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Suitability assessment of artificial neural network to approximate surface subsidence due to rock mass drainage

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ABSTRACT

Based on the previous studies conducted by the authors, a new approach was proposed, namely the tools of artificial intelligence. One of neural networks is a multilayer perceptron network *(MLP)*, which has already found applications in many fields of science. Sequentially, a series of calculations was made for different *MLP* neural network configuration and the best of them was selected. Mean square error *(MSE)* and the correlation coefficient *R* were adopted as the selection criterion for the optimal network. The obtained results were characterized with a considerable dispersion. With an increase in the amount of hidden neurons, the *MSE* of the network increased while the correlation coefficient *R* decreased. Similar conclusions were drawn for the network with a small number of hidden neurons. The analysis allowed to select a network composed of 24 neurons as the best one for the issue under question. The obtained final answers of artificial neural network were presented in a histogram as differences between the calculated and expected value.

1. Introduction

Exploitation of deep-lying minerals is accompanied by adverse transformations in the ground surface. In addition to the direct effects associated with the resulting post-exploitation void, indirect effects can be distinguished, which include i.a. rock drainage. Formed on the surface of the ground, the so-called drainage basin is usually summed with the direct effects. The subsidence observed on the surface are the sum of these two types of interactions. In the analyses of transformations effects and subsidence forecasts, indirect influences are often omitted due to the low values of these type of subsidence occurring in the vast time horizon. A difficult issue is also the very process of forecasting dewatering-induced changes associated with the complexity of the problem of aquifers compaction.

In the world literature a variety of approaches to modelling this problem, not only in mining areas can be found. A thorough discussion of the existing methods of computation has been included in the publication *"Review of computational models using to subsidence prediction due to fluid withdrawal"* (Witkowski, 2014). An overview of the existing solutions and their usefulness in the prediction process of ground surface and rock mass displacements caused by drainage of water-bearing horizons is presented there. The simplest of the

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cited approaches are empirical methods, which by using the information about the current state of surface deformations allow subsidence prediction in the short term. However, they do not take into consideration physical and mechanical properties of the individual layers of the rock mass. Semi-theoretical models are slightly more complex. They use fundamental physical parameters describing the aquifers. The calculations are based on generalized information about the geological conditions without taking into account the complexity of the compaction process of compressible layers. Another approach that can be distinguished in the prediction of drainage changes is hydrogeological modelling, in which the problem of fluid flow and rock medium deformations is perceived theoretically. Such a solution in a complete manner describes the phenomenon and does not require large amounts of measurement data, but also adopts assumptions simplifying the complex nature of compaction phenomenon. Repeatedly, the computational process must be preceded by the calibration of the theoretical model formed for the local geological conditions. Another of the approaches to the issue are solutions based on the theory of influence functions. However, they also adopt considerable simplifications and require the appointment of local values of the theory parameters based on geodetic survey data.

With this critical overview of the existing solutions follows the concept of employing a different approach to the prediction of dewatering-induced changes. Treating the compaction process as complex and difficult to describe thoroughly, using classic methods of calculation, it has been decided to use methods of artificial intelligence. Testing the concept outlined above will enable the verification of the working thesis. In the light of this thesis, the mathematical tools, which are artificial neural networks can be regarded as universal approximators that can successfully reproduce the compaction process of aquifers.

In this paper, it has been decided to use a multi-layer perceptron (*MLP*) network to set large-surface approximation of drainage basin in the area of one of the Polish underground mines. The task which was given for the network was to process measurement information to determine the mapping process.

2. Methods

Knowledge of the construction and operation of the human brain has allowed the development of a separate field of science called artificial intelligence. Widely developing branches are i.a. artificial neural networks, which are successfully used in engineering problems (Tadeusiewicz, 1993, 2013). Each network consists of single neurons of different types and structure. In 1943, one of the first models of the *McCulloch-Pitts* neuron (Osowski, 2006) was formed, which sums input signals x_i to the neuron with appropriate weights w_i and compares them with the assumed threshold w_{i0}. Output signal y_i is expressed by:

$$y_i = f\left(\sum_{i=1}^{N} w_i x_i + w_{i0}\right) \tag{2.1}$$

Function f is called activation function, which in the model of the *McCulloch-Pitts* neuron adopts the form of step-function:

