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Research Article

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The use of classical methods and neural networks in deformation studies of hydrotechnical objects

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Abstract: Objects' measurements often boil down to the determination of changes due to external factors affecting on their structure. The estimation of changes in a tested object, in addition to proper measuring equipment, requires the use of appropriate measuring methods and experimental data result processing methods. This study presents a statement of results of geometrical measurements of a steel cylinder that constitutes the main structural component of the historical weir Czersko Polskie in Bydgoszcz. In the initial stage, the estimation of reliable changes taking place in the cylinder structure involved the selection of measuring points essential for mapping its geometry. Due to the continuous operation of the weir, the points covered only about one-third of the cylinder area. The set of points allowed us to determine the position of the cylinder axis as well as skews and deformations of the cylinder surface. In the next stage, the use of methods based on artificial neural networks allowed us to predict the changes in the tested object. Artificial neural networks have proved to be useful in determining displacements of building structures, particularly hydro-technical objects. The above-mentioned methods supplement classical measurements that create the opportunity for carrying out additional analyses of changes in a spatial position of such structures. The purpose of the tests is to confirm the suitability of artificial neural networks for predicting displacements of building structures, particularly hydro-technical objects.

Keywords: hydro structures, displacements survey, artificial intelligence

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1 Introduction

Hydro-technical structures, including their technical devices and systems, are used in water management and development of water resources. There are intended for

- water lifting (dams, weirs),
- water transfer (ducts, pipelines),
- flow control [1].

Their contact with water surface is one of the essential characteristics. Such structures, depending on material applied (concrete and steel), are subject to destructive factors and influences similar to that of the majority of other building structures. Therefore, most methods applied to diagnostic tests of the said structures are identical to those applied in the building industry or land surveying. However, these methods should be properly adjusted to a hydro-technical object and its operating conditions [2,3]. In assessing the safety of hydro-technical objects, it is necessary to combine different measuring techniques, calculations and experiences. With technical assessment and modelling of object behaviour, the more comprehensive evaluation should be conducted. It is important to select such technology to obtain the geometric data of a structure. Measurements with surveying instruments may be more or less accurate and characterised by different accuracy levels. The correctness of selected data acquisition methods is a precondition for proper monitoring of the said structures [4–7]. Regarding hydro-technical objects, several methods of geodetic determination of displacements and deformations are applied – from accurate polygonisation, measurements of angularlinear networks or levelling up to methods of relative measurement, including feeler gauges, inclinometers, strain gauges or clinometers [1,8,9]. Terrestrial laser scanning or observations with a thermal camera, in particular of hardly accessible composition structures, also allow us to obtain proper output data to analyse deformations of structural elements of such buildings.

In the second stage, solutions adjusted to output data in the form of results of measurements are applied and correlated with other methods to obtain best algorithms or calculation methods as possible. Over the last years, artificial neural networks featuring strong theoretical bases and usefulness in practice have become increasingly important as algorithms of modelling and analysing measuring data [10]. Similar possible applications were confirmed by resolving building, surveying, cartography, cadastre, geotechnical and photogrammetry issues [11–18]. In this study, the development of results with polar and intersection methods was correlated with the analysis using a neural network. The tested object is the historical weir "Czersko-Polskie" in Bydgoszcz, particularly its component – the steel cylinder. The weir has been designed to maintain the constant water level in the Brda river, to protect the area of Bydgoszcz against flood and to be used for energy purposes.

The research structure is characterized by a difficult access capability of geometry measurements. The geodetic measurement method used allows the determination of changes in its structure provided that it is possible to observe the adopted network of controlled points between successive measurement series. Sometimes, when network measurement is complicated, and there is a lack of measurement data, or there is a need to examine the trend of geometry changes, algorithms based on artificial intelligence can be used to search for missing data and predict changes. The algorithms used in the research were used to determine the predicted course of the Z-axis of the object based on the results of previous measurements.

Herein, the research presented aims to show the possibility of using the unidirectional multilayer neural network model (multilayer perceptron) to predict the displacements of a hydrotechnical object. Such a model assumes conducting an earlier process of learning the network to minimise the objective function being the sum of squares of differences between the obtained and expected values of the output signal. This aim is related to the research question whether the use of the above neural network model is applicable in this type of research.

