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DYNAMIC SOIL PROPERTIES IDENTIFICATION USING EARTHQUAKE RECORDS: A NN APPROXIMATION

Silvia R. GARCIA[1] and Miguel P. ROMO[2]

SUMMARY

Earthquake records constitute a helpful source of knowledge on the dynamic behavior of geotechnical systems. This data represents valuable information on site and earth dam response over a wide range of loading conditions that are difficult to be covered by full-scale testing or laboratory procedures. Using the capabilities of neural networks for solving spatio-temporal problems and in particular their ability to acquire, represent, and perform a mapping from one multivariate space of information to another, a neural model that identifies the patterns of materials behavior (accelerations time series) and permits to assess the variations of shear modulus (G) and damping ratio (λ) with strain amplitudes, is put together. The study reported here shows that a multiple input-output instrument array coupled with powerful analysis techniques constitutes an important base to develop systems that capture the dynamic response mechanisms of complex soil systems such as earth dams.

INTRODUCTION

Motion earthquake records provide a valuable source of information on the dynamic behavior of full-scale soil-systems at large-amplitude deformations, and even at potentially damage-level response. A detailed monitoring of the entire response of such systems may not be technically possible, and would generally be prohibitively expensive, by the opposite; a sparse monitoring of soil systems generally does not provide enough information to uniquely and accurately identify local response mechanisms due to the broad range of complex response patterns when seismic excitations are imposed to them.

To extract meaningful conclusions about a complicated system using time series data from a single sensor (acceleration records), one of the most powerful analysis and design tools –and often one of the most difficult to create- is a good model. System Identification (SID) is the process of identifying a dynamic model of an unknown system. Any representation designed for reasoning about models of such systems has to be both flexible enough to handle various degrees of uncertainty and complexity, and yet powerful.

[1] PhD Student, Institute of Engineering, National University of Mexico, sgab@pumas.iingen.unam.mx
[2] Head Geotechnical Department, Institute of Engineering, National University of Mexico, mromo@pumas.iingen.unam.mx

System identification entails two steps: structural identification, wherein one ascertains the general form of the model (e.g., the ODE –ordinary differential equation- for a simple pendulum), and then parameter estimation, in which specific parameters values for the unknown coefficients that fit that model to the observed data are found.

Although the vast majority of natural and man-made geotechnical systems is non linear, almost all time series analysis are limited to linear systems. Soft Computing (SC) provides us with complementary reasoning and searching methods to develop the single-sensor reconstruction of ill-defined phenomena, using experts' hypothesis about physics involved, observations (interpreted and described symbolically or graphically) in varying formats and degrees of precision and physical measurements made directly on the system.

Within this context, a system identification procedure is presented to analyze the nonlinear dynamic response of embankment systems using earthquake records. Neural Networks (NNs), as computational structures that can be trained to learn patterns from examples, are used to find the relation between inputs and outputs (recorded ground motions) by a supervised learning algorithm that performs fine-granule local optimization. The result of the neural training stage is a nonlinear function of several variables that can predict behaviors and classify objects.

The proposed framework consists of: (1) pattern recognition and nonparametric identification analyses (2) model development based on the information gathered from a multiple input-output array of accelerometers installed in El Infiernillo dam (Mexico) and (3) validation and assessment of the quality of the identified models and parameters.

SYSTEM IDENTIFICACTION USING NNS

Structural identification and parameter estimation depend upon input-output analysis wherein the relationship between drive and response is used to infer information about internal system dynamics (Casdagli, [1]). For nonlinear systems, parameter estimation is difficult and structural identification is even harder. SC techniques can be used to automate the former (Bradley [2]), but the latter has, until now, remained the purview of human experts.