$$f(u) = \begin{cases} 1, & u > 0 \\ 0, & u \le 0 \end{cases} \tag{2.2}$$

Similarly as in a nerve cell, the sum of all excitations must be greater than the threshold of a nerve cell activation. Only in this case, an electric signal can be sent in the form of a nerve impulse. Likewise, in the presented neuron model, the appropriate product sum of signals and weights can allow the activation of the neuron as an output signal $y_i = 1$. In addition to the presented neuron, there are a number of other models such as neurons of sigmoidal, radial, the Adaline, instar and Grosseberg's outstar, the WTA and Hebb type as well as stochastic model of a neuron. The most popular model from the utilitarian point of view is the sigmoidal neuron with a continuous function with unipolar activation in the form:

$$f(x) = \frac{1}{1 + e^{-\beta x}} \tag{2.3}$$

or a bipolar function in the form:

$$f(x) = tgh(\beta x) \tag{2.4}$$

where β is a parameter selected by the user and determines the shape of the activation function.

Only a juxtaposition of many neurons in a coherent system creates an artificial neural network and determines its ability to process signals similarly to the human body. Depending on the way of signal flow through the structure, one-way or recursive networks with the so-called reciprocal action be distinguished. Among the many existing models of neural networks, the most popular can be considered the one-way, multi-layered artificial neural network with sigmoid activation function also known as multi-layer perceptron (MLP) network. The most important problem in creating a network is an optimal choice of connection weights between neurons. They contain all the acquired and generalized “knowledge”. The most optimal selection of weights takes place in the process of network learning. It can occur in two variants, supervised learning (with a teacher) or unsupervised learning (without a teacher). The first method is performed by comparing the responses from the network with pre-set, expected values. On their basis the objective function is minimized. Adoption of continuous activation function allows the use of gradient network learning methods such as steepest descent method, variable metric algorithm and *Levenberg–Marquardt* algorithm considered the most effective in the artificial neural networks learning (Osowski, 2006). Properly trained network is able to generalize the acquired knowledge. It can be said that in this way the network becomes a universal approximator of several variables function, realizing some nonlinear mapping of input vector $\boldsymbol{x}$ into the expected response vector $\boldsymbol{y}$:

$$\boldsymbol{y} = f(\boldsymbol{x}) \tag{2.5}$$

In the engineering problems, artificial intelligence is used for such issues as approximation and interpolation, pattern recognition and classification, data compression, prediction, control and identification (Osowski, 2006; Tadeusiewicz, 2013).

Artificial neural networks have been applied also in scientific fields such as geology (Subbaiah, 2011; Xia-Ting, Young Jia, & Jian Guo, 1996; Zhu et al., 2013), hydrology (Adamowski & Chan, 2011; Ghose, Panda, & Swain, 2010; Kumar, Raghuwanshi, & Singh, 2010; Li, Shu, Liu, Yin, & Wen, 2012) or surface protection (Ambrožič & Turk, 2003; Gruszczyński, 2007; Jung, Cheon, & Choi, 2005; Kim, Lee, & Oh, 2008; Lee, Park, & Choi, 2012; Oh & Lee, 2011; Park, Choi, Jin Lee, & Lee, 2012; Pawluś, 2007; Yang & Xia, 2013; Zhang, Liu, & Liu, 2011).

3. Field studies

In order to monitor the development of depression cone in the subsequent water-bearing complexes, a vast network of piezometers going far beyond the mining area of the mine has been formed (Fig. 1). Performed periodic measurements of free surface of water helped to determine the course of the piezometric surface in the subsequent years of deposit exploitation. In the analysed area, four water-bearing complexes can be distinguished, which consist of a network of devices in the form of:

- 9 piezometers in I aquifer,
- 21 piezometers in II aquifer,
- 44 piezometers in III aquifer,
- 8 piezometers in IV aquifer.

