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# 1 A PRELIMINARY APPROACH OF DYNAMIC 2 IDENTIFICATION OF SLENDER BUILDINGS BY 3 NEURONAL NETWORKS

4  
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12

## 13 Abstract

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

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

**36 1. INTRODUCTION**

37 The study of the dynamic behavior of slender masonry structures has been extensively  
38 investigated by several authors ([1], [2], [3]). Some studies are developed to make a dynamic  
39 identification and / or characterization of the structural behavior of the structure [3]. In other  
40 cases the dynamic behavior have been analyzed to obtain the structural response under  
41 different loads [2] such as earthquakes, or dynamic actions produced by the swinging of bells  
42 [1], [4] either to study its serviceability limit state (SLS) or its ultimate limit state (ULS) [5].

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

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

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

63 The aim of this paper is to present a methodology based on neural networks to determine the  
64 depth of the water table under a slender masonry structure from the ambient vibration  
65 accelerations obtained at different points on the structure. In an indirect way, through the  
66 registration of accelerations at known points of structure, their main frequencies influenced by

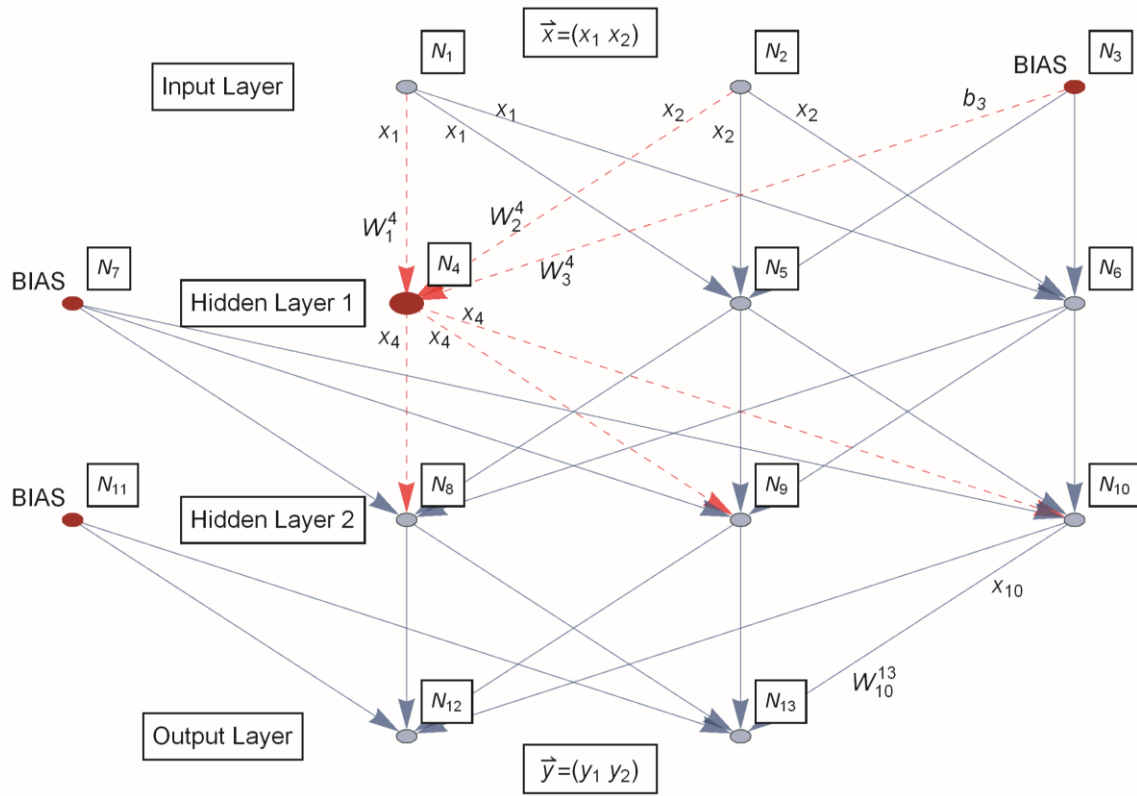
67 the rigidity of the soil-structure interface and corresponding mode shapes are determined. In  
68 this paper, the methodology will be validated using results from numerical models.