Formalizing the connection between data and knowledge can be addressed by two (antagonistic) ways: modeling -build a function that can mimic the data accurately and gives good results on new data sets- and abstracting -build a system that produces articulated knowledge from the data-. In the first approach, emphasis is put on the ability to reproduce what has been observed. NNs are well-adapted to this problem. In the second approach, emphasis is put on the ability to understand and explain the data in a human-friendly way. It is by linking the estimated model constraints to the important phenomena parameters that a designer can represent the human-originated knowledge using a numerical approximation, in what is commonly known as SID.

Neural Networks. NNs and Perceptrons started in the early 60s as algorithms to train adaptive elements. Their origins can be traced to the works of Rosenblatt [2] on spontaneous learning, Stark [4] on competitive learning, and Widrow [5] on the development of ADALINE and MADALINE algorithms. Typically NNs are divided into Feed-Forward (FF) and Recurrent/Feedback networks (RN). The FF networks include single-layer perceptrons, multilayer perceptrons, and Radial Basis Function (RBF) nets [see Moody [6]], while RN cover Competitive networks, Kohonen [7], Self Organizing Maps, Hopfield, [8], and ART models [see Carpenter [9],[10], [11]].

In the context of this paper only FFNNs will be considered. A FF multilayer NN is composed of a network of processing units or neurons. Each neuron performs the weighted sum of its input, using the resulting sum as the argument of a non-linear activation function. Originally the activation functions were sharp thresholds functions, which evolved to piecewise linear saturation functions, to differentiable saturation functions (or sigmoids), and to gaussian functions (for RBFs).

For a given interconnection topology, NNs train their weight vector to minimize a quadratic error function. Prior to Backpropagation BP, proposed by Werbos [12], there was no sound theoretical way to train multilayers FFNNs with nonlinear neurons. With the advent of BP, most researchers on NNs have focused their efforts on improving BP's converge speed: by using estimates of the second derivatives, under simplifying assumptions of a quadratic error surface, as in Quickprop QP [see Fahlman [13]]; by changing the size of the step size in a self-adapting fashion, or by using second order information. QP is used to train all the nets proposed in this investigation.

The structural and parametric neural learning, which are the counterpart of system identification and parameter estimation in classical system theory (Bonissone [14]), means the synthesis of the network topology (i.e., the number of hidden layers and nodes), while parametric learning implies determining the weight vectors that are associated to each link in a given topology.

Neural *learning* can be facilitated by the availability of complete or partial feedback. In the case of total feedback a training set describes the correct output for a given input vector in that is called *supervised learning*. When only partial feedback (evaluation as success/fails) is available *reinforcement learning* is being developed. If no feedback is available all the adjustments are made by *unsupervised learning*. Most of the engineering applications are *supervised* and they deal principally with parameter identification once the structure has been fixed.

In this work, an optimization process is included in the NN generation. Genetic Algorithms (GAs), that provide continuous and discrete function optimization, system synthesis, tuning and testing modeling (Holland [15]) are used here to synthesize and tune the NN: to evolve the network topology (number of hidden layers, hidden nodes, and number of links) and to find the optimal set of weights for a given topology replacing the back-learning algorithm and to evolve the reward function, making it adaptive.

INVERSE ANALYSIS OF DYNAMIC PROPERTIES

Proper identification of dynamic soil parameters for specific soil conditions is a central aspect when amplification of ground motions is being analyzed. Several inverse analyses for parameter estimation have been introduced by many researchers, and can be classified as: time domain procedures, frequency domain procedures and modal analyses (i.e., Beck, [16], Hoshiya [17], Sawada [18], Zeghal [19], Honda [20], Glaser, [21], Zeghal [22], Ghanem [23], Glaser, [24], Zhai [25], Satoh [26], Glaser [27], Zeghal [28], Zeghal [29], among others).

Traditional approximations, because of their optimization procedures (i.e., gradient-based search methods), have difficulties associated with selecting a discontinuous solution space and with considering non-linearities. Unlike the traditional optimization methods, soft computing tools and particularly GAs efficiently find an optimal solution from the complex and possibly discontinuous solution space. GAs have been applied as an effective optimization search technique in various fields, including the soil-parameters identification problem (Taboada [30]). However, these methodologies have focused on the GA searching capabilities to find the dynamic parameters related with the 1D wave propagation theory, no improvements are made to the functional in order to model the non-linearity and multidimensional soil behavior. Even worse it is the fact that many of these genetic models need a previous knowledge about the dynamic parameters range (in a close sense) for constructing the error function to optimize.

