The Use of Artificial Neural Networks in Predicting Vertical Displacements of Structures

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Abstract

Geodesy can make a significant contribution to the monitoring of structures. The geodetic methods that have been developed can give reliable results. The aim of this article is to use the results obtained through the monitoring of a structure to predict its position in the future, using ANNs. It presents a detailed study on the development of an ANN that can be used to predict vertical displacements in a cultural heritage monument, with the ultimate aim of preventing it from falling apart. To this end, a geodetic network of 15 control points was established. The results of twelve series of geodetic measurements and adjustments to this network are used in this study. Using the trained ANN, the vertical displacement (ΔH) of any specific point in the monument's geodetic network can be predicted for a certain time in the future, with an uncertainty of ±0.5mm.

Keywords: artificial neural networks, geodesy, prediction, vertical control network, vertical displacements, Monument

Introduction

Over the years, the need to monitor modern or heritage structures has intensified. Recording the displacement or change of a structure's body over time and preventing potential future damages are the main reasons why monitoring is necessary. The determination of displacements or deformations in these structures, as well as the earth's crustal movements, are among the main subjects of Geodesy. Various methods are applied to study these aspects. One of the most well-known methods is the establishment of an appropriate geodetic monitoring point network in the structure's body and surrounding area.

This control network is measured and adjusted using the least square method, which ensures reliable quantitative and qualitative results in one, two or three dimensions. It is realised by special permanent marks, and measured by means of modern accurate instrumentation and methodologies. More precisely, vertical control network measurements are obtained using the digital levelling and accurate trigonometric heighting methods. Moreover, high-end total stations are used to measure the horizontal and 3D control angles and distances between the network's points. Moreover GNSS receivers are used, where the spatial conditions allow. However, where the spatial conditions allowed, GNSS receivers were used.

A series of measurements are carried out at specific time intervals to track the development of this phenomenon (e.g. landslides). Thus, our efforts are focused on our capacity to predict the future course of a phenomenon in order to prevent damages or accidents. To this end, certain prediction methods are used depending on the type of movement. The linear method is a common one (Telioni, 2003).

In this procedure, an observation equation is formed for each point, using the results of two consecutive series of measurements. This way, the vector of the linear velocity of the point is calculated. In cases where more than three series of measurements have been executed, the movements may be approximated by an acceleration speed model (Dermanis and Kotsakis, 2006; Dermanis, 2011; Welsch and Heunecke, 2011; Eichhorn, 2007). In the 50 years since their introduction in Neuroscience, the use of ANNs has expanded to numerous other fields, including Economics, Defence, Meteorology etc or forecasting and decision making (Hill et al., 1994).

Moreover, ANNs have recently been introduced to solve various problems of Geodesy. More precisely, ANN models have been used in the regional mapping of the Geoid (Veronez et al., 2011), sea level prediction (Makarynskyy et al., 2004) coordinate transformation (Turgut, 2010) etc.

The aim of this paper is to examine the use of ANNs in the prediction of a structure's vertical displacements. More specifically, this application involves the prediction of vertical displacements in the Byzantine church of ″Megali Panagia″ in Samarina, Grevena (Greece).

The displacement trend was identified through a study of pre-existing measurements originating from a vertical geodetic monitoring network that had been installed both inside and outside of the church. In order to implement and design an ANN that would produce correct results and eventually make predictions of sufficient accuracy, all the key steps for designing ANNs were followed.

Overview of ANNs

The study of human brain functions triggered the development of the science of neural networks. It was Neuroscience that first attempted to explain the way that the human brain works on the basis of simple mathematical models. An ANN consists of ″artificial neurons″ inspired from biological neurons. Artificial neurons are typically organized in layers, so that each ANN includes:

- *An input layer*: for input data. This layer has as many neurons as the ANN's input variants. Input layer neurons are connected to the neurons of the hidden layers or to neurons in the next layer.
- *Hidden layers*: Each hidden layer can have n neurons linked in different ways to the other hidden layers or to the output layer. Hidden layer neurons can get their input through the input layer or some other hidden layer or, in some cases, even the output layer.
- *An output layer*: through which the output vector passes. This layer has as many neurons as the ANN's output variants. Output layer neurons can get their input through the input layer or the hidden layers.