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

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

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

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



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

97

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

$$104 \quad x_4 = \sigma(x_1 w_1^4 + x_2 w_2^4 + b_3 w_3^4) = \sigma(x_1 w_1^4 + x_2 w_2^4 + b_3^4) \quad (1)$$

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

$$107 \quad x_j = \sigma \left( \sum_{i=m}^{n-1} x_i w_i^j + b_n^j \right) \quad (2)$$

108 where

- 109  $x_j$ : Result of neurone j of layer k  
 110  $\sigma(x)$ : Activation function  
 111  $m$ : Number of the first neurone in the previous layer  
 112  $n$ : Number of the first neurone in the previous layer (BIAS)  
 113  $x_i$ : Result of neurone i of layer k-1  
 114  $w_i^j$ : Synaptic weight of i, j connection  
 115  $b_n^j$ : Connection weight BIAS

116

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

123123

## 124 2. CASE STUDY

125 To perform a generic analysis of a slender masonry structure, a bell tower of 35 m height with  
 126 a square section of 5x5 m has been considered, with a constant thickness over the entire  
 127 height of the tower of 0.5 m (Figure 2a). In order to simulate the soil-structure interaction and  
 128 the influence of variation of the water table in the ground stiffness under the structure, these  
 129 possible stiffness variations are simulated each 0.25 m, from level 0 to a depth of 20 m. (Figure  
 130 2a).

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

135 81 numerical models of this tower were calculated. Each model has a different stiffness on the  
 136 foundation, where each stiffness correspond to an increment of the foundation depth of 0.25  
 137 m. (Figures 2b and 2c). An initial non-linear analysis was developed for the self-weight loads  
 138 considering the non-linear behaviour of a generic masonry [14]. A modal analysis was  
 139 calculated with the stiffness of the soil-structure model obtained by the non-linear analyses.  
 140 The Non Linear staged construction procedure was implemented where the initial non-linear

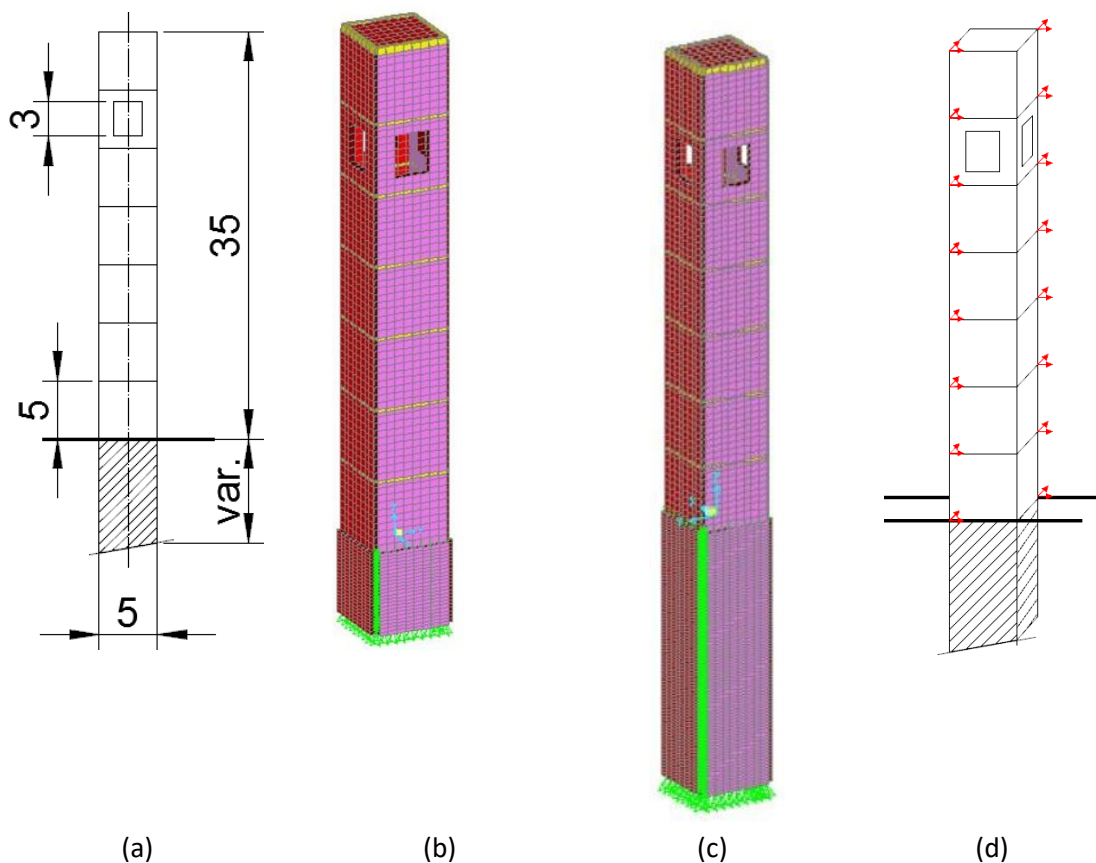
141 static analysis was calculated before the modal analysis, developing it with the deformed  
142 structure after the non-linear static analysis.

