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EVALUATING THE SEISMIC RESPONSE OF EMBANKMENTS VIA NN-BASED METAMODELS

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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 numerical 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 earthquake engineering problems. 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 the nonlinear behavior of the geo-materials can be taken into account by an equivalent-linear procedure. This extremely time-consuming process is replaced in the present study by properly trained ANNs.

Keywords: Artificial Neural Networks, dynamic non-linear response, embankments

INTRODUCTION

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) or Artificial Intelligence (AI) 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. SC methods are used either to reduce the computational cost, or when the complexity and/or the size of the problem forbids the use of conventional techniques (Lagaros & Tsompanakis, 2006).

On the other hand, it is generally accepted that uncertainties and simplifying approximations are inherent and inevitable in geotechnical earthquake engineering practice. Therefore, accurate approximation methods, such as ANNs, can be applied very effectively in such problems. Over the last decade an increasing number of articles presenting ANNs 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,

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2003), which is a very 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 a characteristic embankment. In general, the embankments (water dams, tailings dams, solid waste landfills, etc.) constitute large-scale important geo-structures, the safety and serviceability of which are directly related to environmental and social-economical issues (Psarropoulos et al., 2006). 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 to predict the dynamic behaviour of an embankment under various seismic excitations a specially tailored back propagation ANN has been used in the current investigation, in order to reduce the aforementioned computational cost. 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.

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, either by amplifying the intensity of ground motion, by elongating its duration, or generating differential motions. These, so-called “aggravation”, phenomena in most cases depend 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 due to local site conditions, and to investigate the relationship between this aggravation and the potential nonlinear behavior of soil. To accomplish this goal, parametric 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 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.

ARTIFICIAL NEURAL NETWORKS

An ANN is an information processing paradigm that is inspired by the biological nervous systems, such as the brain process information. 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 repeats. 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 (i.e. the number of hidden layers and the nodes per layer), 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.

NUMERICAL STUDY

In order to examine the effectiveness of ANNs in replacing the computationally expensive dynamic finite-elements analyses, the 2–D numerical model of a typical embankment, shown in Figure 1, has been investigated. The embankment is assumed to be founded on stiff rock, and its shear-wave velocity V_S at small strain levels was set equal to 250m/s. While the geometry and the properties of the model are kept constant, the seismic excitations varied during the analyses. Assuming plane-strain conditions, the seismic response of the embankment examined was evaluated using the popular QUAD4M code, which is capable of performing 2–D equivalent-linear finite-element analyses (Hudson et al., 1994). The examined numerical model was discretized with a dense grid of three-noded triangular finite elements. The size of the finite elements was tailored to the wavelengths of interest. Nonlinearity of the soil material 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 cyclic shear strain. Stiffness degradation and damping increase for the soil were based on the curves proposed by Idriss and Sun (1992).

Regarding the excitation, to cover a wide range of values of the most important ground motion characteristics, two suites of accelerograms have been used as seismic excitations of the embankment: (a) a set of four (4) idealized pulses, and (b) a large set of forty-three (43) recorded earthquake motions. The pulse excitations were simple Ricker pulses with a varying central frequency: $f_o = 2, 2.5, 3, 4$ Hz, respectively. The advantages of using such "accelerograms" is mainly the simplicity of their waveform (which offers a better understanding of the results), and the fact that Ricker wavelet covers a broad range of frequencies up to nearly $3f_o$. Note that pulses were used at the first phase of the current investigation, while in the sequence, the more complicated set of real records were used in order to test the efficiency of the proposed implementation in realistic situations.

The examined numerical model is studied under different seismic excitations and also under various levels of the imposed ground motion (following the principles of Performance-based Earthquake Engineering) in order to examine more thoroughly the influence of material nonlinearity. Therefore, in order to cover a sufficient range of nonlinear behaviour (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:

- Case I (linear behavior): 0.01g
- Case II (almost linear behavior): 0.05g
- Case III (low level of nonlinearity): 0.10g
- Case IV (medium level of nonlinearity): 0.20g
- Case V (high level of nonlinearity): 0.50g

The simple embankment examined in this study can be regarded as a relative small-scale earth embankment, the dynamic behavior of which has thoroughly been examined in the past by other researchers. According to Gazetas (1987) the first eigenperiod, T_D, of a trapezoidal earth embankment (under small strain levels) founded on rock is given approximately by:

$$T_D \approx \frac{2.5H_D}{V_S^D} \tag{1}$$

where H_D is the height of the embankment, and V_S^D it's average shear wave velocity.

