# A Neurogenetic Method for System-Identification

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*Abstract:* - Models of real systems are of fundamental importance in virtually all disciplines. Models make possible to predict or simulate a system's behavior. Since the quality of the model typically determines an upper bound on the quality of the final problem solution, modeling is often the bottleneck in the development of the whole system. As a consequence, a strong demand for advanced modeling and identification schemes arises. In this paper it is shown, via the development of a system for the analysis of the seismic response of rockfill dams, that neurogenetic techniques are a better option than analytically-based procedures in this kind of studies. To buttress this assertion, El Infiernillo dam, which has an ample history of being shaken by a great variety of seismic events, is used to this end.

*Key-Words:* - system-identification, modeling, neurogenetic networks, seismic response, soil-dynamic properties, finite element method, rockfill dams

## 1 Introduction

Many combinations and nuances of theoretical modeling from first principles, i.e., physical laws, and empirical modeling based on measurement data can be pursued. [1] and [2] developed an analytically-based system to study the seismic behavior of El Infiernillo dam. They resorted to a theoretical approach that drew support from measured responses (data) of this dam to several earthquakes. Besides the knowledge from first principles and the information oriented in the measurement data, qualitative knowledge formulated in rules were also utilized in the development of the model. The determination of the model structure relied strongly on prior knowledge and the model parameters were mainly determined from measurement data. This model has shown to be fairly good at extrapolating and providing good understanding of the physical phenomenon. From the engineering view point is reliable and scalable. However, it is time consuming and requires a degree of expertise on dam engineering to be applied in design.

During the past years the authors have been using *connectionism* for developing alternate procedures to solve geotechnical (i.e. [3], [4]) and earthquake geotechnical engineering problems [5], [6]. Considering that these and further experiences have proven that knowledge-based neural techniques constitute an alternative with a number of advantages over analytical methods, it was just natural to step up the complexity of the problems dealt with. In this paper, a neurogenetic model is developed to extract information about the seismic behavior of El Infiernillo dam from its responses recorded during several earthquakes. Herein, this procedure is compared both with analytical model results and "unknown" measurement data.

## 2 System Identification

Science deals with the inference of models from the comprehension of recorded data properties. System identification handles the problem of making analytical models of dynamical systems on the bases of observed data from the system behavior. Herein system is understood as an object in which variables of different kinds interact and produce discernible signals, usually called outputs. The external signals (stimuli) that can be manipulated by the observer are called inputs but there may also be disturbances that cannot be fully controlled by the observer [7].

One of the key aspects of system identification is the definition of the model parameters. This can be achieved by extracting the required information from observed data. The procedure of modeling is, usually, application dependent and often has its roots in tradition and specific techniques in the application area in question [7]. Basic techniques typically involve structuring of the process into block diagrams with blocks consisting of simple elements. Assembling these blocks is, now days, frequently done by means of computers, thus the final product is a software-system.

In Fig. 1 a single-degree-of-freedom oscillator is used to illustrate the procedures involved in developing a model. Assume that the oscillator is capable of modeling the behavior of a variety of structures. If this is so, then it is a matter of defining the characteristics of the model parameters such as the spring stiffness $k$, the damping $c$, and the mass $m$ to develop a system. The equation of motion describing the response of this system is given by

$$m\,\ddot{x}(t)+c\,\dot{x}(t)+k\,x(t)=-m\,\ddot{y}(t) \qquad (1)$$

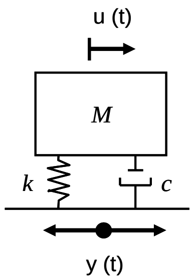



Fig. 1. Single-degree-of-freedom mechanical system

Traditionally, through a linear modal analysis of mechanical systems, the physical parameters in the proposed equation are determined from measured data [8]. This procedure is valid only for linear systems, if nonlinearities were involved in the input-output data, the results would be meaningless [9].

For extracting the parameters values, frequency response functions are included in the procedure but this step introduces both random and bias errors. The key to successful applications is an understanding of these errors and a diligent effort to minimize them. The most common approach to minimization is the supervised technique that optimizes the performance (loss function). The errors come from the corruption of the outputs by noise $n(t)$ that cause differences between the measured system, $u_y(t)$, and model output $\hat{u}(t)$, for a specified number $N$ of input samples. The procedure to achieve the error minimization and then optimum system is depicted in Fig. 2.

The natural logical flow to an identification procedure is collecting data, followed by selecting a model set, and then the most accurate model is chosen. More often than not, the model first picked will not pass the validation test.

