural damage is further derived based on the reliability theory. Other advanced studies include application of neural network techniques for damage detection has been studied by [28]. In order to simulate and estimate structural response of two-storey shear building by training the model for a particular earthquake using the powerful technique of artificial neural network models has been presented by [29]. It may be seen from above that artificial neural networks provide a fundamentally different approach to damage detection problems subjected to different earthquakes.

It is revealed from the above literature review that various authors developed different identification methodologies using ANN. They supposed that the data obtained are in exact or crisp form. But in actual practice the experimental data obtained from equipments are with errors that may be due to human or equipment errors thereby giving uncertain form of the data. Although one may also use probabilistic methods to handle such problems. But the probabilistic method requires huge quantity of data which may not be easy or feasible in particular to the structural parameters. In view of the above various research works are being

developed using Interval Neural Networks (INN) in different fields. [30] defined interval neural network and categorized general three-layer neural network training problems into two types i.e. type1 and type 2 according to their mathematical model. Using these general algorithms one can develop specific software which can efficiently solve interval weighted neural network problems. An algorithm for Interval Neural Networks was also presented by [31]. [32] presented an application of interval valued neural networks to a regression. Their work was concerned with exploiting uncertainty in order to develop a robust regression algorithm for a pre-sliding friction process based on a nonlinear Auto-Regressive with eXogeneous inputs neural network. In addition to this, they have also shown that an interval-valued neural network allows a trade-off between the model error and the interval width of the network weights or a 'degree of uncertainty' parameter. The interval analysis technique for structural damage identification has been proposed by [33]. Influences of uncertainties in the measurements and modelling errors on the identification were also investigated in this paper. [34] proposed a numerically efficient approach to treat modelling errors as intervals which results in bounded values for obtaining the identified parameters. An Interval GA (Genetic Algorithm) for evolving neural networks with interval weights and biases was developed by [35] where they have proposed an extension of genetic algorithm for neuro evolution of interval-valued neural networks. In order to handle the interval-valued genotypes, interval-valued GA (IvGA) extends its processes of initialization of populations, fitness evaluation, crossover and mutation. They have applied the IvGA to approximate modeling of interval functions with interval-valued neural networks. [36] proposed identification methodologies for multi-storey shear buildings using Interval Artificial Neural Network (IANN) which can estimate the structural parameters.

In the present work, Chamoli and Uttarkashi earthquake ground acceleration, recorded at Barkot in NE (North-East) direction has been considered in interval form. From their interval ground acceleration, the responses in interval form are computed using the proposed procedure. Then the ground acceleration and the corresponding response in interval form are trained using INN 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 different intensity earthquake data (generated numerically) 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. INTERVAL ARITHMETIC

Let us assume A and B as numbers expressed as interval. For all $\underline{a}, \bar{a}, \underline{b}, \bar{b} \in \mathrm{R}$ where

$\mathrm{A} = \left[\underline{a}, \bar{a}\right]$, $\mathrm{B} = \left[\underline{b}, \bar{b}\right]$, the main operations of intervals may be written as [37],

1) Addition
$$\left[\underline{a}, \bar{a}\right](+)\left[\underline{b}, \bar{b}\right] = \left[\underline{a} + \underline{b},\ \bar{a} + \bar{b}\right]$$
2) Subtraction
$$\left[\underline{a}, \bar{a}\right](-)\left[\underline{b}, \bar{b}\right] = \left[\underline{a} - \bar{b},\ \bar{a} - \underline{b}\right]$$

3) Multiplication
$\left[\underline{a},\overline{a}\right](\times)\left[\underline{b},\overline{b}\right]=\left[\min\left(\underline{a}\times\underline{b},\underline{a}\times\overline{b},\overline{a}\times\underline{b},\overline{a}\times\overline{b}\right),\max\left(\underline{a}\times\underline{b},\underline{a}\times\overline{b},\overline{a}\times\underline{b},\overline{a}\times\overline{b}\right)\right]$
4) Division
$\left[\underline{a},\overline{a}\right](\div)\left[\underline{b},\overline{b}\right]=\left[\min\left(\underline{a}\div\underline{b},\underline{a}\div\overline{b},\overline{a}\div\underline{b},\overline{a}\div\overline{b}\right),\max\left(\underline{a}\div\underline{b},\underline{a}\div\overline{b},\overline{a}\div\underline{b},\overline{a}\div\overline{b}\right)\right]$
excluding the case $\underline{b}=0$ or $\overline{b}=0$

3. INTERVAL NEURAL NETWORK AND LEARNING ALGORITHM FOR INN

Interval Neural Network (INN) is a network in which either inputs, outputs or the connection weights are in interval. The topological architecture for INN is identical to the crisp neural network. Traditional Neural Network (NN) and Error Back Propagation (EBP) are well known but here for the sake of completeness those are developed in intervals. The inputs, outputs, weights and biases of the standard feed forward neural network and the learning algorithm can be extended in intervals as in [31]. Here, Error Back Propagation Training algorithm and Feed Forward recall has been used but to handle the uncertain system. The following IANN is computed based on the interval computation defined above. The interval weights and interval biases are also calculated based on above interval computations. The typical network may be understood from Fig. 1.

$\tilde{\tilde{Z}}_i$, $\tilde{\tilde{P}}_j$ and $\tilde{\tilde{O}}_k$ are input, hidden and output layer, respectively. The weights between input and hidden layers are denoted by $\tilde{\tilde{v}}_{ji}$ and the weights between hidden and output layers are denoted by $\tilde{\tilde{w}}_{mj}$ which are all in intervals. The input $\tilde{\tilde{Z}}_i=\tilde{\tilde{a}}_i=\left[\underline{\underline{a}}_i,\overline{\overline{a}}_i\right]$ are the ground acceleration in interval and the output $\tilde{\tilde{O}}_m=\tilde{\tilde{\ddot{x}}}_m=\left[\underline{\underline{\ddot{x}}}_m,\overline{\overline{\ddot{x}}}_m\right]$ are responses of the structure in interval form. The procedure may easily be written down for the processing of this algorithm.

