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MAREK DUDZIK*, DAWID ŁĄTKA, MICHAŁ REPELEWICZ**,
EDWARD STEWARSKI***, ANNA M. STRĘK****

A PRELIMINARY FEASIBILITY STUDY OF A SHORT-TERM PROGNOSIS OF MINING TOWERS TOPS' DISPLACEMENTS WITH THE USE OF ARTIFICIAL NEURAL NETWORKS

WSTĘPNE STUDIUM WYKONALNOŚCI KRÓTKOTERMINOWEJ PROGNOZY PRZEMIESZCZEŃ SZCZYTÓW WIEŻ GÓRNICZYCH Z WYKORZYSTANIEM SZTUCZNYCH SIECI NEURONOWYCH

Abstract

Mining industry is a key sector of many national economies, thus even a small crack in a mining site echoes nationwide. This strategic sector is subjected to special safety care in every aspect, including operational safety of engineering structures. The newest technologies are employed to diagnose and monitor the working structures and buildings. In this article we propose an innovative idea of combining GPS monitoring system with artificial neural network prognosing to build a prediction tool for displacement of mining shafts in operational conditions. The paper describes a training of a neural network system whose task is to prognose the displacements of the top of a mine shaft tower in direction in a selected period of time. The data used for the training come from the GPS monitoring of displacements of the top of the S 1.2 mining shaft tower. The tower is located in the mining works LW "Bogdanka".

Keywords: artificial neural network, artificial neural network training, displacement of the top of mining shaft tower, GPS monitoring

Streszczenie

Przemysł wydobywczy jest kluczowym sektorem wielu gospodarek narodowych, w związku z tym nawet najmniejsza usterka w obrębie kopalni zawsze odbija się echem w całym kraju. Ten strategiczny sektor jest więc poddany szczególnej trosce o bezpieczeństwo, w każdym aspekcie, włączając bezpieczeństwo eksploatacji konstrukcji inżynierskich. Najnowsze technologie są używane do badania i monitorowania pracujących obiektów i budowli. W tym artykule proponujemy nowatorski pomysł połączenia monitoringu GPS z prognozowaniem za pomocą sztucznych sieci neuronowych w celu zbudowania narzędzia prognozowania przemieszczenia szybów kopalni w warunkach eksploatacyjnych. Artykuł prezentuje trening sztucznej sieci neuronowej, której zadaniem jest prognozowanie przemieszczenia szczytu wieży szybu kopalnianego dla jednego kierunku w wybranym okresie czasu. Analizowane w artykule wyniki pomiarów pochodzą z monitoringu przemieszczeniowego szczytu wieży szybu S 1.2 w kopalni LW „Bogdanka". Uzyskane wyniki obliczeń dla wybranego fragmentu okresu letniego prezentują się obiecująco.

Słowa kluczowe: sztuczna sieć neuronowa, trening sztucznej sieci neuronowej, przemieszczenia szczytu wieży szybu kopalnianego, monitoring GPS

* M.Sc. Eng. Marek Dudzik, Institute of Industrial Electrical Engineering and Computer Technology, Faculty of Electrical and Computer Engineering, Cracow University of Technology.

** M.Sc. Eng. Dawid Łątka, M.Sc. Eng. Michał Repelewicz, Institute of Building Materials and Structures, Faculty of Civil Engineering, Cracow University of Technology.

*** Ph.D. Eng. Edward Stewarski, AGH University of Science and Technology, Faculty of Mining and Geoengineering, Department of Geomechanics, Civil Engineering and Geotechnics.

**** M.Sc. Eng. Anna Stręk, AGH University of Science and Technology, Faculty of Mechanical Engineering and Robotics, Department of Strength and Fatigue of Materials and Structures.

1. Introduction

GPS measurements – a modern satellite technology – became increasingly popular in various applications. They may be used, for example, for monitoring [1], displacements analyses and displacements prognoses of mine shafts towers. Such prognoses might prove to be important in safety systems, thanks to the possibility to inform the miners working underground about a potentially hazardous state. One of the tools used for displacement prognoses might be a novel idea of the said GPS measurements combined with neural networks. We present the concept in this article.

The paper shows a training of a neural network system which was designed to prognose the displacements of the tower top of a mining shaft. The aim of this preliminary training study was to verify whether the designed neural network could be trained based on the GPS measurement data (feasibility study). The used data came from the GPS monitoring in the mining works LW "Bogdanka" [1] and comprised measurements of the displacements of the S 1.2 mining shaft tower top. The presented results refer to the displacements in one direction in a selected period of the summer season: from 31st July 2013 03:01:00 AM to 3rd August 2013 08:00:00 AM.

However, the condition that neural displacement prognoses in the mining industry lead to safety betterment is that they have to be feasible and accurate. Implementation of algorithms which fulfill these two requirements might, apart from the improvement of life protection, also result in lowering potential costs, which could arise due to stability loss of the monitored structures.