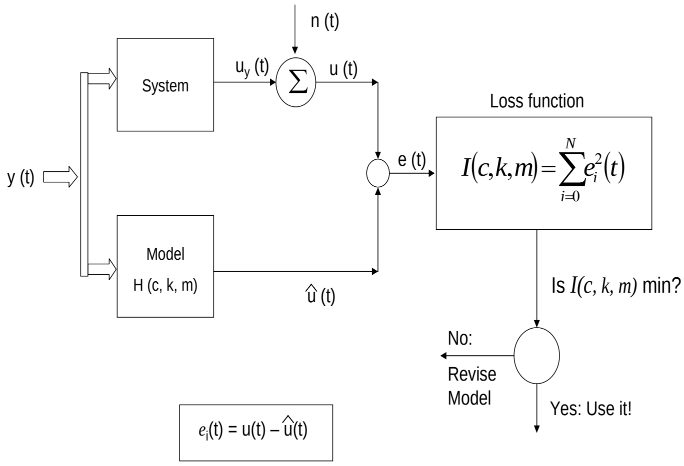



Fig. 2. Minimization process to model optimization

Thus, the various steps of the procedure should be revised again (Fig. 3). There are several reasons why the model may be deficient: a) the numerical procedure failed to locate the more accurate model according to the convergence criterion imposed, b) the criterion was not properly chosen, c) the model was wrongly defined in the sense that it did not contain any appropriate description of the system, and d) the data set provided misleading information.

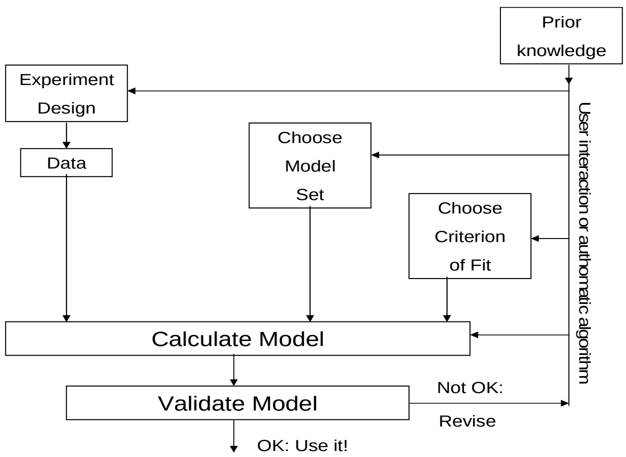



Fig. 3. System identification loop

## 3 SI Neurogenetic Approach

In the process of identifying a dynamic model of an unknown system, any representation designed for reasoning about such system has to be both flexible enough to handle various degrees of uncertainty and complexity, and yet powerful. 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 System Identification, SID.

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 [10]. For nonlinear systems, parameter estimation is difficult and structural identification is even harder. Soft Computing, SC, techniques can be used to automate the former [11], but the latter has, until now, remained the purview of human experts. The aim of this work is building a SC layer to automate the SID process (diagrammed in Fig. 4) around the traditional mathematical techniques and its engineering parameters. This layer automates the high-level stages of the modeling process (normally performed by a human expert) reasoning from the input-output information to automatically choose, invoke, and interpret the data and the system results, defining phenomena parameters most broadly applicable (well formalized) and generating improvements (better understanding) for models in current use.

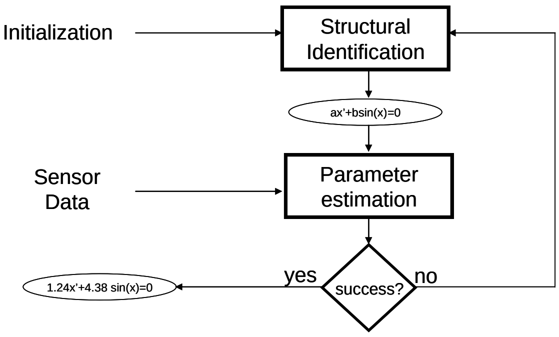



Fig. 4. System identification phases

## 3.1 Neural Networks generated by Genetic Algorithms

SC [12] is now a widely accepted term to cover those techniques including neural networks, NNs, fuzzy logic, FL, evolutionary computing, EC, and various probabilistic approaches. These methods are used in a variety of applications that demonstrate, in some way, their ability to tackle problems that contain uncertainty or imprecision. NNs [13] offer the ability of modeling highly non-linear relationships. Evolutionary computing is a term that includes genetic algorithms GAs and genetic programming GP, techniques particularly useful for optimal searching. In this work, a hybrid NN-GAs system was selected to develop the SID task. The structural and parametric neural learning, which are the counterpart of system identification and parameter estimation in classical system theory [14], mean 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.

