International Journal of Non-Linear Mechanics 80 (2016) 183–189

Contents lists available at ScienceDirect

International Journal of Non-Linear Mechanics

journal homepage: www.elsevier.com/locate/nlm

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

S. Ivorra [a], V. Brotóns [a], D. Foti [b], M. Diaferio [b]

[a] Department of Civil Engineering, University of Alicante, Spain
[b] Department of Sciences of Civil Engineering & Architecture, Technical University of Bari, Italy

ARTICLE INFO

Article history:
Received 1 April 2015
Received in revised form
20 November 2015
Accepted 21 November 2015
Available online 14 December 2015

Keywords:
Dynamic identification
Phreatic level
Masonry
Slender structures
Dynamic soil–structure interaction

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 the variation of its main frequencies along the seasons of the year: temperature and humidity. Moreover, these dynamic properties also vary 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 is possible to predict the water table depth.

1. Introduction

The study of the dynamic behavior of slender masonry structures has been extensively investigated by several authors [1–3]. 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 has 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 analyse the stiffness changes of a bell tower because of some restoration activities or Saisi [7] works where the stiffness changes of a tower are analyzed 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 the phenomenon of subsidence is particularly remarkable [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 these rigidity changes in the soil–structure interaction in dynamic response of a bell tower 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

E-mail addresses: sivorra@ua.es (S. Ivorra), Vicente.Brotons@ua.es (V. Brotóns), dora.foti@poliba.it (D. Foti), mariella.diaferio@poliba.it (M. Diaferio).

http://dx.doi.org/10.1016/j.ijnonlinmec.2015.11.009
0020-7462/

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 used tool in a variety of fields such as 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 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.

Fig. 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).

The mathematical process for an individual neuron, for example N_4 in Fig. 1, is: each input from a neuron of the previous layer (included the bias signal) that is multiplied by a weight w_i^j and the sum of this product is computed. This summatory is transformed using a non-linear 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 Eq. (1).

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

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 Eq. (2).

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

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.

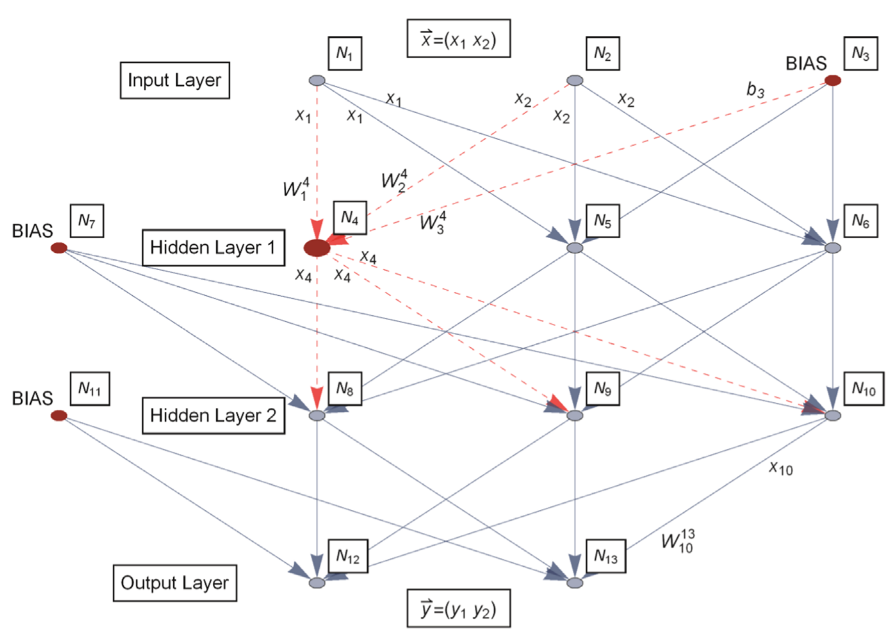

Fig. 1. A feedforward neural network with two hidden layers. N_1 N_2: input-neurons; N_3, N_7, N_{11}: Bias-neurons; N_4, N_5, N_6: first hidden layer neurons; N_8, N_9, N_{10}: second hidden layer neurons; N_{12}, N_{13}: output-neurons.