Neural Network Software for Dam-Reservoir-Foundation Interaction

Abdolreza Joghataie, Mehrdad Shafiei Dizaji, Farzad Shafiei Dizaji

***Abstract*—** A software has been developed to use artificial neural networks (ANNs) for the modelling of nonlinear hysteretic response of concrete gravity dams under earthquake loading when reservoir and foundation interactions are included. The neural network which is designed for a given dam has been called the "Neuro-modeller" of that dam. Pine flat dam has been studied as example problem. Firstly using an analysis software, the dam has been analyzed under different earthquakes to collect a large number of data for training the "Neuro-modeller" which has then been used for the analysis of the dam under other earthquakes. Numerical tests using other earthquakes have been done to verify the capabilities of the neuro-modeller, all of which have been successful.

***Keywords*—** Concrete gravity dam, Dam-Reservoir-Foundation Interaction, Hysteresis, Neuro-modeller, Nonlinear response.

I. Introduction

MODELLING complicated nonlinear hysteretic response behavior of concrete gravity dams, under earthquake and hydrodynamic loading due to the impact of earthquake on reservoir when water and foundation interaction has been included, has been considered of great importance [1]-[6].Various types of mathematical models for numerical nonlinear hysteretic analysis of concrete gravity dams have been presented [7]-[15]. Although considering dam-reservoir-foundation interaction will lead to greater accuracy in the result, it makes the nonlinear analysis more complicated and time-consuming. An aim of this study has been to decrease the time required for the analysis. Another disadvantage of numerical methods in analyzing concrete gravity dams is their poor accuracy. Another purpose of this study has been to investigate the possibility to use neural networks to enhance the precision.

A new neural network is designed and trained which is called "neuro-modeller". In this new neural network there is no need to define nonlinear parameters or different nonlinear models for concrete neither to model dam-reservoir-foundation interaction in that the neural network learns the dynamic nonlinear behavior of the dam and works similar to the numerical analysis software to estimate the dam behavior from the input it receives about the past response of the dam.

The results obtained from dynamic analysis by the neuro-modeler of Pine Flat dam have been compared with the results obtained from the finite element software, NSAG-DRI [1]. The comparison has proven the noteworthy potential of neural networks in learning and analyzing the nonlinear dynamic behavior of Pine Flat dam.

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II. Smeared Crack Model

For numerical modeling of the nonlinear hysteretic behavior of concrete gravity dams, NSAG-DRI software and smeared crack model have been used. Figure 1 shows the basics of analysis by this method [8]-[10].

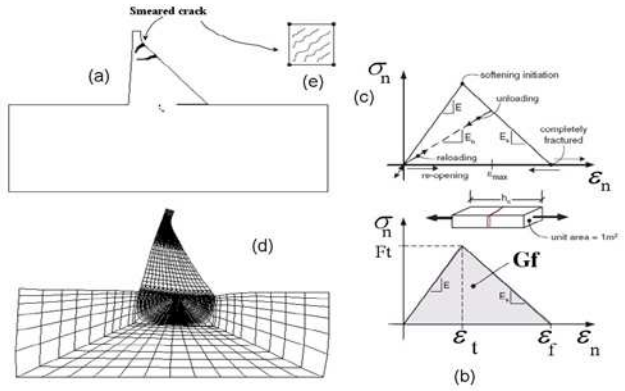


Fig. 1 Smeared crack model, (a) smeared crack in pine flat concrete gravity dam after it has been subjected to El Centro earthquake, (b) Stress-strain diagram and damage energy, (c) Hysteretic loading and unloading in stress-strain curve (drawn based on [10]), (d) profile of deformation under El Centro earthquake, (e) A 4-node element in the smeared crack model [8]-[10].

III. Artificial Neural Networks

Neural networks are parallel processing systems developed based on our knowledge about how the natural brain functions. Figure 2 shows the general structure of a multi layer feed forward neural network (MLFFNN) composed of several processing units called neurons. Every neuron acts as a processor. Neurons are attached to each other by wire-like connections. The nodes in a layer are attached to the nodes in their neighboring layers. The variable coefficients are called connection weights. The first layer on the left is called the input layer and the last layer is called the output layer. There are many references on the theoretic principles and application

of neural networks, [16]-[17]. Also there is a vast number of works on the application of neural networks in structural engineering such as [18]-[26].

