Nonlinear Analysis of Concrete Gravity Dams by Neural Networks

Abdolreza Joghataie and Mehrdad Shafiei Dizaji

***Abstract*—Multi-layer neural networks have been used in this paper for modeling nonlinear behaviour of concrete gravity dams under earthquake excitation. Koyna dam which has been studied extensively by other authors in the past has been studied as test example in this paper too, where the nonlinear response of its crest has been modelled by the proposed algorithm. The main steps of the algorithm are as follows: First the concrete gravity dam has been numerically analyzed for its nonlinear behaviour under earthquake excitation to generate numerical data to be used in the training of the neural networks. To this end the dam has been subjected to a white noise excitation so that the generated data could be rich enough for the training of a general neuro-modeller of the dam response. The neuro-modeller has then been trained on the generated data to learn the hysteretic behaviour of the dam implicitly. Then the neural network has been tested on a number of earthquakes including near field as well as very strong earthquakes for verification. The results obtained in this study prove that the method has been successful regarding the generalization capabilities of the trained neuro-modeller where other earthquakes than those used in its training have been used in its testing. In the tests, the neuro-modeller could predict the response with high precision. One significant benefit of using this algorithm is in cases where it is desired to use collected data from tests on experimental models or through monitoring of the response of a dam to prepare a suitable model for predicting its response under any earthquake. Another benefit is the time of analysis which can be reduced by this method. Once the neuro-modeller is trained, it can predict the response of the dam to any earthquake without the need to be updated.**

***Index Terms*—Concrete Gravity Dams, Dam Model, Earthquake, Neural networks, Neuro-modeller, Nonlinear Hysteresis.**

I. INTRODUCTION

The behaviour of concrete gravity dams subject to earthquakes is complicated because dams might experience cracking at places where the induced tensile stresses are higher than the tensile strength of concrete.

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Cracking and also material nonlinearity result in nonlinear behaviour which is hysteretic too. The nonlinear hysteretic response of concrete gravity dams can be modelled using any of the commercially available finite element analysis softwares or especial computer programs which have been developed for the modelling of this type of dams. Nonlinear analysis by conventional methods are time consuming though very helpful. Also when it is desired to provide a precise numerical model for the nonlinear behaviour of a dam, it is necessary to identify the parameters of the material. To this end, it is required to collect data on the real response of the dam and then try to determine the parameters of the material to be used in the computer programs, so that the simulated response to be as close to the observed response as possible. The material model obtained from the identification is often approximate and hence the analysis based on the model will not be precise either. Noticing neural networks have been successful in many other applications in modelling materials with high nonlinearity and hysteresis [1-7], it is expected that they could be helpful for modelling the nonlinear response of concrete gravity dams too.

Multilayer neural networks which are sometimes referred to as perceptrons, are simple models of several connected neurons similar to what is seen in the natural neural networks of animals. The main objective of building these artificial models of brain has been to design systems which can show some learning capabilities like the natural brain. A simple model of perceptrons can be seen in Fig.1. The network is generally comprised of an input, an output and one or more inside layers of neurons. The neurons are connected in a feed-forward manner, i.e. the neurons in each layer are connected to the neurons in its immediate previous and next layers. Mainly the connections of a neural network are the adaptive adjustable parts of it. Each neuron is a processing unit. Given an input vector to its input layer, the input signals propagate forward inside the neural network until it reaches the output layer. The vector of signals which appears in the output layer is considered as the output vector of the neural network, associated with the given input. The training of a neural network is the procedure of gradual modification of the connection weights until the output from a given input vector is close to the desirable target output vector. When it is desired to build a neural network to learn an ordered set of many input-output vectors, the training and learning procedure can be very complicated and might even diverge or converge to a set of connection weights for which the neural network can not produce desirable predictions, in which case the modelling fails. The training of the neural networks on data representing nonlinear behaviour of materials and systems, like the problem of this paper, is generally challenging.

