Simulating the seismic response of an embankment using soft computing techniques

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ABSTRACT: Geotechnical earthquake engineering can generally be considered as an "imprecise" area due to the unavoidable uncertainties and simplifications. Therefore, relatively accurate predictions, using advanced *Soft Computing (SC) techniques,* can be tolerated rather than solving a problem conventionally. Artificial Neural Networks (ANNs), being one of the most popular SC techniques, have been used in many fields of science and technology, as well as, an increasing number of problems in engineering. In the present study the application of ANNs is focused on the simulation of the seismic response of an embankment. Typically, the dynamic response of an embankment is evaluated utilizing the finite-element method, where nonlinearity of geo-materials can be taken into account by an equivalent-linear procedure. This extremely time-consuming process is replaced by properly trained ANNs.

1 INTRODUCTION

Uncertainties and approximations are inherent in geotechnical earthquake engineering practice. Therefore, realistically accurate approximation methods can be applied very effectively. On the other hand, advances in computational hardware and software resources since the early 90's resulted in the development of new non-conventional data processing and simulation methods. Techniques based on *Metamodels* that belong to Soft Computing (SC) methods are gaining popularity very rapidly lately in various time-consuming, large-scale applications in structural and geotechnical engineering. Among SC methods, Artificial Neural Networks (ANNs) has to be mentioned as one of the most eminent approaches of the so-called intelligent methods of information processing.

From among general problems that can be analyzed by means of ANNs the simulation and identification problems can be classified as follows:

- *simulation* is related to direct methods of structural or geotechnical analysis, i.e., for known inputs (e.g., excitations of mechanical systems (MS)) and characteristics of structures, geo-structures, or materials outputs (responses of MS) are searched;
- *inverse simulation* (partial identification, for example, of an unknown excitation) takes place if inputs correspond to known responses of MS and excitations are searched as outputs of ANNs; and
- *identification* is associated with the inverse analysis of structures, geo-structures and materials, i.e., excitations and responses are known and MS characteristics are searched.

Over the last decade an increasing number of articles presenting ANN applications in geotechnical earthquake engineering has been published. Most of these studies are focused on liquefaction potential under seismic excitations (Chouicha et al. 1994, Goh 1994, Wang & Rahman 1999, Baziar & Nilipour 2003), which is an extremely computationally intensive task and therefore suitable for ANNs. Recently, some of the studies in this field are examining the applicability of ANNs in soil dynamic analysis (Hurtado et al. 2001, Garcia et al. 2002, Paolucci et al. 2002, Garcia & Romo 2004, Kerh & Ting 2005).

In the present study the application of ANNs is focused on the simulation of the seismic response of an embankment. The embankments (water dams, tailings dams, solid waste landfills, etc.) usually constitute important large-scale geo-structures, the safety and serviceability of which are directly related to environmental and social-economical issues (Psarropoulos et al. 2006a). This kind of structures became subject of systematic research following the Northridge (1994) and Kobe (1995) earthquakes, after which extended investigations took place to examine the failures, occurred in embankments due to seismic actions.

Usually, the dynamic nonlinear response of an embankment is evaluated utilizing the finite-element method. This strategy has been also used in the present study, where nonlinearity of materials is taken into account by a time-consuming equivalent-linear procedure. Since a large number of dynamic analyses are required in order to simulate the dynamic behavior of the embankment under various seismic excitations, in order to reduce the aforementioned computational cost, a specially tailored back propagation ANN has been used. Initially, the ANN is trained utilizing available information generated from selected dynamic analyses of the geo-structure. In the sequence, the trained ANN is used to accurately predict the response of the examined geo-structure to various seismic excitations replacing the conventional analysis procedure. The results demonstrate the efficiency of the proposed methodology for treating large-scale problems in geotechnical earthquake engineering.

2 SEISMIC RESPONSE OF EMBANKMENTS

As most of the failures of embankments are related to slope instabilities (either of the embankment mass or of the supporting soil), seismic slope stability analysis is certainly a critical component of the design process. Recent practice is based on three main families of methods that differ primarily in the accuracy with which the earthquake motion and the dynamic slope response are represented.