Generally, the need for an efficient computational tool for the simulation of the seismic response of large-scale geo-structures is indisputable. The application of efficient ANN-based Metamodels was motivated by the fact that the examined 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 at a Pentium IV PC with 2.53GHz CPU processor and 1GB RAM. While, for a more "complex" run (a real earthquake 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 obtaining an ANN prediction (after the completion of network training) in all cases, regardless of the imposed motion or the PGA level, was only a few seconds.

The ANN software used in this study has been developed by one of the authors. 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 so-called "receivers" (i.e. the points where the local seismic response is evaluated and used for ANN calculations) had been "placed". The total number of these receivers was 138, and, due to the symmetric shape of the geo-structure, they were placed only at the left half of the embankment. The ANN configurations used were properly trained in order to predict the acceleration for new excitations. The records used were identified using a set of Intensity Measures (IMs) in order to provide ANN with the necessary data that characterize the excitations. 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.

A significant number of different IMs can be found in the literature. Furthermore, IMs can be classified either as only record dependent or as both structure and record dependent. In the present investigation, in addition to the IMs available in Kramer (1987), the A_{95} parameter (Sarma & Yang, 1995) was used. This parameter defines the acceleration level of a record below which 95% of the total Arias Intensity (Ia) is contained. For instance, if the entire accelerogram yields a value of Ia equal to 100 then the A_{95} parameter is the threshold of acceleration such that integrating all the values of the accelerogram below it one gets Ia=95. The most significant IMs were used in this study, after examining various combinations of them for each "load-case" (i.e. different set of excitations), in order to provide the best possible training to ANNs.

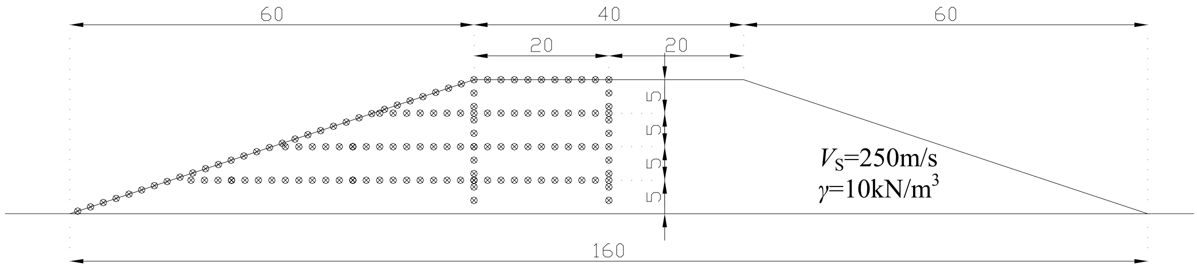

Figure 1. Geometry and material properties of the examined embankment. Bullets represent the position of the "receivers"

Ricker Pulse Excitations

Initially, the embankment was excited with the four Ricker pulses and the five different hazard levels, resulting to 20 runs in total. In Figures 2 and 3 the time-histories showing the response at the corner point of the crest are shown for the 0.01g (linear) and 0.50g (high level of non-linearity), where the effect of the frequency content (even of these rather similar and simple "excitations") and also the influence of the material nonlinear behavior is evident.

The ANN model was trained with the data derived from the three Ricker pulse with 2, 3, 4 Hz central frequency and it was subsequently used to evaluate the embankment's response for the Ricker pulse with 2.5 Hz predominant frequency. Despite the rather small size of the training set and also the discrepancy of the results (see Figures 2 and 3) the performance of ANN was proven very satisfactory. 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 pulses. The output was the seismic response (i.e. the maximum horizontal acceleration) of each receiver for the specific Ricker pulse excitation.

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 (I_C), specific energy density (SED), cumulative absolute velocity (CAV), acceleration spectrum intensity (ASI), velocity spectrum intensity (VSI), effective design acceleration (EDA), A_{95} parameter and predominant period (T_P)), the hidden layer and the output layer with one node (response). After an initial investigation about the optimum number of hidden layers and their nodes the ANN configuration resulted in one hidden layer with 50 nodes, thus the ANN had a [17-50-1] architecture.

