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Prediction of Vertical Displacements in Civil Structures Using Artificial Neural Networks

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Abstract. This article attempts to analyse and predict vertical displacements of measurement-and- control network points located on civil structures founded on expansive soils, using artificial neural networks. Geodetic monitoring of civil structures consists in regular measurements of control point networks and interpretation of results. The obtained values of displacement provide sets of significant data which enable determination of the influence of changes in ground-water conditions of the subsoil on the deformation processes occurring in structures founded on it. Using such data sets, it is possible to draw conclusions regarding the dynamics of the occurrence of deformation and to develop a geometric model of displacements.
In recent years, methods of prediction based on artificial intelligence have been increasingly prominent. Neural networks and evolutionary algorithms, which can supplement each other, make advanced tools applied in the process of prediction of deformations. In order to forecast displacements of control points, demonstrating changes in a civil structure, multi-layer artificial neural networks are employed in this article, taught using the method of error backpropagation and gradient optimization methods. The analysed results in the form of height differences were obtained through a series of measurements on a civil structure, taken by means of precise levelling at monthly intervals.

Keywords: surveying, vertical displacements, displacement model, neural networks.

Conference topic: Technologies of Geodesy and Cadastre.

Introduction

Geodetic monitoring often comes down to the determination of the dynamics of the phenomenon which consists in uneven settlement of buildings and structures founded on expansive soils. The extent of identified settlement triggered by permanent deformation of the subsoil is the fundamental criterion in the process of design of structures. Permanent deformations may be caused by changes in the soil density or by dislocation of soil masses.

In order to estimate displacements correctly, geodetic monitoring needs not only appropriate measuring instruments and equipment, but also suitable methods of processing the results obtained from experimental data. The estimation of reliable values of displacement involves selecting points for which significant displacement is observed and points which remain stable throughout the period of measurements. This is particularly important if there is no possibility to refer a network to mutually constant points located outside the area affected by deformations occurring in a given structure (Wolski 2006).

Methods based on artificial intelligence have recently become more and more important among the methods of prediction (Helt *et al.* 2012; Sztubecka, Sztubecki 2016). These include fuzzy logic, neural networks and evolutionary algorithms which can be used in combination to form an advanced set of tools used in the prediction process (Fig. 1).

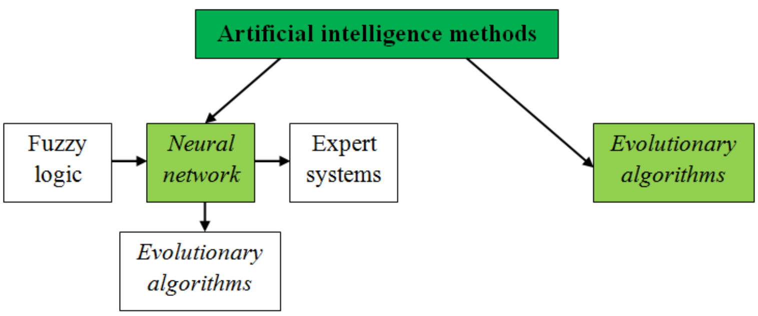


Fig. 1. Artificial intelligence methods used in prediction (Source: Helt *et al.* 2012)

Neural networks make it possible to obtain better results of prediction thanks to their ability to associate connections between factors influencing prediction (input data) and predicted elements (output data). The whole prediction process in which artificial neural networks are used runs without the need to present the correlations between input and output data in an explicit way. Moreover, owing to their generalization capability, neural networks can carry out the learning process correctly even if the input data set is incomplete or inaccurate (Helt *et al.* 2012).

This article contains a proposition to apply a Hopfield neural network to evaluate the stability of points in a geodetic measurement and control network which are exposed to factors activating expansive properties of soil, and to predict vertical displacements over a selected period of time.

The application of a continuous hopfield model of neural network to prediction and in the development of a geometric model of displacements

Displacements of measurement points representing the analysed structure were described by means of two static models of the control network, depending on the definition of the frame of reference used for the structure. It should be noted here that the problem of geodetic definition of displacements was discussed extensively by (Prószyński, Kwaśniak 2006).