Given R training pairs $\left\{\tilde{\tilde{Z}}_1,\tilde{\tilde{d}}_1;\tilde{\tilde{Z}}_2,\tilde{\tilde{d}}_2;....\tilde{\tilde{Z}}_R,\tilde{\tilde{d}}_R\right\}$ where $\tilde{\tilde{Z}}_i(I\times 1)$ are input and $\tilde{\tilde{d}}_i(M\times 1)$ are desired values for the given inputs, the total input to the j-th hidden unit in the second layer can be calculated as

$$\tilde{\tilde{P}}_j=\left[\underline{P}_j,\overline{P}_j\right]=\left[\underline{v}_{ji},\overline{v}_{ji}\right]\cdot\left[\underline{Z}_i,\overline{Z}_i\right]+\left[\underline{\theta}_j,\overline{\theta}_j\right] \tag{1}$$

where right hand side of the above equation is to be computed by interval multiplication and interval addition. Here, $\left[\underline{\theta}_j,\overline{\theta}_j\right]$ are the bias weights of the hidden layer. Then the output of the hidden unit can be evaluated as

$$\tilde{\tilde{U}}_j=\left[f\left(\underline{P}_j\right),f\left(\overline{P}_j\right)\right]=\left[\underline{U}_j,\overline{U}_j\right]$$

where f is the unipolar activation function defined by $f(net)=1\Big/\left[1+\exp(-\gamma\, net)\right]$.

The total input from hidden to the output unit is calculated as

$$\tilde{Y}_m = \left[\underline{Y}_m , \overline{Y}_m\right] = \left[\underline{w}_{mj} , \overline{w}_{mj}\right] \cdot \left[\underline{U}_j , \overline{U}_j\right] + \left[\underline{\theta}_m , \overline{\theta}_m\right] \tag{2}$$

Again the right hand side involves interval multiplication and interval addition

where $\left[\underline{\theta}_m , \overline{\theta}_m\right]$ are the bias weights of the output layer. Finally, the response of the net is given as

$$\tilde{O}_m = \left[f\left(\underline{Y}_m\right), f\left(\overline{Y}_m\right)\right] = \left[\underline{O}_m , \overline{O}_m\right]$$

The error value is computed as

$$\tilde{E} = \frac{1}{2}\left[\left(\underline{d}_m - \underline{O}_m\right)^2 + \left(\overline{d}_m - \overline{O}_m\right)^2\right], \text{ m=1, 2...M} \tag{3}$$

for the present neural network . From the cost function (3), a learning rule can be derived for the interval weight $\left(\tilde{v}_{ji}\right)$ between the hidden and the input layer. The interval weights are updated as,

$$\tilde{v}_{ji}^{(New)} = \left[\underline{v}_{ji}^{(New)} , \overline{v}_{ji}^{(New)}\right] = \left[\underline{v}_{ji}^{(old)} , \overline{v}_{ji}^{(old)}\right] + \left[\Delta\underline{v}_{ji} , \Delta\overline{v}_{ji}\right] \text{ j=1, 2…J and i=1, 2…I} \tag{4}$$

where change in weights are calculated as

$$\Delta\tilde{v}_{ji} = \left[\Delta\underline{v}_{ji} , \Delta\overline{v}_{ji}\right] = \left[-\eta\frac{\partial\tilde{E}}{\partial\underline{v}_{ji}} , -\eta\frac{\partial\tilde{E}}{\partial\overline{v}_{ji}}\right] \text{ , j=1, 2... J and i=1, 2... I} \tag{5}$$

Consequently, output layer weights $\left(\tilde{w}_{mj}\right)$ between the output layer and the hidden layer are

adjusted as,

$$\tilde{w}_{mj}^{(New)} = \left[\underline{w}_{mj}^{(New)} , \overline{w}_{mj}^{(New)}\right] = \left[\underline{w}_{mj}^{(old)} , \overline{w}_{mj}^{(old)}\right] + \left[\Delta\underline{w}_{mj} , \Delta\overline{w}_{mj}\right] \text{ m=1, 2... M and j=1, 2... J} \tag{6}$$

where change in weights are calculated as

$$\Delta\tilde{w}_{mj} = \left[\Delta\underline{w}_{mj} , \Delta\overline{w}_{mj}\right] = \left[-\eta\frac{\partial\tilde{E}}{\partial\underline{w}_{mj}} , -\eta\frac{\partial\tilde{E}}{\partial\overline{w}_{mj}}\right] \text{ , m=1, 2... M and j=1, 2... J} \tag{7}$$

and η is the learning constant. While modifying $\underline{v}_{ji}$, $\overline{v}_{ji}$ and $\underline{w}_{mj}$, $\overline{w}_{mj}$ by (4)-(7), it is undesirable but possible sometimes that $\underline{v}_{ji} > \overline{v}_{ji}$ and $\underline{w}_{mj} > \overline{w}_{mj}$. In order to cope with this

situation, the interval weights from input to hidden layer and from hidden to output layer are then determined as,

$$\tilde{v}_{ji}^{(New)} = \left[\min\left\{\underline{v}_{ji}^{(New)}, \bar{v}_{ji}^{(New)}\right\}, \max\left\{\underline{v}_{ji}^{(New)}, \bar{v}_{ji}^{(New)}\right\}\right] \tag{8}$$

$$\tilde{w}_{mj}^{(New)} = \left[\min\left\{\underline{w}_{mj}^{(New)}, \bar{w}_{mj}^{(New)}\right\}, \max\left\{\underline{w}_{mj}^{(New)}, \bar{w}_{mj}^{(New)}\right\}\right] \tag{9}$$

In the similar fashion the interval biases $\tilde{\theta}_j$ and $\tilde{\theta}_m$ are also updated.