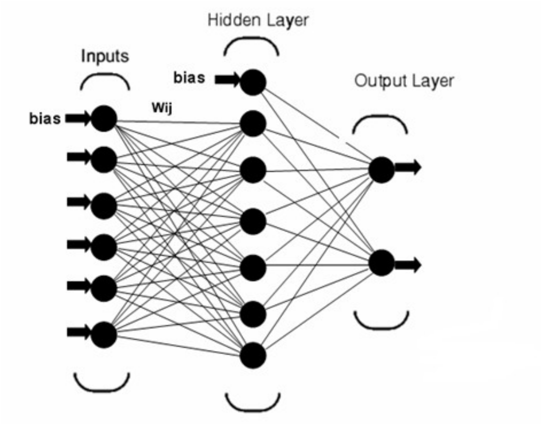


Fig. 1 Architecture of a perceptron

II NON-LINEAR MODELS FOR CONCRETE

Since the dynamic response of dam crest is hysteretic, the model for concrete should be capable of representing cyclic behaviour. In 1984 Bazant and his co-workers proposed a nonlinear model to represent the stress-strain relationship of concrete during the repeated cycles of opening and closure of cracks. De Borst and Nauta in 1985 and Gambarova and Valente in 1990 have also proposed simple models. Dahlblom and Ottosen in 1990 has proposed the following relationship for closing and reopening cycles of partially fractured concrete :

$$\varepsilon = [\lambda + (1-\lambda)\frac{\sigma}{\sigma_{\max}}]\varepsilon_{\max} \tag{1}$$

where λ is the ratio between the residual strain upon closing of cracks and the strain of its opening. It appears that the techniques applied by de Borst and Nauta in 1985 and Gambarova and Valente in 1990 are subsets of this generalized model with λ =0.0 and 1.0 respectively [8-10].

III KOYNA DAM

In this study, the nonlinear response of the crest of Koyna dam under earthquake excitation has been modeled numerically. The dam was build from concrete in India during 1958 to 1962 and experienced a high magnitude earthquake in 1967, which caused severe damage to the dam. After the damage, the dam became a benchmark problem which has been studied extensively by many researchers both numerically and experimentally. More information can be obtained from [11].

A. Finite Element Analysis of Koyna Dam

Fig. 2 shows the finite element mesh used in numerical modeling of the dam. The model proposed in [12] was used in the finite element analysis. The dam was subjected to different ground excitations which included a white noise, Koyna, El Centro, sakaria and Tabas earthquakes. Response of the dam crest consisting of the time history of its acceleration, velocity and displacement was recorded throughout the time.

Fig.3 shows the time history of the white noise used in the training of neuro-modeller.

IV NEURAL NETWORKS AND MODELLING HYSTERETIC BEHAVIOUR OF MATERIALS AND STRUCTURES

Generally perceptrons are not capable of learning hysteretic data because they lack memory. One way to compensate for this deficiency of perceptrons is to use the feeding back strategy where a number of the previous output vectors of the perceptron are fed back to its input layer to be used in its future prediction. This strategy has been used in many studies on the modelling of different nonlinear problems by neural networks.

