A preliminary approach of dynamic identification of slender buildings by neuronal networks

A PRELIMINARY APPROACH OF DYNAMIC IDENTIFICATION OF SLENDER BUILDINGS BY NEURONAL NETWORKS

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Abstract

The study of the dynamic behavior of slender masonry structures is usually related to the preservation of the historic heritage. This study, for bell towers and industrial masonry chimneys, is particularly relevant in areas with an important seismic hazard. The analysis of the dynamic behavior of masonry structures is particularly complex due to the multiple effects that can affect to the variation of its main frequencies along the seasons of the year: temperature and humidity. Moreover, these dynamic properties also varies considerably in structures built in areas where land subsidence due to the variation of the phreatic level along the year is particularly evident: the stiffness of the soil-structure interaction also varies. This paper presents a study to evaluate the possibility of detecting the variation of groundwater level based on the readings obtained using accelerometers in different positions on the structure. To do this a general case study was considered: a 3D numerical model of a bellower. The variation of the phreatic level was evaluated between 0 and -20 m, and 81 cases studies were developed modifying the rigidity of the soil-structure interaction associated to a position of the phreatic level. To simulate the dispositions of accelerometers on a real construction, 16 points of the numerical model were selected along the structure to obtain modal displacements in two orthogonal directions. Through an adjustment by using neural networks, a good correlation has been observed between the predicted position of the water table and acceleration readings obtained from the numerical model. It is possible to conclude that with a discrete register of accelerations on the tower it´s possible to predict the water table depth.

Keywords: Dynamic identification, phreatic level, masonry, slender structures, dynamic soil-structure interaction.

1. INTRODUCTION

The study of the dynamic behavior of slender masonry structures has been extensively investigated by several authors ([1], [2], [3]). Some studies are developed to make a dynamic identification and / or characterization of the structural behavior of the structure [3]. In other cases the dynamic behavior have been analyzed to obtain the structural response under different loads [2] such as earthquakes, or dynamic actions produced by the swinging of bells [1], [4] either to study its serviceability limit state (SLS) or its ultimate limit state (ULS) [5].

Examples of these case studies may be the Osmancikli works [6] that analyses the stiffness changes of a bell tower because of some restoration activities or the Saisi [7] works where the stiffness changes of a tower are analysed due to a seismic event. There are very limited studies analyzing the variation of the dynamic behavior of masonry structures depending on the humidity and temperature, but is fully shown that when continuous records are performed during different seasons in the same structure, the variation of the main frequencies can be detected [8].

Regarding the seismic behavior of these structures, a basic parameter are their main frequencies and their possible interactions with the frequency components of the seismic accelerogram for the location of the structure. If these frequencies vary, the same structure may have a different response to the same earthquake depending on the season due to the changes of humidity and temperature on the structure.

In some areas is particularly remarkable the phenomenon of subsidence [9], and therefore the variation of the water table under construction along the different seasons. This phenomenon generates some changes on the stiffness of the soil and therefore the variation of the stiffness of the soil-structure interaction, thereby producing ultimately a variation on the main frequencies of the structure and ultimately varying the response of this structure against the possible seismic loads. Ivorra [10] studied the influence of this rigidity changes in the soil-structure interaction in dynamic response of a belltower with forces generated by the bell ringing.

The aim of this paper is to present a methodology based on neural networks to determine the depth of the water table under a slender masonry structure from the ambient vibration accelerations obtained at different points on the structure. In an indirect way, through the registration of accelerations at known points of structure, their main frequencies influenced by the rigidity of the soil-structure interface and corresponding mode shapes are determined. In this paper, the methodology will be validated using results from numerical models.

The changes on the main frequencies of a structure can be produced by temperature and most important for masonry structures, the humidity level. Some authors have detected changes along the winter-spring-summer-autumn seasons due to temperature and humidity changes. In this theoretical paper, we only study the effect of the table level because we only put accelerometer sensors, in the case of humidity changes and temperature changes its necessary put more specific sensors on the structure and introduce the results of these sensors on the neural network procedure.

There are diverse neural network applications to masonry structures [11]. However, as background of its dynamic applications, can be cited the work of Facchini [12] in which the neural networks are used for the modal identification of structural systems, presenting satisfactory results. In this case, the progressive stiffness change of the structure is based on the generation of a known damage in some parts of a steel structure. In some selected point of this structure, ambient vibrations accelerations are recorded and these movements are some of the parameters used for training and validate the network.