The NN topology selection can be optimized via GAs. GAs [15] can be deployed to optimize, at the same time, different architecture's parameters, such as activation functions, hidden nodes, and input variables, among others. In this work, an optimization process is included in the NN generation. GAs are used to synthesize the network topology (number of hidden layers, hidden nodes, and number of links) letting then Back-Propagation BP tune the learning net [16].

Typically NNs using BP converge faster than GAs due to their exploitation of local knowledge. However, this local search frequently causes the NNs to get stuck in a local minimum. GAs achieve efficient coarse granularity search (finding the promising region where the global minimum is located) but they are very inefficient in the fine-granularity search (finding the minimum). These characteristics motivated [17] to propose an interesting hybrid algorithm in which the GA would find a good parameter region which was then used to initialize the NN. At that point, Back-Propagation would perform the final parameter tuning. For an extensive review of the use of GAs in NNs, the reader is encouraged to consult [18], [19].

# 4 Applications to El Infiernillo Dam

In spite of the tremendous advances in the field of earthquake-dam engineering with the development of numerical methods such as the finite element, a series of problems have to be fully resolved for the confidence on this analytical method to be improved: first, the matter of modeling rockfill materials; secondly, the balance between the degree of complexity of the analytical technique used and the level of knowledge of the material properties; and, thirdly, the adequacy of the numerical technique in capturing the variables that determine the dynamic behavior of dams.

Regarding the modeling of rockfill materials there is still much to be learned due to the colossal difficulties of testing representative samples in the laboratory and the relatively limited applicability of geophysical field tests. Thus, one has to resort to case histories where seismic motions and the ensuing earthquake-induced dynamic movements have been recorded during a number of seismic events with various intensities and frequency contents. Two procedures are included in this paper that show how to overcome (at least partially) this obstacle. One is based on the application of a three dimensional finite element procedure and the other consists on the use of a neurogenetic technique.

The Hydroelectric project El Infiernillo was completed in 1964 on the Balsas River about 70 km from the Pacific Ocean. The maximum section of the embankment is 150 m high with average external slopes of 1.85:1 (Horizontal:Vertical) considering the up- and downstream berms (main section in Fig. 5). Construction details of the dam, materials as well as their treatment are broadly described elsewhere ([20], [21]). The seismic instrumentation consists of digital accelerometers (Fig. 5): three on the embankment (E, F and G), four on rock (A, B, C and D) and a vertical array (H and I).

The seismicity of the zone is one of the highest in Mexico and since its construction the dam has been subjected to earthquake forces of different characteristics and intensities. After the September 1985 seismic events, the activity at the dam site has decreased significantly and although numerous earthquakes have been recorded, none of them has caused appreciable dam displacement or damage. Of all recorded seismic movements, the events S1, S2, S3, S4 and S5 have shaken the dam more severely (Table 1). In general, these earthquakes have caused permanent displacements that have induced shallow cracking, mainly parallel to the dam axis.

Table 1. Main characteristics of the more significant seismic events

| | | Transverse | Longitudinal | Vertical |
|---|---|---|---|---|
| Event | Station | $A_{max}$ (cm$^2$) | $A_{max}$ (cm$^2$) | $A_{max}$ (cm$^2$) |
| S-1 | right bank | 72.8 | 53.7 | 31.1 |
| 11/X/1975 | Berm | 89.7 | 83.7 | 112.1 |
| | Crest | 300.2 | 76.6 | 107.3 |
| S-2 | right bank | 40.8 | 52.1 | 28.7 |
| 15/XI/1975 | Berm | 82.6 | 80.1 | 58.9 |
| | Crest | 191.6 | 62.1 | 44.9 |
| S-3 | right bank | 17 | 18 | 15 |
| 14/III/1979 | Berm | 133 | 124 | 60 |
| | Crest | 371 | 155 | 184 |
| S-4 | right bank | 85 | 83 | 52 |
| 25/X/1981 | Berm | 131 | 108 | 70 |
| | Crest | 338 | 194 | 151 |
| S-5 | right bank | 131.7 | 91.4 | 77.4 |
| 19/IX/1985 | Berm | 294.6 | 379.3 | 294.6 |
| | Crest | | | |