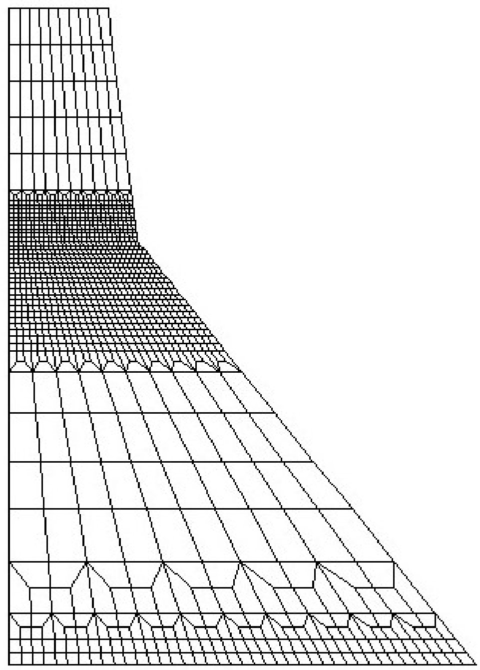


Fig.2. Finite element model of Koyna dam

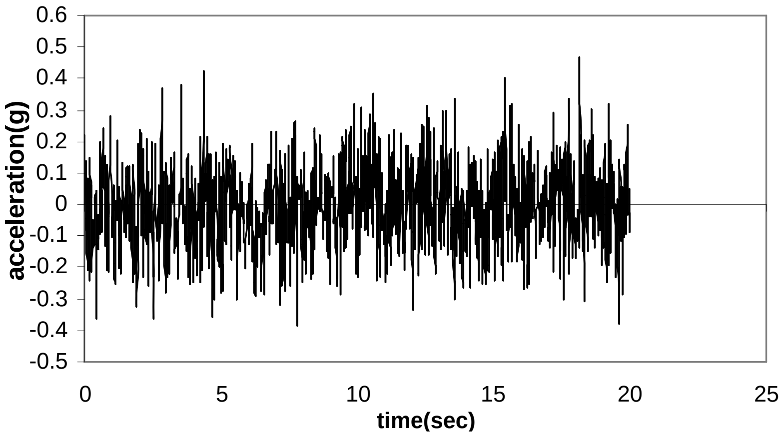


Fig.3. Time history of white noise earthquake

A. Training of Neuro-Modeller

After a number of trial and errors, the optimum architecture of the neuro-modeller was obtained as in Fig. 4a, where the input layer consists of the history of response and excitation. In this figure Y_i =displacement, $\dot{Y}_i$ = velocity and $\ddot{X}_i$ = earth acceleration. Also Fig. 4b shows how the neuro-modeller has been trained and used for the modelling.

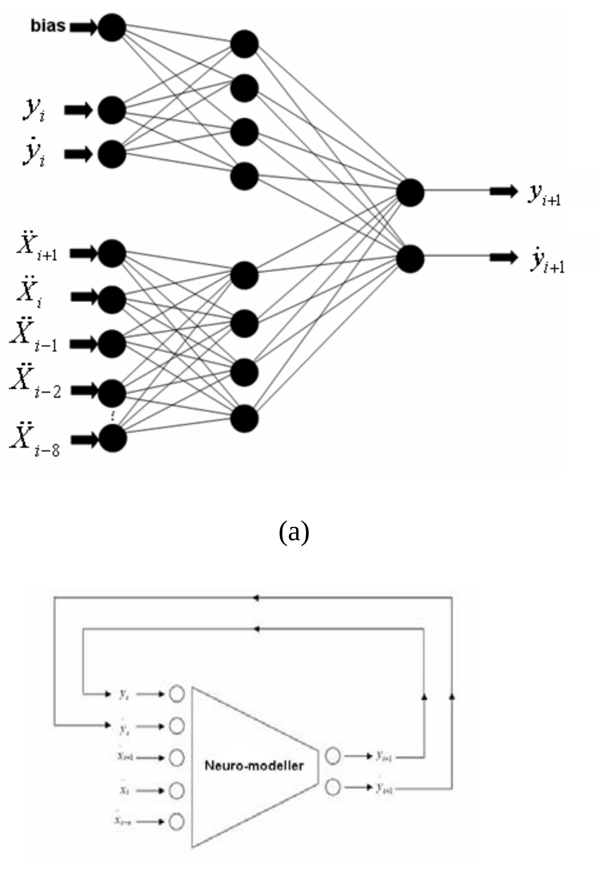
The neuro-modeller was trained on the data collected from the analysis of Koyna dam under white-noise excitation. Different techniques for training have been explained and used in many references and studies such as [13]. Since the training techniques used in this study were combinations of different older basic techniques, because of space limitations, their explanation are not included here.

The training was stopped when the mean square error, calculated as:

$$MSE = \frac{1}{N}\sum_{j=1}^{N}(\hat{y}_j - y_j)^2 \tag{2}$$

reached 8E-4, where N= number of training pairs, y_j = the corresponding target output vector and $\hat{y}_j$ is the output vector of the neural network.