In the authors' concept, the frame of reference can be defined on the basis of identification of such observed changes in the height difference whose values do not vary significantly during the observations. A continuous Hopfield neural network model, a diagram of which is shown in Figure 2, was applied to evaluate the intensity of changes in the results of measurements.

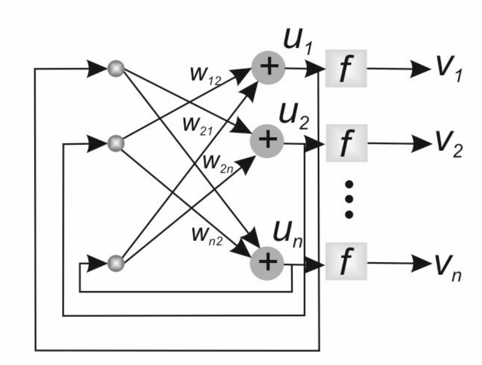


Fig. 2. Diagram of a Hopfield neural network (Source: Mrówczyńska 2015)

In order to verify the method of identification of the points of reference, as proposed by the authors, the frame of reference was defined in a conventional way, on the basis of adjustment of changes in height differences and minimisation of the sum of absolute deviations (Gil 1995), whereas the ultimate values of displacement in both cases were obtained by rigorous adjustment of changes in height differences.

In general, the application of a Hopfield neural network to solve the defined task requires implementation of a network learning process involving the formation of areas of attraction of individual points of equilibrium which correspond to the teaching data. For different initiating vectors, the system may evolve into different final states, known as attractors. Figure 3 presents a division of space into regions of attraction for 3 attractors.

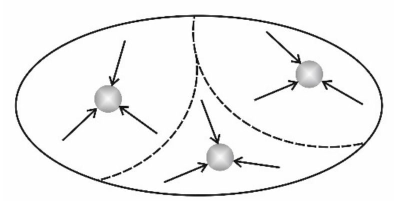


Fig. 3. Phase space of attractors (Source: Mrówczyńska 2015)

A continuous neural network model was used to solve the issue of stability of the measurement and control network points, in which input signals can take any values within the range (–1, 1). Continuous models, unlike discrete models, are characterised by continuous time and a continuous bipolar activation function $f(x) = tgh(\alpha x)$. If analogue signals are identified as v_i, the following formula will be obtained (Osowski 2006):

$$v_i = f(u_i) = f(\sum_{j=1}^{n} W_{ij} v_j), \tag{1}$$

where W_{ij} ($i = 1, 2, ..., n,\quad j = 1, 2, ..., n$) is a defined weighting matrix. In a steady-state system the following equation is true:

$$-v_i + f(\sum_{j=1}^{n} W_{ij} v_j) = 0. \tag{2}$$

If the network equation in the steady state is expressed as:

$$-u_i + \sum_{j=1}^{n} W_{ij} v_j = 0, \tag{3}$$

the dynamic state of the network can be described by the following differential equation:

$$\tau_i \frac{du_i}{dt} = -u_i + \sum_{j=1}^{n} W_{ij} f(u_j), \tag{4}$$

where τ_i is the time constant of the adaptation process (method time step). In the steady state, changes of u_i and v_i equal to zero and the network is in equilibrium.

In the process of analysis of artificial neural networks the concept of energy function is frequently used. The energy function of a neural network either decreases or remains constant in the process of pattern matching. For an analogue network, Hopfield defined the energy function as:

$$E = -\frac{1}{2}\sum_{i=1}^{n}\sum_{j=1}^{n} W_{ij} v_i v_j + \sum_{i=1}^{n}\int_{0}^{v_i} g^{-1}(v)dv, \tag{5}$$

where $g^{-1}(v) = \frac{1}{2}\ln(\frac{1+v}{1-v})/\lambda$ (Mańdziuk 2000). The energy function (5) does not change over time (Lyapunov function) and in the process of input vector matching to one of remembered patterns it achieves the local minimum in one of attractors.

The diagram of a Hopfield neural network shown in Figure 2 indicates that it is a kind of recursive network, typically represented by auto-associative memory. The main purpose of auto-associative memory is to remember a specific set of teaching patterns in such a way, as to enable the system to generate one of the remembered patterns, located the nearest – using the Hamming distance – relative to the tested pattern, if confronted with an unknown pattern.