The main feature of ANNs is their inherent capacity to learn, a key component of their intelligence. Learning is achieved through *training*, a repetitive process of gradual adaptation of the network's parameters to the values required to solve a problem. There are three training methods: supervised training, unsupervised training and reinforced training (Minsky 1961; Minsky & Papert 1969; http://www.mathworks.com). The most common training method is supervised training. An ANN is an information processing system consisting of simple processing elements, called artificial neurons. Therefore, it is essential to understand the function of an artificial neuron, which involves the following components:

- The *input signals* x_j or *input information.*
- The *synapses,* which are accompanied by a *synaptic weight*. Each input signal x_j at the synapsis entry, which is connected to the neuron k, is multiplied with its respective weight w_{kj}.
- The *summing junction* or *adder* Σ of the input signals, after they have been adapted with the use of their synaptic weights.
- The activation or transfer function φ(.) To limit the neuron's output range in a closed unit interval [0,1] or [-1,1]. Any function can be used as activation function, and each ANN can have neurons with different function. There are various types of activation functions, including linear function, piecewise-linear function, step function, stochastic function, sigmoidal function etc.
- The output signal y_k, which is essentially the result produced by the artificial neuron k. It is also referred to as the artificial neuron's actual response (Veronez et al 2011).

Finally, the artificial neuron includes a term that is applied externally, i.e. the *bias* b_k. This external term helps prevent errors in cases of zero input data. The above simplified structure of an artificial neuron can be mathematically expressed by equations (1) and (2).

$$u_k = \sum_{j=1}^{n} w_{kj} \cdot x_j + b_k \qquad (1) \qquad\qquad y_k = \varphi(u_k) \qquad (2)$$

Where $x_1, x_2, x_3, \ldots, x_n$: the input signals

$w_{k1}, w_{k2}, w_{k3}, \ldots, w_{kn}$: the synaptic weights of the input signals

u_k : the output of the summing junction $\sum$

$\varphi(.)$: the activation function.

Multilayer Perceptrons (MLPs) are a very common type of ANN. They belong to feed-forward ANNs and can be trained using the supervised training method. Their training is based on the error back propagation algorithm, which was first formulated by Paul Werbos (Werbos, 1974). A number of variants of the back-propagation algorithm have been developed and widely used to train MLPs. These variants include back-propagation with momentum, Levenberg-Marquardt, Newton and Resilient back-propagation. The data used are divided into three categories: *training data*, *validation data* and *test data*. As its name indicates, the first type of data is used at the training stage to adapt the neurons' synaptic weights and bias.

The second type is used to monitor the training process and prevent overfitting, while the third type is not involved in the training, but only used to evaluate and compare different models. Upon designing and developing an ANN, a series of trials are performed, modifying various elements until the most appropriate ANN is developed to solve a specific problem. These modifications initially involve the network's architecture, as well as the training method and algorithm. They may also involve the number of the network's hidden layers or the number of hidden neurons in every hidden layer. Another modification involves the activation function used by each artificial neuron, as well as the participation of each of the three sets used.

Generally, the right selection of variants has a direct impact on the ANN's reliability (Argirakis, 2001; Gullu, 2010). The various trials that are performed need to be followed by an evaluation process in order to select the best network. This evaluation process is based on the results of the test set. To this end, one or more criteria are selected from a range of criteria, and finally the best ANN is the one whose values for the selected criteria are the lowest in the test set. The main evaluation criteria which are used include the mean square error (MSE), root mean square error (RMSE), mean relative error (MRE), and mean absolute error (MAE).