The first pizometric measurements were made nearly forty years ago. In subsequent years, the network of the observed piezometers was gradually enlarged. Unfortunately, with the passage of time some of the equipment was destroyed or became obstructed. By 2011, there were only 45 devices well-functioning, which represents only 55% of all the piezometers installed in the history of the mine. Due to the limited number of devices in different aquifers, information about pizometric pressure changes repeatedly cover only part of the mining area (Fig. 2). In the case of artificial neural networks, deficiencies in the information held can be adopted. As far as possible, such situations should be avoided since incomplete information may disrupt the learning process and especially the desired generalization of the acquired knowledge. However, in the undertaken task, it has been decided to use the existing information and allow the neural network to locate the relationship between the assumed cause of the phenomenon and the observed effect on the surface.

All information has been collected and processed in the *GIS*-type programme. Using the available tools, the learning vectors have been prepared that were used in subsequent analyses. Due to the incompleteness of both, the geological and piezometric data, there were areas with limited information, which is presented in Fig. 2. The sample gaps in data have been marked in red. Fig. 2 shows two vectors for which the collected information can be seen as good *(a)* and as weak *(b)*. A total of 700 learning vectors have been prepared for the analysis.

Finally, it was decided at the entrance to the network to use information such as:

- information from a network of piezometric holes (changes in piezometric levels) – assuming that the change in the pressure existing in the aquifer initiates the process of medium compaction;
- thickness of the individual aquifers – the bigger, the larger the expected medium compaction in your area;
- information on the location of the main fault in the vicinity of the mining area – it is a natural hydrogeological window, which influences the distribution of dewatering-induced displacements on the surface of the ground.

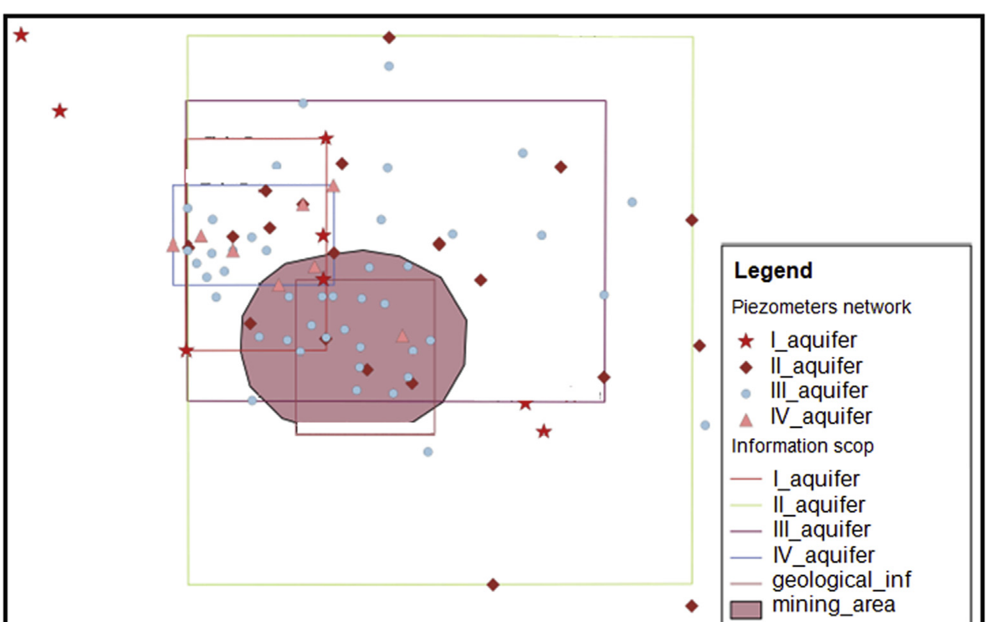

Fig. 1 – The range of current information on individual aquifers and their geology.