For this reason, the storage capacity, or the capability to efficiently remember a given number of patterns, is a crucial parameter of the auto-associative memory. The concept of memory capacity is connected with the following parameter:

$$c_i^{(l)} = -x_i^{(l)} \frac{1}{n} \sum_{j=1}^{n} \sum_{\substack{k=1 \\ k \neq l}}^{p} x_i^{(k)} x_j^{(k)} x_j^{(l)}, \tag{6}$$

known as crosstalk (noise component). If for the l value of the teaching pattern $c_i^{(l)} < 1$, then – in spite of a certain incompatibility of the bites – the $x_i^{(l)}$ component is stable, because the crosstalk component $c_i^{(l)}$ has the same sign as $x_i^{(l)}$. Instability, understood as a change of the initial state of the neuron, occurs when the maximum storage capacity of the memory is exceeded. The value distribution of $c_i^{(l)}$ is binomial, which in the case of high values of n and p is closer to a normal distribution. The value of probability

$$\varpi = P(c_i^{(l)} > 1) \tag{7}$$

increases with the increase of the number of remembered patterns p and of the n dimension of vector x.

We will consider a time-invariant system, where there is a family of curves of changes in height differences. Taking two curves into account, that is the part which describes the time evolution of the system for initial conditions determining the two adjacent trajectories, we will consider their stability directions. The convergence, or divergence of the trajectories may be described using Lyapunov exponents (Kosiński 2002).

Two adjacent trajectories: $\Delta h_1(0)$ and $\Delta h_2(0)$, running at a distance of $\varepsilon(0)$ at first, when t time passes, will run at a distance of

$$\varepsilon(t) = \varepsilon e^{\lambda t}, \tag{8}$$

where λ is the Lyapunov exponent (Fig. 4).

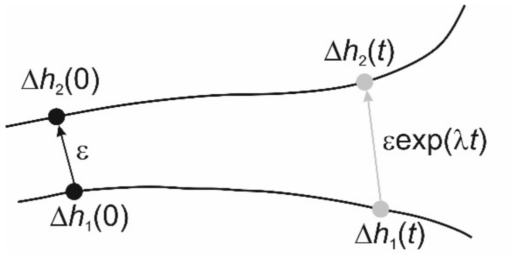


Fig. 4. The distance of the trajectories in time (Source: *Kosiński* 2002)

The formula (16) is now rearranged as follows:

$$f[\Delta h_2(t)] - f[\Delta h_1(t)] = \varepsilon e^{\lambda t}, \tag{9}$$

hence:

$$\lambda = \frac{1}{t}\ln\{f[\Delta h_2(t) - f[\Delta h_1(t)] / \varepsilon\}. \tag{10}$$

If $\lambda < 0$, then the trajectories are convergent, otherwise the movement is chaotic.

Study process

The dynamics of the phenomenon of uneven (differential) settlement caused by changes in the hydrologic regime was observed on the basis of experimental data in the form of values of displacement of measurement points. The observations were carried out on a building founded on expansive soil. The building was represented by 11 points stabilised within its foundation. In 2014, 14 periodic measurements were taken at equal intervals of one month. The experimental data was supplemented by information on the intensity of precipitation in relevant measurement epochs and on the reach of the influence of high trees (lime, oak) which cause changes in the moisture content of the subsoil through transpiration. The monthly water demand of a single tree for transpiration depends on the season of the year and reaches up to 15% of its annual water demand in spring, 25% in summer and 5% in autumn (Jerzy Przystański, Ed., collaborative work, 1991).

It may be assumed, for practical reasons, that the zone of influence of a tree on changes in the soil moisture content is in the shape of an inverted cone with a more-or-less circular base whose radius is approx. 1.5 times the height of the tree.