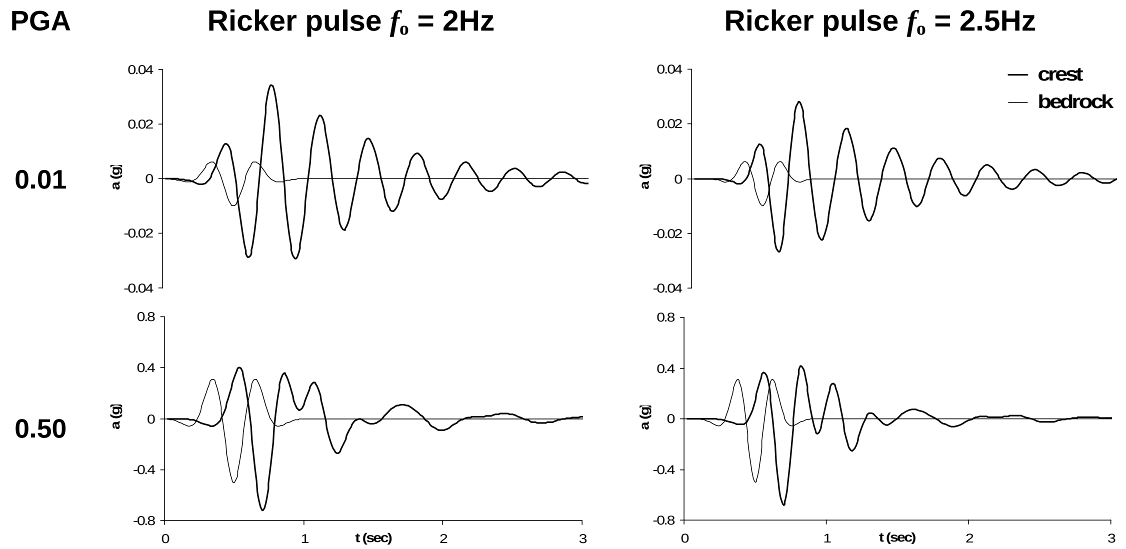

Figure 2. Response of the embankment at crest in the case of Ricker pulse excitation with central frequency f_o = 2Hz and 2.5Hz, respectively, for the 0.01g (linear) and 0.50g (high level of non-linearity) in g (acceleration of gravity)

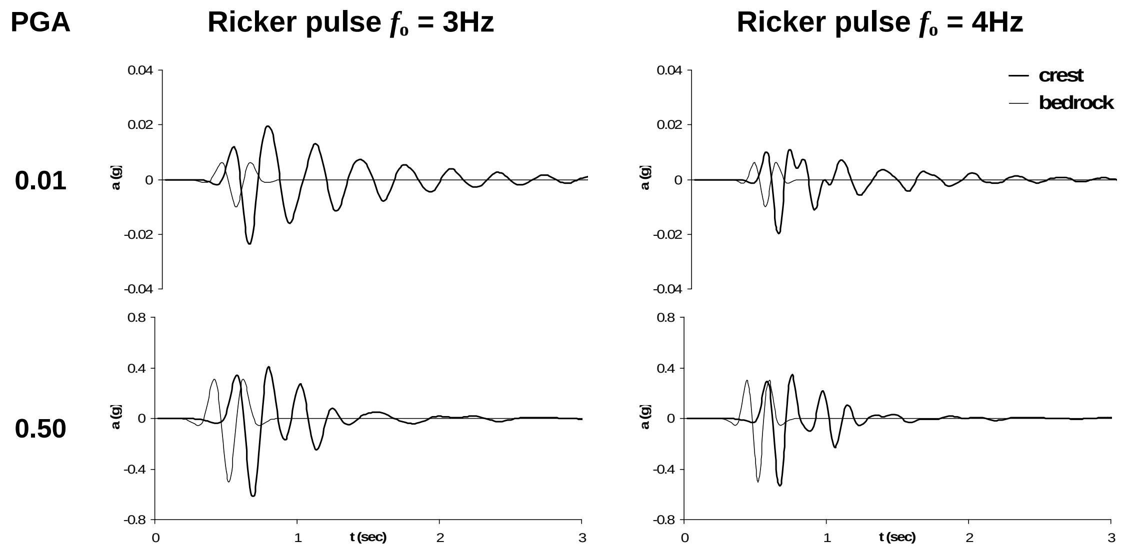

Figure 3. Response of the embankment at crest in the case of Ricker pulse excitation with central frequency f_o = 3Hz and 4Hz, respectively, for the 0.01g (linear) and 0.50g (high level of non-linearity)in g (acceleration of gravity)