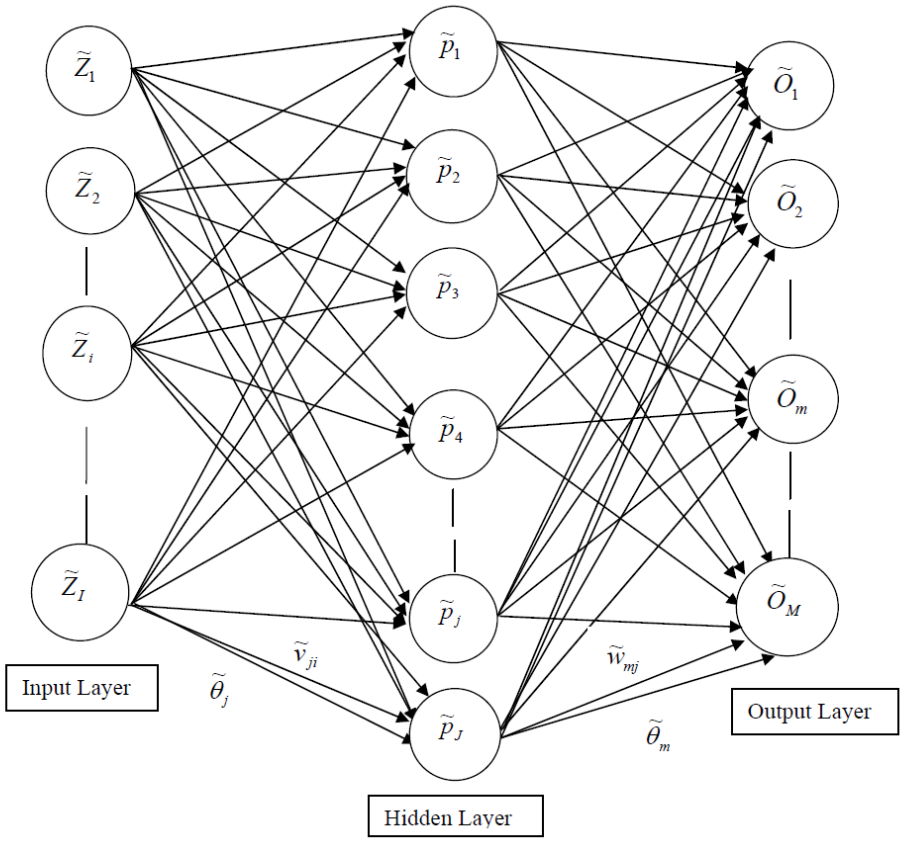

Figure 1. Layered feed-forward interval neural network

4. STRATEGY FOR RESPONSE PREDICTION

Basic concept behind the proposed methodology is to predict the structural response (in intervals) of uncertain shear structural system subjected to earthquake forces which are also in interval. Two scenarios viz without damping and with damping have been considered for the analysis.

4.1 Without damping

Here we will discuss the procedure for an example problem of Single Degree of Freedom (SDOF) systems. Let $\tilde{M}$ be the mass of the generalized one storey structure, $\tilde{K}$ the stiffness of the structure and $\tilde{X}$ be the displacement relative to the ground all in interval form. Then the equation of motion may be written as

$$\begin{aligned} &\tilde{M}\ddot{\tilde{X}} + \tilde{K}\tilde{X} = -\tilde{M}\ddot{\tilde{a}} \\ \text{where } &\ddot{\tilde{X}} = \text{Acceleration in interval,} \\ &\tilde{X} = \text{Displacement in interval,} \\ &\ddot{\tilde{a}} = \text{Ground acceleration in interval.} \end{aligned} \tag{10}$$

Equation (10) may be written as,

$$\ddot{\tilde{X}} + \tilde{\omega}^2\tilde{X} = -\ddot{\tilde{a}} \tag{11}$$

where $\tilde{\omega}^2$ is the interval natural frequency parameter of the undamped structure. It may be noted that the above equation can be solved by Interval Duhamel integral. Here to obtain the solution for equation (11), the Duhamel integral are considered for different sets of lower and upper form. This is done to avoid complicacy raised while getting the above solution. And that is why now we will drop '~' from all notations and will consider the case for lower form first and similarly for upper form. Hence the solution of equation (11), [38] in lower form is written as

$$\underline{X(t)} = -\frac{1}{\underline{\omega}}\int_0^t \underline{\ddot{a}}(\tau)\sin\left[\underline{\omega}(t-\tau)\right]d\tau \tag{12}$$

From this solution the response of the structure viz. acceleration in lower form is obtained for no damping. In the similar fashion we can compute for upper form.

4.2 With damping

Let $\tilde{M}$ be the mass of the generalized one storey structure in interval form, $\tilde{K}$ the stiffness of the structure in interval form, $\tilde{C}$ the damping and $\tilde{X}$ be the displacement relative to the ground all are in intervals. Then the equation of motion may be written as

$$\begin{aligned} &\tilde{M}\ddot{\tilde{X}} + \tilde{C}\dot{\tilde{X}} + \tilde{K}\tilde{X} = -\tilde{M}\ddot{\tilde{a}} \\ \text{where, } &\ddot{\tilde{X}} = \text{Acceleration in interval,} \\ &\dot{\tilde{X}} = \text{Velocity in interval} \\ &\ddot{\tilde{a}} = \text{Ground acceleration in interval,} \\ &\tilde{X} = \text{Displacement in interval} \end{aligned} \tag{13}$$

Equation (13) may be written as,

$$\ddot{\tilde{X}} + 2\tilde{\xi}\tilde{\omega}\dot{\tilde{X}} + \tilde{\omega}^2\tilde{X} = -\ddot{\tilde{a}} \tag{14}$$

where $\tilde{\xi}\tilde{\omega}$ and $\tilde{\omega}^2$ are the natural frequency parameter of the damped and undamped structure in interval. Here also solution is obtained for different sets in lower and upper form. Hence the solution of equation (14) in lower form is given as

$$\underline{X(t)} = -\frac{1}{\underline{\omega}}\int_0^t \underline{\ddot{a}}(\tau)\exp\left[-\underline{\xi}\,\underline{\omega}(t-\tau)\right]\sin\left[\underline{\omega}(t-\tau)\right]d\tau \tag{15}$$

From this solution the response of the structure viz. acceleration in lower form with damping is obtained. In the similar manner we can compute for the upper form. Hence, the neural network architecture is constructed taking interval ground acceleration as input and the interval responses obtained from the above solution as output for each time step.