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

145 The main assumptions for the numerical model are:

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

153

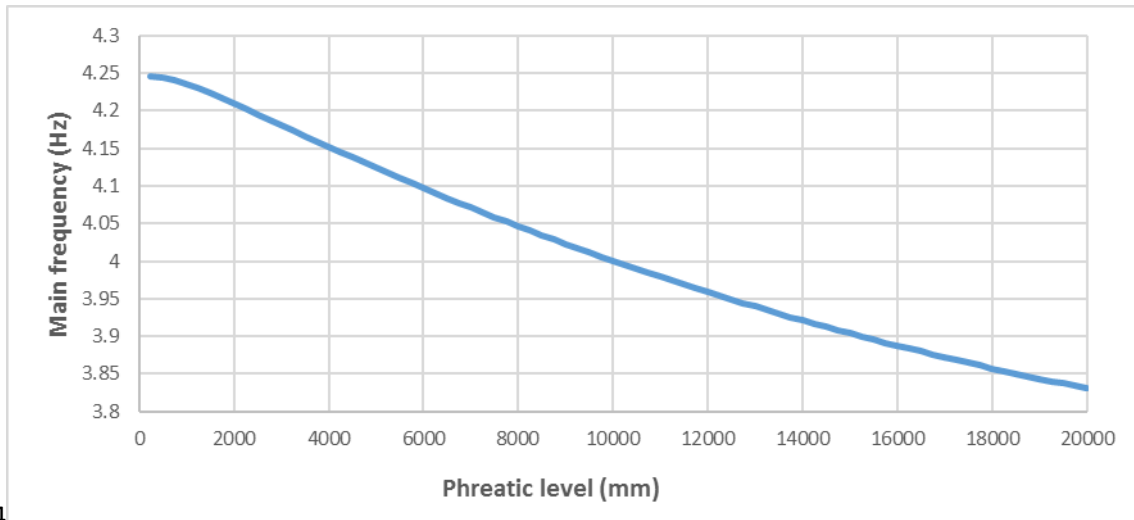


154 **Figure 2.** Generic model for a slender masonry structure. (a) General description. (b) Numerical  
155 model with the phreatic level at -8.25m. (c) Numerical model with the phreatic level at -20 m.  
156 (d) Location of the registered displacements to training the network.

157

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

163



164

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

167

### 168 3. VALIDATION PROCEDURE. THE USE OF NEURAL NETWORKS

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

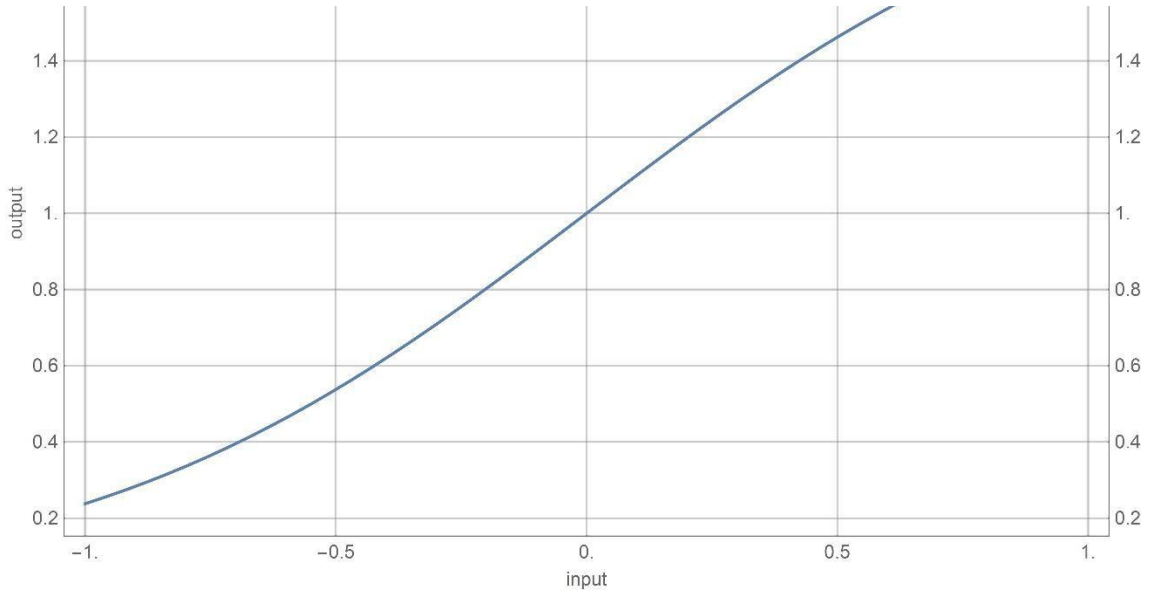
173 The neural network has been implemented with © Wolfram Mathematica general purpose  
174 software, and used the Neural Network Package for Mathematica MathLink for the definition  
175 and basic training of the network. The graphics output and graphs network architecture have  
176 been specially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

