Nonlinear Adaptive Simulation of Concrete Gravity Dams using Generalized Prandtl Neural Networks

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Abstract - *Generalized Prandtl Neural Networks (GPNNs) has been used in Nonlinear Dynamic analysis of concrete gravity dams. GPNNs are the new type of neural networks, by which deteriorating hysteresis behavior of materials, in this case concrete, can be simulated implicitly and precisely. The architecture of GPNNs is the same as Multi-Layer Feed-Forward Neural Networks (MLFFNNs), but the only difference is that instead of sigmoidal activation function, the new kind of activation function has been utilized in the neurons of the hidden layer which has capability of learning nonlinear deteriorating hysteresis behavior of materials, called Deteriorating Stop (DS). The behavior of concrete gravity dams under earthquakes is complicated because of cracks which can be resulted in having deteriorating hysteresis behavior in concrete of the dam. Because of the micro-cracking, the hysteresis loops of concrete are usually degraded under cyclic and transient loading and resulted to have asymmetric and non-congruent hysteresis loops. In this paper a smeared crack model is used for collecting nonlinear data to train the neuro-modeller, and its free parameters are adjusted through identification. Conventionally, mathematical models that have some free parameters are assumed for the simulation of nonlinear behavior of concrete. Unfortunately, there is no unique mathematical form that can be utilized for modeling nonlinear behavior of concrete. This is the main drawback of mathematical models. Owing to this, MLFFNNs as general approximator tools have found a special place in the identification of material behavior as model-free systems. However, MLFFNNs cannot learn hysteresis behavior of concrete precisely because they are static systems and have no internal memories, whereas nonlinear autoregressive exogenous (NARX) neural networks compensate for this lack by placing a simple past-state memory in the input layer of conventional MLFFNNs. In this paper based on the GPNN, a neuro-modeler is designed and utilized in the nonlinear dynamic analysis of concrete gravity dams under seismic loads with severe damage. Koyna dam has been used as an example. A comparison of the results shows that the GPNN type of the neuro-modeler is much more successful than the previously proposed neuro-modeller based on conventional MLFFNN.*

***Key Words*: Generalized Prandtl Neural Networks, Nonlinear dynamic analysis, concrete gravity dam, neuro-modeller, hysteresis**

1.INTRODUCTION

Recently artificial neural networks (ANNs) have been utilized as systems that are trained to learn to solve many different structural engineering problems [1-7]. Among the different kinds of ANNs, Multi-Layer feed-forward neural networks (MLFFNNs) have been vastly used in the field of nonparametric identification of dynamic systems. In 2009, Joghataie and Dizaji [8] introduced a new architecture of MLFFNNs for simulating the nonlinear behavior of concrete gravity dams under earthquake excitation. However, Multilayer feedforward neural networks are static systems and have no internal memories, whereas nonlinear autoregressive with external input (NARX) neural networks [9] compensate for this lack by placing a simple past state memory in the input layer of conventional MLFFNNs. This type of neural network has been used in the literature for dynamic problems. For instance, Joghataie and Dizaji (2011, 2012, 2013) [10-12] used MFFNNs with past state memory in their input layers for the nonlinear dynamic analysis of concrete gravity dams. One can use NARX neural networks with dynamic input/output to model dynamic systems without an internal non-measurable state. In particular, limitations arise for processes with non-unique nonlinearities, such as hysteresis and backlash, where internal non-measurable states play a decisive role[13]. In addition, other types of conventional neural networks, such as recurrent and time-delay neural networks, do not have a perfect capability to learn hysteretic behaviors. To compensate for this drawback of conventional neural networks in hysteresis learning, attempts have been made to devise new types of neural networks for hysteretic problems [14-15]. In 2008, Joghataie and Farrokh [14] proposed a new neural network called a Prandtl neural network (PNN) and used it successfully in the dynamic analysis of nonlinear inelastic frames and trusses (2008, 2011). The PNN uses stop neurons in its hidden layer. Each stop neuron has a complete memory for hysteresis and an adaptive parameter that is tuned during the training of the PNN. These two characteristics of stop neurons enable the PNN to learn hysteretic behaviors without any data on the past state or non-measurable internal variables in its input layer; thus, the PNN is not prone to error accumulation (Fig. 1). However, the PNN is suitable for hysteretic problems that do not undergo degradation. Because of microcracking, the hysteresis loops of some materials are usually degraded under cyclic and transient loading, and PNNs cannot learn them because they use stop-activation functions, which do not deteriorate. Recently, Farrokh et al.[16] introduced a new type of neural networks called a Generalized Prandtl neural network (GPNN) and applied it successfully in the simulating hysteresis deteriorating behavior of materials. In this paper, a new kind of activation function using a particular combination of stop and play operators is proposed and used in a feedforward neural network to improve its learning capability in the identification of nonlinear hysteretic material behavior with both stiffness and strength degradation. Moreover, using the proposed neural network, a neuro-modeler is designed and used in the dynamic analysis of a one-story shear frame under seismic loads with severe damage. By comparing the results, the authors can conclude that the generalized Prandtl neural network type of the neuro-modeler is more successful and appropriated than the previously proposed Prandtl neural network type. In order to show the performance of the GPNN, the comparison between the GPNN response and the other model is helpful. Recently Joghataie and Dizaji. (2013) [12] proposed a new architecture neural network for modeling the nonlinear hysteretic behavior of concrete gravity dams. In this short paper, in a more applied case, in order to show the capability of GPNN, results of the aforementioned paper has been compared with the results obtained from GPNN. A comparison of the results obtained from GPNN with the results obtained from using MLFFNNs, shows the significant improvement in terms of the dam response and size of the neural network, made by the GPNN.