5. NUMERICAL RESULTS AND DISCUSSIONS

For present study two Indian earthquakes viz. the Chamoli earthquake at Barkot in NE (north east) direction and the Uttarkashi earthquake at Barkot in NE (north-east) direction have been considered for training and testing for different cases. Different cases are discussed below,

Case (i) Without damping, Ground acceleration as well as response data in interval form with crisp frequency.

Case (ii) Without damping, Ground acceleration as well as response data in interval form with interval frequency.

Case (iii) With damping, Ground acceleration as well as response data in interval form with crisp frequency and interval damping.

Case (iv) With damping, Ground acceleration as well as response data in interval form with interval frequency and interval damping.

Case (v) Testing for different earthquake data with / without damping.

It is worth mentioning that the earthquake acceleration data are actually both positive and negative. But the present IANN cannot handle the data with negative sign due to the complexity in interval computation and also in the IANN model. As such we have taken all the earthquake data as absolute (positive) value and then those have been trained. Accordingly, all the plots are presented in the positive y-axis. This is also due to the fact we may concentrate on the amplitude of the acceleration at any instant of time.

As mentioned earlier for case (i), initially the system without damping is studied and for that the system is subjected to Chamoli earthquake with maximum ground acceleration in interval form as [19.088, 20.088] cm/sec/sec at Barkot in NE (north-east) direction was used to compute the response for single storey structure using Eq. (12). The obtained response of the structure and the ground acceleration in interval form are trained first for the assumed frequency parameters in crisp form as ω=0.5 with time range 0 to 14.96 secs. (749 data

points) for the mentioned earthquake and are shown in Figs. 2(a) and 2(b). Fig. 2(a) shows the plot for lower values and Fig. 2(b) depicts the upper values. Similar plots with ω=0.02 are shown in Figs. 3(a) and 3(b). Simulations have been done for different hidden layer nodes and it was seen that the response result is almost same and good for 15 to 18 nodes in the hidden layer. However, 18 hidden layer nodes are used here to generate the results for 749 data points.

In case (ii), the system is considered without damping with the same earthquake. The earthquake has maximum ground acceleration in interval form as [19.088, 20.088] cm/sec/sec and the response obtained are also in interval form. The neural network architecture is trained within the time range 0 to 14.96 secs. (749 data points) but for two sets of frequency parameters taken in interval form as $\omega = [0.4, 0.6]$ and $\omega = [0.01, 0.03]$. Training has been done for different hidden layer nodes. Again 18 hidden layer nodes are used to generate the results for 749 data points. The results are plotted in Figs. 4(a), 4(b) and 5(a), 5(b).

The system with damping is considered in case (iii). Considering the ground acceleration of Uttarkashi earthquake at Barkot (NE) in interval form, the response is computed using Eq. (15). Obtained responses and the ground acceleration in interval form are trained by the said IANN model for an example structural system with frequency parameter in crisp form as ω = 0.68981 and damping as [1.48033, 1.68033]. Training was done for the total time range 0 to 14.96 secs. (749 data points). After training, ground acceleration and response data for Uttarkashi earthquake for various nodes in hidden layer it was confirmed that 18 nodes are again sufficient for the prediction. So, the weights corresponding to 18 hidden nodes are stored and they are used to predict responses for various intensity earthquakes. Figs. 6(a) and 6(b) show the response comparison between the desired and IANN data.

For case (iv) the system is again considered with damping. Ground acceleration in interval form is used to calculate the required response of the structure in interval form with frequency parameter in interval form as $\omega = [0.58981, 0.78981]$ and damping as [1.48033, 1.68033]. The data are trained with different hidden nodes in the hidden layer and it was found that 16 hidden nodes are sufficient to get an accuracy of 0.001. Comparison between the desired and IANN are shown in Figs. 7(a) and 7(b). After training the ground acceleration and response data in interval form for Uttarkashi earthquake at Barkot (NE) for different hidden nodes in hidden layer, the weights are stored and they are used to predict responses for various intensity earthquakes.

Finally in case (v) the training is extended with various intensities for time range 0 to 9.98 secs. (500 data points) and tested with different hidden layer nodes. It was found that the response result is almost same and good for 15 to 20 nodes in the hidden layer. But here 16 hidden layer nodes are used to generate the results for 500 data points without damping with frequency parameter in interval form. Figs. 8(a) and 8(b) show response comparison between ANN and desired for the 80% of Uttarkashi earthquake at Barkot (NE) for $\omega = [0.4, 0.6]$ using the stored converged weights of Chamoli earthquake directly. Similarly, the response comparison for 120% Uttarkashi earthquake at Barkot (NE) for $\omega = [0.01, 0.03]$ using the converged weights of Chamoli earthquake are shown in Figs. 9(a) and 9(b).

The training is also extended with damping for various intensities within the time range 0

to 9.98 secs. (500 data points) and tested with different hidden layer nodes. It was found that the response result is almost same and good for 16 hidden layer nodes. The comparison between the desired and ANN response data for 80% of Chamoli earthquake acceleration at Barkot (NE) with $\omega = [0.58981, 0.78981]$ and damping = [1.48033, 1.68033] using the converged weights of Uttarkashi earthquake are shown in Figs. 10(a) and 10(b). Similarly, for 120% of Chamoli earthquake acceleration at Barkot (NE) with $\omega = [0.58981, 0.78981]$ and damping = [1.48033, 1.68033] and the response comparison between neural and desired are plotted in Figs. 11(a) and 11(b).

Comparison between desired and INN peak acceleration values (testing) with various intensities of Uttarkashi (without damping) and Chamoli earthquake acceleration at Barkot (NE) (with damping) has been presented in Table 1.

6. CONCLUSION

This paper uses the powerful soft computing technique viz Interval Artificial Neural Network (IANN) to compute interval structural response of structural system subject to Indian earthquakes at Chamoli and Uttarkashi ground motion data. It is shown here that once the training is done then the trained architecture may be used to simulate for various intensity earthquakes, thereby showing the responses of the system which depend upon the structural properties (mass and stiffness) of the structure. If the INN is trained for various time periods of one earthquake with its corresponding maximum responses then the model can predict the maximum response in interval form directly (to the corresponding time period) for other earthquake that had not been used during the training. In this way the safety of the structural systems in interval form may be predicted in case of future earthquakes.