The most accurate methods are considered to be the *stress-deformation methods*, which are typically performed using dynamic finite-element analysis. In general, these methods are used to describe the nonlinear behavior of the material with the highest possible accuracy, but they require sophisticated constitutive models involving a large number of parameters that cannot be easily quantified in the laboratory or in situ. Because of their complexity, these methods are usually excluded from the seismic design of embankments. On the other hand, simplified seismic stability procedures are widely used in geotechnical practice. A crude index of seismic slope stability (or instability) is the *factor of safety* evaluated in a pseudo-static fashion in the realm of conventional limit-equilibrium analysis. Finally, an alternative family of methods utilizes displacement-based approaches to predict permanent slope displacements induced by earthquake shaking.

The key issue in limit-equilibrium methods is the selection of a proper seismic coefficient, as the later controls the pseudo-static forces in the soil masses, whereas in the displacement-based methods permanent displacements are calculated using either acceleration time histories (Newmark 1965) or seismic coefficients (Makdisi & Seed 1978). Thus, it becomes evident that slope stability methods require an accurate estimation of the acceleration levels induced on the embankment under examination. Therefore, pertinent response analyses incorporating the "*local site conditions*" should precede any kind of seismic slope stability analysis. The term "local site conditions" is used here to describe not only soil conditions (stratigraphy, geomorphology, topography) of the site, but the geometric and mechanical properties of the embankment as well.

Records and analyses of valleys and hills have shown that local site conditions of a site, either in two or in three dimensions, may alter substantially the ground motion (Gazetas et al. 2002) by: a) amplifying the ground motion, b) elongating its duration, and c) generating differential motions, phenomena which will be referred hereafter to as "aggravation". Recent analyses have shown that geomorphic and topographic conditions may profoundly aggravate the surface ground motion in the presence of low levels of material damping, while material nonlinearity may substantially suppress aggravation by diminishing scattered body waves, especially horizontally propagating surface waves (Psarropoulos et al. 2006b). Therefore, in most cases aggravation depends not only on the geometrical and mechanical properties of a surface formation, but also on the amplitude of the excitation.

The aim of the present study is to examine in more detail the aggravation of horizontal acceleration and to investigate the relationship between this aggravation and the potential nonlinear behavior of soil. To accomplish this goal, two-dimensional (2–D) finite element equivalent-linear numerical simulations have been performed utilizing specially tailored ANNs to examine the nonlinear dynamic response of a typical embankment. The main parameters examined are the characteristics of the seismic excitation. Results indicate that local site conditions may play a significant role in the seismic response of an embankment, depending on the circumstances. However, as the material behavior of the geo-structure is directly related to the characteristics of the seismic excitation, this role cannot be judged a priori as beneficial or detrimental for the overall response of the geo-structure.

3 ARTIFICIAL NEURAL NETWORKS

An ANN is an information processing paradigm that is inspired by the biological nervous systems, such as the brain process information network. It is composed of a large number of highly interconnected processing elements (neurons) working in unison to solve specific problems. As in biological systems, learning involves adjustments to the synaptic connections that exist between the neurons. ANNs, with their remarkable ability to derive meaning from complicated or imprecise data, can be used to extract patterns and detect trends that are too complex to be noticed by either humans or conventional computational techniques.

An ANN is configured for a specific application, such as pattern recognition or data classification, through a learning process. ANNs, like human beings, learn by example. A trained ANN provides a rapid mapping of a given input into the desired output quantities, thereby enhancing the efficiency of the analysis process. This major advantage of a trained ANN over a conventional procedure, under the provision that the predicted results fall within acceptable tolerances, is that it leads to results that can be produced in a few clock cycles, representing orders of magnitude less computational effort than the conventional procedure.

In this work a fully connected network with one hidden layer is used. The learning algorithm, which was employed in this study for the ANN training, is the well-known Back Propagation (BP) algorithm. The BP algorithm progresses iteratively, through a number of epochs. On each epoch the training cases are submitted in turn to the network and target and actual outputs are compared and the error is calculated. This error, together with the error surface gradient, is used to adjust the weights, and then the process is repeated. Training stops when a given number of epochs elapses, or when the error reaches an acceptable level, or when the error ceases to decrease (user-defined convergence criteria). The ANN training comprises the following tasks: (i) select the proper training set, (ii) find a suitable network architecture and (iii) determine the appropriate values of characteristic parameters such as the learning rate and momentum term; two user defined BP parameters that effect the learning procedure.