Neural networks have been established as an increasingly tool used in a variety of fields such adjustment functions, pattern recognition or data clustering, among others. The basic feature of these networks is their ability to learn to assess the participation of the input variables at the output from a set of input-output training. Therefore they are be able to supply a vector of output from a not present in the training data entry, which is very useful in adjusting functions with multiple input variables, whose analytical expression is unknown. That is, we only need one set of input-output data known to train the network, which functions as a black box of adjustable parameters automatically.

Figure 1 shows a typical neural network comprising an input layer of two neurons (input vector components), two hidden layers and an output layer of two neurons (output vector components).

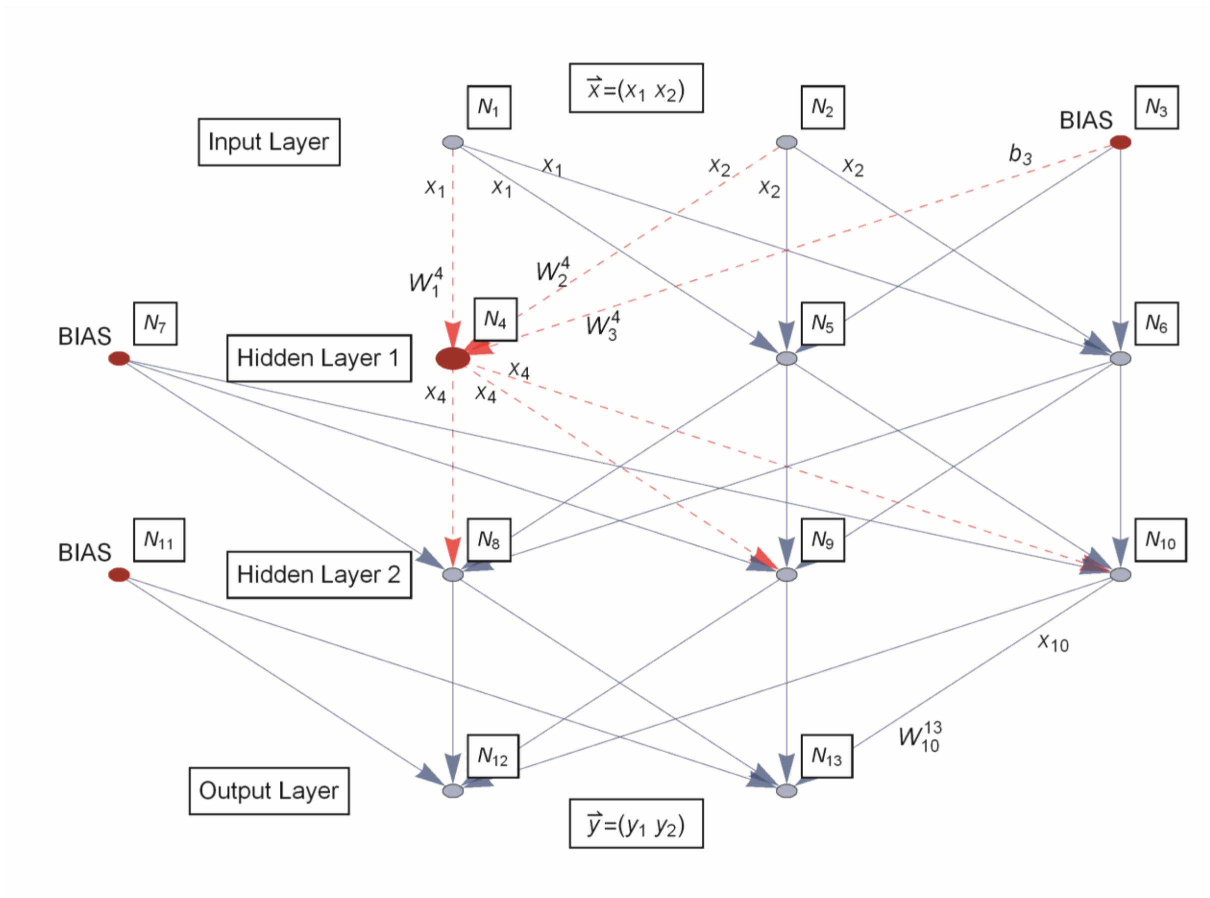

Figure 1. A feedforward neural network with two hidden layers. N_1 N_2: input-neurons; N_3, N_7, N_{11}: Bias-neurons; N_4, N_5, N_6: first hidden layer neurons; N_8, N_9, N_{10}: second hidden layer neurons; N_{12}, N_{13}: output-neurons.