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 4. The results shown in Figure 4 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. By carefully inspecting the results it was observed that more accurate results were obtained for the linear cases (Cases I & II) than for the nonlinear ones. It was also 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 of the ANN predictions for the surface receivers is much better, as it is clearly shown in Figure 5 and Table 2. This may be attributed to the complex wave propagation phenomena that affect the response in the body of the embankment, especially as the nonlinearity increases. This fact amplifies the difficulty for ANN to capture the real response in the interior of the geo-structure.

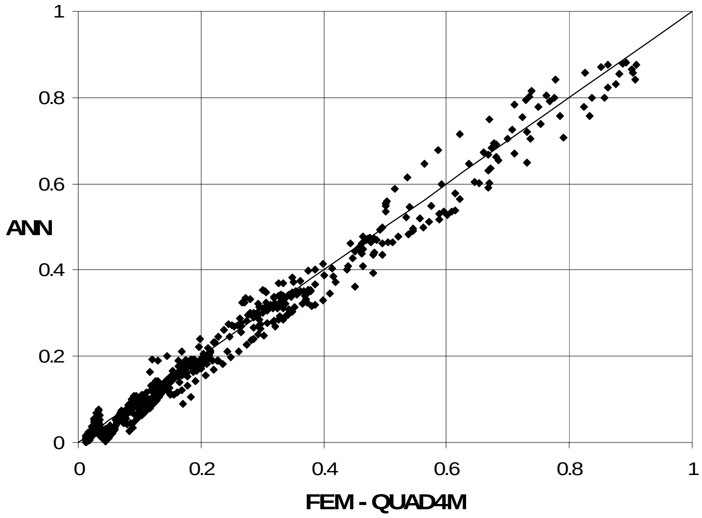

Figure 4. Computed (FEM-QUAD4M) vs. predicted (ANN) seismic response in terms of peak acceleration for the five cases of induced PGA (0.01g to 0.50g) for the entire embankment (Ricker pulse)

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

Earthquake Excitations

As mentioned above, the next stage in the present study was to use, instead of the relatively simple Ricker pulses, real records. The wide-ranging set of earthquakes records (43 accelerograms) used for ANN training is presented in Table 3. Each record has been scaled, with respect to the desired PGA value, to the five aforementioned intensity levels. Following the same considerations as for the previous calculations for Ricker pulses, and after an extensive investigation on the hidden layer(s), a [16-20-1] architecture was used in this case for the prediction of the seismic response of the geo-structure. In addition, after considering various possible IMs combinations (in order to determine possible correlations and to find out which IMs are more crucial for the ANN performance) 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, A_{95} parameter and predominant period.

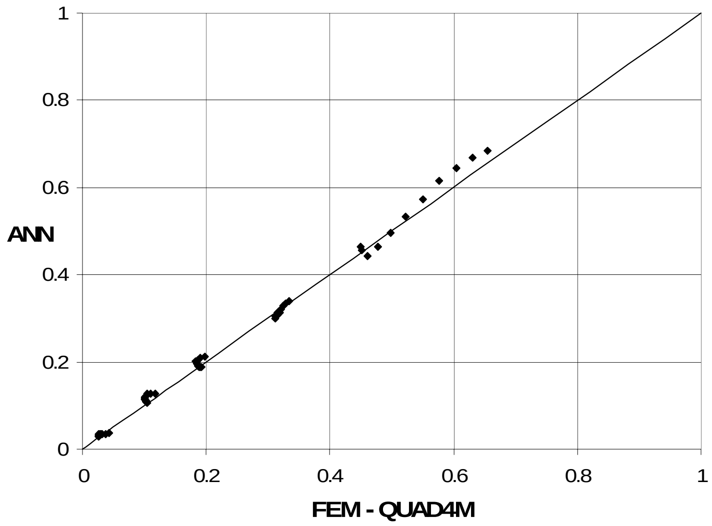

Figure 5. Computed (FEM-QUAD4M) versus predicted (ANN) seismic response in terms of peak acceleration for the five cases of induced PGA (0.01g to 0.50g) for the upper boundary of the embankment (Ricker pulse)

