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PREDICTION OF DEFLECTION FROM FLATNESS AND A VERTICAL POSITION WITH THE USE OF NEURAL NETWORKS

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The paper presents an attempt to apply unidirectional multilayer neural networks in the prediction of the deflections from flatness and from a vertical position of building walls, on an example of periodic measurements in the church of the Blessed Virgin Mary in Toruń. The applied methods of artificial intelligence in a form of sigmoid neural networks were taught with the use of the backpropagation method, which bases on the gradient methods described in optimization theories. The prognosis of the values of the deflections from flatness and from vertical position was carried out for a single measurement epoch on the basis of ten periodic measurements performed at several-year intervals.

Keywords: neural networks, deflections from flatness, prediction

1. INTRODUCTION

Unidirectional multilayer neural networks with sigmoid activation functions (multilayer perceptron) are applied in solving numerous practical problems. They most frequently constitute a component controlling the process or a decisive part transmitting the executive signal to the elements of the devise which is not directly connected with neural networks. Neural networks perform various functions which may be presented in some basic groups: approximation and interpolation, pattern recognition and classification, compression, identification and prediction. In each of the applications, a network works as universal approximation of a function of several variables, and which realises a non-linear function:

$$\mathbf{y} = f(\mathbf{x}) \tag{1}$$

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where $\mathbf{x}$ is a input vector, whereas $\mathbf{y}$ is a realised function of several variables. As far as prediction is concerned, a neural network's task is to determine future responses of a system on the bases of the values known from the past. If the the values of input $\mathbf{x}$ are known at the moments prior to prediction $\mathbf{x}(k-1), \mathbf{x}(k-2), \ldots, \mathbf{x}(k-n)$, the network is able to estimate the value of vector $\tilde{\mathbf{x}}(k)$ in current moment k. The estimation takes place in a learning process which for a multilayer percptron is carried out with the use of the backpropagation method. During the teaching process, the net's weights are adapted, applying the current prediction error $\varepsilon = \mathbf{x}(k) - \tilde{\mathbf{x}}(k)$ as well as the value of this error at previous moments (Osowski, 2006; Rutkowski, 2006).

2. NEURAL NETWORK MODEL

Unidirectional multilayer neural networks with a bipolar activation function (multilayer prceptron) were applied to predict the deflection of a wall surface from flatness and from the vertical position. In order to realise the input – output mapping, a net of a two layer structure was applied (fig.1). The neurons of the hidden structure were stimulated by a nonlinear continuous activation function (Bishop, 1995,2006)

$$y = f\left(\mathbf{w}_i^t \mathbf{x}\right) = f(net) \qquad (i = 1,2,\ldots,n), \tag{2}$$

the domain of which is a set of total neural excitations. To solve such a defined task, a sigmoid bipolar activation function $f(net) = \tanh(\lambda net)$ was applied, where λ is a descent coefficient of the activation function. The application of the continuous activation function allows assuming the strategy for the weights selection on the basis of gradient optimisation methods. In the process of the numerical realisation, the weight correction consists in the minimisation of error function

$$E = \frac{1}{2}\sum_{j=1}^{m}\left(d_j - z_j\right)^2 \tag{3}$$

defined as a sum of squared differences between the values of input and output signals: expected d_j and current z_j (j=1,2,...,m). It should be added that neurons of the outer layer had the linear activation function (Rivas & Personnaz, 2000, 2003). For two layer networks (fig.1), output signal **z** expresses the relation written in a matrix form (Żurada i in., 1996)

$$\mathbf{z} = \Gamma[\mathbf{W}\mathbf{y}] = \Gamma[\mathbf{W}\Gamma[\mathbf{V}\mathbf{x}]] \tag{4}$$

where **W** is a matrix of weights in the output layer, **V** is a matrix of weights in the hidden layer, whereas $\mathbf{\Gamma}$ is a nonlinear operator in a form of a diagonal matrix containing the values of the activation function $f(net)$ on its main diagonal. The teaching process was carried out with the backpropagation method, utilising the gradient methods described in the optimisation theories. During the teaching process, the weights are corrected according to the relation:

$$\mathbf{w}_k(n+1) = \mathbf{w}_i(n) + \eta\mathbf{p}(n) \quad (5)$$

where n is an teaching current step, $\mathbf{p}(n)$ - minimisation direction, η - teaching coefficient