Nonparametric identification of a continuum. The goal of the neural SID proposed here, is to invert recorded data to generate a NN model of a particular geotechnical system. The data are input-output pairs of recorded earthquake ground motions (vertical arrays) and the system is the intervening soil layers. The mechanical information about soil formation is commonly obtained by solving the inverse problem for the system transfer function via a simple ratio of weighted polynomials. In a NN model, weights are the parameters that allow relating input-output data and they contain all the information about the physics involved in the system behavior. Once the training stage is complete, the obtained neural functional is a kind of nonlinear-multidimensional transfer function that approximate all the laws of mechanics that the actual phenomena obeys. See (Fahlman, [13]) for a complete description of the FFNN-QP numerical/parametrical functional structure.

Using the information about motions into the bottom of the soil layer of interest and out of the top layer, as illustrated by the sketch in Figure 1, a NN is trained with accelerations (time series arrangement) from an input propagating control point –used just to express numerically the excitation characteristics-, and from the output motion to describe the soil column behavior. To demonstrate the analysis procedure, soil strata properties were modeled via Voigt type elements, allowing computing the resulting acceleration, velocity and displacement ought to the seismic waves traveling through a soil deposit characterized via stiffness module and damping ratio (Botero [31]).

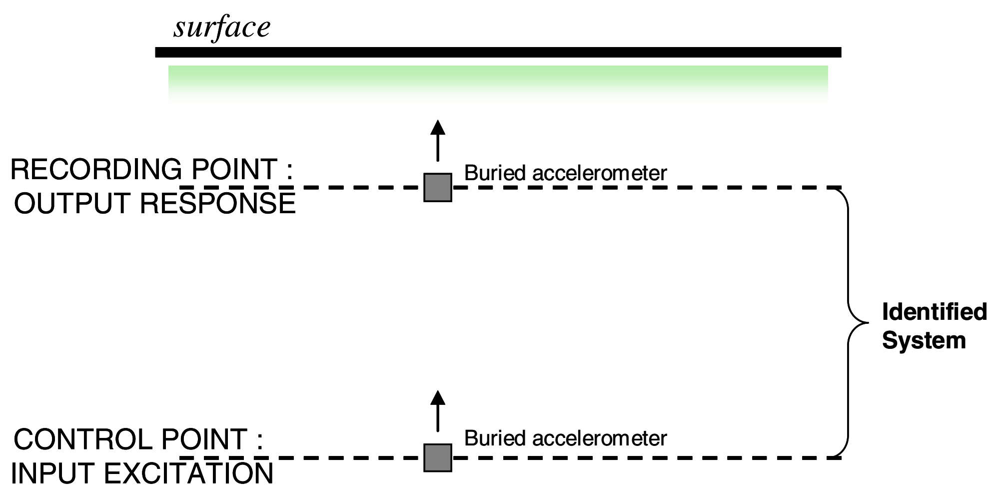

Figure 1. Configuration of the nonparametric system identification

In Figure 2 it is depicted the 4-50/50-1 [inputs- hidden nodes- output] FFNN/QP/Sigmoid topology proposed for modeling a deposit subjected to seismic loading. The acceleration responses $\left(\ddot{u}\right)$ are forecasted through one step at a time based on the 4 input numerical descriptions: 1) acceleration records $\left(\ddot{y}_g\right)$, 2) velocity histories $\left(\dot{y}_g\right)$, 3) displacement histories $\left(y_g\right)$ and 4) low/high -earthquake intensity-

(binary classification node to specify linear/nonlinear behavior). Dynamic parameters are not included as inputs. G y λ will be implicit in the final weights matrix that can be related to their behavior curves (G vs. γ and λ vs. γ; where γ: shear strain).