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

After its training the aforementioned ANN metamodel was used to predict the response for Sepolia record (1999 Parnitha earthquake, Greece). This record was chosen since its IMs values are close to the mean values of the IMs of all records considered. It has to be noted here that the same IMs and ANN characteristics: architecture ([16-20-1]) and epochs (1000) have been used for all the PGA intensity levels. As it can be seen in Figure 6 and Table 4, in this case the complexity of motions and nonlinearity affect more the performance of ANN. Nevertheless, even under these more demanding (and more computationally intensive) circumstances, ANN manage to approximate with a relative high level of accuracy the seismic response of the embankment, especially for the external receivers (like in the case of the Ricker pulse excitations).

Table 3. Earthquake records for the training of the ANN

Earthquake's name (Region)	Magnitude	Number of records
Lefkada, Greece (1973)	6.2	1
Mexico City, Mexico (1981)	7.4	4
Kalamata, Greece (1986)	6.0	1
Northridge, USA (1994)	6.7	14
Kobe, Japan (1995)	6.9	9
Aigio, Greece (1995)	6.1	1
Kocaeli, Turkey (1999)	7.6	7
Parnitha, Greece (1999)	5.9	4
Lefkada, Greece (2003)	6.4	2

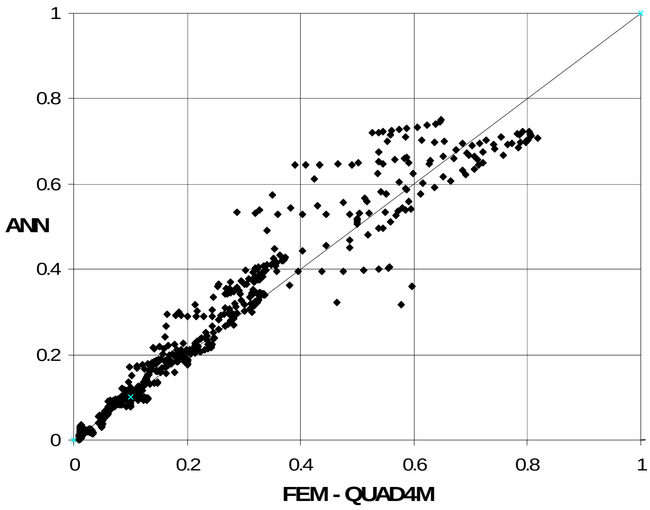

Figure 6. Computed (FEM – QUAD4M) versus predicted (ANN) response (“complete” training set) in terms of peak acceleration for the five cases of induced PGA (0.01g to 0.50g) for the entire embankment in the case of the Sepolia record

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

Table 5. Earthquake records that were used for the “reduced” training and testing of the ANN

Earthquake’s name (Region)	Records for testing	Records for training
Mexico City, Mexico	CDAO-000, CDAO-090	SCT-000
Northridge, USA	Sylmar-090, S. Monica-090, Jensen-292, Rinaldi-318	Newhall-360
Kobe, Japan	Nishi Akashi-000, Nishi Akashi-090, Takarazuka-090, Takatori-090	JMA-090
Kocaeli, Turkey	Yarimca-060, Yarimca-330, Duzce-180	Izmit-090
Parnitha, Greece	Monastiraki	-
Lefkada, Greece	Lefkada Long	-
Aigio, Greece	-	Aigio, Greece

Table 6. Intensity Measures for each PGA level’s ANN (“reduced” training set)