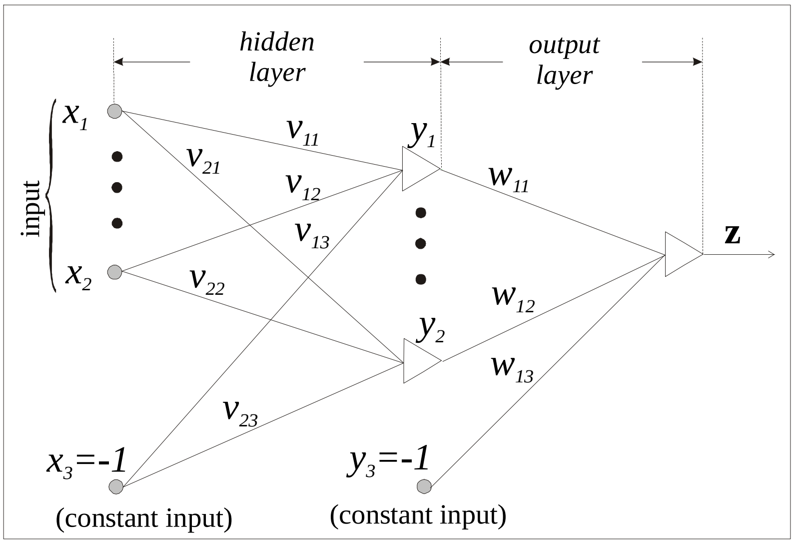

Fig. 1. The structure of a unidirectional two-layer neural network

To predict the deflection from flatness and vertical position, the following gradient methods were applied: the steepest descent method, a variable metric method, Levenberg – Marquardt's method and conjugate-gradient method (Duch i in., 2000; Osowski, 2000; Riedmiller & Braun 1992,). Table 1 presents the list of applied methods together with the determination of minimisation direction $\mathbf{p}(n)$ in subsequent iterations. An important issue occurring in the process is the selection of the criterion that causes the backpropagation algorithm to stop. It is obvious that when the minimum (local or global) is obtained, gradient vector $\mathbf{g}(\mathbf{w}(n))$ takes value 0. The algorithm was stopped, if the value of the Euclidean norm of the gradient vector fell below the target threshold, value of which was assumed at $1e^{-10}$ level.

Table. 1. List of gradient optimisation methods (Stachurski & Wierzbicki, 2001)

No.	Optimisation method	Minimisation direction $\mathbf{p}(n)$
1	The steepest descent method	$\mathbf{p}(n) = -\mathbf{g}(\mathbf{w}(n)) = -\nabla\mathbf{E}(\mathbf{w}(n))$
2	The variable metric method	$\mathbf{p}(n) = -[\mathbf{H}(\mathbf{w}(n))]^{-1}\mathbf{g}(\mathbf{w}(n))$
4	The Levenberg – Marquardt's method	$\mathbf{p}(n) = -\frac{\mathbf{g}(\mathbf{w}(n))}{v_n}$
3	The conjugate-gradient method	$\mathbf{p}(n) = -\mathbf{g}(\mathbf{w}(n)) + \beta_{n-1}\mathbf{p}_{n-1}$