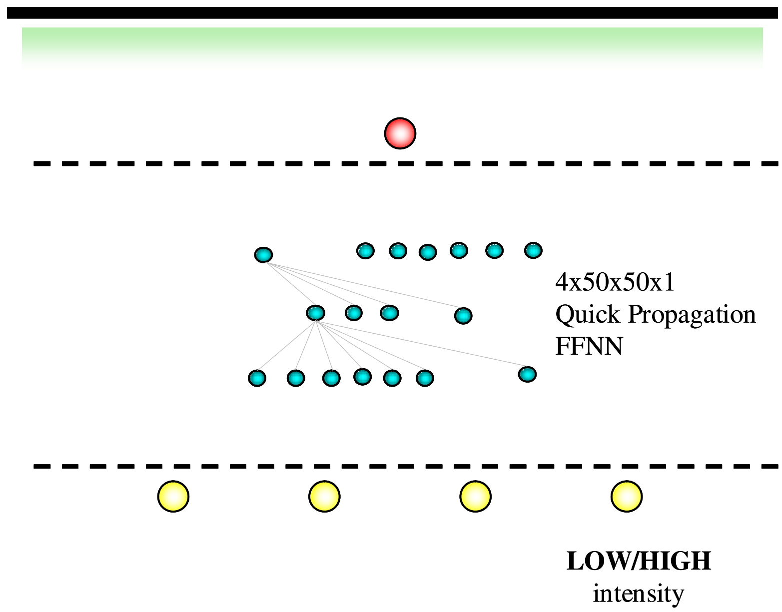

Figure 2. NN topology for a vertical array

The neural capabilities to find parametric patterns are demonstrated in Figure 3, where the evaluated acceleration histories reproduced satisfactorily unseen time series. The additional information concerning the nature of the underlying system aided to the model (velocity, displacement and intensity) is fundamental for developing the NN generalization capacity; however, this forces the obtaining of a specific net only suitable for homogeneous deposits, whose dynamic properties run in a close range.

This pattern recognition analysis using nonparametric identification analyses provide direct information on the dynamic response of a soil column, the constructed computer model, without any knowledge of the particular physical system, take seismic input data and provides as output the response (acceleration time histories) of the geotechnical formation.

Mapping of neural model parameters to soil properties: El Infiernillo Dam. A detailed study of the El Infiernillo dam (Michoacan, Mexico) was performed using a suite of six events to monitor the boundary conditions (left and right abutment) and to portray the dam response (see Figure 4). The dam has a central clay core and large conglomerate and diorite rockfill shells which were dumped in place without watering (Marsal [32]), its multiple-input-output environment consisting of 9 accelerometer stations, thus, the array comprised a total of 27 accelerations records linked to a common triggering mechanism (horizontal and vertical directions) for each earthquake. A description of the data base used for neuronal training/testing stages is presented in Table 1.