The mathematical process for an individual neuron, for example N_4 in figure 1, is: each input from a neuron of the previous layer (included the bias signal) is multiplied by a weight w_i^j and the sum of this product is computed. This summatory is transformed using a nonlinear function activation σ, and the resulting output is passed to all neurons of the next layer. This process is repeated on all neurons in the network. The output of this neurone N4 is shown in equation (1).

$$x_4 = \sigma(x_1 w_1^4 + x_2 w_2^4 + b_3 w_3^4) = \sigma(x_1 w_1^4 + x_2 w_2^4 + b_3^4) \qquad (1)$$

In compact form, the functionality of an active (no bias) neuron in the hidden layer (and the output if the same activation function is used), can be written as in equation (2).

$$x_j = \sigma\left(\sum_{i=m}^{n-1} x_i w_i^j + b_n^j\right) \qquad (2)$$

where

x_j: Result of neurone j of layer k

$\sigma(x)$: Activation function

m: Number of the first neurone in the previous layer

n: Number of the first neurone in the previous layer (BIAS)

x_i: Result of neurone i of layer k-1

w_i^j: Synaptic weight of i, j connection

b_n^j: Connection weight BIAS

During learning, the synaptic weights are adjusted automatically. While the number of neurons in the input and output layers is given by the dimensions of the corresponding vectors, the number of hidden layers and neurons in each of these layers depends on the characteristics of the particular problem to be solved, there being no established rule for choosing them. Most problems can be solved with one or two hidden layers and number of neurons involved must be determined by tests with different network architectures.

2. CASE STUDY

To perform a generic analysis of a slender masonry structure, a bell tower of 35 m height with a square section of 5x5 m has been considered, with a constant thickness over the entire height of the tower of 0.5 m (Figure 2a). In order to simulate the soil-structure interaction and the influence of variation of the water table in the ground stiffness under the structure, these possible stiffness variations are simulated each 0.25 m, from level 0 to a depth of 20 m. (Figure 2a).

Some numerical models were developed including the structure and the soil rigidity. These models were calculated using SAP2000™ commercial software [13]. 4-node area finite elements were used to mesh the model with three degrees of freedom per node. The same finite area elements were used to model the masonry structure and the soil.

81 numerical models of this tower were calculated. Each model has a different stiffness on the foundation, where each stiffness correspond to an increment of the foundation depth of 0.25 m. (Figures 2b and 2c). An initial non-linear analysis was developed for the self-weight loads considering the non-linear behaviour of a generic masonry [14]. A modal analysis was calculated with the stiffness of the soil-structure model obtained by the non-linear analyses. The Non Linear staged construction procedure was implemented where the initial non-linear

static analysis was calculated before the modal analysis, developing it with the deformed structure after the non-linear static analysis.

Only the 3 main frequencies are calculated, assuming that in an experimental dynamic test in a real structure these values are the usually obtained.

The main assumptions for the numerical model are:

- Constant average material density 18 kN/m^3 for masonry structure and for the soil material model.
- The Poisson's ratio of the masonry was held constant and equal to 0.15 and 0.5 for soil.
- The interaction between soil and structure is considered by modelling the soil by Area 4-node finite elements with one-meter thickness.
- All the nodes of the soil have restricted the horizontal displacements, only the lower soil layer has restrained all the displacements.