## 4.1 Analytically-based System Identification

In case of complex structures such as a dam, finite element techniques are usually applied to compute the transfer function $H(f)$. This model and the system function obtained from the recorded motions are used to define the loss function (see Fig.2) which is minimized using a least square approach [2]. Both, model and system transfer functions are dependent of the material shear modulus $G$ and material damping ratio $\lambda$ that follow the constitutive model given by Eqs. 1 and 2. The parameters $a$, $b$ and $\gamma_r$ are material dependent (function of plasticity index).

$$G = G_{\max}\left[1 - \frac{(\gamma/\gamma_r)}{a + b(\gamma/\gamma_r)}\right] \qquad (2)$$

$$\lambda = \lambda_{\min} + \left[\frac{(\gamma/\gamma_r)}{\dfrac{1}{\gamma_{\min}} + \dfrac{1}{(\gamma_{\max} - \gamma_{\min})}\left(\dfrac{\gamma}{\gamma_r}\right)}\right] \qquad (3)$$

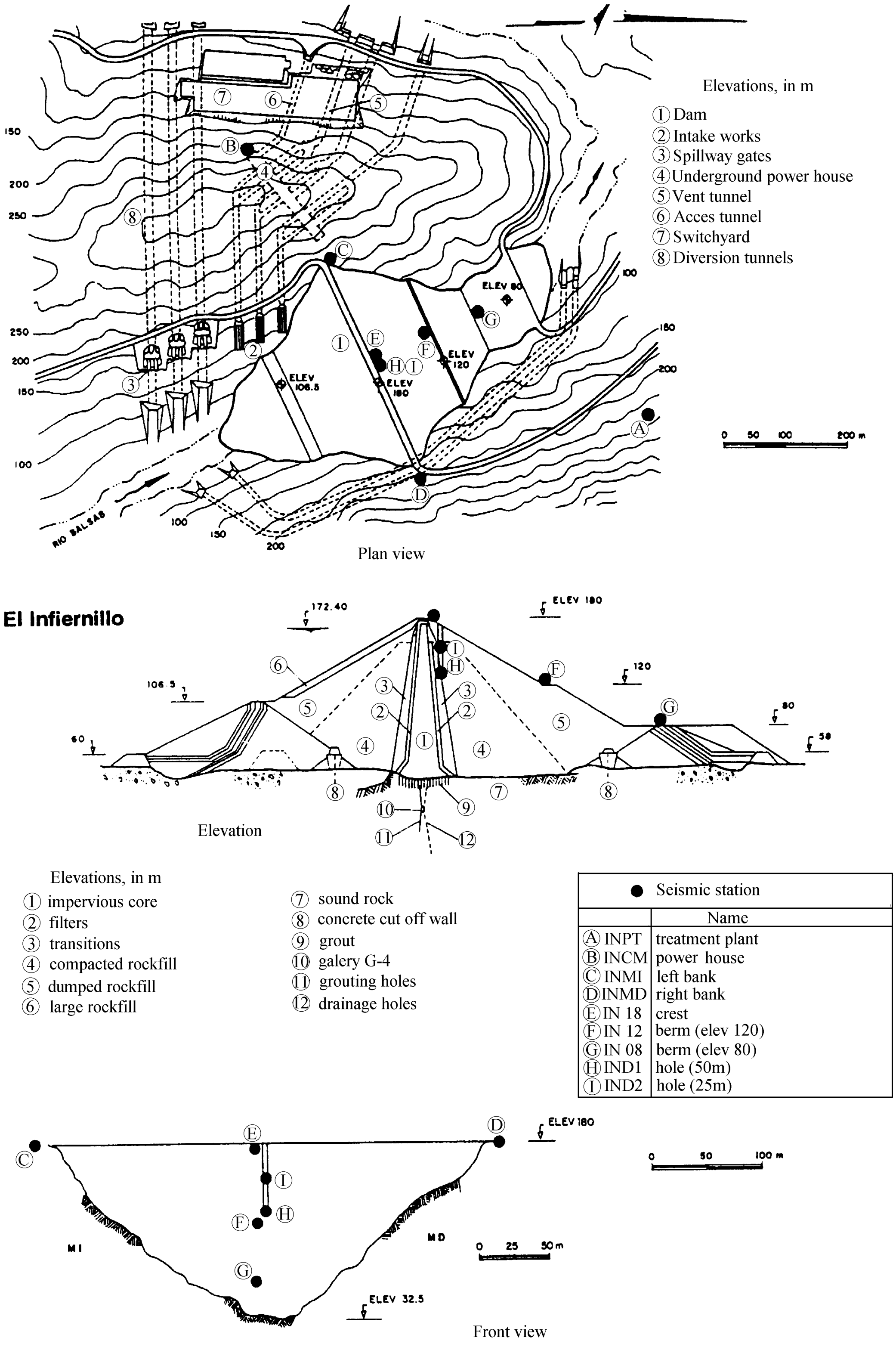
where $G_{\max}$ is the quasi-elastic shear modulus, $\lambda_{\min}$ is the damping ratio for strain values of $10^{-4}$%, $\lambda_{\max}$ is the damping ratio for strain values of 10%. The value of $G_{\max}$ was evaluated based on Seed and Idriss (1970)'s recommendation for granular materials: $G_{\max} = 1000K_2(\sigma_m)^{1/2}$, where $\sigma_m$ is the mean normal effective stress in lb/ft$^2$ and $K_2$ is a soil parameter that depends mainly on the void ratio. The maximum shear modulus for the core material was evaluated using [22]: $G_{\max} = 2200S_u$, where $S_u$ (in lb/ft$^2$) is the undrained shear strength of the clay soils defined from the envelope of the failure lines obtained from undrained, unconsolidated, laboratory tests.