A comparison between the target and predicted response when the dam was subjected to the white noise excitation used in the training by the neuro-modeller is made in Fig. 5 which shows the crest displacement both for 5 and 10 seconds. Fig. 6 shows the mean square error during the training, where the error has monotonically reduced as training has advanced.



(a)

(b)

Fig.4. (a) Neural network architecture of the example in this paper (b) neuro-modeller with its feedback loops

B. Testing Generalization Capabilities of Neuro-Modeller

After its successful training, the neuro-modeller was tested on some of the earthquakes including Koyna, El Centro, Sakaria and Tabas, where predictions by the emulator has been compared with the target values. The results corresponding to the above mentioned earthquakes are plotted in Fig.7. As can be seen the predictions by the neuro-modeller are very well representing the response of the dam crest.

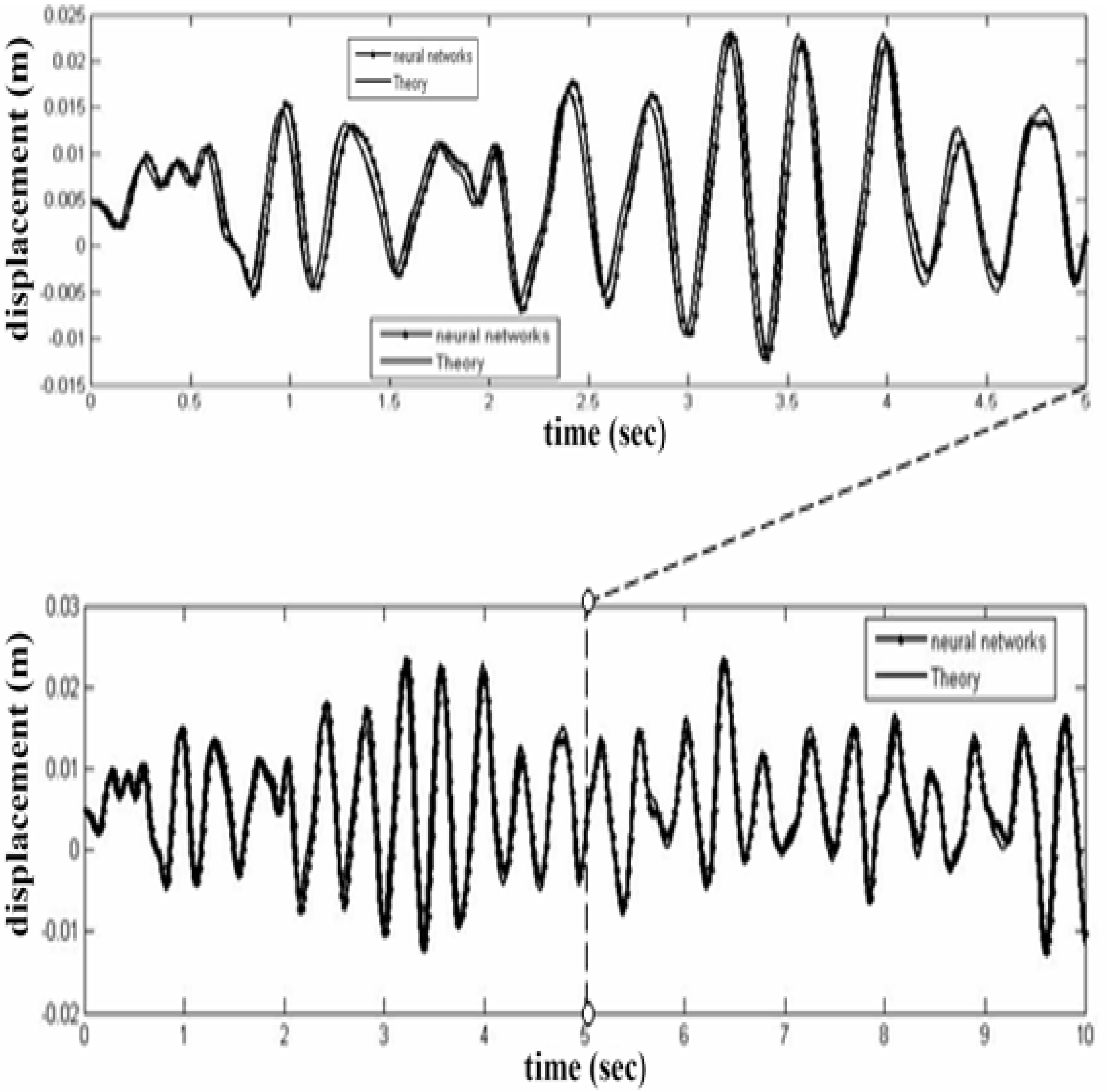


Fig.5. Comparing crest displacement obtained from analysis and predictions by NN for white noise earthquake

V. CONCLUSION