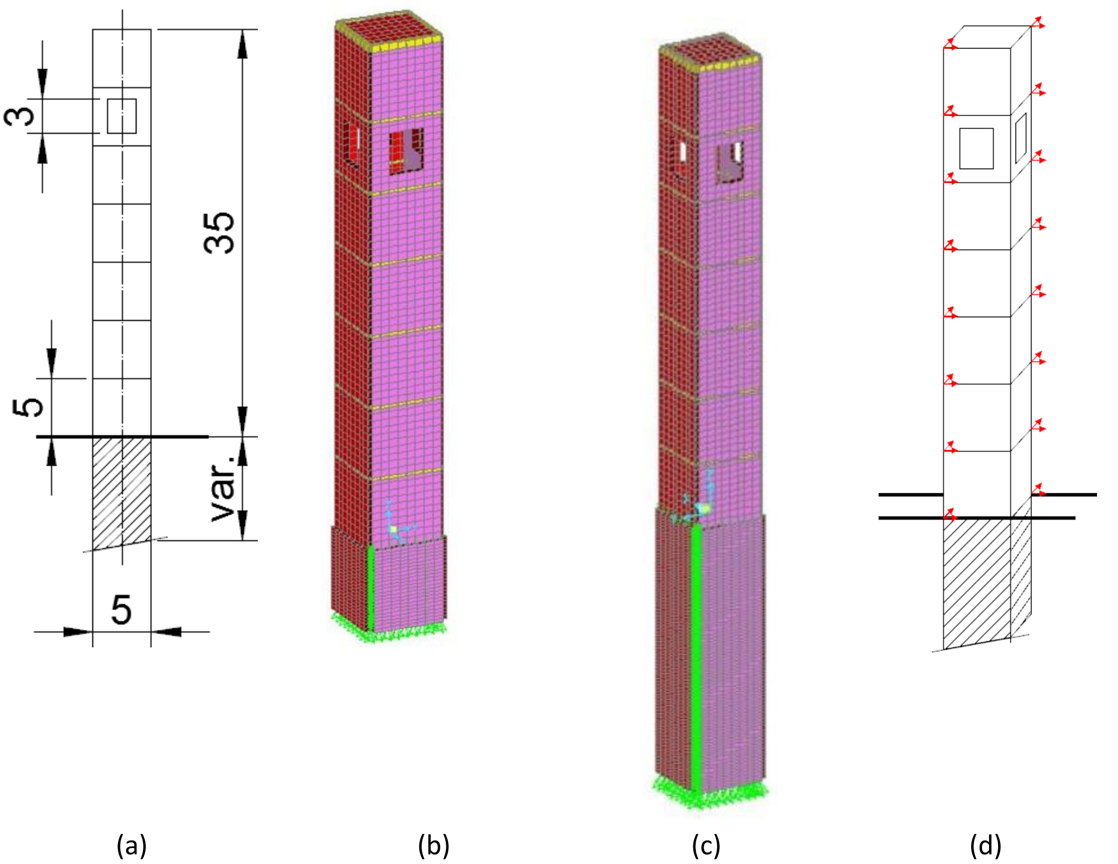

Figure 2. Generic model for a slender masonry structure. (a) General description. (b) Numerical model with the phreatic level at -8.25m. (c) Numerical model with the phreatic level at -20 m. (d) Location of the registered displacements to training the network.

In this structure, the numerical model shows two main bending frequencies an a third frequency of torsion, as the results obtained in similar experimental cases ([3], [4]). Figure 3 shows the changes on the main frequency of this tower when the stiffness of the soil changes: Lower stiffness shows lower main frequency. These stiffness changes can be associated with changes in the position of the phreatic level.

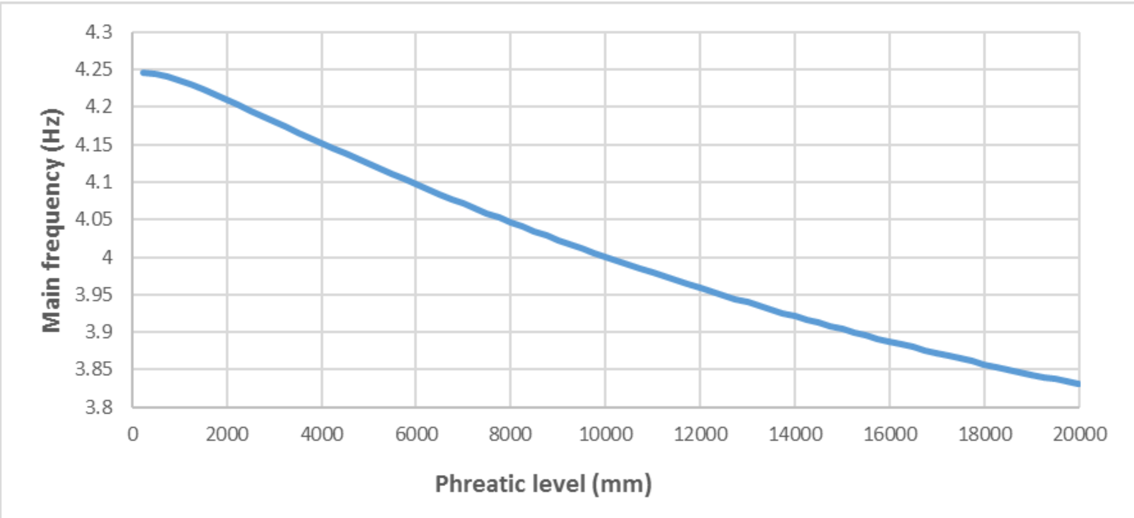

Figure 3. Results of the numerical model. Changes on the soil stiffness, changes on the main frequencies (Lower frequency of the modal analysis) of the structural model.

3. VALIDATION PROCEDURE. THE USE OF NEURAL NETWORKS

The problem to solve is to predict a numerical value output (water table depth) based on an input vector of 87 components (displacement of 14 knots and 3 modal frequencies). In our case, the problem is obtain an approximation function; the Feedforward type network has been used.