4 NUMERICAL STUDY

In order to examine more thoroughly the effectiveness of ANNs in computationally expensive dynamic finite-elements problems, the 2–D numerical model, shown in Figure 1, was investigated. The discretization of the finite element model is presented in Figure 2. The embankment is founded on stiff rock. Shear-wave velocity of the embankment soil material at small strain levels was set equal to 250m/s and unit weight of the soil was considered to be 10kN/m^3. While the geometry and the properties of the model remained constant, the seismic excitations varied during the analyses.

The simple embankment examined herein can be regarded as a relatively small-scale earth embankment, the dynamic behavior of which has thoroughly been examined in the past by other researchers (Gazetas 1987). Assuming plane-strain conditions, the seismic response of the embankment examined was evaluated using QUAD4M code (Hudson et al. 1994), which is capable of performing 2–D equivalent-linear finite-element analyses. As shown in Figure 2, the model was discretized with three-noded triangular finite elements. The size of the finite elements was tailored to the wavelengths of interest. Material nonlinearity for soil was taken into account approximately by an iterative procedure, according to which the values of material stiffness and material damping are consistent with the level of maximum shear strain. Stiffness degradation and damping increase for the soil were based on the curves proposed by Idriss & Sun (1992).

A suite of characteristic accelerograms has been used as seismic excitations: namely 43 recorded earthquake motions (presented in Table 3) and 3 idealized pulses. The three pulse excitations were simple Ricker pulses with a varying central frequency: f_o = 2, 3, 4 Hz, respectively. Furthermore, in order to cover a sufficient range of nonlinear behavior (strains) of the soil, all input motions were scaled to peak ground acceleration (PGA) ranging from 0.01g to 0.5g. Thus, five cases were examined:

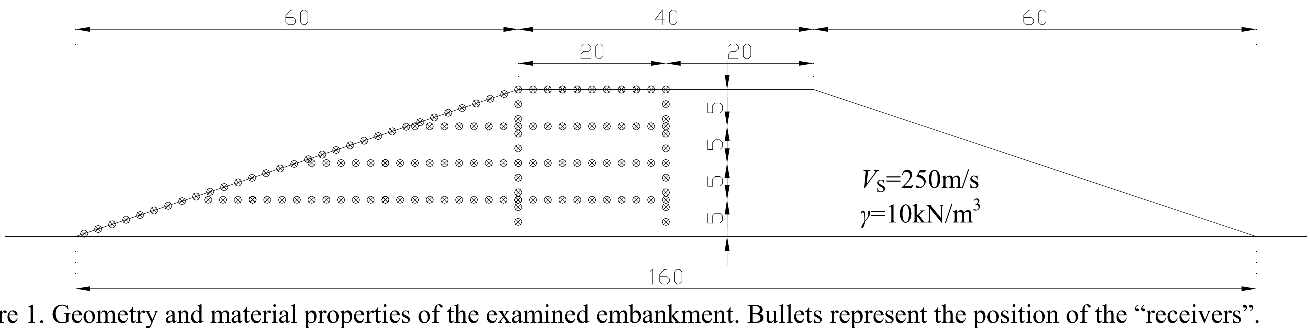

Figure 1. Geometry and material properties of the examined embankment. Bullets represent the position of the "receivers".

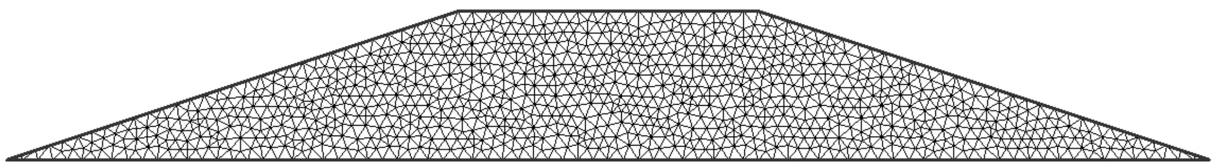

Figure 2. Discretization of the embankment into three-noded triangular finite elements.