The application of a multi-layer feed forward neural network which receives feed back from its output layer, in the analysis of the response of Koyna dam, as a benchmark problem, proved successful. The neuro-modeller could predict with high precision the response of Koyna dam crest under several testing earthquakes. It could make predictions about the crest displacement and velocity throughout the time of excitation just by receiving input about earthquake acceleration.

One of the benefits of this approach is that once the neuro-modeller is trained, it can be used in the analysis directly to replace the integration methods and thus can significantly reduce the time required for analysis. However the method requires a considerable time for the training of the neuro-modeller. It is expected that the

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method can be extended for application to the dynamic analysis of stress and strain inside the dams too.

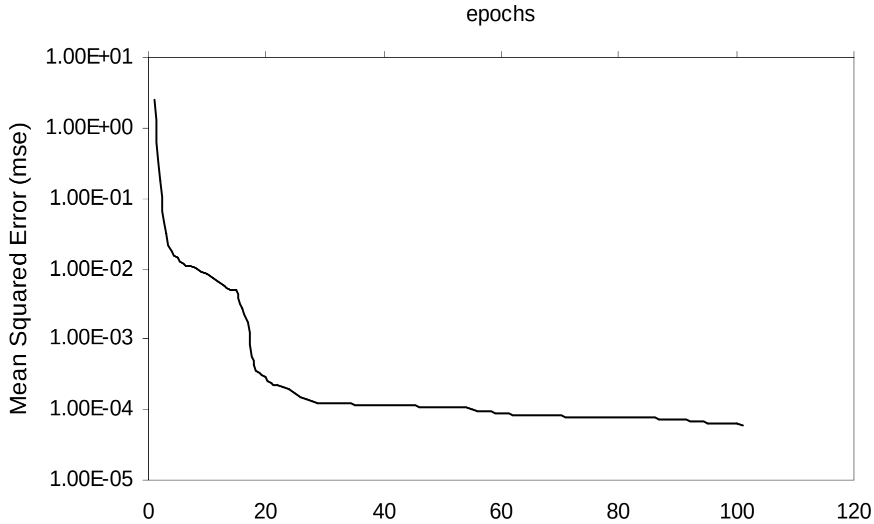

Fig.6. Mean square error of training versus training cycles

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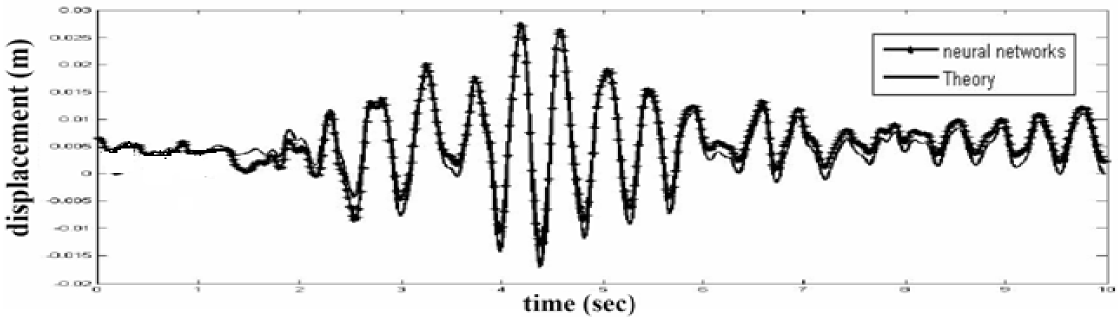