The neural network has been implemented with © Wolfram Mathematica general purpose software, and used the Neural Network Package for Mathematica MathLink for the definition and basic training of the network. The graphics output and graphs network architecture have been specially programmed for this job using Wolfram Language, Combinatorics and Graph Utilities Package. In our case, being an approximation problem function. We used a Feedforward network type as described in Section 1-Introduction. This type of network is also used for classification and dynamic systems modelling, one of the most versatile and widely disseminated. For specific use in classification, they exist Hopfield, Perceptron or Vector quantization type. For clustering and self-organizing maps are more suitable type of Unsupervised.

The nonlinear activation function used for the hidden and output layers has been the Sigmoid Simmetric σ(x) in the interval [-1, +1]. This function is shown in equation 3 and represented in Figure 4. This is a nonlinear step function; the slope can be adjusted using the coefficient exponent s.

$$\sigma(x) = \frac{1}{1+e^{-s\,x}} \qquad (3)$$

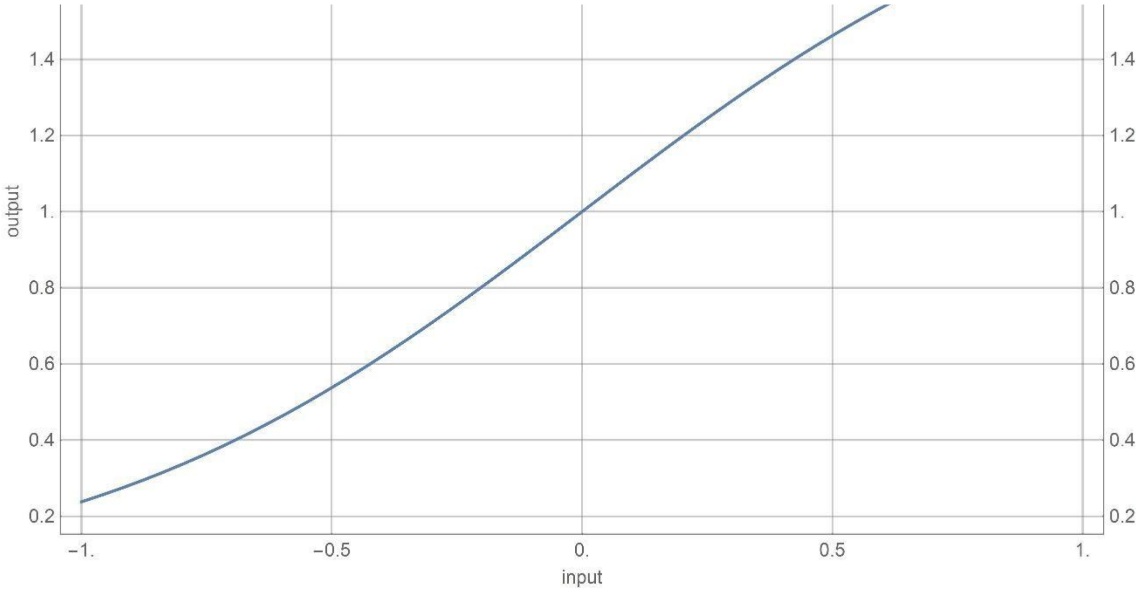

Figure 4. Sigmoid Symmetric activation function.

The network used in this study contains 87 neurons in each of the input and output layers and two hidden layers with 44 neurons each, plus 3 neurons bias to correct the bias of the hidden and output layers. The total number of neurons is 265 and the network topology used, have created 9,767 synaptic connections (Figure 5).

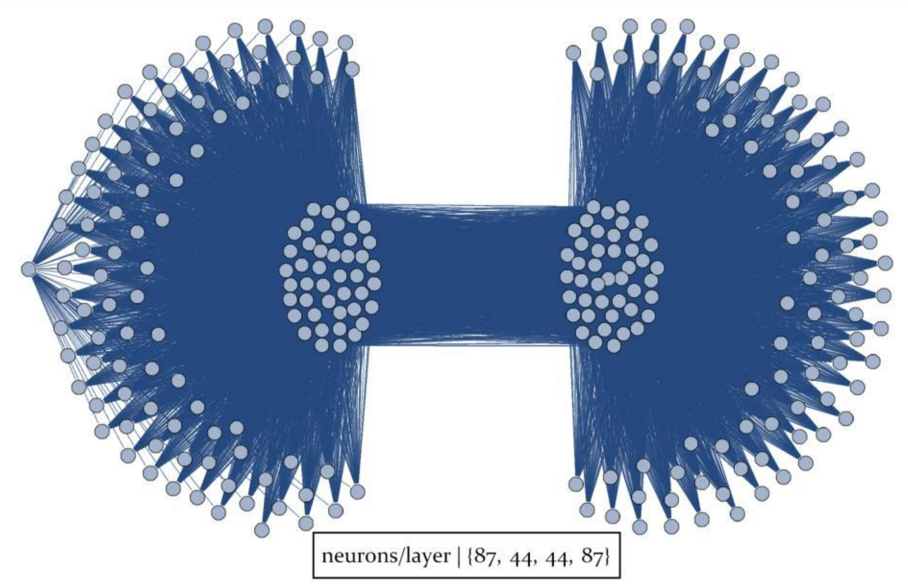

Figure 5. Overview of the neural network used..