ANN	PGA (g)	IM
1	0.01	x, y, T0, Ia, Ic, ASI, Vmax, Dmax, Vmax/Amax, Vrms, Drms, SED, CAV, SMV
2	0.05	x, y, T0, Ia, Ic, Vmax, Dmax, Vmax/Amax, Vrms, Drms, SED, CAV, VSI, SMV, EDA
3	0.10	x, y, T0, ASI, Vrms, Drms, SED, EDA
4	0.20	x, y, A95, ASI, VSI, EDA
5	0.50	x, y, A95, Arms, Ic, ASI, Vmax, Vmax/Amax, EDA

Table 7. ANNs' architectures that were used for each PGA level ("reduced" training set)

ANN	PGA (g)	Architecture	Epochs
1	0.01	[14-50-1]	3000
2	0.05	[15-40-1]	1000
3	0.10	[8-200-1]	2000
4	0.20	[6-300-1]	3000
5	0.50	[9-50-1]	1000

Finally, an effort was made to shrink the training set so as to reduce the time for the completion of the dynamic finite-element computations needed for the ANN training. Applying the methodology that was used in the previous stage (five different ANNs, one for each PGA level), fifteen earthquake records were selected as the training set and five records as the testing set (these records are presented in Table 5). The trained ANN was used in the sequence for predicting embankment's response for the rest (23) records and all the intensity levels. As in the previous "complete" training set case, a thorough investigation was performed in order to provide the more important input data and therefore to enhance the predictions of the ANN. The IMs and the architecture and the number of epochs of each ANN that were used for the "reduced" training set are presented in Tables 6 and 7, respectively. The results of the ANN performance for the five PGA levels (separately and totally) are presented in Figure 7 and in Table 8. From these results it can be seen that the accuracy of the ANNs is not deteriorated significantly by the reduction of the training data and the greater variety of the approximated values: 23 x 138 = 3174 data for each of the five intensity levels.

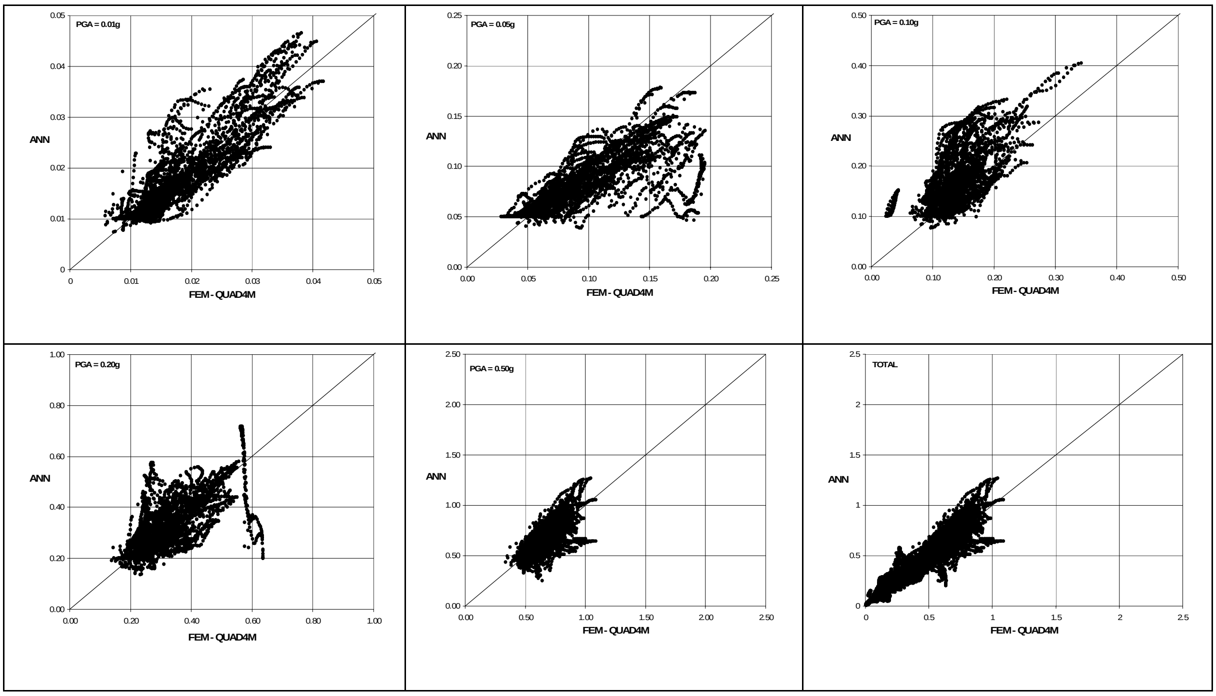

Figure 7. Computed (FEM-QUAD4M) vs. predicted (ANN) response ("reduced" training set) in terms of peak acceleration for the five cases of induced PGA. The figure at the right bottom (TOTAL) includes the results from all the previous five cases (prediction set: 23 record)