ANN Structure

The Byzantine church of ″Megali Panagia″ in the Samarina village of the Grevena prefecture in North-western Greece has been characterized by UNESCO as one of world's cultural heritage monuments. The vertical displacements that have occurred in the wider area are considered significant, as large cracks have appeared on the church's body. This monument is made of local stone and has very shallow foundations, sitting on unfavourable ground, composed mainly of clay, silt and peat, while solid rock can only be found in depths of more than 15m below the surface of earth (Delikaraoglou et al., 2010). The aim of this study is to examine the design and development of an ANN that can predict vertical displacements using the results obtained from the vertical monitoring geodetic network. (Alevizakou, 2012). This way, the course of this phenomenon could be placed under control, and appropriate measures could be taken to prevent the monument from falling apart.

Data

A geodetic vertical control network was installed inside and outside the church to monitor the vertical displacement of the monument (Figure 1). The network consisted of 15 control points. Six of them were established around the church, while nine more station points were installed inside the church. Within this network, measurements were carried out at regular time intervals. The digital spirit levelling method was used to measure the height differences between the points. The geodetic network was adjusted using the least square method in order to determine the height of each point with an uncertainty of ±0.2mm to ±1mm.

Afterwards the vertical displacements (ΔH_i) of these 15 points were calculated for June-July (1st period), July-August (2nd period), August-September (3rd period) of the years 2009, 2010, 2011, 2012 (Table 1).

Thus, 180 data items were used to develop this ANN, as 12 vertical displacement values were available for each of the points (three periods per year). These data items were divided in three sets: training set - 108 (60%), validation set - 36 (20%), and test set - 36 (20%).

Neural Network Architecture

The ANN was developed using MATLAB® 7.10.0 and, more precisely, its ″neural networks toolbox″ (version 6.0.4) (http://www.mathworks.com; Demuth and Beale, 2002). First, the network's input and output variants were determined. It was decided that the network would consist of six inputs:

- The coordinates X,Y,H of each point
- The period during which the displacement was observed
- The year in which displacement took place
- The location of the point, i.e. inside or outside the church

One output was defined namely the resulting vertical displacement (ΔH) of each point, in mm.As MLPs with supervised training - using the back-propagation algorithm - have been successfully employed in solving several problems (Siripitayananon et al., 2001), it was decided to use them in the present application too. Based on other geodetic applications, it was also decided that the ANN would involve a fully connected multilayer feed-forward network (MLP) and that it would be trained epoch by epoch (″batch training″).To identify the right network topology, 264 trials were performed until the best ANN was identified. These trials differed in terms of:

- The number of hidden layers
- The number of hidden neurons
- The training algorithm
- The activation function of hidden and
- Output neurons.

The mean squared error (MSE), root mean square error (RMSE) and correlation coefficient (R) of the test set were used as criteria to evaluate and select the best ANN. Finally, after these trials, it was discovered that the best results in terms of predicting vertical displacements are given by a network with two hidden layers and a 6×4×10×1 architecture (Figure 2). This means that the network consists of 6 inputs, two hidden layers with 4 and 10 hidden neurons respectively, and one output.

Training Results

On the basis of this 6×4×10×1 architecture further trials were performed, using various training algorithms in order to identify the best network. In each case, the RMSE of the test set was, as mentioned, taken into account. These results are presented in Figure 3. The following algorithms were tested: Levenberg-Marquardt backpropagation (***trainlm***), Resilient backpropagation (***trainrp***), Scaled conjugate gradient backpropagation (***trainscg***), BFGS quasi-Newton (***trainbfg***), Gradient descent with adaptive learning rate backpropagation (***traingda***) and Gradient descent with momentum & adaptive learning rate backpropagation (***traingdx***).

The following graph reveals that the best results – i.e. the lowest RMSE value – are achieved when ***trainlm*** – a variant of the back-propagation algorithm – is the training algorithm and sigmoid function the activation function for the hidden neurons. During the test set evaluation process, the network displayed its optimal results. More precisely, this network predicts vertical displacements with MSE= ±0.2mm and RMSE= ±0.5mm for the test set. The actual responses (actual outputs) given by the ANN for the 36 items of the test set are presented in the table 2, together with their respective desired outputs.