2. Artificial neural network

The artificial neural network that was designed for the analysis and prediction of the displacements of the S 1.2 tower top is shown in Figure 1.

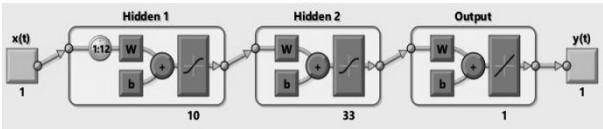

Fig. 1. The assumed artificial neural network structure

The chosen structure was a focused time-delay neural network structure with two hidden layers (Hidden 1, Hidden 2). On the other hand, it is worth noticing, that the chosen structure also corresponded to a feedforward neural network type, but for the tapped delay data line vector implemented before the input port of the first hidden layer. This vector was the basis of the input data for the neural network training. On the basis of these vector data the neural network prognosis $y(t)$ was calculated (Fig. 1).

The first hidden layer consisted of 10 neurons. At the input of this layer one input signal was assigned. At the output – 10 output ports were assigned. Before this first hidden layer a vector of 12 delays was implemented. This means that input signal in the first hidden layer was a vector data consisting of 12 elements. The elements were considered displacement delayed from 1 to 12 minute. The activation function in the hidden layer was a hyperbolic tangent sigmoid transfer function (tansig).

The second neural network hidden layer consisted of 33 neurons. This layer had 10 input ports and 33 output ports. There were no delays implemented for the second hidden layer. The activation function in the second hidden layer was a hyperbolic tangent sigmoid transfer function (tansig).

The output layer (Output) used a linear activation function. At the entrance of the output layer there were 33 input ports. At the output of this layer there was one output port implemented. The signal that was produced at this last port was the desired prognosis. There were no delays implemented for the output layer.

The presented network was constructed arbitrarily. The architecture of the chosen ANN may be studied in other variants, for example networks with another number of neurons and layers may be built and compared to the one presented here. This might be a further project development stage.

3. Input data

The recorded displacement data were imported from the GPS using the Trimble program. The data were imported in three directions (*X*, *Y*, *Z*). Basing on a referent comparative data sheet provided with the input data, the direction *X* was identified as the northing position, the direction *Y* as the easting position and the direction *Z* as the height position. The paper presents the analysis for the training in one chosen direction – the *X* direction, that is the northing.

In order to transform the tower top's position values to the most convenient form for calculations, those values were processed in the following way. A reference point was chosen as a mean value of all analysed data. Next, the value of the reference point coordinate was simply subtracted from the analysed coordinates *X*, in order to shift vectors in the direction *X*.

Calculations were performed using Excel and Matlab Simulink programs. The assumed sampling time was 1 minute, because the prognosis was a short-term prognosis and was supposed to foresee an instantaneous value of the displacement in the chosen *X* direction to be read by the GPS device one minute later.

The data chosen for the artificial neural network training comprised the instantaneous values of the displacements of the S 1.2 tower top. The displacements in the *X* direction (relative to the reference position) ranged from –0.0358 to 0.0392 m. Such a small order of magnitude of the data values and their changes might have reduced the efficiency possibility of the neural network training; therefore, the values were multiplied by 10^4.

4. Neural network efficiency results

Results presented in the paper were obtained for the following neural network training settings:

- sample time = 60 sec;
- performance goal = 0;
- learning rate = 0.01;
- momentum = 0.9;
- maximum validation failures = 12;
- maximum number of epochs to train = 33333;
- minimum performance gradient = 1e-10;
- epochs between displays (NaN for no displays) = 25;
- maximum time to train in seconds = infinite.

In order to train the designed artificial neural network, the one-way network (up to 3 layers) training was used according to the Leveneberg-Marquardt algorithm.

Figure 2 shows the error histogram obtained from the artificial neural network training with a teacher. On the abscissa axis there are marked absolute error values calculated as the difference between the actual value measured by the GPS device (target) and the response of the neural network $y(t)$ (output). On the ordinate axis there are marked instances. The absolute value of the maximum absolute error obtained from neural network training was $101.3 \cdot 10^{-4}$ m ≈ 0.0101 m, which means that the value was about 10 mm.

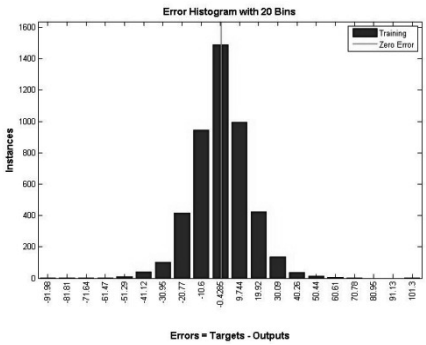

Fig. 2. The neural network training with teacher error histogram

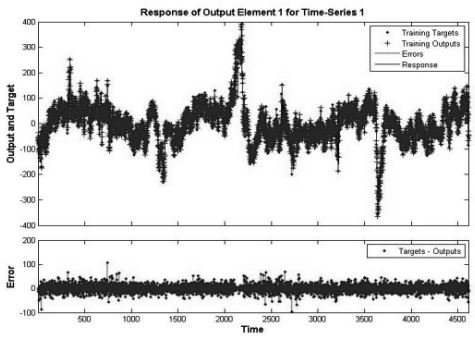

Fig. 3. The comparison of the prognosed displacement with the actual measured data

The comparison of the displacement values in the X direction prognosed by the neural network with the actual measured and recorded displacement values for the considered period is shown in Figure 3. Dot markings in Figure 4 correspond to actual measured values of the displacement. Cross markings refer to the neural network displacement prognosis values. Orange lines represent the instantaneous values of absolute errors (target minus the neural network output $y(t)$). These values are plotted for neural network input signal after changing the order of magnitude by the factor of 10^4.