- Case I (essentially linear behavior): 0.01g
- Case II (almost linear behavior): 0.05g
- Case III (low level of nonlinearity): 0.1g
- Case IV (medium level of nonlinearity): 0.2g
- Case V (high level of nonlinearity): 0.5g

The use of ANN in this study was motivated by the fact that the finite-element models are time-consuming: approximately 30 minutes for a "simple" run (linear run (Case I) with a short duration Ricker pulse) of the examined 2-D model of Figure 2 (with 850 nodes and 1540 elements) at a Pentium IV PC with 2.53GHz CPU processor and 1GB RAM. While, for a more "complex" run (a real record with larger duration and/or for a higher level of nonlinearity) the computing time increased significantly, up to 60 minutes. On the other hand, the computational cost for the calculation of an ANN prediction in all cases was only a few seconds.

Therefore, the need for an efficient computational tool for the simulation of the seismic response of large-scale geo-structures is indisputable. The ANN software used in this study has been developed by one of the authors (Lagaros & Papadrakakis 2004). For the needs of the present paper, the ANN-based simulation has been compared with the results of non-linear finite element models obtained using QUAD4M. The ANN has been used for the prediction of the seismic response in terms of peak ground horizontal accelerations at the embankment's surface, as well as in the embankment's body. For this reason the embankment has been separated into zones, as it is presented in Figure 1, where the "receivers" for recording the local seismic response had been placed. The total number of the receivers was 138, placed at the left half of the embankment, because of the symmetric shape of the geo-structure.

The ANN configurations used were properly trained in order to predict the acceleration for new earthquake records. The records used were identified using a set of Intensity Measures (IMs). The term *Intensity Measure* is used to denote a number of commonly used ground motion parameters, which represent the amplitude, the frequency content, the duration or any other important ground motion parameter. In addition, IMs can be classified as only record dependent, or as both structure and record dependent.

A significant number of different IMs can be found in the literature. In the present investigation, in addition to the IMs available in Kramer (1996), the A95 parameter (Sarma & Yang 1987) was used. This parameter defines the acceleration level of a record below which 95% of the total Arias Intensity (I_a) is contained. For instance, if the entire accelerogram yields a value of I_a equal to 100 then the *A95* parameter is the threshold of acceleration such that integrating all the values of the accelerogram below it one gets I_a=95. The most significant IMs were used in this study, after examining various combinations of them for each "load-case", in order to provide the best possible training to ANN metamodels.

4.1 *Ricker Pulse Excitations*

Initially, the embankment was excited with the three Ricker pulses and the five different maximum acceleration levels, resulting to 15 models in total. The input data for the ANN metamodel were the coordinates of the receivers, which are positioned in an axial distance 2m at x-axis and at y-axis (at the surface and inside the body of the embankment) and several IMs that described efficiently the Ricker pulse. The output was the seismic response of each receiver for the specific Ricker pulse.

The ANN that has been used for the prediction of the embankment's response excited by the Ricker pulses consisted of three layers: the input layer with seventeen nodes (receiver's coordinates –x, y–, *PGA*, *PGV*, *PGD*, *PGV*/*PGA*, A_{RMS}, V_{RMS}, D_{RMS}, characteristic intensity, specific energy density, cumulative absolute velocity, acceleration spectrum intensity, velocity spectrum intensity, effective design acceleration, *A95* parameter and predominant period), the hidden layer and the output layer with one node (response). After an initial investigation about the number of the hidden layer's nodes, the ANN configuration resulted in a [17-50-1] architecture.

The ANN model trained with the Ricker input data was used to evaluate embankment's response for a Ricker pulse with 2.5 Hz predominant frequency and its performance was very satisfactory. The maximum tolerance between the computed by QUAD4M and the predicted through the ANN (for all Cases I to V) are presented in the diagram of Figure 3. The results shown in Figure 3 can also be presented in a table form, according to the percentage of the absolute value of the tolerance between the computed and the predicted value of the seismic response, as it is depicted in Table 1.

Furthermore, in order to evaluate more efficiently the performance of ANN metamodel, a coefficient of correlation was used, which was defined as follows:

$$r = \frac{\sum_{i=1}^{m}(x_i - \bar{x})(y_i - \bar{y})}{\sqrt{\sum_{i=1}^{m}(x_i - \bar{x})^2 \sum_{i=1}^{m}(y_i - \bar{y})^2}} \qquad (1)$$

where x_i and $\bar{x}$ are the recorded and the averaged response values; y_i and $\bar{y}$ are the ones estimated by ANN and their averaged value; and m denotes the number of ANN training data sets. This coefficient may have a positive or negative value, therefore, its square value r^2 can be used instead in order to represent the degree of correlation of the recorded data and their approximation by the ANN metamodel. In Figures 3 to 5 the mean value (for all receivers and Cases) of the correlation parameter is depicted.