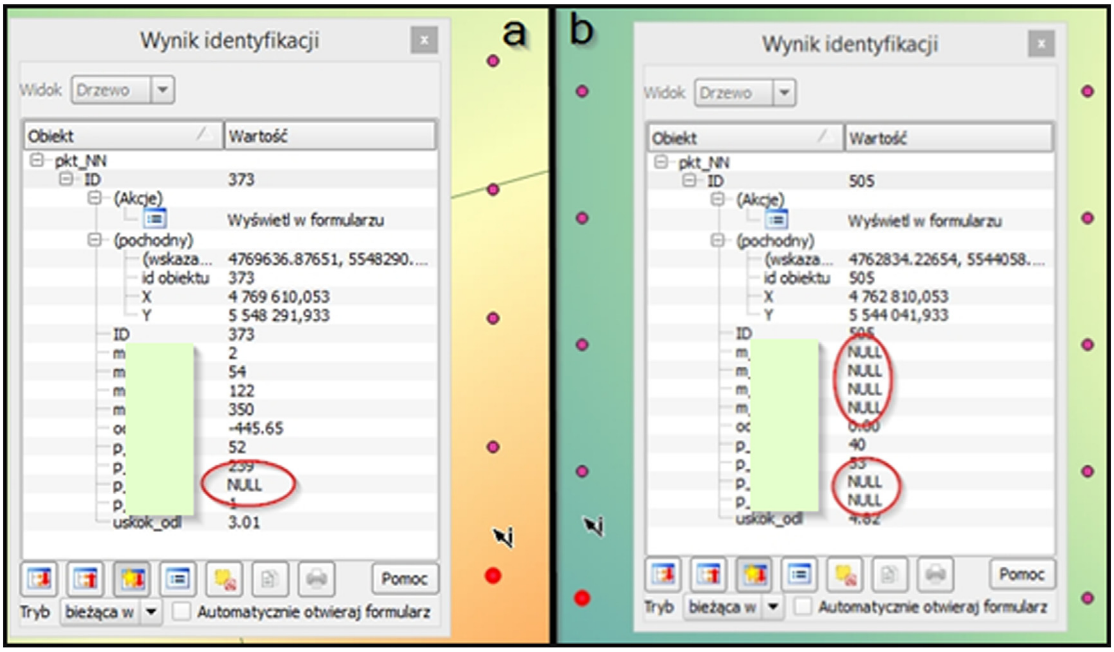

Fig. 2 – Examples of training vectors with a good (a) or weak (b) information.

4. Results and discussion

Using the information previously presented, learning data sets **x** have been created in three variants. The first one assumes training a network based solely on the value of piezometric pressure changes in the subsequent aquifers. In the second one, additionally the information about the thickness of each compressible layer was used. The third variant was accompanied by information about the distance from the fault zone. The whole of the analyzes was performed using *Matlab R2010a* software with an available extension *Neural Network Toolbox*. In the analyzes it has been decided to use a multi-layered perceptron network *MLP* with one hidden layer. For the first layer, a bipolar sigmoid activation function of the parameter $\beta = 1$, was adopted whereas for the input layer a linear activation function was adopted. In the following calculations were used 2, 4, 8, 12, 16, 20, 24, 28, 32, 36, 42, 48, 56, 64, 72, 84, 92 and 100 neurons in the hidden layer. For each of the networks, a training process was performed 30 times with initialization of connection weights each time. In the learning process, an implemented *Levenberg–Marquardt* algorithm was used. Calculations were performed using pre-prepared information in the form of 700 learning vectors. The fragment of values accepted for the calculation is presented in Table 1 where:

– *w* – value of dewatering-induced subsidence;
– *dh_I* – *dh_IV* – value of pizometric surface subsidence;
– *odl_us* – distance from the fault zone;
– *m_I* – *m_IV* – thickness of particular aquifers.

In the first stage of the calculations, each of the information was used independently such as height change of piezometric levels *(Piezo)*, the distance from the fault zone *(Odl)* and the information about the thickness of aquifers *(Geol)*. As an assessment criterion, mean square error *(MSE)* was adopted, calculated in the validation process of neural network. The resulting error values from the trained network in the first stage of the calculation is shown in figure (Fig. 3). It is clearly visible that information about pizometric pressure change *(Piezo)* result in lower error values in relation to the remaining two variants.

In the next stage of the network learning process, it was decided to use a combination of the existing information. Simultaneous use of piezometric and geological data reduced

Table 1 – Fragment of data used for neural network training.