Moreover, a linear regression (fig. 4) was performed between the ANN's actual and target outputs to determine their degree of identification. Finally, besides the linear regression equation, the correlation coefficient (R) between the actual and desired (target) outputs was found to be 0.993, which indicates that there is a very high correlation.

Concluding Remarks

ANNs can be used to successfully predict vertical displacements, on the basis of measurements obtained from geodetic displacement control networks.

Supervised training proved to be the most effective type of training for these networks while the Levenberg-Marquardt back propagation algorithm gave the lowest RMS for the same data. However, as in most ANN applications, the use of a larger amount of data in the training set is desirable in order to minimize the RMSE and achieve optimal adaptation of the actual outputs to the target/desired outputs, taking special care to prevent the phenomenon of overfitting. Moreover, any changes to the input data may play a major role in the final result.

So far, the best ANN (6×4×10×1) has consisted of six inputs, two hidden layers of four and ten neurons respectively, and one output, i.e. the vertical displacement of each point for a specific time interval and future year. The architecture of this ANN predicts vertical displacements with an uncertainty of ± 0.5mm and gives a correlation coefficient of R=0.9928 for the test set. Additionally, the adaptation of target outputs to the actual ones is a straight line with b=1.0003~1. Further investigation and trials would be useful in order to take uncertainty into account as an input for the determination of displacements, and potentially also extent the use of ANNs to the study not only of vertical but also of 3D displacement prediction.

Thus, the use of accurate high-end geodetic instrumentation can nowadays make it possible for geodesy to contribute to the detailed monitoring of a structure's displacements. On the basis of these reliable geodetic results, it can be argued that the capabilities of ANNs can be successfully deployed to predict the dynamic behaviour of modern and monumental structures.

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Table 1: The vertical displacements (ΔH_i) of the 15 control points of the network - Data

CODE	COORDINATES			2009			2010			2011			2012		
				JUNE-JULY	JULY-AUG	AUG-SEPT	JUNE-JULY	JULY-AUG	AUG-SEPT	JUNE-JULY	JULY-AUG	AUG-SEPT	JUNE-JULY	JULY-AUG	AUG-SEPT
	X (m)	Y (m)	H (m)	ΔH_i (mm)	ΔH_i (mm)	ΔH_i (mm)	ΔH_i (mm)	ΔH_i (mm)	ΔH_i (mm)	ΔH_i (mm)	ΔH_i (mm)	ΔH_i (mm)	ΔH_i (mm)	ΔH_i (mm)	ΔH_i (mm)
1	100.000	100.000	10.000	1.8	-2.9	10.4	2.0	-3.1	10.6	1.4	-2.5	10.0	1.9	-3.0	10.5
2	131.357	127.094	9.339	0.0	0.0	0.0	0.2	-0.2	0.2	-0.4	-0.4	-0.4	0.1	0.1	0.1
3	122.704	145.690	10.180	-1.6	-7.0	6.7	-1.8	-7.2	6.9	-1.2	-6.6	6.3	-1.7	-7.1	6.8
4	103.775	142.079	11.511	1.5	-1.5	-4.9	1.7	-1.7	-5.1	1.1	-1.1	-4.5	1.6	-1.6	-5.0
5	65.910	136.834	15.538	-1.8	0.1	-3.7	-2.0	0.3	-3.9	-1.4	-0.3	-3.3	-1.9	0.2	-3.8
6	76.974	94.788	11.922	-2.2	-3.2	-4.9	-2.4	-3.4	-5.1	-1.8	-2.8	-4.5	-2.3	-3.3	-5.0
7	98.281	114.420	10.201	-0.3	5.0	-9.3	-0.5	5.2	-9.5	0.1	4.6	-8.9	-0.4	5.1	-9.4
8	80.091	121.045	11.812	-1.9	1.6	-2.6	-2.1	1.8	-2.8	-1.5	1.2	-2.2	-2.0	1.7	-2.7
9	96.648	123.524	9.972	-3.1	2.2	-2.7	-3.3	2.4	-2.9	-2.7	1.8	-2.3	-3.2	2.3	-2.8
10	107.197	119.925	9.915	-3.4	2.4	-3.2	-3.6	2.6	-3.4	-3.0	2.0	-2.8	-3.5	2.5	-3.3
11	113.077	120.872	10.071	-2.3	1.0	-4.0	-2.5	1.2	-4.2	-1.9	0.6	-3.6	-2.4	1.1	-4.1
12	111.948	130.470	10.041	-5.2	0.1	-1.6	-5.4	0.3	-1.8	-4.8	-0.3	-1.2	-5.3	0.2	-1.7
13	106.270	129.193	9.915	-2.5	1.6	-3.4	-2.7	1.8	-3.6	-2.1	1.2	-3.0	-2.6	1.7	-3.5
14	85.150	123.043	11.164	0.9	-0.1	-4.5	1.1	-0.3	-4.7	0.5	0.3	-4.1	1.0	-0.2	-4.6
15	115.521	126.089	10.020	-1.9	0.9	-4.0	-2.1	1.1	-4.2	-1.5	0.5	-3.6	-2.0	1.0	-4.1