The large number of connections and neurons prevents detailed network observation that, despite its complexity, has allowed training times of less than 1.75 s / 1000 epochs in a computer equipped with i7 processor with a set of 70 pairs of input-output vectors. Figure 6 and Figure 7 show partial details of the start and middle of the network.

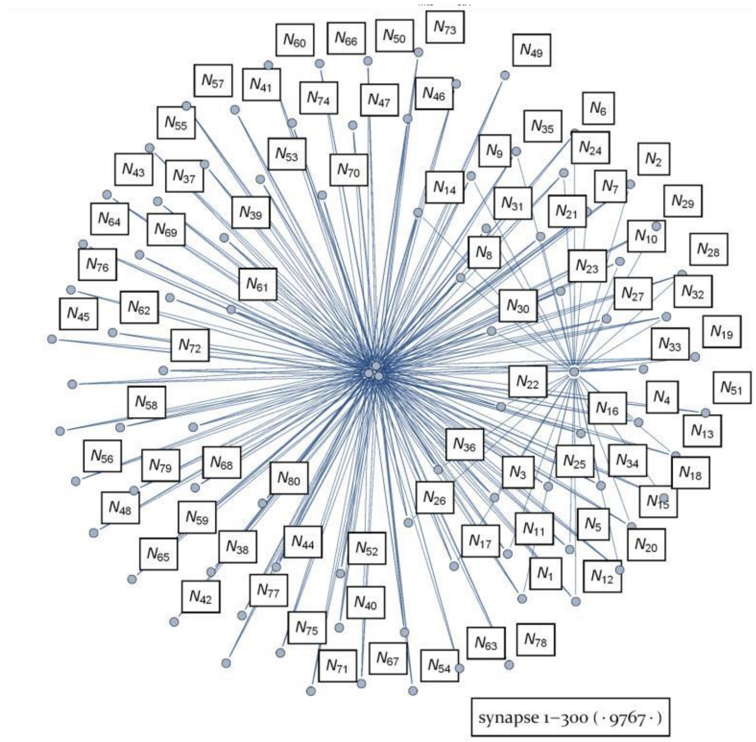

Figure 6. Partial view of the neural network used. Synaptic connections 1-300.

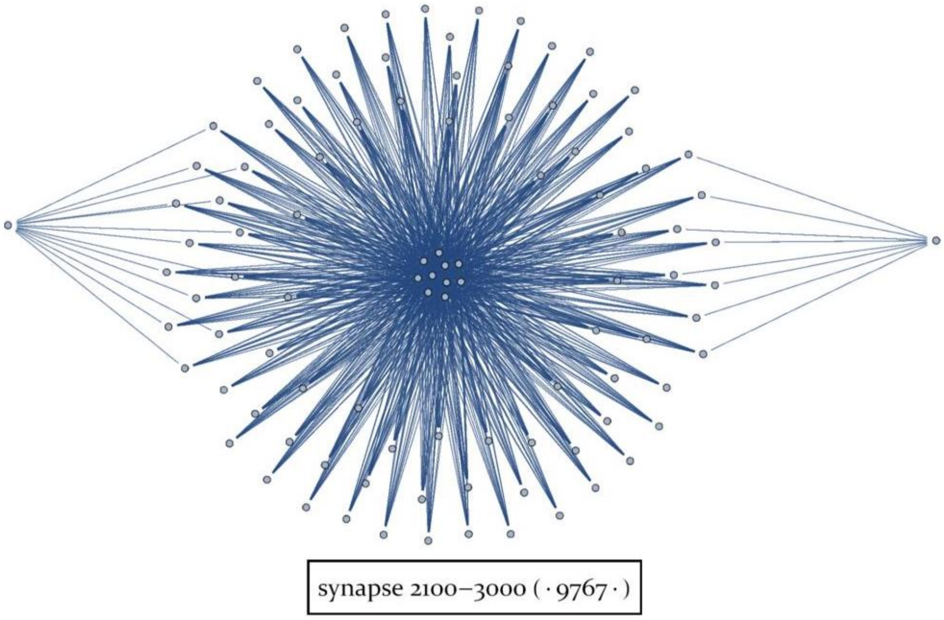

Figure 7. Partial view of the neural network used. Synaptic connections 2.100 a 3.000.