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

187

$$\sigma(x) = \frac{1}{1+e^{-sx}} \quad (3)$$

188



189

190

Figure 4. Sigmoid Symmetric activation function.

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

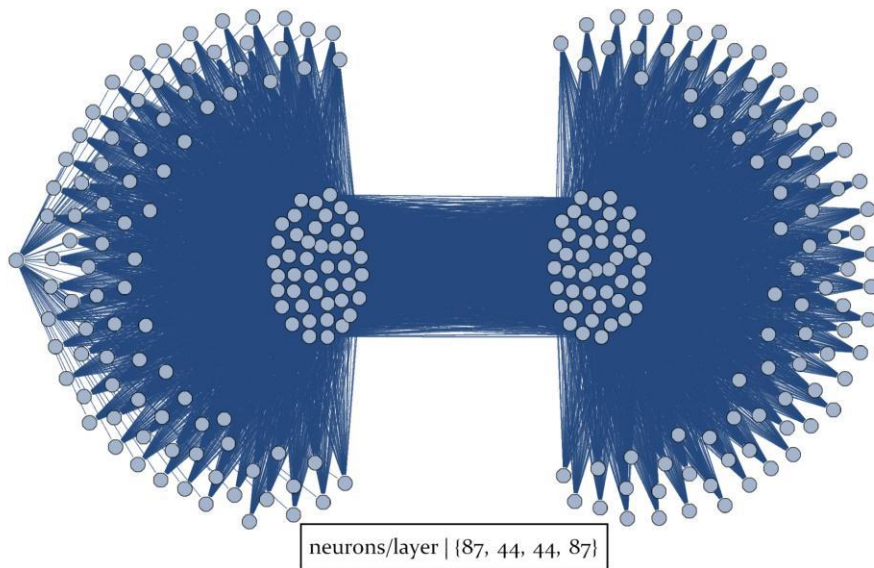


Figure 5. Overview of the neural network used..