ID	w [mm]	dh_I [m]	dh_II [m]	dh_III [m]	dh_IV [m]	odl_us [km]	m_I [m]	m_II [m]	m_III [m]	m_IV [m]
344	330.81	1	39	200	–	3.02	–	–	–	–
345	407.19	1	47	218	–	3.63	53	2	120	349
346	457.80	1	54	230	–	4.23	52	1	121	344
347	480.25	–	61	237	–	4.84	46	1	122	341
348	486.52	–	66	240	–	5.44	40	2	123	335
…										

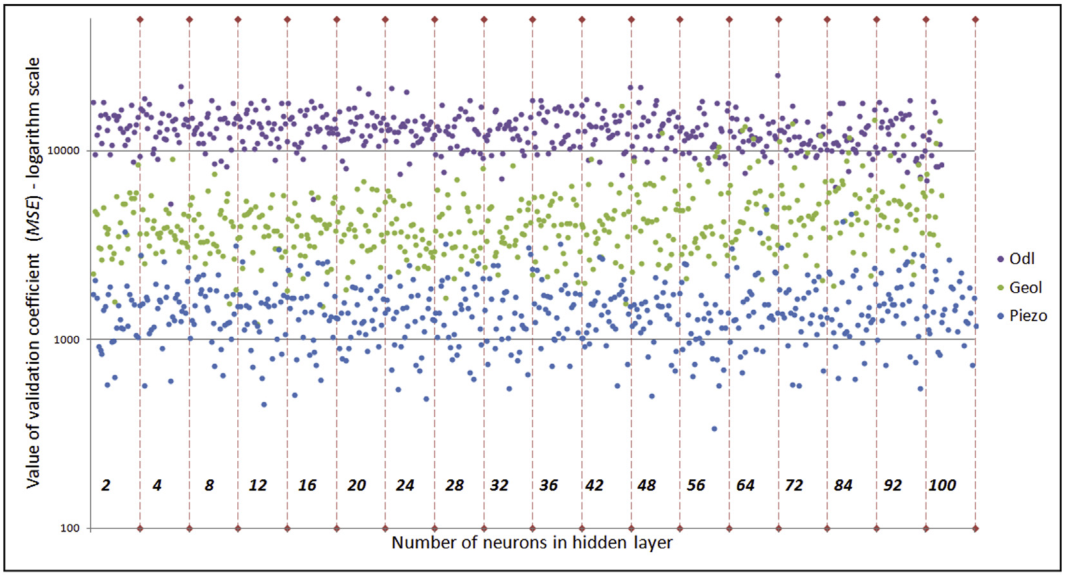

Fig. 3 – Graph of *MSE* values for the different input data.

error values (Fig. 4 – *Piezo_geol*). Adding the information about the distance from the fault zone resulted in a further improvement of the obtained results. However, as the graph shows, in this case there were problems with determination of the optimal solution which was seen in the form of randomly occurring extreme values of errors (Fig. 4 – *Piezo_geol_odl*). A zone was also clearly marked in which the selection of an appropriate amount of hidden neurons enhances the learning process. Up to 12 neurons, hidden values of errors hardly fall below 100. It is only in the range of from 16 to 24 hidden neurons that occasionally low error values of *MSE* are observed.

The degree of adjusting the data to the expected value is demonstrated by the correlation coefficient (*R*), assigned to each cycle of calculation. Fig. 5 shows the distribution of this value in subsequent calculations, for different numbers of hidden neurons. The coefficient adopts a value in the range from 0.55 to 0.99. An area can be distinguished for 24 and 28 hidden neurons, where the correlation did not fall below 0.95. Taking into account this fact and the previous findings, it was decided to carry out a final calculation for the structure with one hidden layer composed of 24 neurons. A mean square error within the limits of 100 and correlation coefficient at the level of 0.98 were expected. The final network has been trained in 21 computing ages obtaining *MSE* equal to *100.1* with a correlation coefficient of *0.998*. Responses obtained as a result of modelling were compared with input values, measured in the area of drainage-induced subsidence. The difference in the obtained results was presented in the figure in the form of a histogram distribution of differences (Fig. 6). In most cases the differences in the network response and measurements fluctuated in the range of 15 mm. Single points