This study consisted of the following sections: Section 2 – it describes the research object and methods used; Section 3 – the results obtained were described and analysed; Section 4, where the validity of the method used and its potential are described.

2 Materials and methods

Hydro-technical structures are essential from the economic point of view. It is important to maintain them in the best technical condition possible. Condition control analyses include the assessment of geometrical changes in such structures, etc. Tests described herein refer to the steel cylinder constituting a part of the historical weir "Czersko Polskie" in Bydgoszcz. Its location is shown in Figure 1.

2.1 Steel cylinder geometry tests

The main structural component of the said weir is a steel cylinder of a total length of 24.90 m and a diameter of

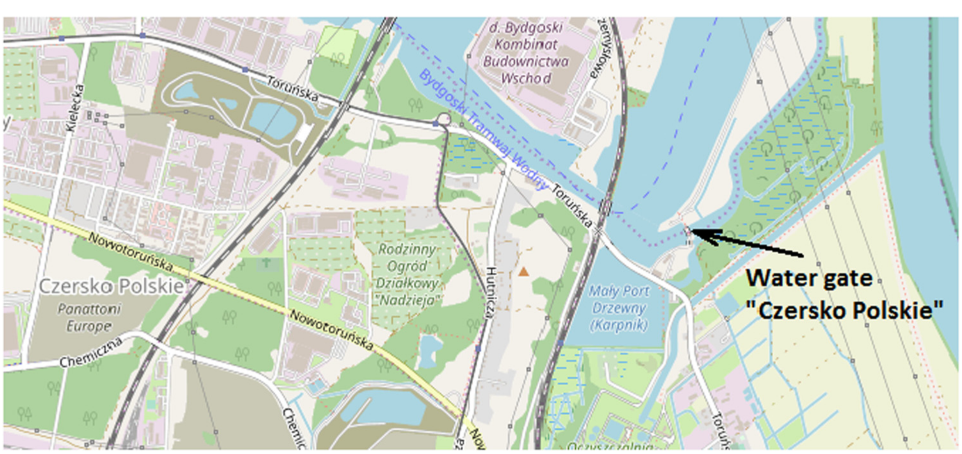

Figure 1: Location of the tested object.

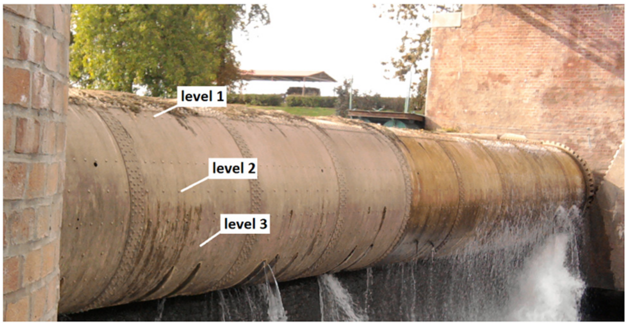

Figure 2: A view of the cylinder with rivet levels shown.

2.50 m. The cylinder surface consists of 22 metal sheets of 14 mm in thickness joined together with rivets. Circumferential sprocket wheels put on both ends of the cylinder are used to lift it with a chain mechanism.

As the cylinder layer is hardly accessible, only from the bottom waterside, selected points in the form of rivets positioned in three rows were observed during the survey (Figure 2). The position of the axis skews and deformations of the cylinder were determined when analysing the results.

An assumption was made in calculations that the cylinder components have a repetitive arrangement of connecting rivets. Then, groups of three points in planes cutting the cylinder perpendicularly were determined. Such groups of three points in the applied system of coordinates are shown in Figure 3.

Coordinates of geometrical centres of the said triangles were specified, which are used to determine a dimensional position of the cylinder axis. Askew of the weir structural component was defined by comparing the position of the triangles concerning one another. A positive skew was taken towards the outflow of water through the structure. It was also possible to determine the deformation of the cylinder surface along the line of rivets for levels 1, 2 and 3.