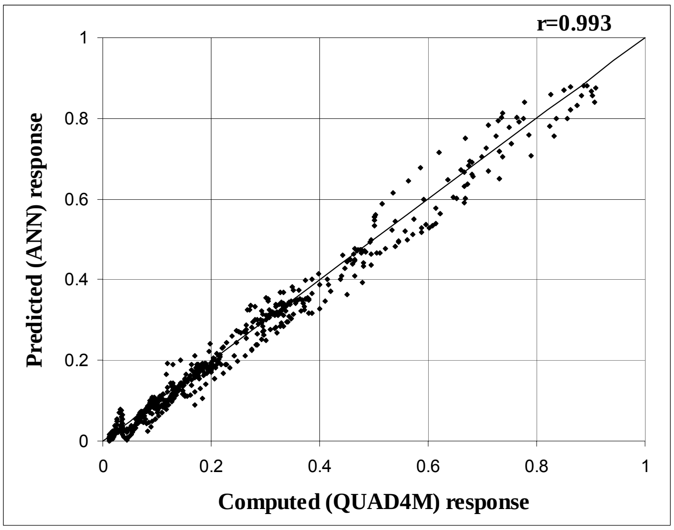

Figure 3. Computed versus Predicted seismic response for the entire embankment (Ricker Pulse).

Table 1. Percentage of receivers that exceeds different levels of tolerance for the entire embankment (Ricker Pulse).

Tolerance (%)	No of receivers	Receivers (%)	Total Receivers (%)
0 to 5	216	31.3	31.3
5 to 10	139	20.1	51.4
10 to 20	156	22.6	74.0
20 to 30	46	6.6	80.7
30 to 40	31	4.4	85.2
40 to 50	23	3.3	88.5
50 to 60	7	1.0	89.5
60 to 70	11	1.5	91.1

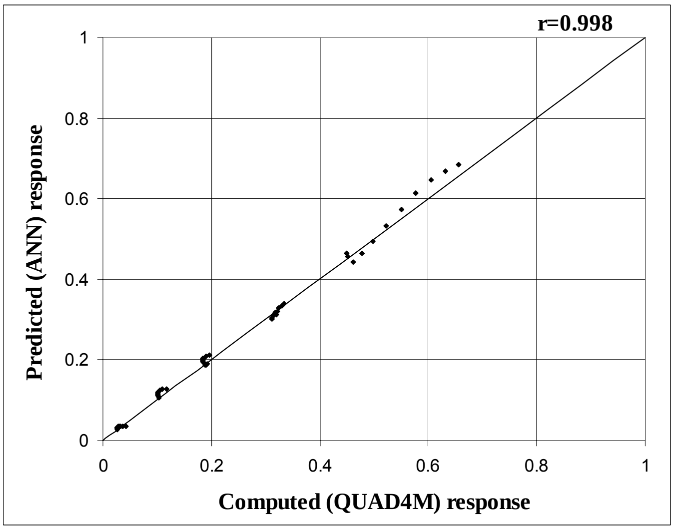

Figure 4. Computed versus Predicted seismic response for the upper boundary of the embankment (Ricker Pulse).

It was observed that a higher discrepancy between the predicted and the calculated values of the seismic response occurred for the receivers that were located inside the embankment's body. If the internal receivers are ignored then the accuracy for the external receivers is much better, as it is clearly shown in Figure 4 and Table 2.

Table 2. Percentage of receivers that exceeds different levels of tolerance for the upper boundary of the embankment.