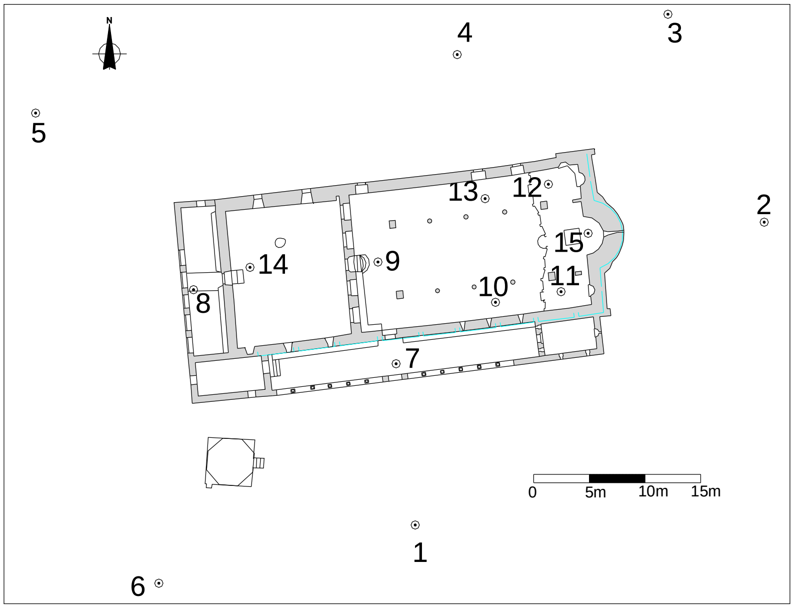

Figure 1: The geodetic network

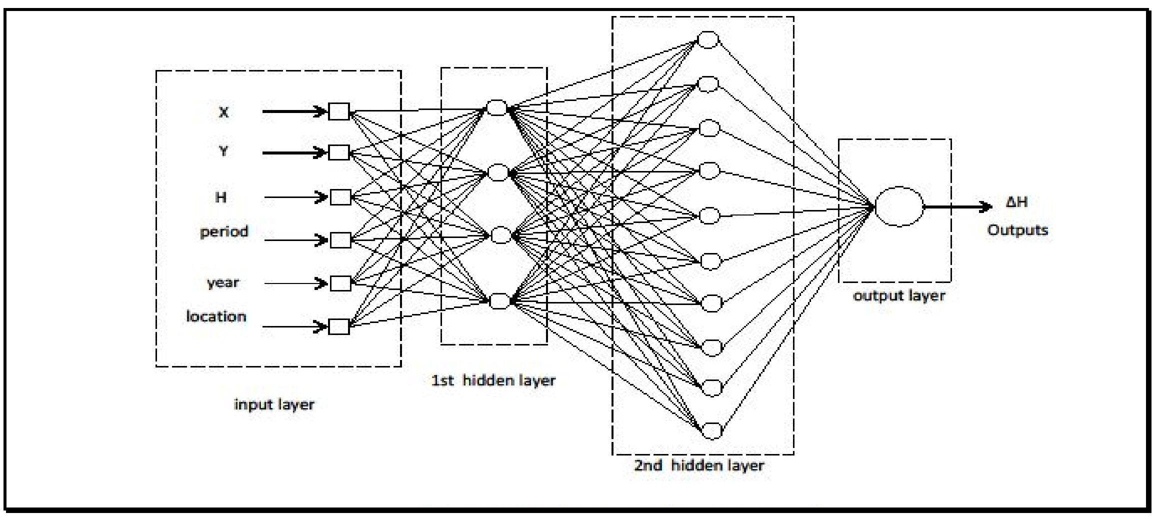

Figure 2: A schematic representation of the best ANN for predicting vertical displacements.

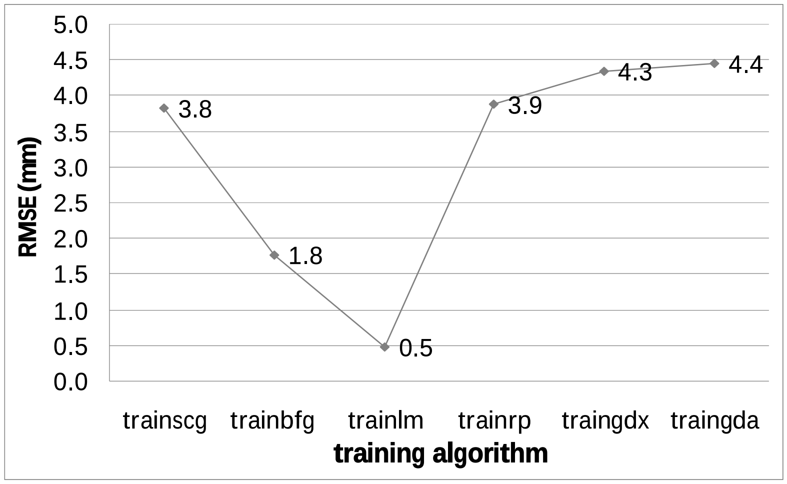

Figure 3: RMSE variation for different training algorithms

Table 2: The ANN's actual and desired outputs

i	actual output (y_i) (mm)	desired output (d_i) (mm)	i	actual output (y_i) (mm)	desired output (d_i) (mm)	i	actual output (y_i) (mm)	desired output (d_i) (mm)	i	actual output (y_i) (mm)	desired output (d_i) (mm)
1	-4.4	-2.3	10	5.4	5.1	19	-1.6	-1.6	28	-4.0	-4.1
2	-3.3	-3.5	11	10.3	10.5	20	-4.7	-5	29	0.2	0.2
3	-1.6	-1.9	12	-9.2	-9.4	21	0.3	0.2	30	-1.5	-1.7
4	-9.3	-8.9	13	0.0	0.1	22	-3.6	-3.8	31	1.6	1.7
5	-2.5	-2.4	14	-2.9	-2.7	23	-3.2	-3.3	32	-3.9	-3.5
6	-4.6	-5.3	15	-7.2	-7.1	24	-4.9	-5	33	-0.3	-0.2
7	-4.2	-3	16	6.9	6.8	25	2.9	2.5	34	-4.1	-4.6
8	1.6	1.7	17	2.2	2.3	26	-3.5	-3.3	35	0.8	1
9	-0.5	0.1	18	-2.8	-2.8	27	1.5	1.1	36	-4.1	-4.1

Figure 4: Linear regression between the outputs and targets of the final ANN