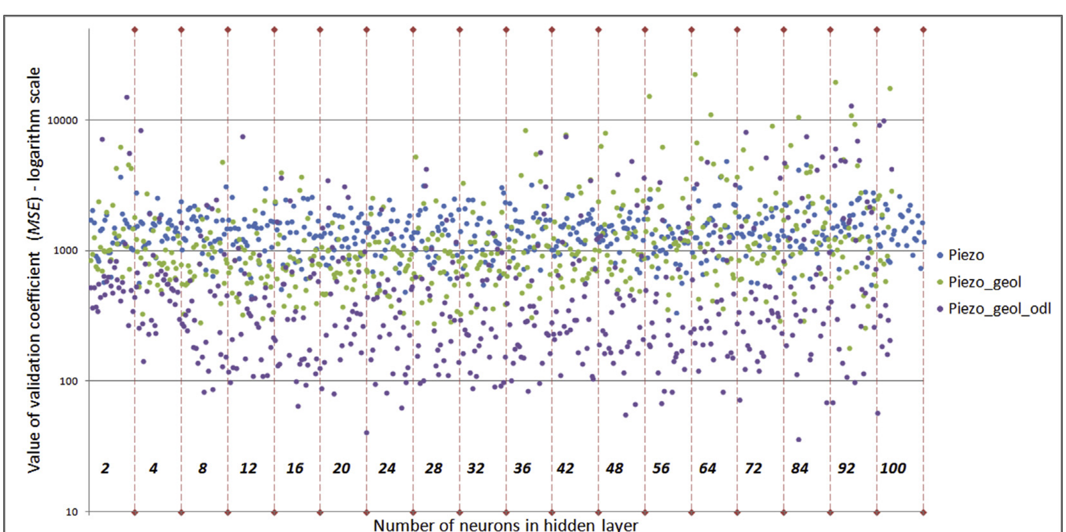

Fig. 4 – Graph of *MSE* values in the variant of combining input data.

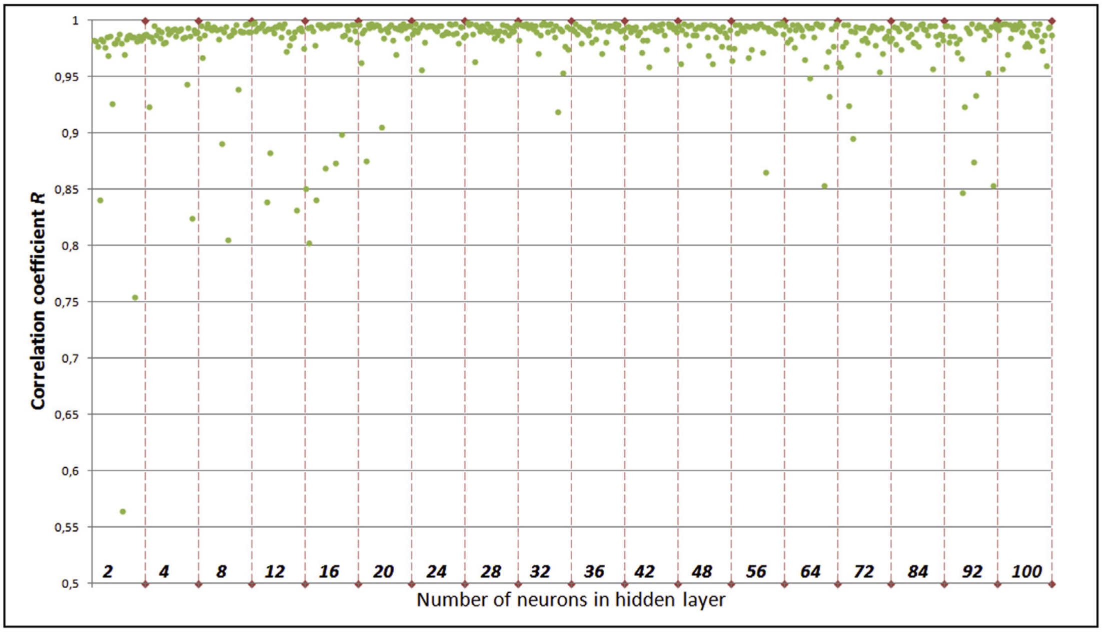

Fig. 5 – Graph of the correlation coefficient value of the obtained networks responses.

received higher or lower values. In conclusion, it can be said that so network prepared in this way well-approximated the set surface despite the incompleteness of the training data.