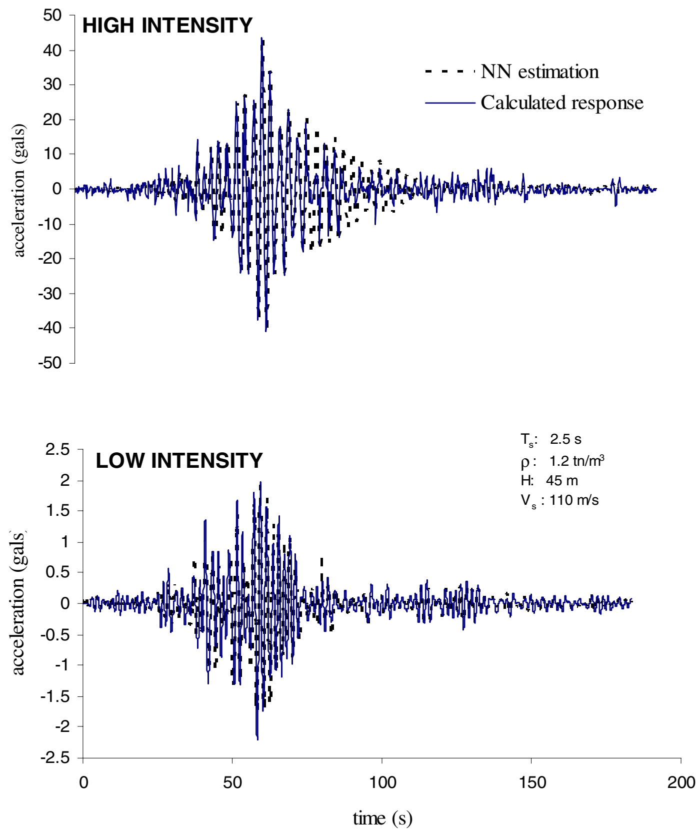

Figure 3. Comparison of the calculated and NN estimated acceleration time series

Multidimensional conditions. The non-controlled nature of seismic excitations, along with the limited number of sensors used to monitor system responses, make the modeling of dynamic behavior of full-scale soil-systems (such as earth dams) a quite difficult task. In this paper, a new system identification technique was developed using the closely spaced accelerometers arranged in a 3D configuration. The NN proposed is capable of using "indeterminate" records and the sensors spatial configuration to describe the dimensionality of the system response.

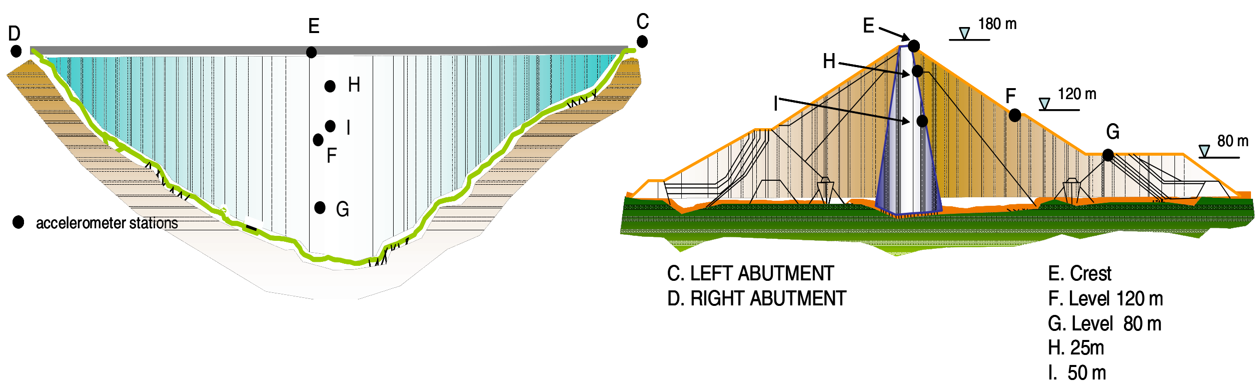

Figure 4. El Infiernillo Dam: seismic instrumentation

Table 1. Data base used for developing the neural models

	75/11/25	85/09/19	92/02/12	94/12/10	96/07/15	97/01/16
	EQ-1	EQ-2	EQ-3	EQ-4	EQ-5	EQ-6
M_{max}	5.5	8.1	5.1	6.6	6.5	5.1
A_{max} (abutment)	104.5/87.7/129.0	83.7/99.6/142.6	8.1/21.53/22.97	269.9/376.6/541	18.04/31.5/26.18	8.13/19.23/16.2
Lat EIPICENTER	17.58	18.08	17.73	18.02	17.45	17.94
Long	102.28	102.94	101.06	101.56	101.16	102.76

* TRANSVERSAL / LONGITUDINAL / VERTICAL (gals)

The identified system is the specific dam element (geometry and materials), described by given intervals of soil lying between pairs of accelerometers. The recording stations used in the model as control points, are characterized by their position - {x,y,z}coordinates - and a class condition: i) boundary situation or ii) dam response information (Figure 5). First class is included as excitation node and the second one illustrates the material behavior and location. The two mechanical soil properties estimated by this SID process are the shear modulus (G) and the damping ratio (λ). These computed "equivalent" properties are based on the "effective" layer values between the sensors included in the neural training stage. The acceleration records and material properties predictions are calculated at discrete points that can be located between two sensors or in any zone of the earth element (described appropriately as class ii).