CONCLUSIONS

The objective of the present study was to investigate the ability of ANNs to capture the dynamic nonlinear response of a typical embankment under various seismic excitations. The main aim was to reduce the excessive computational cost of such a large-scale geotechnical earthquake engineering problem. To achieve this goal, a very elaborate investigation has been performed where various parameters have been examined.

Table 8. Percentage of receivers, for PGA = 0.01g to 0.50g, as well as the total number of receivers that exceeds different levels of tolerance for the entire embankment (Prediction set: 23 records, 3174 (= 23x138) receivers for each PGA level)

PGA	0.01g			0.05g		
Tolerance (%)	No of receivers	Receivers (%)	Total Receivers (%)	No of receivers	Receivers (%)	Total Receivers (%)
0 to 5	672	21.17	21.17	589	18.56	18.56
5 to 10	596	18.78	39.95	507	15.97	34.53
10 to 20	917	28.89	68.84	821	25.87	60.40
20 to 30	630	19.85	88.69	457	14.40	74.80
30 to 40	227	7.15	95.84	284	8.95	83.74
40 to 50	92	2.90	98.74	150	4.73	88.47
50 to 60	27	0.85	99.59	78	2.46	90.93
60 to 70	9	0.28	99.87	56	1.76	92.69
PGA	0.10g			0.20g		
Tolerance (%)	No of receivers	Receivers (%)	Total Receivers (%)	No of receivers	Receivers (%)	Total Receivers (%)
0 to 5	490	15.44	15.44	705	22.21	22.21
5 to 10	395	12.44	27.88	585	18.43	40.64
10 to 20	797	25.11	52.99	839	26.43	67.08
20 to 30	594	18.71	71.71	511	16.10	83.18
30 to 40	376	11.85	83.55	202	6.36	89.54
40 to 50	337	10.62	94.17	151	4.76	94.30
50 to 60	46	1.45	95.62	84	2.65	96.94
60 to 70	23	0.72	96.35	39	1.23	98.17
PGA	0.50g			TOTAL (0.10g to 0.50g)		
Tolerance (%)	No of receivers	Receivers (%)	Total Receivers (%)	No of receivers	Receivers (%)	Total Receivers (%)
0 to 5	804	25.33	25.33	3260	20.54	20.54
5 to 10	698	21.99	47.32	2781	17.52	38.07
10 to 20	1046	32.96	80.28	4420	27.85	65.92
20 to 30	342	10.78	91.05	2534	15.97	81.88
30 to 40	119	3.75	94.80	1208	7.61	89.50
40 to 50	61	1.92	96.72	791	4.98	94.48
50 to 60	44	1.39	98.11	279	1.76	96.24
60 to 70	29	0.91	99.02	156	0.98	97.22

According to the results, ANN achieved a better approximation of the response of the receivers that are positioned at the crest, the upper part of the embankment and the inclined part of the slope than the corresponding response of the receivers that are positioned in the core of the embankment. Furthermore, comparing the results obtained via ANN for various excitations, it becomes evident that when the soil material of the embankment behaves linearly or moderately nonlinearly, the response of the embankment is approximated very accurately by the ANN-based metamodel. On the contrary, the high soil nonlinearity that takes place during a severe seismic excitation deteriorates the accuracy of ANN predictions. However, also in that case the accuracy may be improved substantially if the ANNs are separated according to their PGA level (five PGA levels, and one ANN for each level).

Conclusively, considering the complexities of the examined problem and the ANN performance reported in similar applications, the proposed implementation of ANNs can be considered as satisfactory. ANN exhibited a very good performance in marginal computing cost for the evaluation of the seismic response of a relatively large-scale embankment, and thus their applicability in this demanding field of geotechnical earthquake engineering seems very promising.

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