2.2 Artificial neural networks

A model of a one-direction neural network (multi-layer perceptron) was used in this study to predict displacements. The network comprised neurons that are described with a sigmoidal activation function (Figure 4). The proposed approach can be used to map cause-and-effect relationships between input data x_i and the output set y_i. Modelling that uses one-direction neural networks involves the conduction of a prior neural learning process to minimise a function of the objective, which is a sum of squares of differences between the obtained and the expected values of the output signal. For this purpose, data of previous measuring cycles should be entered at data input, considering the time of measurements, whereas the

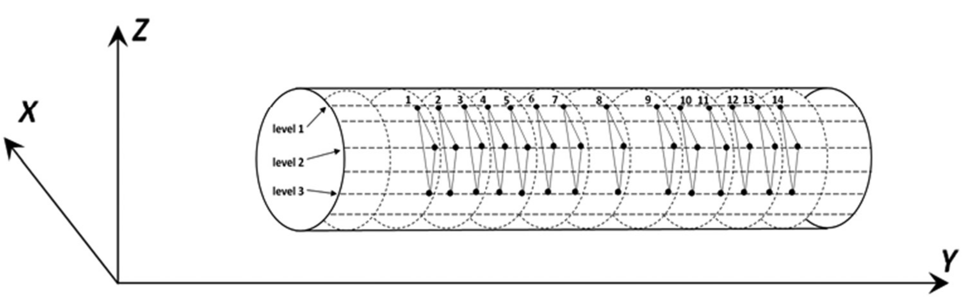

Figure 3: A view of the cylinder with groups of three points indicated.

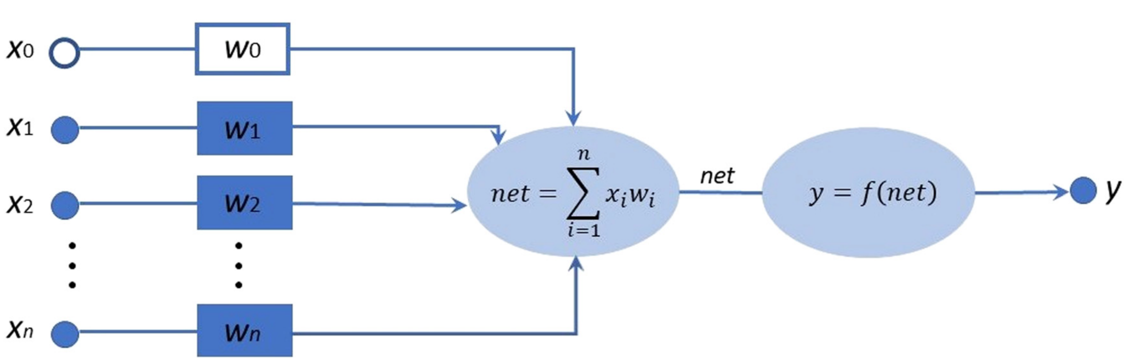

Figure 4: A scheme of a sigmoidal neuron.

values of displacements obtained in previous measurements should be entered at the output.

The basic architecture of neural networks is a multi-layer structure of the one-direction signal flow, which is composed of a proper number of neurons. Thence, an important issue when designing neural networks is the selection of an optimal network architecture [19,20]. As the size of the input layer depends on the input vector size and the size of the output layer depends on the output vector size, the number of hidden layers and the number of neurons in such layers are to be determined. An effective approach is to initiate the learning process with a minimum number of hidden neurons, or even without them, and then increasing this number gradually until a favourable network training level is obtained for the learning set [19]. If the number of neurons taken for a hidden layer is too low, a network is under fitted which manifests itself by a low degree of fitting a network response to required values at the learning stage, and consequently in a huge learning error obtained. Too many neurons in the hidden layer result in a phenomenon called network over dimensioning (overfitting). This effect is manifested by a significant increase in an error for the tested set. Following tests, a two-layer neural network was applied in the study to predict displacements: two hidden layers and one output neuron (Figure 5). Six hidden neurons were taken in the first layer, whereas in the other, one – three neurons.

Learning neural networks involves modification of weighting factors w in a way that responses of a network can be adopted to expected values at the output. At the beginning of network operation, weights responsible for network calculations are randomly selected (from an open interval 0.1) and then modified according to the below formula:

$$w_{ij}^{(k+1)} = w_{ij}^{(k)} + w_{ij}^{(k)}, \tag{1}$$

where k is the number of a subsequent iteration.