The magnitude of the undrained strength $S_u$ was defined for the mean stress $\sigma_m$ values computed in the dam using finite element analyses (Romo and Villarraga, 1989) for the at-the-end-of-construction and first-reservoir-filling conditions. The method of analysis described above was evaluated comparing the theoretical results with the dam responses measured during earthquakes that occurred after 1985.

On May 31, 1990 a 5.5 Richter magnitude earthquake hit the dam. The response of the embankment was recorded at the crest (point E) and point H within the embankment body (vertical array). The results included in Fig. 6 show that the proposed model is capable of reproducing the recorded motions with a good degree of approximation.

## 4.2 Neurogenetic System Identification

The random nature of seismic excitations, along with the limited number of sensors used to monitor the dam-system responses, make the modeling of the dam dynamic behaviors quite a difficult task. Accordingly, a new SID identification technique was




| ● Seismic station | |
|---|---|
| | Name |
| A INPT | treatment plant |
| B INCM | power house |
| C INMI | left bank |
| D INMD | right bank |
| E IN 18 | crest |
| F IN 12 | berm (elev 120) |
| G IN 08 | berm (elev 80) |
| H IND1 | hole (50m) |
| I IND2 | hole (25m) |

Figure 5. Layout of strong motion instruments at El Infiernillo

developed using the relatively closely spaced accelerometers located in the vertical array (clay core). The GA-NN proposed is capable of using "contaminated" records and the sensors spatial configuration to describe the dimensionality of the system response. The data base used for neural training/testing stages is given in Table 2. 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 (Fig.7). The two mechanical soil properties estimated by this SID process are the shear modulus $G$ and the damping ratio $\lambda$. 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.

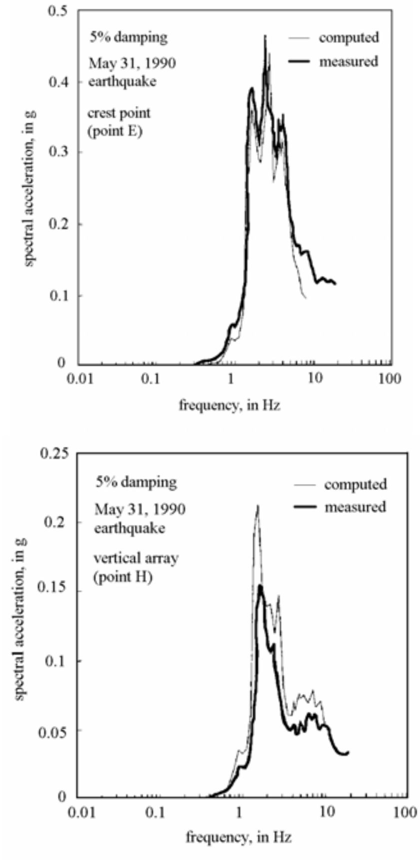



Figure 6. Computed and measured motions at two points on the main section of El Infiernillo dam

Following this SID process, a GA-NN nonparametric framework was obtained to map the input (left abutment recordings) to the output time series (accelerations data inside the dam). In Fig.8, the model and actual values for unseen events (EQ5, EW component) are shown. It is remarkable the capacity of the GA-NN to characterize the time histories of earthquake motions and the accuracy with which reproduces the movements through the dam core, Z direction (Fig.9). Evaluations for *real* and *virtual* accelerometer stations (discrete points) show that this procedure is a worthy alternative for constructing a simple seismic dam-analysis framework (it is not necessary the development of a restrictive mesh for evaluating responses in the whole dam system).