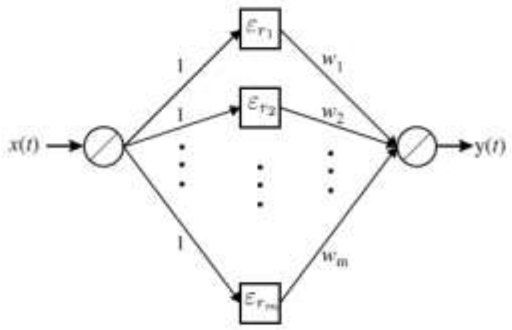

Fig. 1. Architecture of PNN.

2. GENERALIZED PRANDTL NEURAL NETWORKS

In 2015, Farrokh and his coworkers [16] introduced a new type of neural network called Generalized Prandtl neural networks and used it successfully in simulating deteriorating hysteresis behaviors. The structure of GPNN is the same as Prandtl Neural Network (PNN) which was previously introduced by Joghataie and Farrokh (2008) [14], but GPNN uses new neurons with activation function in accordance with DS operator, and this newly defined neuron has been called DS neuron. It enjoys deterioration in its hysteresis loops; therefore, GPNN is able to model hysteresis with deterioration. Therefore, in comparison with PNN, GPNN has capability of learning deteriorating hysteresis behaviors as well which means GPNN is more generalized than PNN. The GPNN has been mathematically stated by:

$$\hat{y}(t) = \sum_{j=1}^{m} \{ w_j \mathcal{DS}_{r_j,\beta_j}[x(t)] \} \quad (1)$$

Eq. (1) could be represented in the form of a multilayer feed-forward neural network with linear neurons in the input and output layers and m DS neurons in the hidden layer. As shown in Fig.2, the connection weights between the input neuron and all neurons in the hidden layer have been assumed to have a value of 1.0 because of the equivalence with Eq. (1). In a GPNN with m DS neurons in the hidden layer, there are totally 3 m free parameters of which m parameters are the connection weights between the hidden layer neurons and the output neuron (w_j; j = 1, 2, ..., m) and *2 m* parameters are the internal free parameters for DS neurons in the hidden layer (r_j, j; j = 1, 2,...,m). It should be mentioned that js can control overall deterioration of the GPNN so that if all the js have the large values the deteriorating capability will diminish and hence it will behave like a PNN. Genetic Algorithm (GA) has been used for tuning r and of the GPNN. The details of the method are explained in Farrokh et al research [16].