195195

196196

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

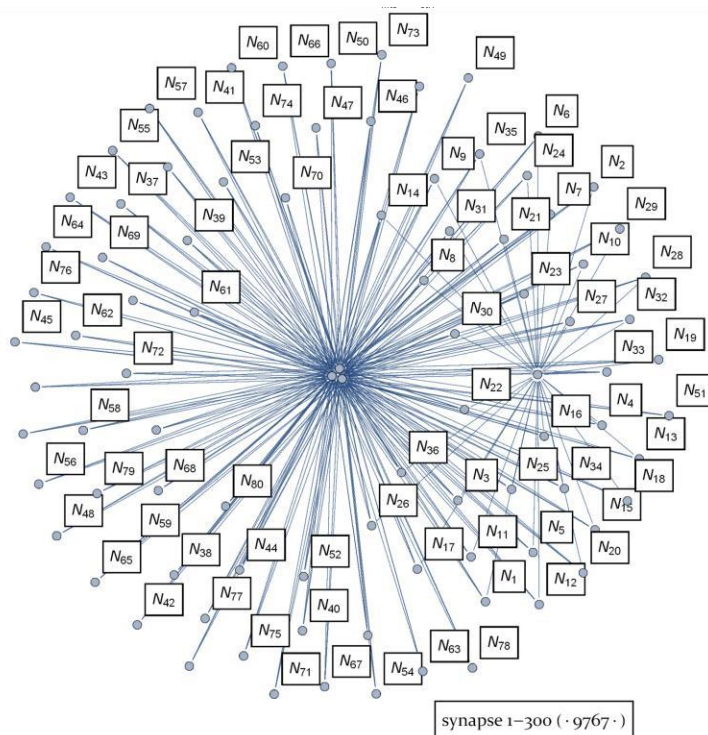
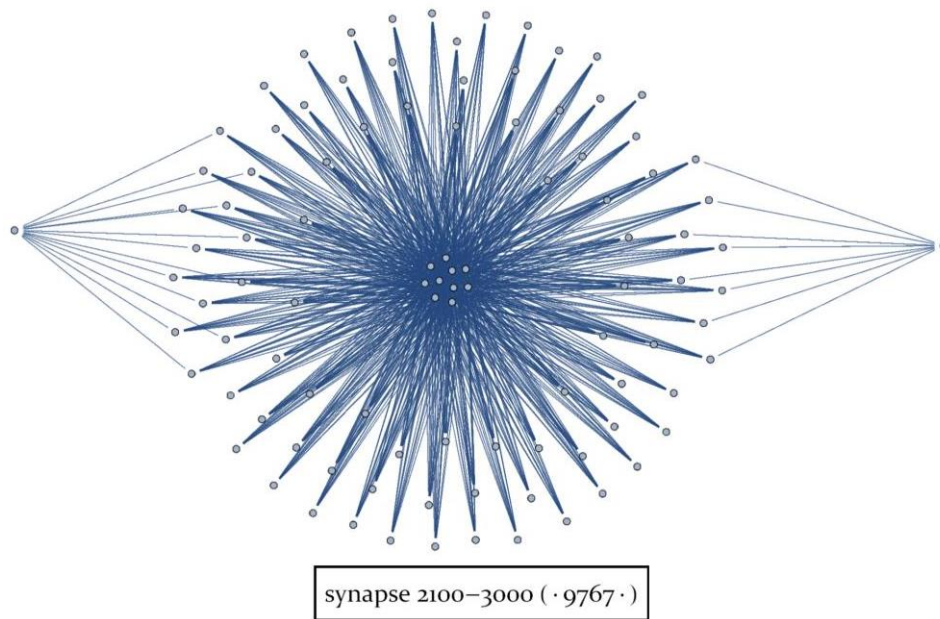


Figure 6. Partial view of the neural network used. Synaptic connections 1-300.