Following the SID process described in the preceding section, a NN nonparametric framework was obtained to map the input (left abutment recordings) to the output time series (accelerations data inside the dam). In Figure 6, the model and actual values for unseen events (EQ5, EW component) are shown. Remarkable neural capacity to characterize the time histories of earthquake motions and successful transmission of the movements through the dam core (Z direction) is proved with these results. A simple identification procedure developed by Zeghal and co-workers (Zeghal [22]) can be used to estimate local shear stress and strain histories from array accelerations. These estimations can be used to locally calibrate models of the constitutive behavior of soil-systems.

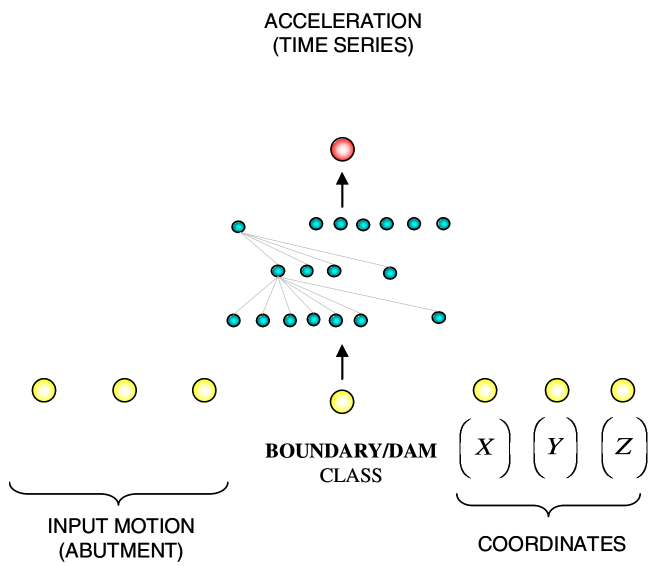

Figure 5. FeedForward Quick Propagation – NN topology

Properties evaluated from the NN evaluated accelerations histories show a good agreement with those obtained by empirical correlations and laboratory studies. This approach is obviously not feasible in analyses of a multidimensional response. A more general local identification algorithm is presented below.

For mapping coordinates to soil properties, a more sophisticated neural model (genetic tuning of the weights and function variables) was developed for describing materials dynamic behavior via G and λ curves. In this model the variables that affect the phenomena are included with a double sense, i.e., as input/output parameters (Fig. 7). In a first step the input variables are the coordinates of the recording station and the outputs are the values of the dynamic properties. Once this process is completed, G/ λ nodes can be interchanged as premises and the coordinates take the role of conclusions to corroborate the adequate description of the soil masses. The forward-back training route, permits to find the parametric changes for optimal estimation of the shear stiffness and equivalent damping ratio, describing the physical soil system (continuous mass system) without trying to adjust the observed behavior to a simple equivalent system (lumped mass models, for example).

As can be seen in Figure 8, this neural model can offer tremendous insight into the complicated soil/rockfill system behavior. Based on the user/designer necessities (i.e., Finite Element Method, calibration methodology) the neuronal structure can offer a general evaluation for each material, for a transition zone or for a discrete point.