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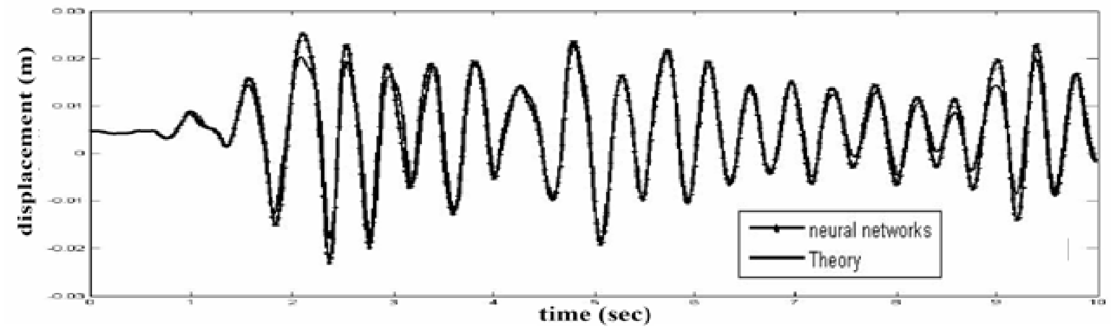

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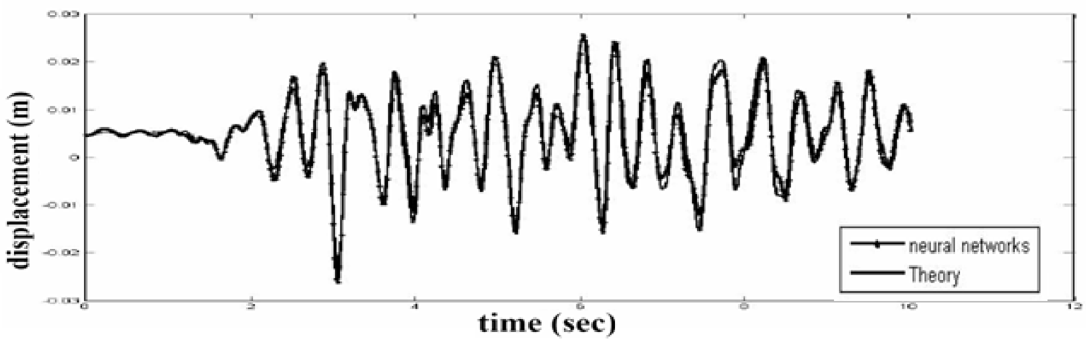

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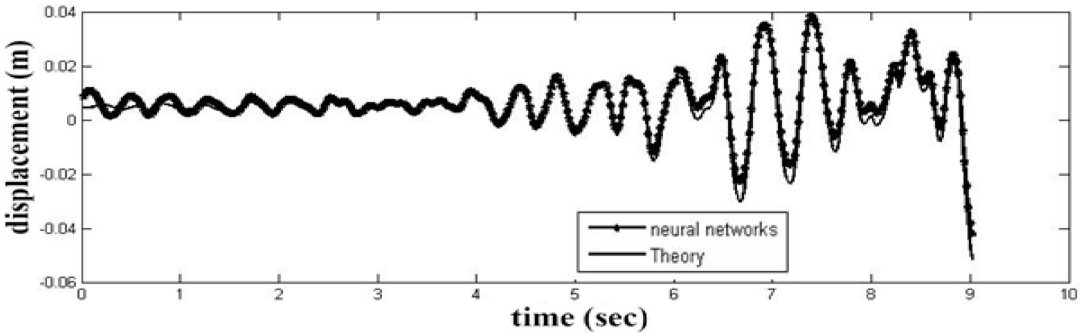

(d)

Fig.7. Comparing response obtained from analysis with predictions by NN for (a) Koyna (b)El centro1940 (c) Sakaria (d) Tabas