Harmful influence of trees on adjacent structures depends on the location of their foundations with respect to the zone of influence of the trees. If the depth of foundation is included in such a zone of influence of trees on the subsoil, there is a threat of uneven settlement between the part of the structure located within that zone and the part founded on non-expansive soil. Cracks in the structure usually appear around the boundary of the two parts. The manifestation of the structural fault depends on the location of the structure relative to the zone of influence of the trees in the subsoil. The following cases can be observed (Fig. 5):

- If the zone of influence overlaps the foundation plan of the structure, cracks may appear on the walls, parts of the building may "sink" or a corner may separate from the rest of the building,
- If the entire foundations are situated within the zone of influence of the tree(s), the structure may tilt.

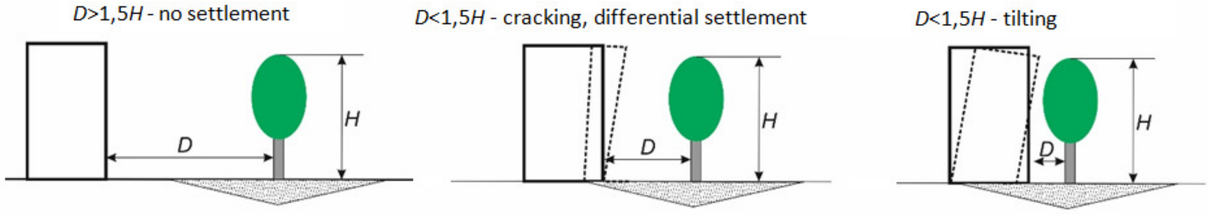
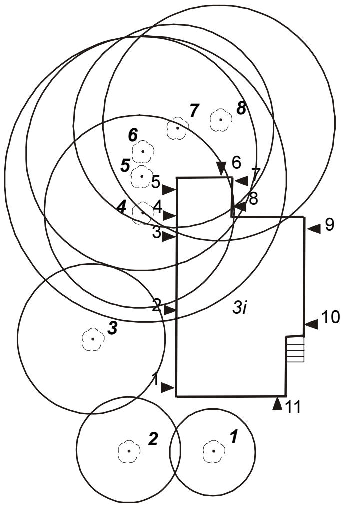


Fig. 5. The influence of trees on the settlement of buildings (Source: Jerzy Przystański, Ed., 1991)

Figure 6 shows a diagram of the location of the measurement points on the building and the location, species and height of the trees planted and growing unrestrictedly in the vicinity of the building, as well as their zones of influence. Note that points 10 and 11 were located outside the influence of the hydrologic regime of the trees.



Tree No.	Species	Height [m]
1	linden	7,20
2	linden	8,10
3	oak	11,70
4	linden	15,10
5	linden	21,90
6	linden	18,30
7	linden	16,10
8	oak	18,20

Fig. 6. Location of the measurement points on the building and the location of the trees (Source: own elaboration)

Numerical example

The numerical example is provided on the basis of an analysis of four changes in the height differences, whose trajectories are shown in Figure 7.

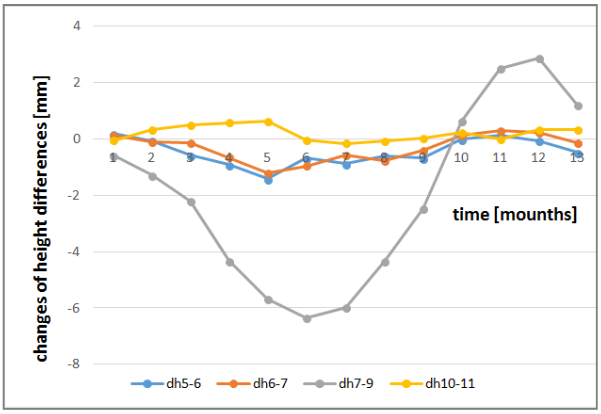


Fig. 7. Trajectories of changes in height differences based on measurements (Source: own elaboration)