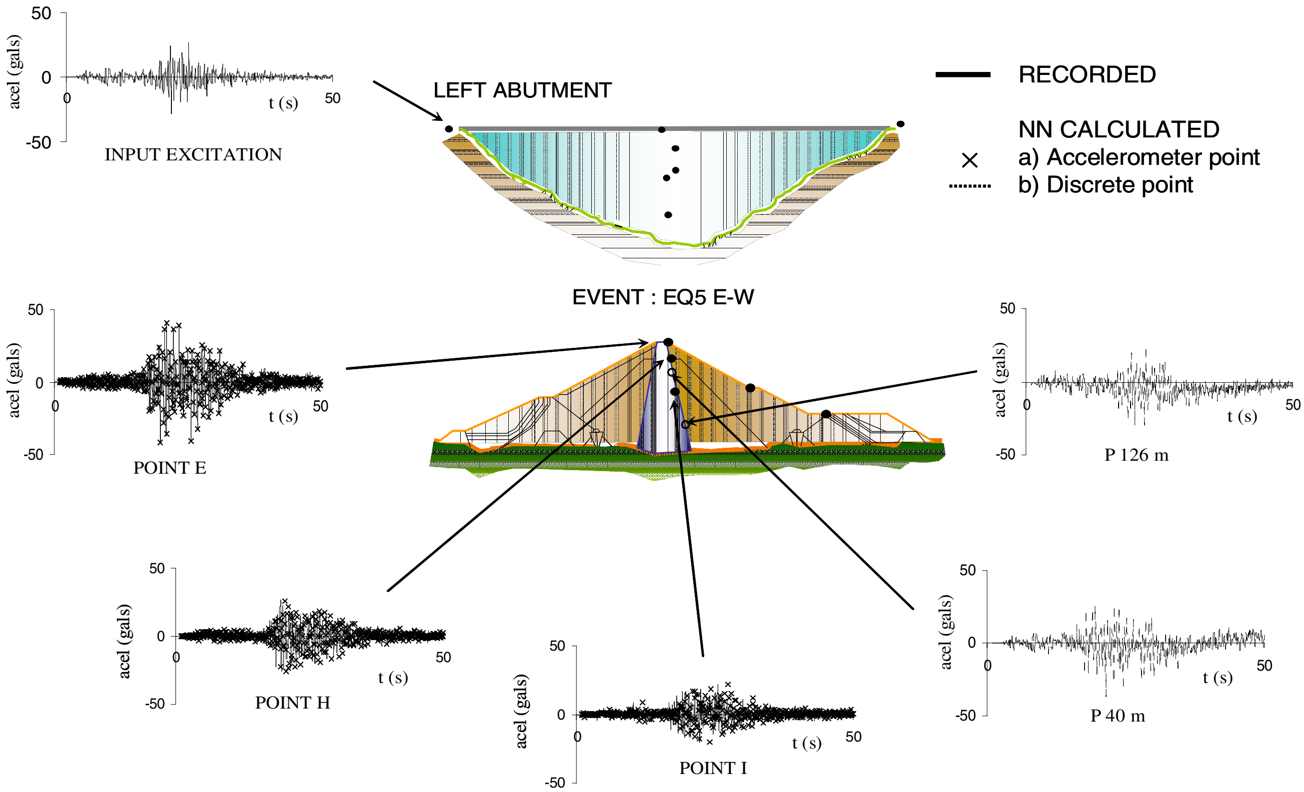

Figure 6. NN model results: testing stage

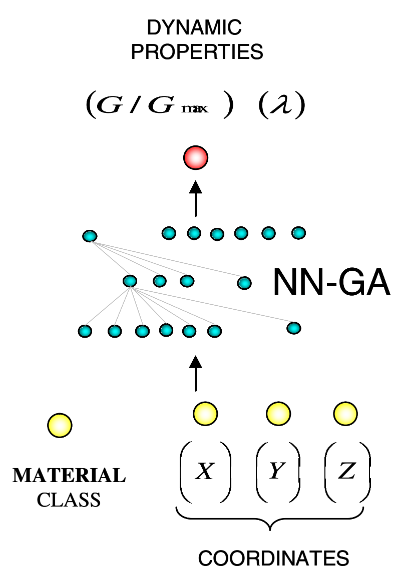

Figure 7. NN-GA model results: testing stage

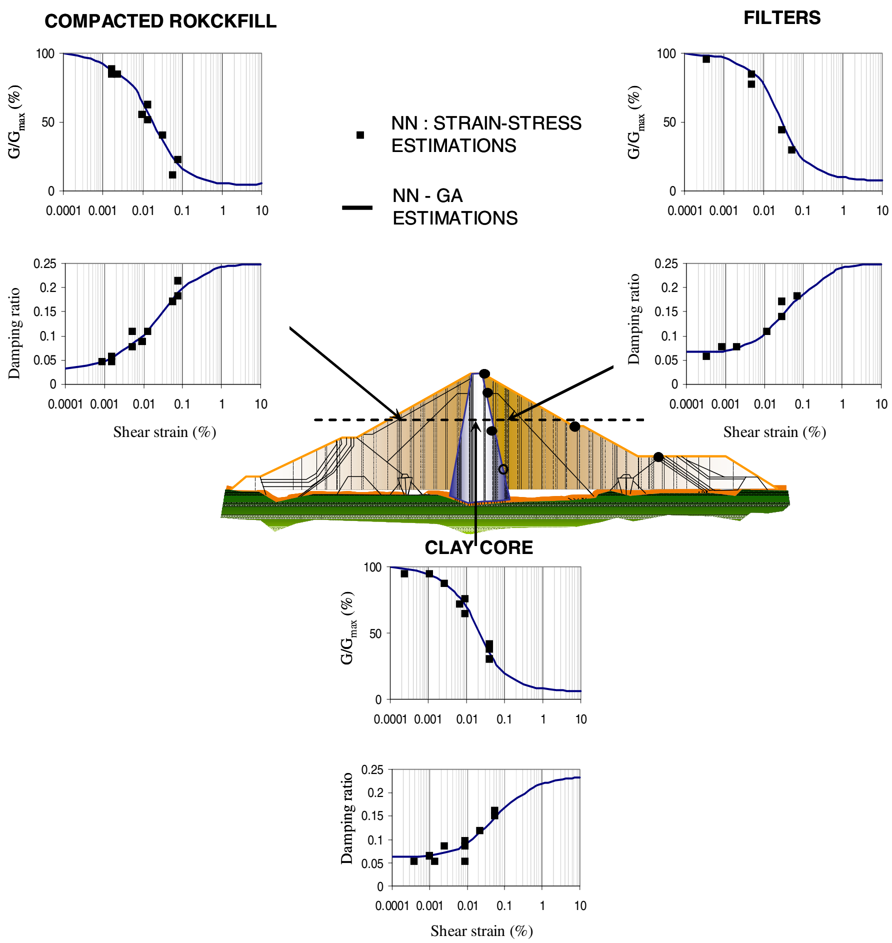

Figure 8. Dynamic properties: NN and NN-GA estimations

CONCLUSIONS

For a complicated system such as wave propagation through natural materials and the large amount of uncertainty inherent to acceleration records and dynamic properties, identifying the "true" underlying earth dam system is an intricate objective, commonly covered using simple equivalent systems that are not ideal models of a continuous mass. It has been demonstrated that SC tools for pattern recognition analyses using nonparametric identification provide essential direct information on the dynamic response of the distributed parameter system. Such information reduces the indeterminacy problem and permits an appropriate model selection.

The advantageous characteristic of the neural model proposed here for analyzing material behavior at discrete points inside the dam structure can help to reveal the most influential aspects in determining seismic responses: material properties (shear modulus and damping coefficient), canyon configuration, materials zonation (geometry), grain size, mineralogy, etc.

There is considerable flexibility in the presented formulation for an easy expansion to a model that include the linguistic/empirical knowledge (fuzzy systems) or to an internal sub-routine in a current design method. Based on the results of the studies discussed in this paper, it is evident that SC techniques perform better than, or as well as, the conventional methods used for identifying these complex and not well understood geotechnical systems.

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