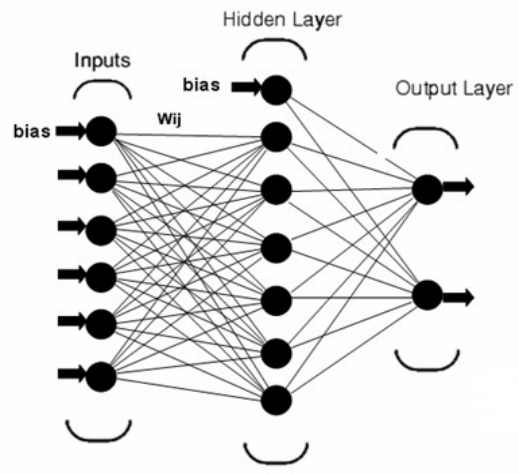


Fig. 2 Architecture of a MLFFNN

IV. The Finite Element Mesh used in Numerical Modeling of Dams

NSAG-DRI is a software developed for two dimensional finite element numerical nonlinear dynamic analysis of concrete gravity dams. Fig. 3 shows the finite element mesh used for Pine Flat, dam considering dam-reservoir-foundation interaction [1].

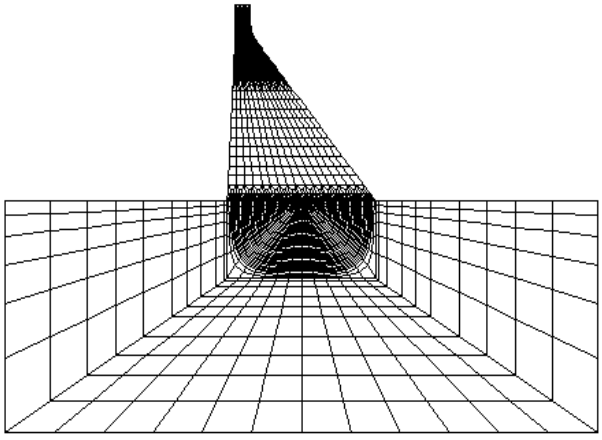
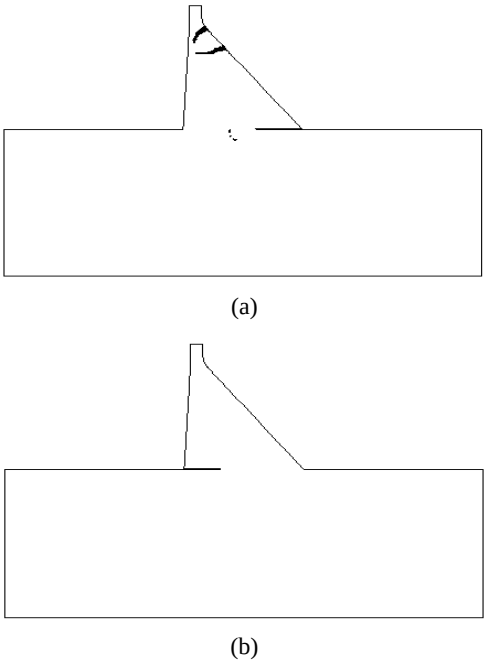


Fig. 3 Cross section of Pine Flat dam and corresponding finite element mesh for its analysis

V. Crack Profile and Propagation in Dams

After nonlinear analysis of Pine Flat dam under a number of different earthquakes, their crack profiles have been as shown in Figure 4.



(a)

(b)

Fig. 4 Crack profiles for Pine Flat dam from 2 different earthquakes: (a) El Centro, (b) Taft

VI. Nonlinear Dynamic Analysis of Concrete Gravity Dams

The nonlinear dynamic analysis of Pine Flat dam considering dam-reservoir-foundation interaction has been conducted by using NSAG-DRI under near-field and far-field earthquakes of various frequency content. The aim has been to show that the "neuro-modeller" can successfully work in very complex nonlinear conditions.

A. Nonlinear Analysis

Dynamic nonlinear analysis of the dam has been carried out under a white noise earthquake for 20 seconds. The time history of white noise earthquake acceleration used in the training of the neuro-modeler has been as shown in Figure 5.

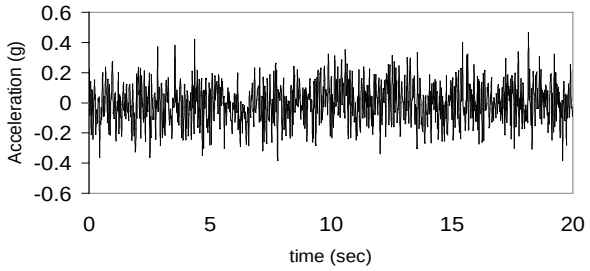


Fig. 5 Time history of White noise earthquake

Also 10 seconds of the results of dynamic nonlinear response of Pine Flat dam under the white noise earthquake has been shown in Figure 6a. The output has been used to train the neuro-modeller. Also Pine Flat dam has been analyzed under different types of earthquakes including El Centro, Taft and Corrolitos. The analysis of nonlinear

response for the displacement of crest of the dam under different types of earthquakes has been as shown in Figures 6b to 6d.