The process of a change of weight values is associated with minimisation of the function of the objective E, which is defined as a mean square error. A basic learning algorithm based on the method of steepest descent tends to stop within an area called a local minimum, where it should reach a global minimum. To avoid this problem, a modification of the basic method referred to as the method of moments was applied in the study. As far as this method is concerned, a moment coefficient, whose size depends on the change of weights in previous learning cycles, is included in a basic weight correction formula (formula (1)). The approach can be vector-recorded using the below formula:

$$\Delta w^{(k)} = -\eta \nabla E(w)^{(k)} + \alpha \Delta w^{(k-1)}, \tag{2}$$

where η is the learning rate and α is the moment coefficient whose value affects the impact of the member of a moment on weight correction.

In the learning process, the input set **X** is used to calculate network responses, whereas the output set **Y** is a basis for the determination of a value of the mean square error at network output. The error value is determined according to the formula:

$$\mathrm{MSE} = \frac{1}{n}\sum_{i=1}^{n}(d_i - y_i)^2, \tag{3}$$

where n is the count of the learning set, y is the network response obtained at output, d is the network response expected at output.

Based on the above-mentioned error, corrections of weight coefficients for individual layers are determined in the direction opposite to the flow of an input signal through the network. Such a learning cycle, depicted in Figure 6, is repeated for all learning vectors.

In this study, a multi-layer one-direction neural network was used to predict vertical displacements of controlled points arranged on a hydro-technical object subject to measurements.

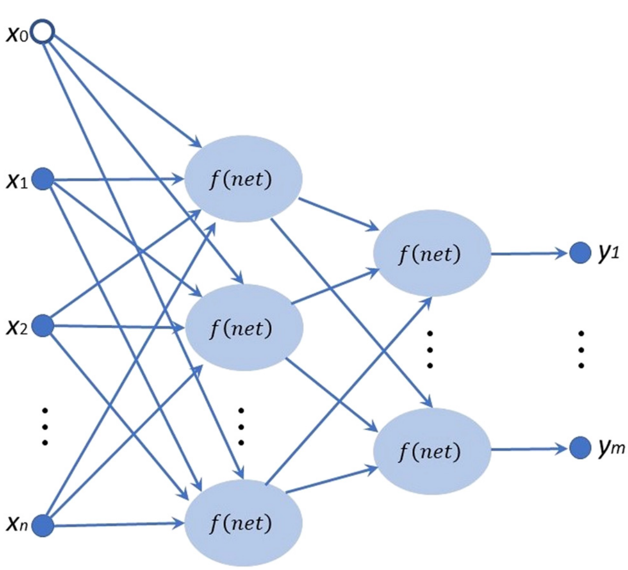

Figure 5: A scheme of a two-layer neural network.

3 Results and discussion

Tests of cylinder displacements were carried out employing polar and intersection methods. Three series of measurements were conducted: measurement 1 – October 2012, measurement 2 – May 2014 and measurement 3 – May 2017.

The following was obtained for three control measurements:

- cylinder axis position,
- cylinder skew angles,
- cylinder surface deformations.

The *Z*-coordinate of the cylinder axis is a parameter essential from an analytical point of view. A change of this coordinate for three measurement series is listed in Table 1.

The object covered by the studies is characterised by a limited possibility of measurements of its changes in space. The applied measurement method enables effective determination of changes in the structure between a subsequent series of measurements provided that the applied network of controlled points can be observed. Sometimes, it becomes necessary to supplement missing measuring data or determine tendencies of changes in