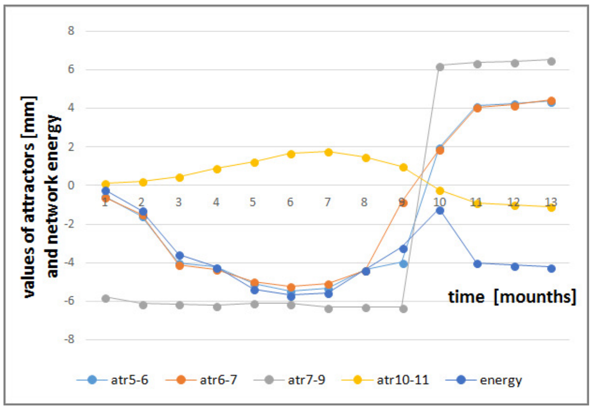


Fig. 8. Minimum values of network energy and respective attractors (Source: own elaboration)

Note that:

- Changes in the difference of heights and are close in value and the directions of their trajectories are similar, whereas changes in the difference of heights are minimal, while in the case of they are substantial (Fig. 7);
- The attractors corresponding to the relatively slight changes in the difference of heights and have high values, whereas on the other hand, the values of the attractors for the small changes in the difference of heights are also small (Fig. 8). This indicates (without being an indisputable proof) that points No. 5, 6 and 7 were subject to parallel displacement, whereas points No. 10 and 11 remained stable;
- On the basis of the number of time evolutions of the changes in the difference of heights and reaching the attractors it may be decided that points No. 5, 6 and 7 underwent parallel displacement, and points No. 10 and 11, located outside the zone of influence of the trees, maintained stability (Fig. 9),
- Two trajectories of changes in the difference of heights and demonstrate a lack of variance, because in the period of observations Lyapunov exponents were negative, whereas in the case of all other changes in the difference of heights the movement could be described as chaotic (Fig. 10).

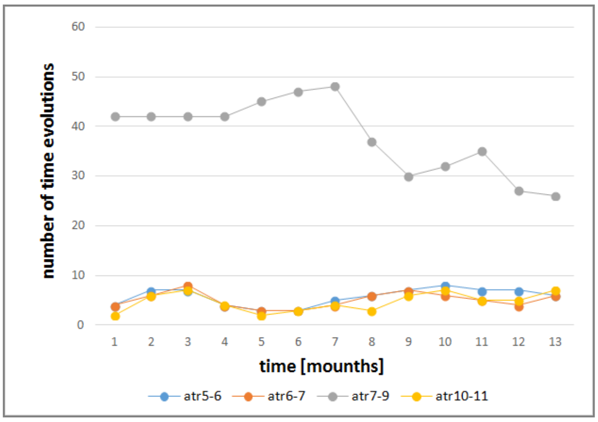


Fig. 9. Number of time evolutions of height differences reaching the attractors (Source: own elaboration)

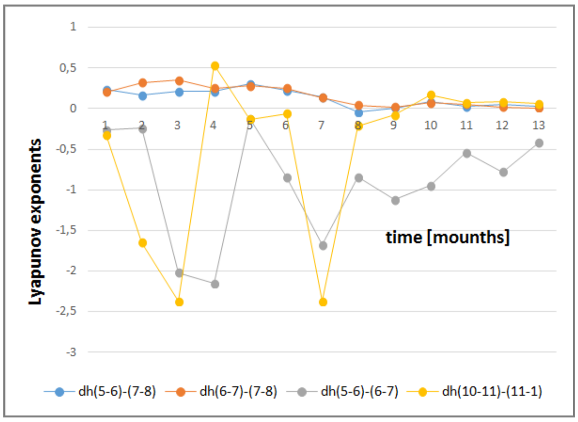


Fig. 10. Values of Lyapunov exponents (Source: own elaboration)

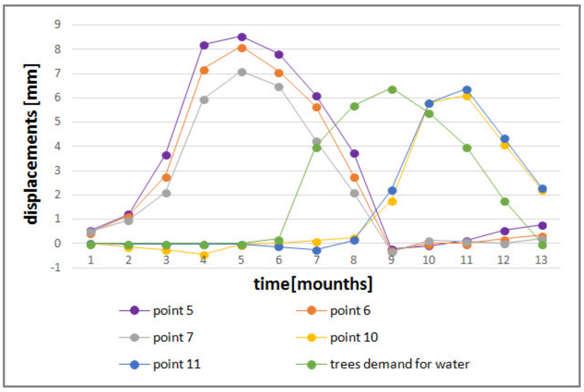


Fig. 11. Displacements determined using a conventional method (Source: own elaboration)