The evaluation of the prediction with the use of the above mentioned gradient methods was carried out on the basis of the value of the root-mean-square error *RSME* (*Root Mean Square Error*), defined with formula

$$RMSE = \sqrt{\sum_{j=1}^{m}(d_j - z_j)^2} \tag{6}$$

3. A NUMERICAL EXAMPLE

The surfaces of the object walls undergo a technical control during their erection and their exploitation (Czaja, 1983). The example utilises the measurements of the walls of the Blessed Virgin Mary church in Toruń, which were carried out with the use of the spatial angular indentation method. The walls neighbouring Virgin Mary's Street were subjected to a particularly thorough analysis (fig. 2 and fig. 3). The church erection was commenced at the end of the 13th century, and the works lasted about 150 years. The building was repeatedly modernised, and obtained its current shape after the renovations carried out after World War II. Nowadays, the church is a three-nave, asymmetrical building with an extended presbytery 27m high and 66m long. As a result of the building and modernisation works, particularly the alterations in the roof structure from a triple-pitched roof into a double-pitched one, the church's walls displayed considerable deformations from the flatness and the vertical position, which initiated the control measurements carried out in 1977 for the first time (Niepokólczycki, 1977, 1981) and in 2011 for the last time (Nagórski 2012).

Fig. 2. Satellite picture of the Blessed Virgin Mary in Toruń

Fig. 3. A wall subjected to the measurements neighbouring Panny Marii Street.

The prognosis of deflections from the flatness and the vertical position was performed with the use of multilayer neural networks taught with the backpropagation method. The values of the estimated displacements were compared with the responding ones obtained from periodic measurements carried out in July 2011. The data constituting the teaching set consisted of the values of deflections from flatness and the vertical position obtained from ten periodic measurements taking place in 1977 – 2010, whereas the testing set consisted of the values of the deflections obtained from the measurements carried out in July 2011. To execute the task, a multilayer neural network of a 3_8_1 architecture was applied. The input vector consisted of measurement data and the time determination for particular periodic measurements. The output vector consisted of the calculated deflections from flatness of the external walls of the church obtained in 55 monitoring points.

The values of deflections obtained in measurements and the ones predicted by the neural networks, for the earlier discussed gradient optimisation methods, were listed in Table 2. Due to the volume of the paper, table 2 depicts only the deflections for selected monitoring points. Fig. 4 presents deflections from flatness obtained with the use of neural networks (the applied optimisation method – conjugate-gradient method), whereas fig. 5 presents deflections obtained from the measurements in 2011. On the basis of the performed measurements and calculations, it can be stated that deflections from flatness and the vertical position of the wall at a height of 23 m amount over 40 cm.

Table 2. A list of deflections from vertical position obtained from the measurements and calculations.

No. of particular monitoring points	Deflections from vertical position obtained from measurements [cm]	Deflections from vertical position obtained with the use of multilayer neural networks				
		The steepest descent method [cm]	The variable metric method [cm]	The conjugate-gradient method [cm]	The Levenberg – Marquardt's method [cm]	Algorithm RPROP [cm]
1	30,9	30,5	30,8	30,9	30,6	30,7
10	7,2	7,8	7,0	7,1	7,3	7,0
20	15,9	16,3	15,9	15,8	16,1	15,8
30	32,4	32,1	32,6	32,5	32,2	32,5
40	-0,2	-0,5	-0,3	-0,2	-0,4	-0,3
50	30,3	30,8	30,4	30,3	30,6	30,4
55	0,3	0,7	0,3	0,3	0,6	0,4

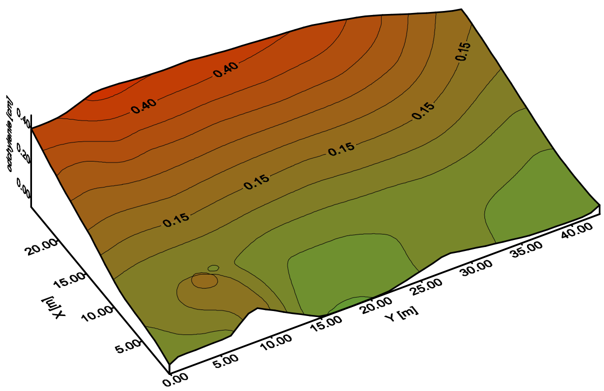

Fig. 4. Prediction of deflections of the wall obtained with the use of neural networks