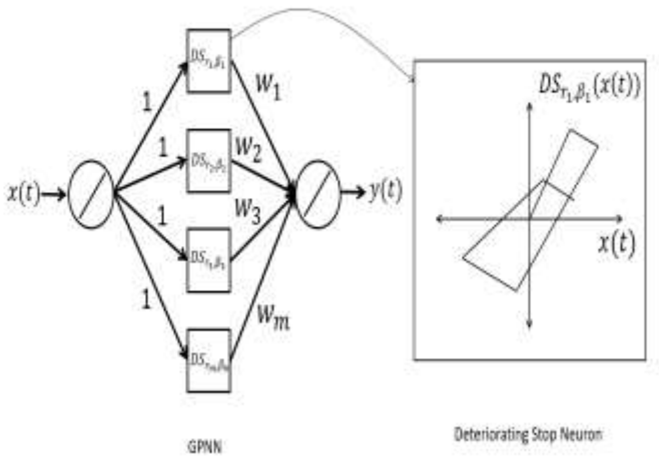

Fig. 2. Architecture of the GPNN

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3. MLFFNN-NEURO MODELER-BASED MODEL

Joghataie and Dizaji (2013) [12] utilized Multi-Layer Feed Forward Neural Networks (MLFFNN) for the modeling of concrete gravity dams with the nonlinear hysteretic response under earthquake loading. As the first study on the subject to prepare a controlled precise data for the training and testing of the neuro-modeler so that the precision of the method could be evaluated and analysis software was used to simulate the experiment. The smeared crack model, which has been one of the models used successfully in the literature to simulate the nonlinear response of the concrete gravity dams, has been used in this study as well. In this paper, the first step is to analyze the dam under study as it is subjected to different earthquake simulations for obtaining large data about its nonlinear response. The second step is to train a neuro-modeler, based on the collected data, to implicitly learn the nonlinear response of the dam being subjected to the training earthquakes. The last step is to test the accuracy and generalization capabilities of the neuro-modeler used for the analysis of the dam under a number of selected and specific earthquakes of different properties including both near- and far-field excitations. After passing all steps and by looking through the successful test, the authors can expect the neuro-modeler can be able to provide valid and precise results about the response of the dam under any special earthquake. Three concrete gravity dams with differing characteristics and in different geographical locations including the Koyna, Pine Flat, and Sefid-Rud dams, which have been both numerically and experimentally studied because they had experienced considerable damage during earthquakes, have been utilized as examples. A neuro-modeler has been trained for each of the dams and tested. The results are reported in this paper. The dam neuro-modelers have been successful in providing resonable results in this numerical simulation of the nonlinear hysteretic behavior of dams.

4. GPNN-NEURO MODELER-BASED MODEL

The main goal of this example is to train a neuro-modeler with the capability to perform a dynamic analysis of the concrete gravity dams shown in Fig.3(a) during an earthquake. The neuro-modeler architecture is shown in Fig. 3(b). The input layer of the neural network is comprised of the displacement and velocity at the beginning of the time step, as well as the ground acceleration during the time step, whereas the output layer contains the displacement and velocity at the end of the time step. In the hidden layer of the neural network, there are two DS neurons, and the other neurons have a linear activation function.

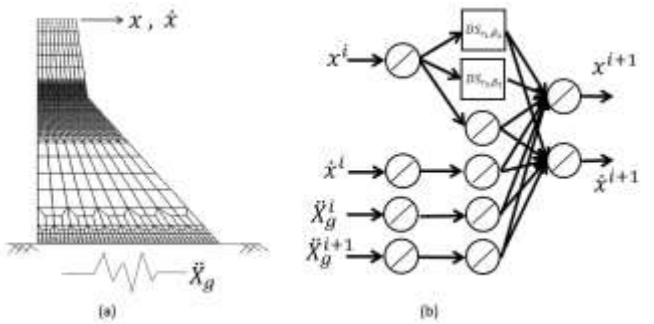

Fig. 3. GPNN-neuro modeler: (a) the concrete gravity dams, (b) The GPNN neuro-modeler architecture

4.1. Example: Nonlinear Dynamic Analysis of the Koyna Dam

For comparison of the precision of the new method (GPNN) and MLFFNNs, the Koyna Dam which is located in India has been used as an example in this paper. The Koyna Dam is categorized as the largest concrete gravity dams in the world, built in India in 1963. Its height is 103 m and length of the crest is 808 m. In 1967, the 6.5 Richter- scale earthquake created severe damage in the dam structure. When the dam was hit by the earthquake the water level was below the top of the crest (around 11 m) and a crack was appeared at around 36 m below the top of the crest. The crack grew and reached to the lower level into its body. Many investigators and researchers have visited and studied the dam and recorded the disaster which has been applied in the development of knowledge related to concrete gravity dams [17-18].