Table 1: Comparison between the Desired and INN Peak Acceleration values (Testing Values)

Case	Intensities	Desired		INN	
		Lower	Upper	Lower	Upper
Without Damping	80%	15.2704	16.0704	14.7954	15.6091
(Uttarkashi at Barkot NE)	120%	22.9056	24.1056	22.3373	23.4528
With Damping (Chamoli	80%	13.108	13.908	12.7279	13.4997
at Barkot NE)	120%	19.662	20.862	19.0955	20.2757

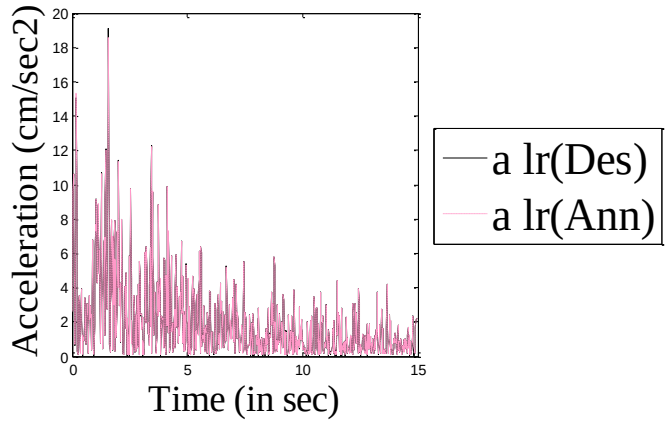

Figure 2(a). Comparison between the Desired and INN Seismic Response for lower values (without damping) for Chamoli Earthquake at Barkot in NE direction with ω =0.5

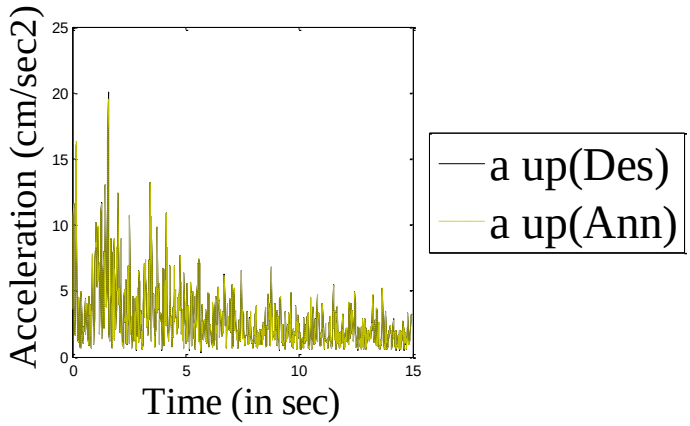

Figure 2(b). Comparison between the Desired and INN Seismic Response for upper values (without damping) for Chamoli Earthquake at Barkot in NE direction with ω =0.5

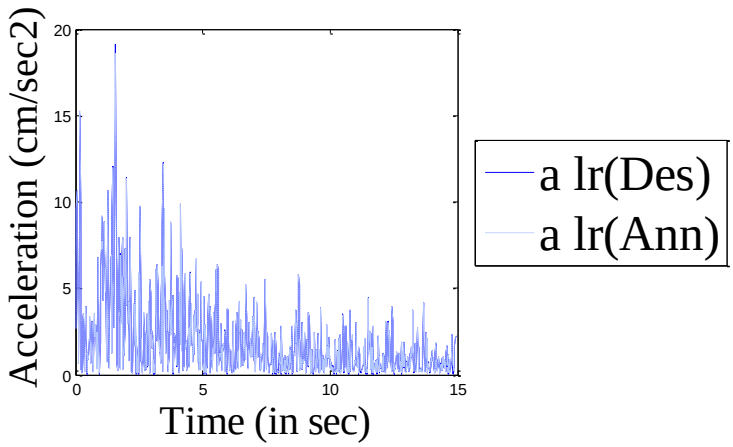

Figure 3(a). Comparison between the Desired and INN Seismic Response for lower values (without damping) for Chamoli Earthquake at Barkot in NE direction with ω =0.02

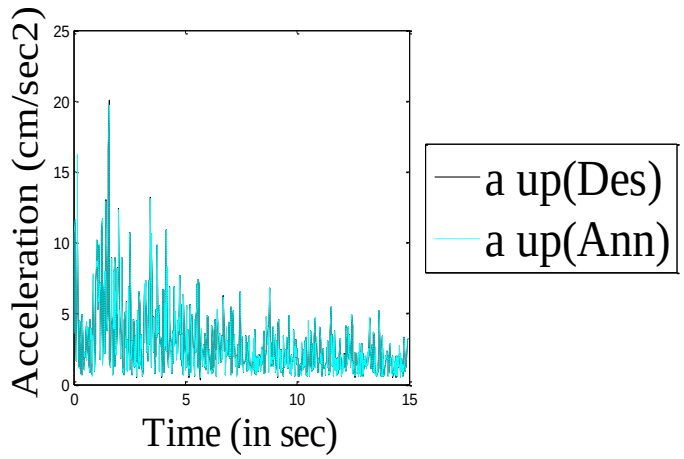

Figure 3(b). Comparison between the Desired and INN Seismic Response for upper values (without damping) for Chamoli Earthquake at Barkot in NE direction with ω =0.02

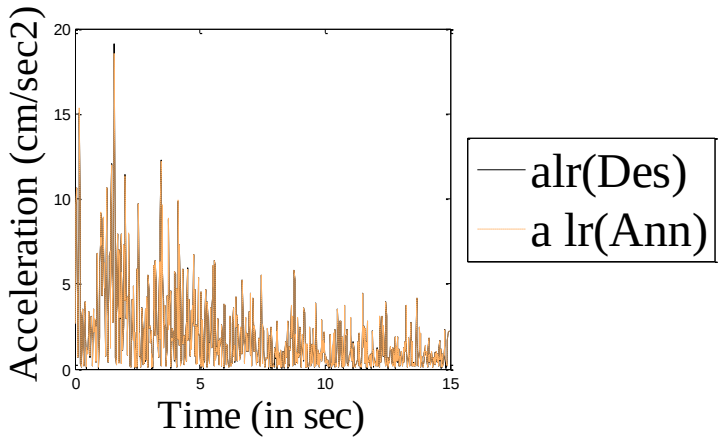

Figure 4(a). Comparison between the Desired and INN Seismic Response for lower values (without damping) for Chamoli Earthquake at Barkot in NE direction with ω = [0.4, 0.6]