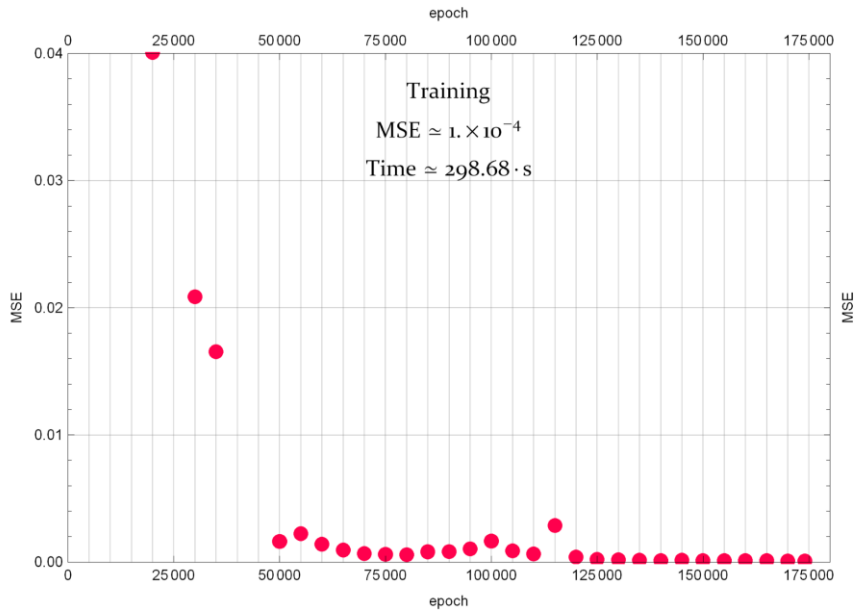
201



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

203 **4. ANALYSIS OF RESULTS OBTAINED BY NEURAL NETWORKS.**

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



210

Figure 8. Training results

211

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

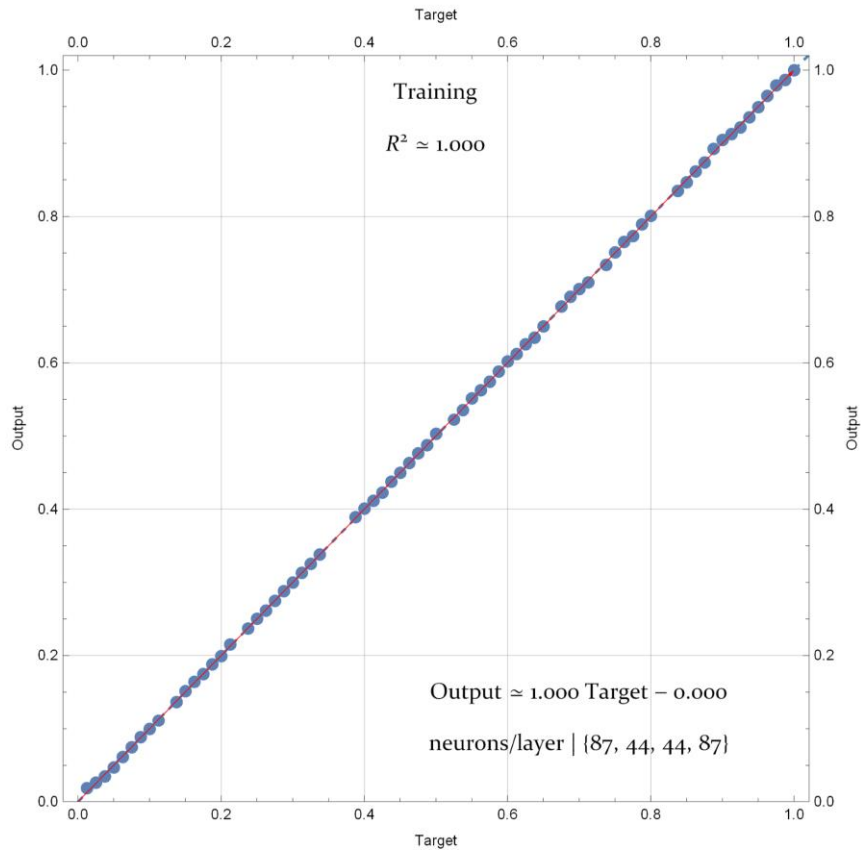
215 The corresponding coefficient of determination was  $R^2 = 0.999$ , with equation 4.

216216

$$Output = 0,0064 + 1,001 Target \quad (4)$$

217217

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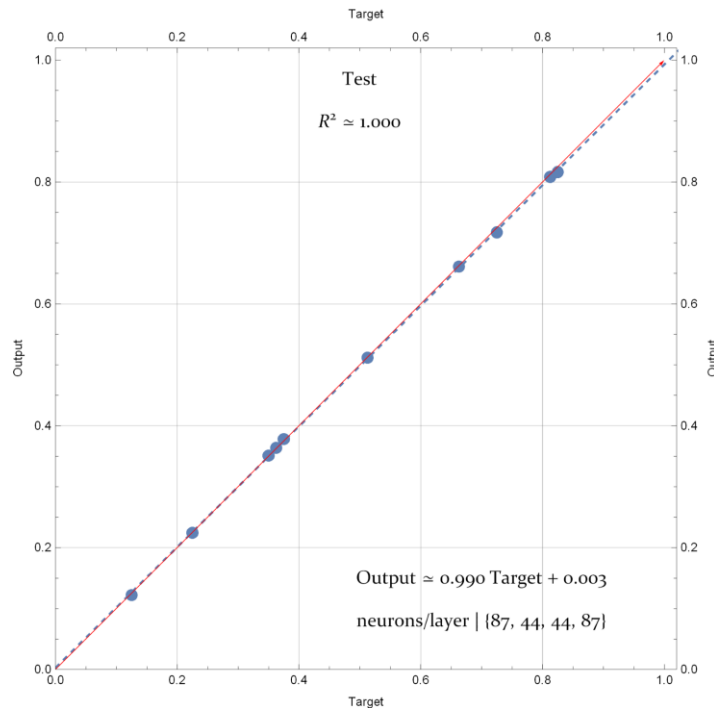


219

Figure 9. Regression Target/Output for the training vectors

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

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



225225

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

226226

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

239 In the specific case of this tower, the target corresponds to the water table associated with the  
 240 input data used for validation. In this case, 10 sets (input vector) of data were used. This input  
 241 vector has 87 components: displacements at different heights for different nodes, directions  
 242 and associated vibration modes. Each input vector has a known water table depth calculated  
 243 numerically with SAP2000™ and this value is the target. For each input vector the network

244 produces another value for the water table depth, this is the output. Hence, the comparison  
245 between target (known data) and output (data predicted by the network) can indicate the  
246 validity of the prediction technique.