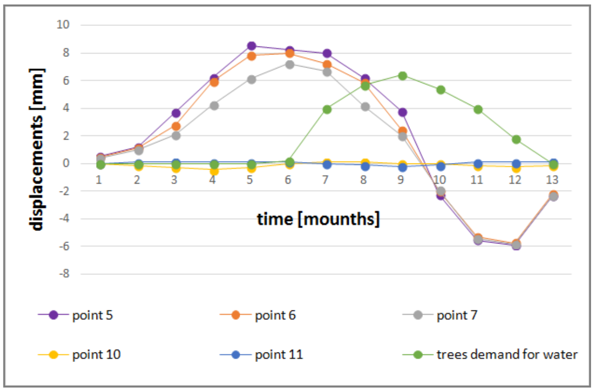


Fig. 12. Displacements determined using the authors' concept (Source: own elaboration)

On the basis of the periodic measurements and information on the amount of precipitation for individual months, vertical displacements were predicted using a Hopfield network model for one period of measurements (July 2015) and the obtained results were then compared with the results from the actual field measurements. The values of vertical displacement, both predicted and measured, are presented in Figures 13 and 14. By looking into the displacement values it may be noticed that the results differ by no more than 0.5 mm, which testifies to a high degree of accuracy of the prediction provided using the Hopfield network.

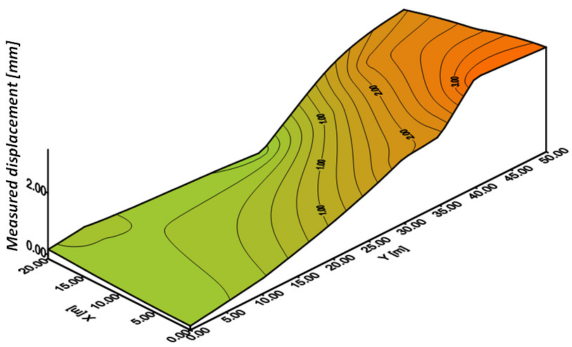


Fig. 13. Prediction of vertical displacements for the measurement period of July 2015 (Source: own elaboration)

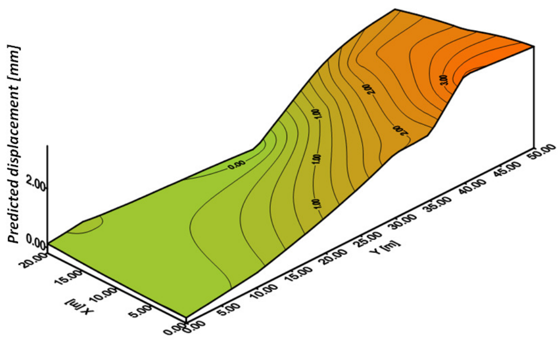


Fig. 14. Displacements actually measured in July 2015 (Source: own elaboration)

Conclusions

The implementation of associative memories by means of recursive networks enables prediction of vertical displacements of measurement and control points and deciding on the choice of a set of points with established mutual stability, particularly where there are objective obstacles to refer a measurement and control network to points located outside the zone of environmental influences on the deformation of the analysed structure.

In this article, dynamic memory with the structure of a Hopfield network was used to estimate stable points. The memory reproduces stored associations related to patterns. The state of the Hopfield associative memory network is described by its energy function which reaches a local minimum in the process of network update in the proximity of an actual attractor. The number of time evolutions in the reaching of the attractor of changes in the height differences provides information on the number of time constants required to reach the state of equilibrium, in which changes in the height differences fall within the measurement accuracy limits.

The authors' concept assumes that the stability of the points of a geodetic measurement and control network, or the extent of vertical displacement of the points and the prediction of vertical displacements can be estimated on the basis of the following:

- The number of time evolutions for changes in height differences to reach the attractors with a predefined accuracy,
- Lyapunov exponents,
- Analysis of the values of changes in height differences.

Considering all of the above-mentioned factors, it can be concluded that only points No. 10 and 11 maintained stability within the measurement accuracy limits, and the results of predicted displacement can be considered as satisfactory.

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