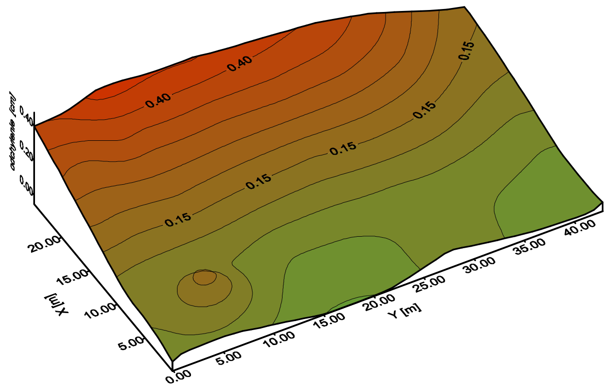

Fig. 5. Deflections of the wall obtained from measurements

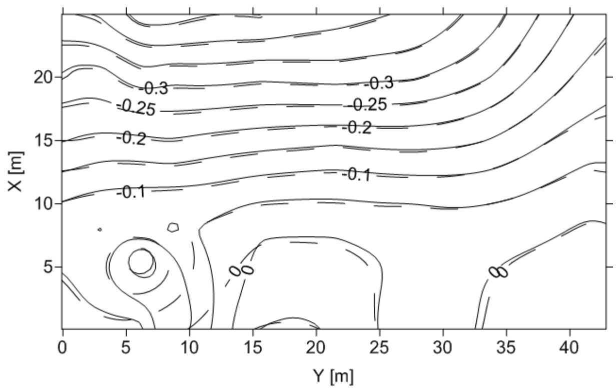

Fig. 6. Differences between the predicted (black isolines)
and measured (dotted isolines) values.

Table 3 presents the error values of the learning and testing of the network in the form of the root mean squared error (Jankowski, 2003), given by (6).

Table 3. Errors of teaching and testing of neural networks

Error type [cm]	Teaching method				
	The conjugate-gradient method	Algorith RPROP	The Levenberg – Marquardt's method	The variable metric method	The steepest descent method
Teaching error	0,07	0,14	0,25	0,23	0,42
Testing error	0,15	0,21	0,48	0,59	1,02

4. SUMMARY

The paper presents an attempt of application of unidirectional multilayer neural networks to determine the deflections from flatness and vertical position of the wall surface in the church of the Blessed Virgin Mary in Toruń, for a single measurement period, on the basis of ten periodic measurements. The best results were obtained with the use of the conjugate-gradient method ($RMSE = 0{,}15cm$), slightly worse for algorithm RPROP ($RMSE = 0{,}21cm$), and the least advantageous for the steepest descent method. It should be noted that the quality of the obtained results depends both on the applied optimisation method and the suitably selected network architecture (the number of layers and the number of neurons in the layers).

On the basis of the obtained results, it can be stated that neural networks may be applied to the prediction of deflection from flatness and vertical position. Analysing figures 4 and 5, it can be noticed that the largest differences between measurements and predictions occur for the lower part of the west wall. The differences for the remaining part of the wall are negligibly small and do not influence the interpretation of the results.

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PREDYKCJA ODCHYLEŃ OD PŁASKOŚCI I POZYCJI PIONOWEJ Z ZASTOSOWANIEM SIECI NEURONOWYCH

S t r e s z c z e n i e

W artykule podjęto próbę wykorzystania sieci neuronowych jednokierunkowych wielowarstwowych do predykcji odchyleń od płaskości i pozycji pionowej ścian budynku, na przykładzie pomiarów okresowych kościoła Najświętszej Maryi Panny w Toruniu. Wykorzystane metody sztucznej inteligencji w postaci sieci neuronowych typu sigmoidalnego były uczone metodą propagacji wstecznej błędu, która bazuje na znanych z teorii optymalizacji metodach gradientowych. Prognoza wielkości wychyleń od pionu i płaskości została przeprowadzona dla jednej epoki pomiarowej na podstawie dziesięciu pomiarów okresowych wykonanych w kilkuletnich odstępach czasu.