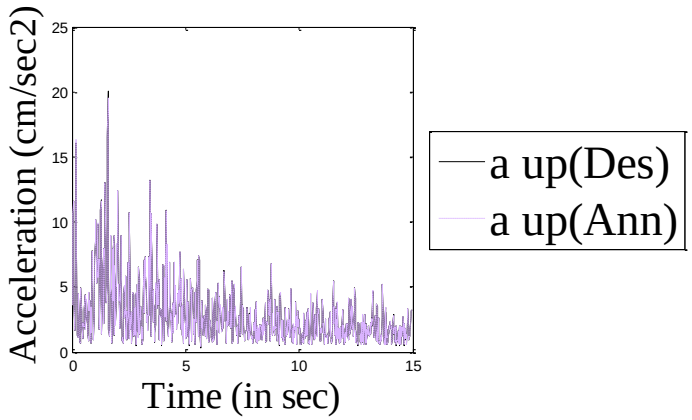

Figure 4 (b). Comparison between the Desired and INN Seismic Response for upper values (without damping) for Chamoli Earthquake at Barkot in NE directions with ω = [0.4, 0.6]

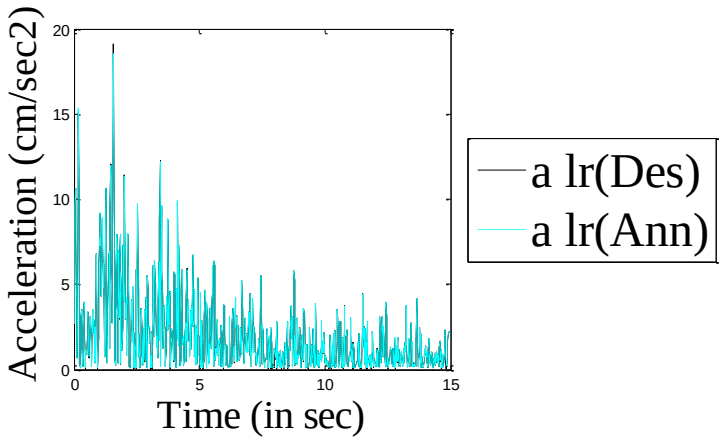

Figure 5(a). Comparison between the Desired and INN Seismic Response for lower values (without damping) for Chamoli Earthquake at Barkot in NE direction with ω = [0.01, 0.03]

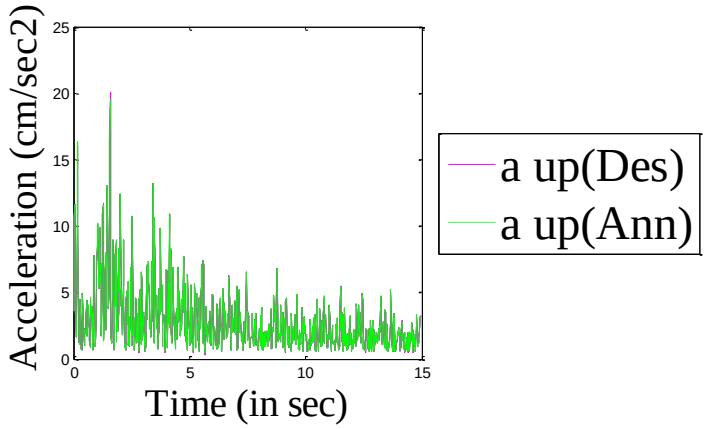

Figure 5 (b). Comparison between the Desired and INN Seismic Response for upper values (without damping) for Chamoli Earthquake at Barkot in NE directions with ω = [0.01, 0.03]

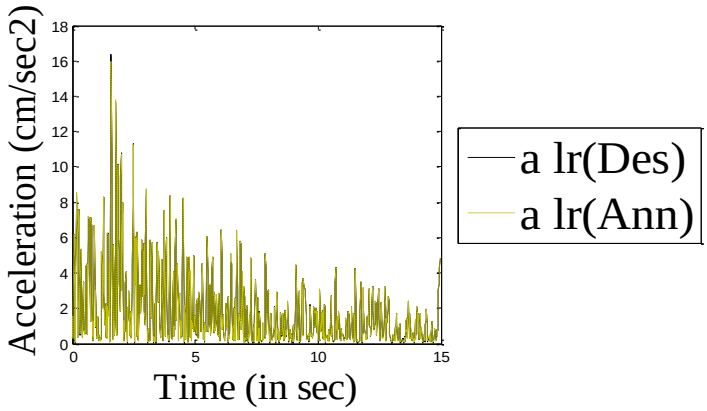

Figure 6(a). Comparison between the Desired and INN Seismic Response for lower values for Uttarkashi Earthquake at Barkot in NE direction with ω =0.68981 and damping [1.48033, 1.68033]

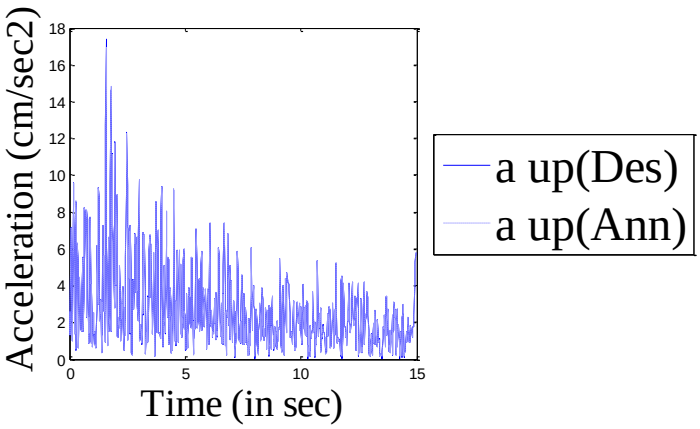

Figure 6(b). Comparison between the Desired and INN Seismic Response for upper values for Uttarkashi Earthquake at Barkot in NE direction with ω =0.68981 and damping [1.48033, 1.68033]