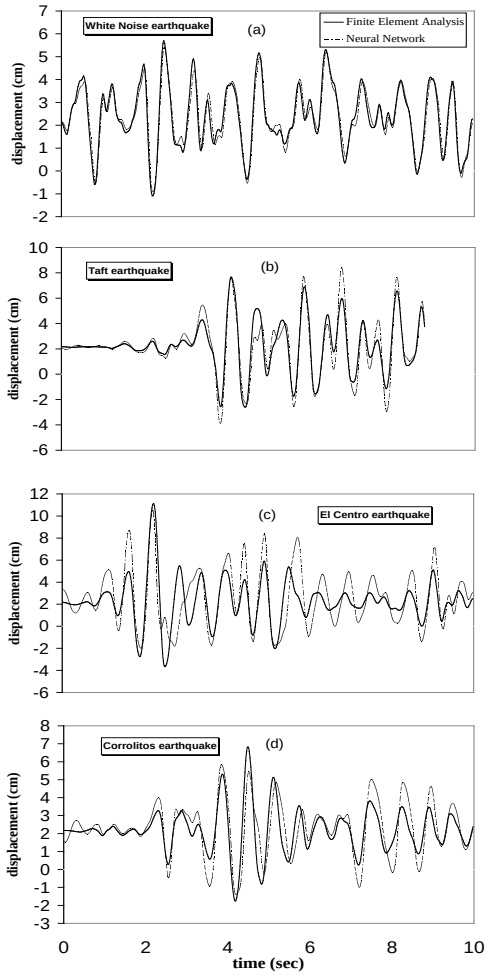


Fig. 6 comparing results of nonlinear analysis by neuron-modeller and finite element method when the dam has been subjected to: (a) White Noise, (b) Taft, (c) El Centro and (d) Corrolitos earthquakes.

VII. Design of Neuro-Modeller

First the neuro-modeler has been designed and then evaluated. Because the input-output data has been nonlinear, sigmoid function has been used for the activation function of the hidden neurons of the neural network.

A. Determination of architecture

Training of the neuro-modeler is carried out by means of the back propagation algorithm. The input-output vectors for designing the neuro-modeler have been obtained through numerical analysis of finite element by NSAG-DRI software under a white noise earthquake. The criterion to stop the training of the neural network has been the mean square error (MSE). Designing a neural network by trail and error is as detailed in Figure 7. The neuro-modeler is composed of input and output layers and a hidden layer. The number of input and output nodes has been 15 and 2, respectively. In the hidden layer, 8 sigmoid function neurons have been used. The activation function of the input and output nodes has been linear.

Input nodes: The input vector has included:

y_i = displacement of the crest of the dam at time step i,

$\dot{y}_i$ = velocity of the crest of the dam at time step i, i=0,1,2,…, and $\ddot{X}$ = the history of earth acceleration.

Output nodes: the output layer has contained the displacement and velocity at the end of the time step. The total number of input nodes has been 2. The output vector has included:

y_{i+1} = displacement of the crest of the dam at time step i+1,

$\dot{y}_{i+1}$ = velocity of the crest of the dam at time step i+1.

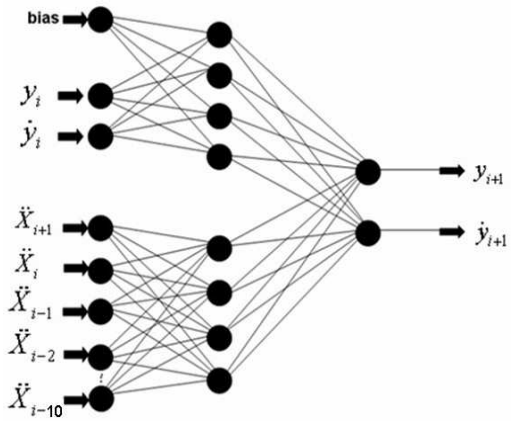


Fig. 7 Neuro-modeller architecture

VIII. Neuro-Modeller and Modelling Hysteretic Behavior of Dams

Multi layer feed forward neural network with back propagation algorithm has static structure in nature and it has limited capability to learn nonlinear records. Hence they suffer from disadvantages, because in such neural networks there is no internal memory. Multi layer feed forward neural networks (MLFFNN) are not capable of modeling and learning hysteretic cyclic behavior because they lack memory. For a neural network to learn hysteretic cycles it should have a memory. Two forms of memories can be considered for the neural networks: first, a memory located inside the neuron and second, to provide a side memory by feeding back information from the output to the input of the neural network [25]-[26]. In this study the second form, i.e. providing a side memory for the network has been used.