Table 2. Data Base Used for Developing the NN

| | 75/11/25 | 85/09/19 | 92/02/12 |
|---|---|---|---|
| | EQ-1 | EQ-2 | EQ-3 |
| $M_{max}$ | 5.5 | 8.1 | 5.1 |
| $A_{max}$ (abutment) | 104.5/87.7/129.0 | 83.7/99.6/142.6 | 8.1/21.53/22.97 |
| Lat EIPICENTER | 17.58 | 18.08 | 17.73 |
| Long | 102.28 | 102.94 | 101.06 |

* TRANSVERSAL / LONGITUDINAL / VERTICAL (gals)

| | 94/12/10 | 96/07/15 | 97/01/16 |
|---|---|---|---|
| | EQ-4 | EQ-5 | EQ-6 |
| | 6.6 | 6.5 | 5.1 |
| | 269.9/376.6/541 | 18.04/31.5/26.18 | 8.13/19.23/16.2 |
| | 18.02 | 17.45 | 17.94 |
| | 101.56 | 101.16 | 102.76 |

In a second stage the properties $G$ and $\lambda$ are evaluated from the GA-NN-accelerations histories show a poor agreement with those obtained by empirical correlations and laboratory studies. A local (for each material and geometry) identification algorithm is required (Fig.10).

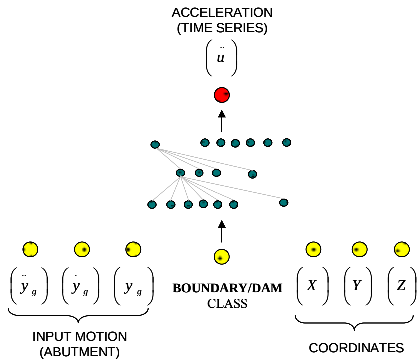



Figure 7. GA-NN topology

To obtain material properties within the dam, it is necessary to map the coordinates of the specific point into soil parameters. To achieve this, a more sophisticated neural model (genetic tuning of the weights and function variables) was developed for describing materials dynamic behavior via $G$ and $\lambda$ versus shear strain curves. The input variables are the coordinates of the recording station and the outputs are the values of the dynamic properties. Once this training process is completed, $G/\lambda$ nodes can be interchanged as premises and the coordinates take the role of conclusions to corroborate the adequate description of the soil mass. The forward-back training route, permits to find the parametric changes for optimal estimation of