4. ANALYSIS OF RESULTS OBTAINED BY NEURAL NETWORKS.

A data set with 80 input-output vectors obtained by the 80 numerical models developed has built (87 components of input and output) representing many other cases of deep water table. The network was trained with 70 of these randomly chosen vectors and then a test of training was carried out with the remaining 10 vectors. Figure 8 shows the results of network training, Mean Squared Error obtaining a between the data and the desired target set equal to that era MSE = 10-4. The total training time was 298.68 s.

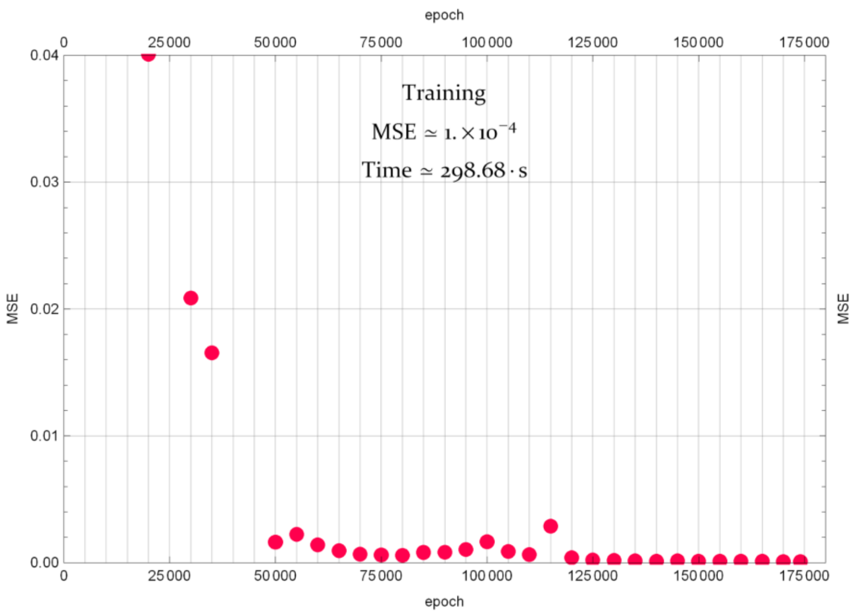

Figure 8. Training results

Linear regression between the target data (used for training) and the output of the network trained with the obtained input parameters corresponding network is obtained to check the validity of the setting, and the result is shown in Figure 9.

The corresponding coefficient of determination was $R^2 = 0.999$, with equation 4.

$$Output = 0{,}0064 + 1{,}001\, Target \tag{4}$$

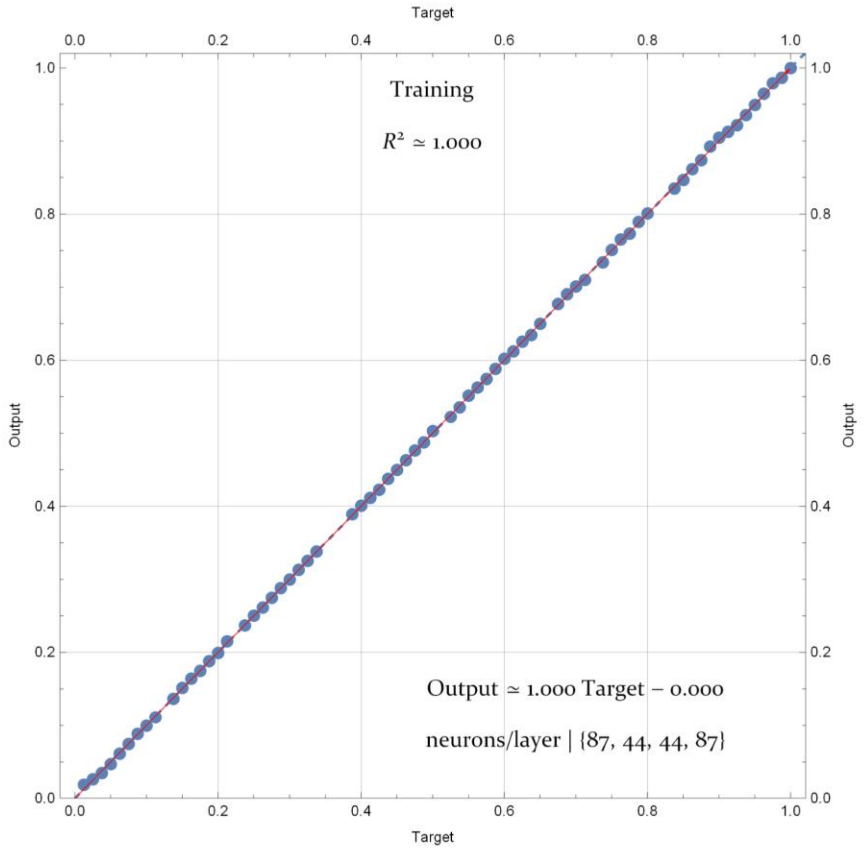

Figure 9. Regression Target/Output for the training vectors

This equation shows as can be seen in Figure 9: The points (Target Output) are too tightly with the line and has a slope of 45 °. It indicates a high quality in the adjusted parameters for the neural network during training.