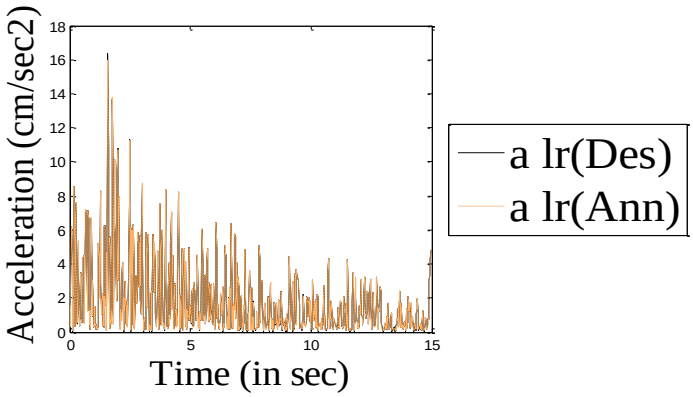

Figure 7(a). Comparison between the Desired and INN Seismic Response for lower values for Uttarkashi Earthquake at Barkot in NE direction with ω = [0.58981, 0.78981] and damping [1.48033, 1.68033]

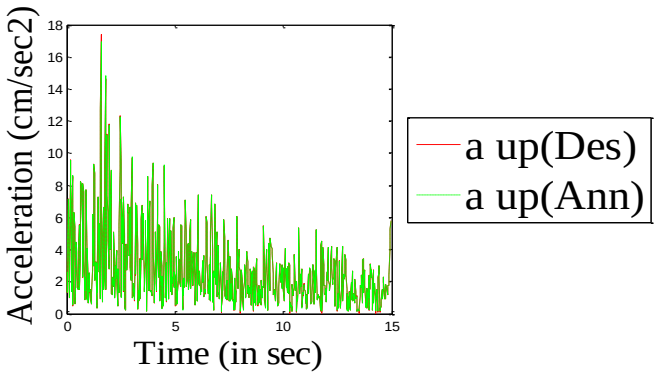

Figure 7 (b). Comparison between the Desired and INN Seismic Response for upper values for Uttarkashi Earthquake at Barkot in NE directions with ω = [0.58981, 0.78981] and damping [1.48033, 1.68033]

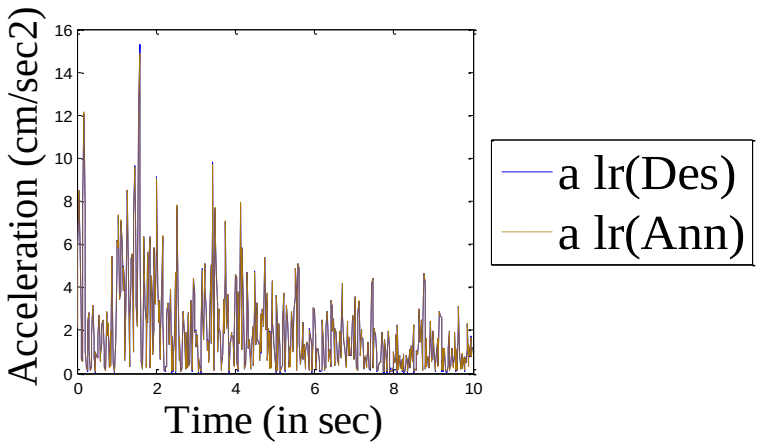

Figure 8(a). Comparison between the Desired and INN of 80% Seismic Response for lower values (without damping) for Uttarkashi Earthquake at Barkot (NE) with $\omega = [0.4, 0.6]$

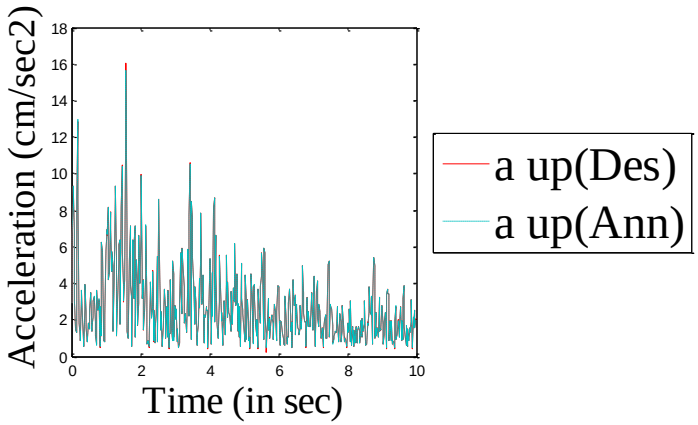

Figure 8(b). Comparison between the Desired and INN of 80% Seismic Response for upper values (without damping) for Uttarkashi Earthquake at Barkot (NE) with $\omega = [0.4, 0.6]$

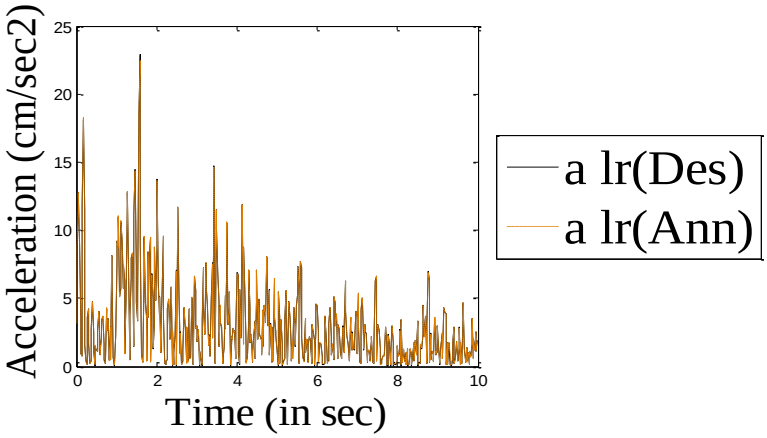

Figure 9(a). Comparison between the Desired and INN of 120% Seismic Response for lower values (without damping) for Uttarkashi Earthquake at Barkot (NE) with $\omega = [0.01, 0.03]$