IX. Training of Neuro-Modeller

To train the neuro-modeller by means of data obtained from the result of analysis by finite element method, 20 seconds of the analysis results by NSAG-DRI software, under a white noise earthquake with the intervals of 0.02s, has been used.

On the other hand, to train the neuro-modeler the input-output pairs have been generated based on the data collected from the analysis of the dam, using NSAG-DRI software under the white noise earthquake acceleration. To generate the training pairs, Δt= 0.02s was selected. As a result, the number of input-output pairs to train the neuro-modeler has been 1000. Hence the analysis time and sampling periods have been 20 and 0.02 seconds respectively.

The neuro-modeller has been trained on the information gained from the nonlinear analysis of Pine Flat dam under the white-noise earthquake. Graphs for the training error of the neuro-modeler have been drawn in Figure 8, where the horizontal axis represents the number of training cycles and the vertical axis refers to the mean square error (MSE). After 20 training cycles, the error converges to 0.0002.

To calculate the error of the neural network, Equation 1 has been used.

In this equation, N stands for the number of training pairs, y_j is for the target value and $\bar{y}_j$ shows the amount obtained from the neural network [19]-[22].

The objective function to be minimized is the Mean Square Error (MSE) following Equation 1:

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

where MSE = Mean Square Error of training or testing.

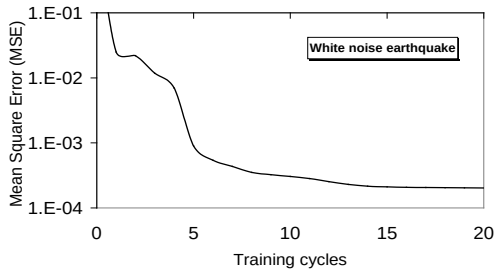


Fig. 8 MSE (Mean Square Error) of training versus training cycles.

X. Analysis by means of Neuro-Modeller

The trained neuro-modeller has been able to analysis the dam response, so that at each time step, only inputs about the earthquake excitation has been needed. Figure 9 shows schematically the analysis algorithm where y_o and $\dot{y}_o$ refer to displacement and velocity of the crest of the dam at the beginning of analysis.

XI. Testing Designed Neuro-Modeller

After the training has been over and its successful learning under white noise earthquake, the neuro-modeller has been tested on a number of other earthquakes including El Centro, Taft and Corrolitos, where predictions by the neuro-modeler have been compared with the target values. The neuro-modeller has been evaluated under different types of earthquakes with various frequency content. The predictions have been recorded throughout the time. The output of the neuro-modeler has been fed back to the neuro-modeler to be used in the prediction of the next time step. The result obtained from the analysis by means of the neuro-modeller and numerical method of finite element has been shown in Figure 6 by dotted and solid lines respectively. As Figure 6 shows, the neuro-modeller has analyzed the concrete gravity dam successfully under different types of earthquakes.

XII. Conclusion

In this study, a new software has been presented for dynamic analysis of concrete gravity dams with nonlinear behavior by taking into account the dam-reservoir-foundation interaction. Multi layer feed forward neural networks have been used for dynamic analysis of dams. Because of the training ability of neural network systems there is no need to specify the dynamic parameters of the dam and/or to specify basic prperties of the nonlinear model. To approve the efficiency of this method, Pine Flat dam with nonlinear behavior has been analyzed under various types of earthquakes as well as by means of the new neural network based method. A neuro-modeller has been trained and then used to analyze the dam under different earthquakes. The results have been compared with the results from using NSAG-DRI software where it has been shown that the neuro-modeller has been capable of providing results similar to those of NSAG-DRI. However once the neuro-modeller has been trained, it could analyze the dam under other earthquakes in a considerably much lower time.

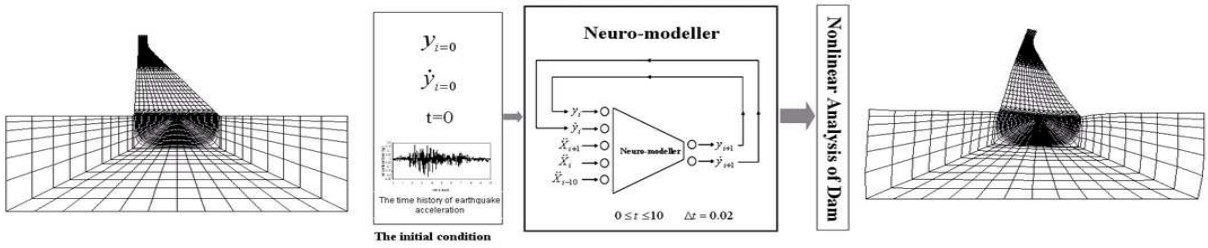


Fig. 9 Schematic presentation of using "Neuro-modeller" in analysis of Pine Flat dam

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