Finally, there has been developed a further check with the 10 vectors that are non-used in the training. The results are shown in Figure 10. These results validate the neural network.

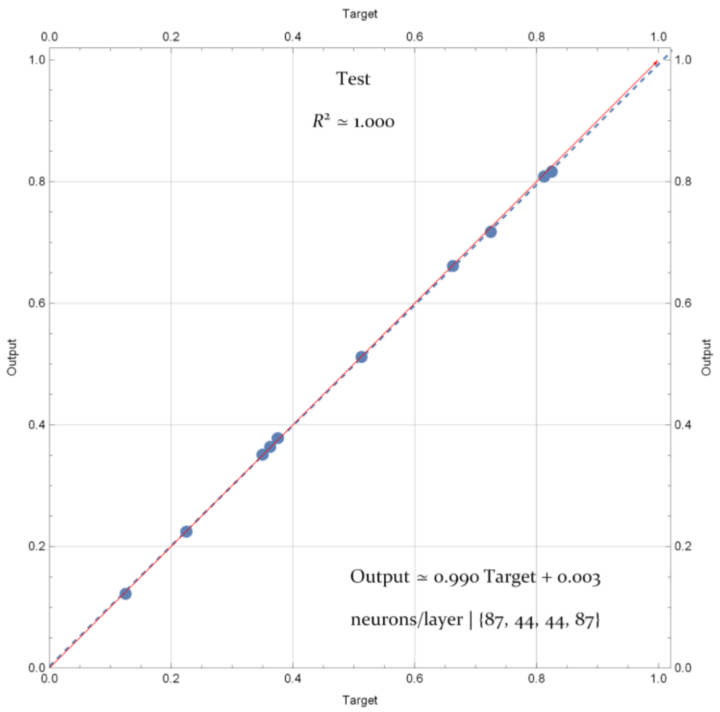

Figure 10. Regression Test/Output for the 10 additional vectors.

In Figures 9 and 10 points whose coordinates are pairs of values (actual and calculated by the network once trained) for different input vectors are represented. Figure 9 relates to the training vectors (70). At each point the abscissa is the desired output value for an input vector (Target), which is the known value used in training, and the ordinate is the output value delivered by the network to the same input vector (Output). Figure 10 refers to the vectors used to test the adjustment (10). At each point the abscissa is the desired output value for an input vector (Target), which is the known value NOT used in training, and the ordinate is the output value delivered by the network to the same input vector (Output). Obviously, in a perfect fit every point would be located on the diagonal, ie Output Target and identical for each input vector both training as Test. As noted above, values are normalized and represented as shown in Figures 9 and 10, all output values (depths) and Output Target vary between 0 and 1.

In the specific case of this tower, the target corresponds to the water table associated with the input data used for validation. In this case, 10 sets (input vector) of data were used. This input vector has 87 components: displacements at different heights for different nodes, directions and associated vibration modes. Each input vector has a known water table depth calculated numerically with SAP2000™ and this value is the target. For each input vector the network produces another value for the water table depth, this is the output. Hence, the comparison between target (known data) and output (data predicted by the network) can indicate the validity of the prediction technique.

5. CONCLUSIONS

A theoretical dynamic study on a masonry bell tower is described in the paper. Main frequencies and modal displacements of selected points are calculated when the stiffness of the soil changes. This change can be associated to variations of the water table depth.

The following conclusions can be drawn from the study:

1. A simplified and low-cost method is described to evaluate the dynamic soil-structure interaction when exist variation of the phreatic level.
2. A non-destructive technique, based on neural networks is presented to obtain the variation and position of the phreatic level.

Through an adjustment by using neural networks, a good correlation has been observed between the predicted position of the water table and displacements readings registers obtained from the numerical model. It’s possible, to conclude that with a discrete register of accelerations on a slender structure it´s possible to predict the water table depth if the neural network is well calibrated with accelerometers and piezometers registers.

This preliminary theoretical analysis will be the base of a more accurate analysis on a slender masonry structure monitored continuously with accelerometers to predict the evolution of the water table depth and its main frequencies.

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