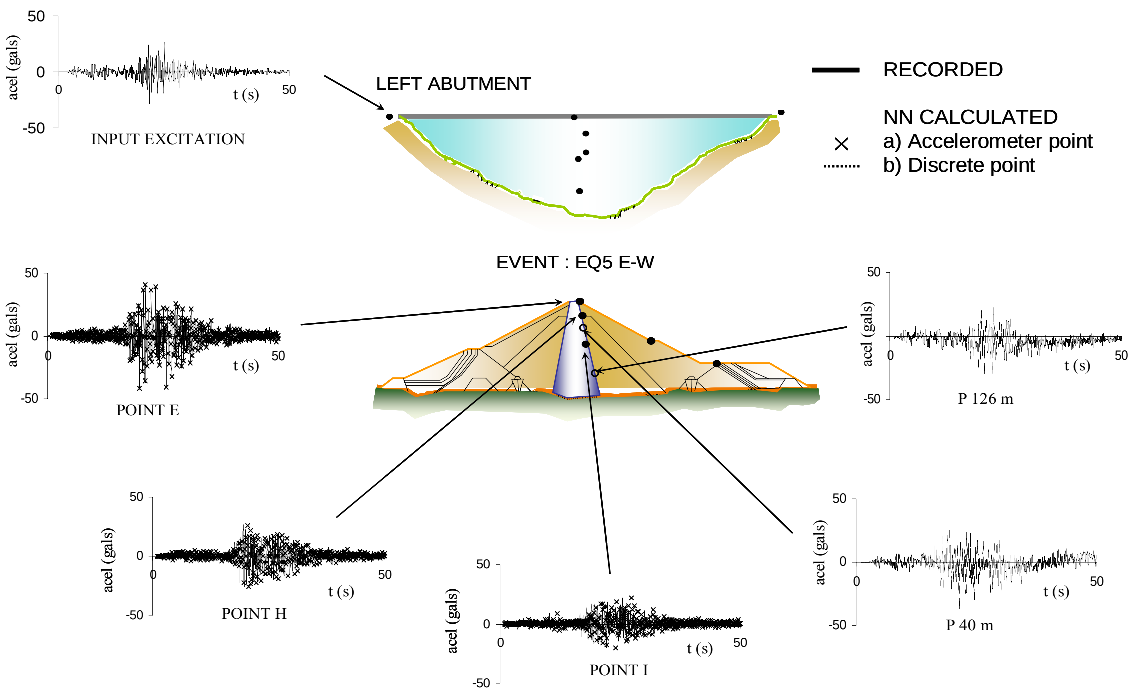



Figure 8. NN model results: testing stage

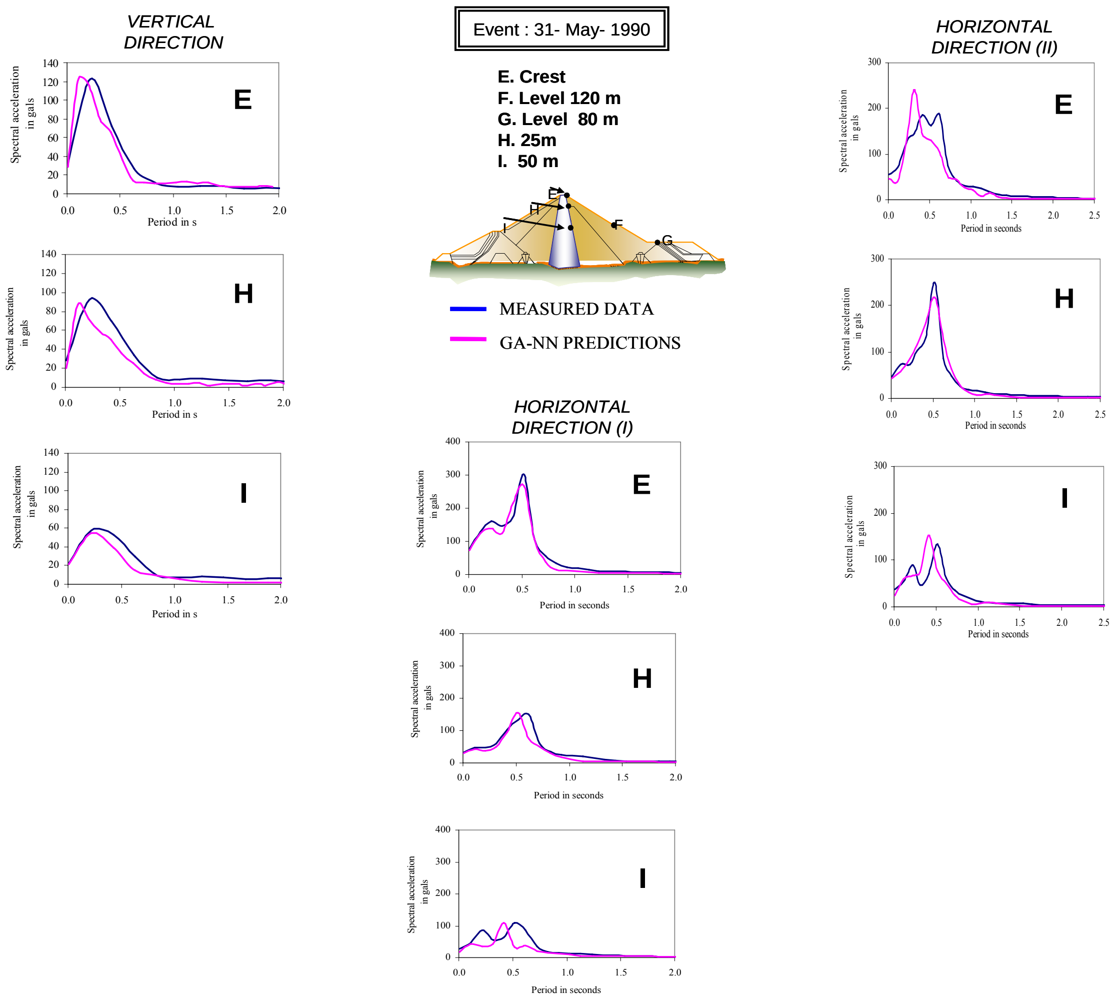



Figure 9 GA-NN results: evaluations through dam core (moving along vertical direction), unseen event

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).