Figure 4 presents the artificial neural network training performance graph. The ordinate axis corresponds to the neural network training performance function values. The mean square error (mse) was chosen as the neural network training performance function. On the abscissa axis there are neural networks training epochs marked. The best neural network training with a teacher performance was reached for the epoch 33333 and it was equal to 215.7194 of the mean square error value. This value was achieved for neural network input signal values after changing their order of magnitude by 10^4. From the epoch 1 to 33333 one can observe a downward trend. This means that the ANN for each new training epoch achieved a better performance training value. There was no such situation while training for which validation failure occurred one after another for 12 times. Therefore, in accordance to neural network training settings, the epoch 33333 was recognized as the global minimum for the training aim for the set neural network structure (Fig. 1). The mentioned epoch number was set as the maximum number of epochs to train; hence, the training process was completed for this epoch.

Figure 5 presents the regression results for the training for all data assigned to the ANN training with a teacher. Here the ordinate axis represents the neural network output $y(t)$ after

their multiplication by 10^4. On the abscissa axis there are shown values measured by the GPS device (targets) after their multiplication by 10^4. Values returned by the ANN $y(t)$ should be convergent to the abscissa axis values (values measured by the GPS). The $R = 1$ regression result means that there exists an unequivocal relation between the actual value (target; from measurement or simulation) and the neural network output value [2]. The regression for the data assigned to the training reached $R = 0.98052$. The total number of data samples assigned to the network training was 4625.

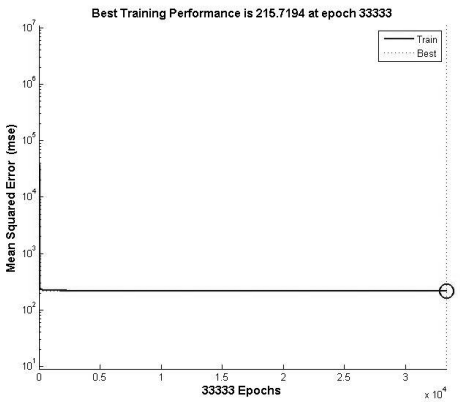

Fig. 4. Artificial neural network training performance graph

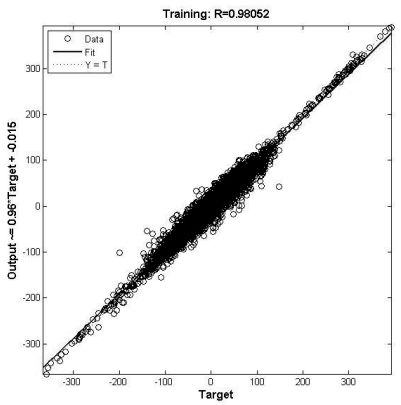

Fig. 5. The regression results for data assigned to the ANN training with a teacher

4. Conclusions and future development of the proposed GPS+ANN method

The neural network training results obtained for the summer period are promising. However, due to different environmental conditions in each season of the year, the applicability of the described neural network system should be assessed for each season separately, as well as for transitional periods between them.

The authors used a focused time-delay neural network (FTDNN) structure type. Nevertheless, they do not preclude the use of a distributed time-delay neural network (DTDNN) structure type.

The subsequent studies of the issue may attempt to reduce the mentioned training error by increasing the maximum number of epochs to train in the artificial neural network training process. Artificial neural networks with one and two hidden layers might also be analyzed, as well as other neural sub-architectures. The research may be performed also for the values imported from the GPS device in other directions (north, east, vertical). Another path of development is to extend the neural network prognosing possibilities by adding the ability to prognose not only regular operating conditions but also catastrophe and failure states. Also, indirect variables, such as the radii vectors, which can be calculated from the imported data, might be studied. The shown prognosis is a short-term one. Naturally, there rises the problem of lengthening the prediction period to a time sufficient (for example) for workers' evacuation; this may be achieved by developing the studied ANN or alternatively proposing a different one to compare them.

Last but not least, the aim of the feasibility study was just to preliminarily state whether it is possible at all to build a network relevant for such mining shaft displacement predictions. Now, having the training phase behind, another data set should be used as material for testing, while only such a procedure can actually give more precise information as to how to develop the studied ANN to the target safety GPS+ANN system that could find actual application.

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