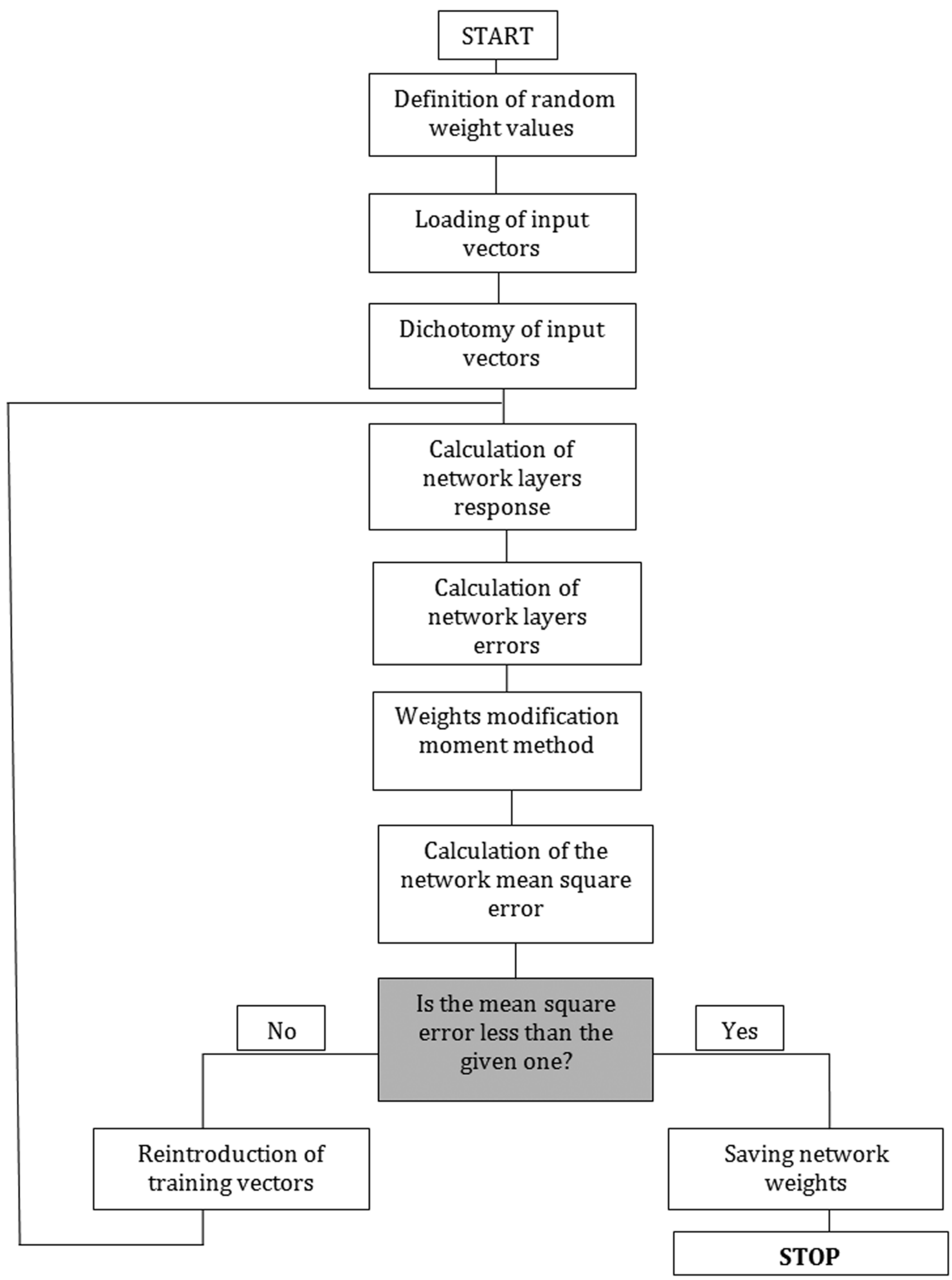

Figure 6: A learning algorithm of a neural network.

Table 1: A change on the *Z*-coordinate of the cylinder axis

Triangle number	ΔZ [mm] Meas. 1	Meas. 2	Meas. 3
1	**0.0**	**0.0**	**0.0**
2	0.7	1.3	−2.8
3	−5.5	−5.7	−9.2
4	−7.4	−7.2	−10.5
5	−8.2	−7.2	−11.0
6	−7.2	−6.8	−9.5
7	−11.3	−10.5	−13.3
8	−17.3	−15.2	−18.5
9	−23.2	−20.5	−25.0
10	−26.0	−23.0	−28.3
11	−25.0	−22.7	−26.3
12	−26.6	−25.3	−29.3
13	−29.0	−26.8	−31.5
14	−29.5	−26.8	−32.5

the geometry of such objects. Increasingly, evolutionary algorithms have been used as a tool for seeking solutions and optimisation of the said objects. Algorithms used in the studies are aimed at determining the expected waveform of the *Z*-axis based on the results of previous measurements.