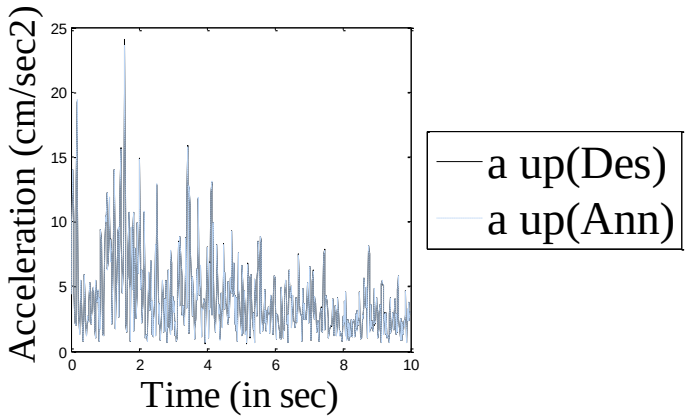

Figure 9(b). Comparison between the Desired and INN of 120% Seismic Response for upper values (without damping) for Uttarkashi Earthquake at Barkot (NE) with ω = [0.01, 0.03]

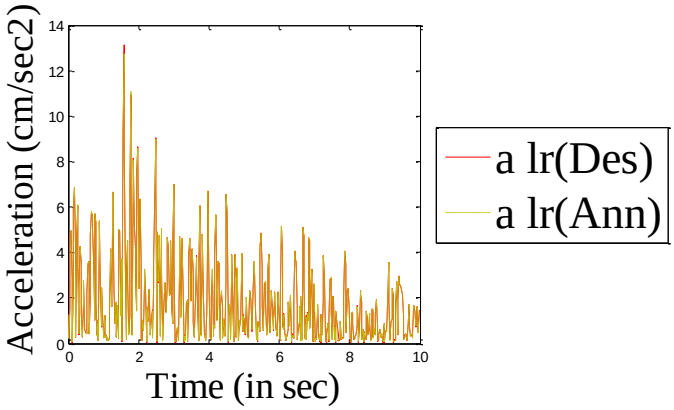

Figure 10(a). Comparison between the Desired and INN of 80% Seismic Response for lower values for Chamoli Earthquake at Barkot (NE) with ω = [0.58981, 0.78981] and damping [1.48033, 1.68033]

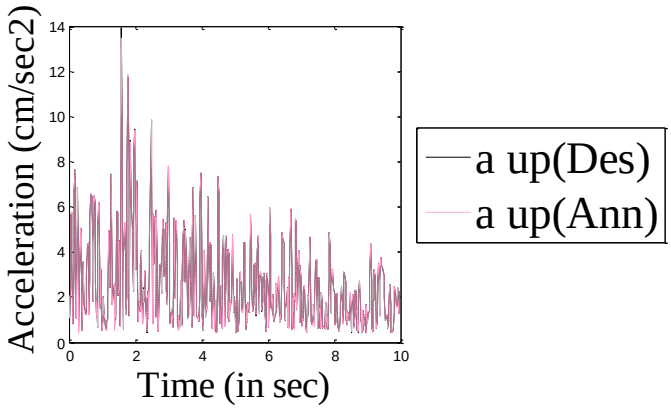

Figure 10(b). Comparison between the Desired and INN of 80% Seismic Response for upper values for Chamoli Earthquake at Barkot (NE) with ω = [0.58981, 0.78981] and damping [1.48033, 1.68033]

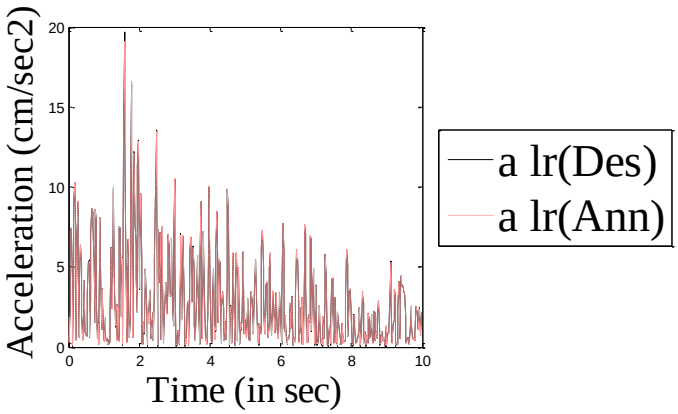

Figure 11(a). Comparison between the Desired and INN of 120% Seismic Response for lower values for Chamoli Earthquake at Barkot (NE) with ω = [0.58981, 0.78981] and damping [1.48033, 1.68033]

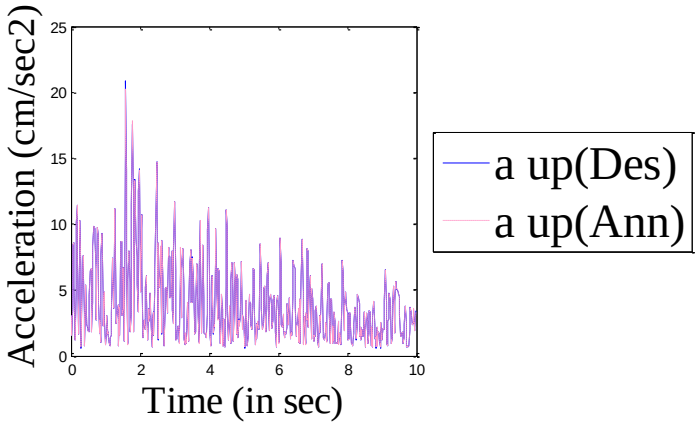

Figure 11(b). Comparison between the Desired and INN of 120% Seismic Response for upper values for Chamoli Earthquake at Barkot (NE) with ω = [0.58981, 0.78981] and damping [1.48033, 1.68033]

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