247247

## 248 **5. CONCLUSIONS**

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

252 The following conclusions can be drawn from the study:

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

257

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

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

266266

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## 272 **REFERENCES**

- 273 [1] Ivorra S, Pallarés F. Dynamic investigations on a masonry bell tower. Engineering  
274 Structures 2006;28(5):660-667.

- 275 [2] Bartoli, G., Betti, M., Giordano, S. In situ static and dynamic investigations on the "Torre  
276 Grossa" masonry tower (2013) *Engineering Structures*, 52, pp. 718-733.
- 277 [3] Gentile, C., Saisi, A., Cabboi, A. Structural identification of a masonry tower based on  
278 operational modal analysis (2015) *International Journal of Architectural Heritage*, 9 (2),  
279 pp. 98-110.
- 280 [4] Ivorra, S., Pallarés, F.J., Adam, J.M. Masonry bell towers: Dynamic considerations. (2011)  
281 *Proceedings of the Institution of Civil Engineers: Structures and Buildings*, 164 (1), pp. 3-  
282 12.
- 283 [5] Foti, D., Diaferio, M., Giannoccaro, N., & Ivorra, S. (2015). Structural identification and  
284 numerical models for slender historical structures. In P. Asteris & V. Plevris  
285 (Eds.), *Handbook of Research on Seismic Assessment and Rehabilitation of Historic*  
286 *Structures*. Hershey, PA: Engineering Science Reference.
- 287 [6] Osmancikli, G., Uaçk, S., Turan, F.N., Türker, T., Bayraktar, A. Investigation of restoration  
288 effects on the dynamic characteristics of the Hagia Sophia bell-tower by ambient  
289 vibration test (2012) *Construction and Building Materials*, 29, pp. 564-572.
- 290 [7] Saisi, A., Gentile, C., Guidobaldi, M. Post-earthquake continuous dynamic monitoring of  
291 the Gabbia Tower in Mantua, Italy (2015) *Construction and Building Materials*, 81, pp.  
292 101-112.
- 293 [8] Ramos, L.F., Marques, L., Lourenço, P.B., De Roeck, G., Campos-Costa, A., Roque, J.  
294 Monitoring historical masonry structures with operational modal analysis: Two case  
295 studies (2010) *Mechanical Systems and Signal Processing*, 24 (5), pp. 1291-1305.
- 296 [9] Tomás, R., García-Barba, J., Cano, M., Sanabria, M.P., Ivorra, S., Duro, J., Herrera, G.  
297 Subsidence damage assessment of a Gothic church using differential interferometry and  
298 field data (2012) *Structural Health Monitoring*, 11 (6), pp. 751-762.
- 299 [10] Salvador Ivorra, Francisco J. Pallarés, Jose M. Adam, Roberto Tomás An evaluation of the  
300 incidence of soil subsidence on the dynamic behaviour of a Gothic bell tower.  
301 *Engineering Structures*, Volume 32, Issue 8, August 2010, Pages 2318-2325
- 302 [11] Garzón-Roca, J., Adam, J.M., Sandoval, C., Roca, P. Estimation of the axial behaviour of  
303 masonry walls based on Artificial Neural Networks. (2013) *Computers and Structures*,  
304 125, pp. 145-152.
- 305 [12] Luca Facchini, Michele Betti, Paolo Biagini, Neural network based modal identification of  
306 structural systems through output-only measurement, *Computers & Structures*, Volume  
307 138, 1 July 2014, Pages 183-194.
- 308 [13] SAP2000 v.14. Analysis Reference Manual. Computers and Structures, Inc. Berkeley (CA,  
309 USA), 2009.

310 [14]Bilgin, H., Korini, O. Seismic capacity evaluation of unreinforced masonry residential  
311 buildings in Albania Nat. Hazards Earth Syst. Sci., 12, 3753–3764, 2012

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