A bipolar function defined by the following formula was applied as an activation function to predict vertical displacements (a change in the *Z*-axis position) of controlled points using a neural network composed of continuous neurons (of a sigmoidal type):

$$y = f(\text{net}) = \frac{1 - \exp(-\lambda \text{net})}{1 - \exp(-\lambda \text{net})}, \qquad (4)$$

where net $\stackrel{\text{def}}{=} [w^T x]$ is an output signal of the linear part of the neuron and λ is the slope coefficient (skew coefficients of the activation function).

An increase in the value of the slope coefficient causes an increase of the inclination of that function. The inclination of the bipolar activation function depending on the parameter λ is shown in Figure 7. Sigmoidal functions (including the bipolar function) are smooth functions limiting unlimited values of linear weighted adders net. For this reason, sigmoidal functions have been widely used in gradient learning methods of neural networks. Also, in this study, the method of reversal error propagation based on the previously described method of steepest descent along with the moment method was applied.

As mentioned earlier, a network consists of two hidden layers and one output neuron. Learning data included results of measurements and values of displacements from two periodic measurements (October 2012 and May 2014), and the prediction was carried out for the periodic measurement of May 2017. Displacements determined with the neural network were characterised by the root-mean-square error of +2.8 mm.

A comparison of dislocation results for measurements 1 and 2 and measurement 3, with results obtained with the use of the neural network, is shown in Figure 8.

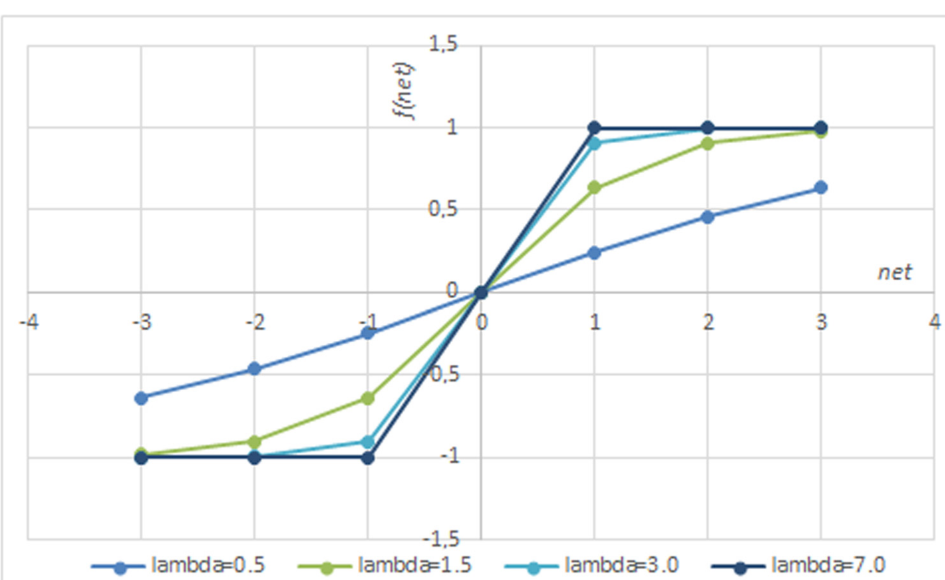

Figure 7: A waveform of the bipolar activation function depending on the value of λ.

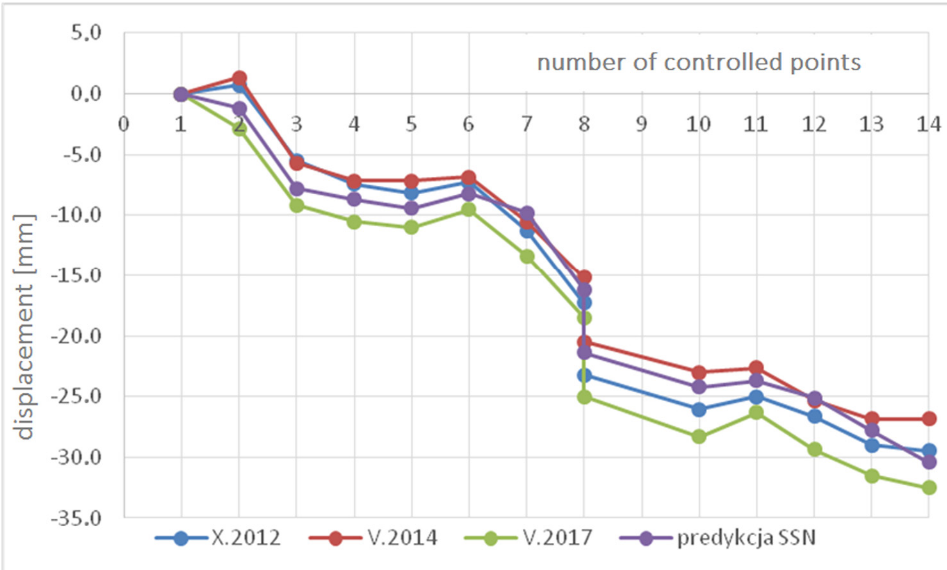

Figure 8: Displacements of controlled points.