Tolerance (%)	No of receivers	Receivers (%)	Total Receivers (%)
0 to 5	26	47.2	47.2
5 to 10	14	25.4	72.7
10 to 15	15	27.2	100.0

4.2 *Earthquake Excitations*

The next stage was to use, instead of relatively simple Ricker pulses, records derived from real earthquakes. The earthquake data from the 43 records used for ANN training are presented in Table 3. For each earthquake record the aforementioned five acceleration levels have been used. Following the same considerations as for the Ricker pulses case and after an extensive investigation a [16-20-1] architecture was used for the prediction of the geostructure's response. After considering various possible IMs combinations, the input layer in this case consisted of sixteen nodes (coordinates –x, y–, *PGA, PGV, PGD, PGV/PGA*, characteristic intensity, specific energy density, cumulative absolute velocity, acceleration spectrum intensity, velocity spectrum intensity, sustained maximum acceleration, sustained maximum velocity, effective design acceleration, A95 parameter and predominant period) in order to provide the more important input data and therefore enhance the predictions of the ANN.

Table 3. Earthquake records for the training of the ANN.

Earthquake's name (Region)	Year of occurrence	Number of records
Lefkada, Greece	1973	1
Mexico City, Mexico	1981	4
Kalamata, Greece	1986	1
Northridge, USA	1994	14
Kobe, Japan	1995	9
Aigio, Greece	1995	1
Kocaeli, Turkey	1999	7
Parnitha, Greece	1999	4
Lefkada, Greece	2003	2

After its training the ANN metamodel was used to predict the response for Sepolia record (Parnitha earthquake, Greece, 1999). This record was chosen due to the fact that its IMs were similar to those of the earthquakes used for the ANN training (an ANN can interpolate, but not extrapolate). As it can be seen in Figure 5 and Table 4 in this case nonlinearity affects more the performance of ANN. Nevertheless, even in this case, which is more computationally intensive, ANN approximate with a relative high level of accuracy the seismic response of the embankment, especially for the external receivers.

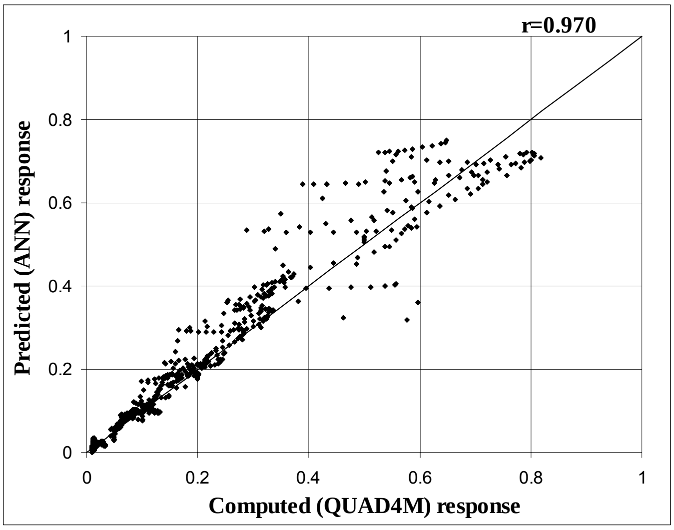

Figure 5. Computed versus Predicted seismic response for the entire embankment (Sepolia record).

Table 4. Percentage of receivers that exceeds different levels of tolerance for the entire embankment (Sepolia record).

Tolerance (%)	No of receivers	Receivers (%)	Total Receivers (%)
0 to 5	144	20.8	20.8
5 to 10	149	21.5	42.4
10 to 20	157	22.7	65.2
20 to 30	96	13.9	79.1
30 to 40	33	4.7	83.9
40 to 50	33	4.7	88.7
50 to 60	20	2.9	91.5
60 to 70	14	2.0	93.6

5 CONCLUSIONS

In the present implementation of ANNs the objective was to investigate their ability to capture the dynamic nonlinear response of an embankment under various seismic excitations and reduce the excessive computational cost. In general, ANN achieved a slightly better approximation of the response for the receivers that are positioned at the crest and the upper part of the embankment than for the receivers that are positioned inside the embankment. Furthermore, comparing the results obtained via ANN for the Ricker pulses and the earthquake records it is obvious that when the embankment material behaves linearly or with a moderate level of nonlinearity then the response of the embankment is approximated very accurately by the ANN-based metamodel. When a severe earthquake occurs, then high nonlinearity deteriorates the accuracy of ANN predictions. However, they can still be considered very satisfactory, while in this case the computational gains are even more than in the linear case. In conclusion, ANN presented a very good performance in marginal computing cost and their applicability in the field is very promising.

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