In this paper, the two dimensions' analysis has been applied for the nonlinear hysteretic response and the proposed dam was discretized by four-node plain 2D FE meshes used by other researchers [18]. For the Koyna Dam, the number of elements was 1240 elements. Finally, for the training data of our neuro model, the displacement and acceleration time histories of the crest were gathered and used. The Koyna Dam can learn to simulate the response of the dam crest by considering this training data. In addition, The Koyna Dam has been used as an example by Joghataie and Dizaji (2013) [12] for analyzing the performance of MLFFNNs, so it could be an appropriate example for applying GPNN and compare its result with previous study.

To get more information regarding heuristic algorithms and optimization techniques one can refer to [19-20].

5. COMPARISON OF GPNN AND MLFFNN-NEURO MODELER- BASED MODELS

A neuro-modeler, whose hidden layer contained three DS neurons instead of six sigmoid neurons, was considered. Also as it can be seen in Fig. 4, number of inputs are reduced significantly compared to MLFFNN-Neuro modeller based model. This neuro-modeler was in accordance with the PNN previously proposed by Joghataie and Farrokh (2008) [14]. The same procedure used for the GPNN-type neuro-modeler was used for its training and testing. A comparison of the results between MLFFNN-neuro modeler based model and GPNN-neuro modeler based model show significant improvement in response of the displacement of the crest. Clearly, the MLFNN-type neuro-modeler performance is much worse than that of the GPNN-type neuro-modeler. The Euclidean error norms of the MLFFNN-neuro modeller are 3.5 and 3.2 cm for white-noise and 200% El Centro excitations, respectively. Also, the Euclidean error norms of the GPNN-neuro modeller are 0.97 and 0.74 cm for white-noise and 200% El Centro excitations, respectively A comparison between the obtained results of the MLFFNN type and the GPNN type of the neuro-modeler shows that the GPNN reduced the simulation error of the neuromodeler by one order of magnitude.

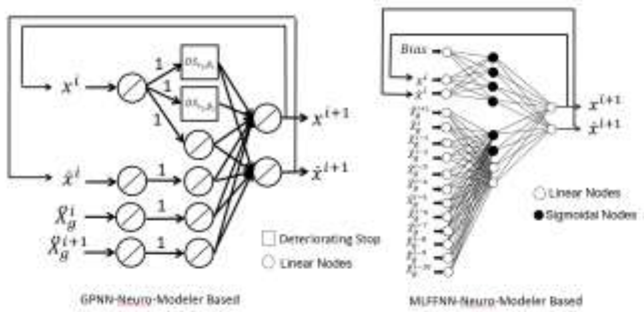

Fig. 4. Comparison of GPNN neuro modeler and MLFFNN neuro modeler

6. DAMAGE DETECTION

As it is mentioned before, beta parameter can control overall deterioration, which means having higher beta shows linearity of the results. Therefore, it can be applied as a tool to detect possibility of damage in the structure, in this case the dam. Owing to it, we have generated some linear analysis data and also nonlinear analysis data to illustrate possibility of damage detection using proposed GPNN neuro modeler. Based on these results GPNN neuro modeler has been tested and the values of the beta's have been compared for the both cases. The comparisons indicate that linear analysis result has got higher values for the beta's and the nonlinear analysis result has obtained much less values for the beta's.

7. FUTRUE WORKS

This is a preliminary research for application of GPNN in full scale structures. In the future this new type of neural network can be applied to more complicated structures with highly nonlinear hysteretic behavior. Also another application of GPNN model can be its application in passive control systems as automated-smart systems.

8.CONCLUSION

The new novel proposed neural network has been applied as a specific method of nonlinear dynamic analysis of concrete gravity dams. The neuro-models are trained to learn the pattern of the response of the crest of dam based on the selected data. In the previous study, the MLFFNNs has been used to predict the response of the crest of three different dams. This new neural network known as GPNN has been proven to be a suitable method to consider memory in neural network, However, some issues exist. By considering these issues in this study, the authors have applied GPNN introduced by Farrokh et al (2015). The researchers proved the capability of GPNN for the nonlinear dynamic analysis of concrete gravity dams by comparing its results with the results obtained by MLFFNNs in the previous study. This comparison confirmed that there is the significant improvement in terms of the dam response, time solving and size of the neural network.

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