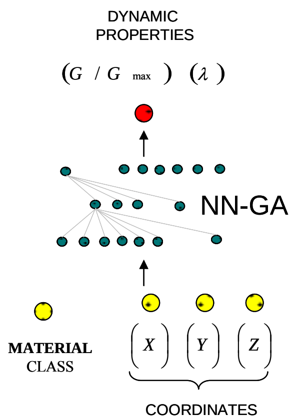



Figure 10. GA-NN model results: testing stage

As can be seen in Fig.11, this neural model offers tremendous insight into the extremely complex soil/rockfill system behavior. Based on the user/designer necessities the neuronal structure can offer a general evaluation for each material, for a transition zone or for a discrete point.

## 4 Conclusion

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 parameter system spatial distribution. Such information reduces the indeterminacy problem and permits an appropriate model selection.

The advantageous characteristic of the neurogenetic model proposed here for evaluating material behavior at discrete points inside the dam structure can help to reveal the most influential aspects related with its seismic responses: material properties ($G$ and $\lambda$), linear or nonlinear material's behavior, canyon configuration, materials zonation (dam-cross-section geometry), grain size, etc.

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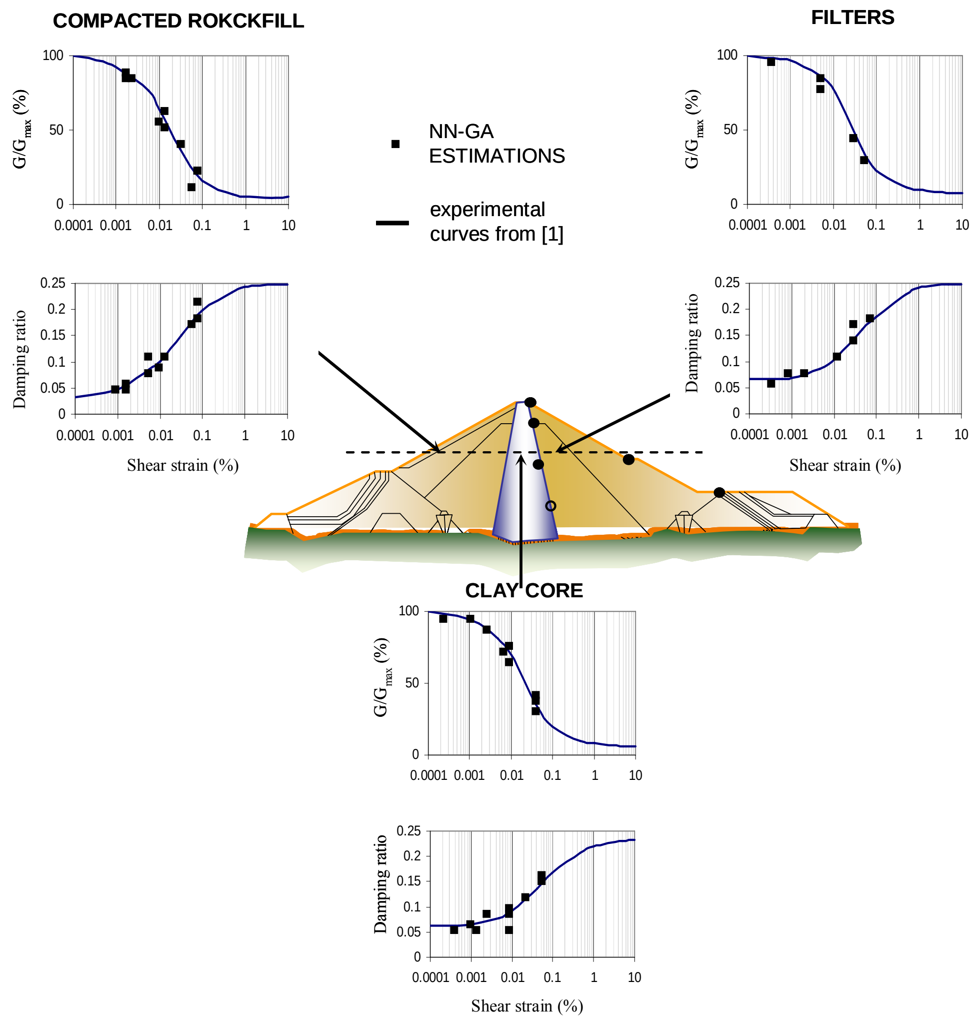


Figure 11. Dynamic properties: GA-NN indirect estimations


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