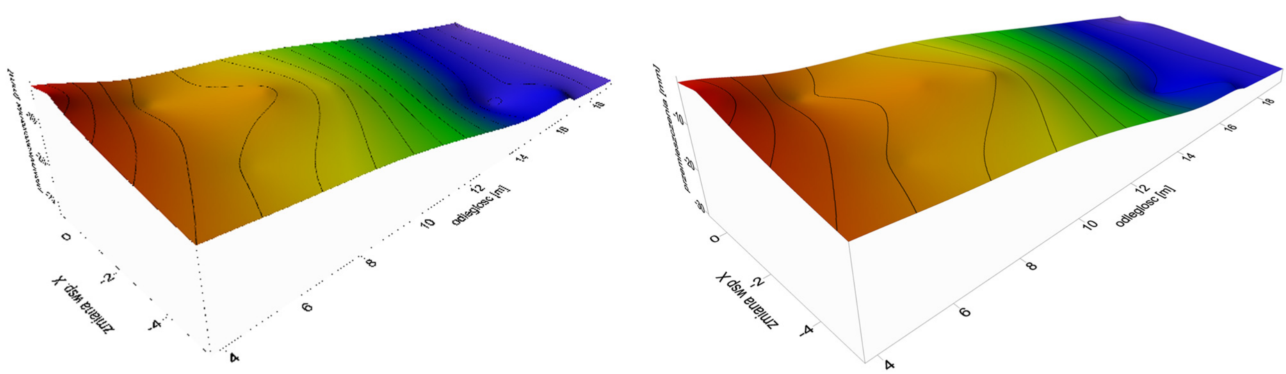

Figure 9: A change of the position of controlled points (a) measurement, (b) prediction with the use of an artificial neural network.

The difference between determined and measured displacements did not exceed 3 mm for any point. Figure 9 shows the changes in the Z-axis position (for measurement 3) against changes on the X-coordinate with the position of controlled points on the cylinder shell (Photo 1).

Photo 1: A view of the weir from the bottom waterside.

4 Conclusion

This study presents measurement and analytical methods employed in studies of spatial changes of a hydro-technical object. The tested object is a steel cylinder constituting a structural component of the weir located near the mouth of the Brda river in Bydgoszcz. Although the weir structure did not provide free access to the entire cylinder surface, the selection of controlled points and the measurement method allowed us to map changes in its spatial position. During measurements and calculations, a characteristic way of connecting structural components of the weir was applied, which proved useful in the process of determining its geometry. Furthermore, a model of a one-direction neural network was used in the studies to determine the prediction of cylinder structure axis displacements. The applied method involving neural networks allowed us to determine cylinder axis displacements with the root-mean-square error of ±2.8 mm. The difference between determined and measured displacements did not exceed 3 mm.

Artificial neural networks confirmed their usefulness in predicting displacements of building structures, particularly hydro-technical objects. They may serve as a method supplementing classical measurements, creating the opportunity for carrying out additional analyses of spatial changes of such structures. It is worth highlighting that a model built with the use of AI may be complemented in the future by data relating to the object structure and data specifying water flows, etc. Such expansion of the input set, taking into account operation of the object caused by external factors, may increase the accuracy of prediction of displacements.

The described way has the potential of both predicting vertical displacements of building objects and determining the dynamics of changes occurring on the objects. The proposed approach can be extended and used to compress the acquired large measurement data sets, sets in the form of point clouds from laser scanning or data obtained by classical methods with a high number of data. Also, methods using artificial intelligence can be used to reduce noise occurring in the measurement results, especially the results obtained through permanent GPS observations and also those performed to determine the object's displacement and deformation.

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