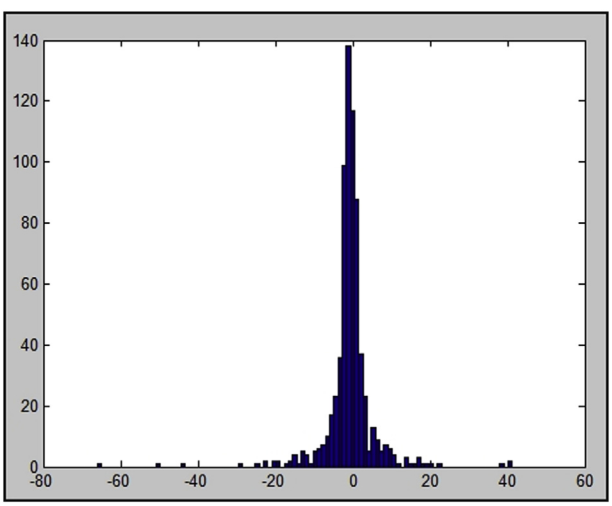

Fig. 6 – The histogram with value differences of the network response and the input data [mm].

5. Conclusions

Artificial intelligence tools provide a good tool for solving engineering problems. The quoted brief review of the literature shows the versatility of this tool in selected areas of science. The aim of the experiment was to measure the problem of limited information coming from the mining area in the context of training and proper operation of an artificial neural network. Based on the carried out studies the following conclusions can be drawn:

– artificial neural networks can successfully be used in problems connected with approximation of changes caused by the carried out rock mass drainage;
– the developed neural network allows the performance of calculations for incomplete input information;
– the use of 24 neurons in the hidden layer assures the acceptable accuracy of calculations and appropriate level of knowledge generalization;
– the resulting network model allows the drainage basin to be approximated with an error at the level of 15 mm.

The next steps in the research will rely on the analysis of the network other than the *MLP* of the presented issue. Ultimately, a model of vertical displacements prediction induced by rock mass drainage will be made.

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REFERENCES

Adamowski, J., & Chan, H. F. (2011). A wavelet neural network conjunction model for groundwater level forecasting. *Journal of Hydrology*, *407*(1-4), 28–40. http://dx.doi.org/10.1016/j.jhydrol.2011.06.013.

Ambrožič, T., & Turk, G. (2003). Prediction of subsidence due to underground mining by artificial neural networks. *Computers & Geosciences*, 29(5), 627–637. http://dx.doi.org/10.1016/S0098-3004(03)00044-X.

Ghose, D. K., Panda, S. S., & Swain, P. C. (2010). Prediction of water table depth in western region, Orissa using BPNN and RBFN neural networks. *Journal of Hydrology, 394*(3-4), 296–304. http://dx.doi.org/10.1016/j.jhydrol.2010.09.003.

Gruszczyński, W. (2007). *Zastosowanie sieci neuronowych do prognozowania deformacji górniczych* [*Application of neural networks for prediction of mining-induced deformations*]. Doctoral dissertation. Kraków: Akademia Górniczo-Hutnicza.

Jung, Y. B., Cheon, D. S., & Choi, S. O. (2005). Estimation of subsidence due to mining using artificial neural network. In Y. Erdem, & T. Solak (Eds.), *Preliminary study. Underground Space Use: Analysis of the Past and Lessons for the Future* (pp. 297–302). London: Taylor & Francis Group.

Kim, K. D., Lee, S., & Oh, H. J. (2008). Prediction of ground subsidence in Samcheok City, Korea using artificial neural networks and GIS. *Environmental Geology, 58*(1), 61–70. http://dx.doi.org/10.1007/s00254-008-1492-9.

Kumar, M., Raghuwanshi, N. S., & Singh, R. (2010). Artificial neural networks approach in evapotranspiration modeling: a review. *Irrigation Science, 29*(1), 11–25. http://dx.doi.org/10.1007/s00271-010-0230-8.

Lee, S., Park, I., & Choi, J. K. (2012). Spatial prediction of ground subsidence susceptibility using an artificial neural network. *Environmental Management, 49*(2), 347–358. http://dx.doi.org/10.1007/s00267-011-9766-5.

Li, X., Shu, L., Liu, L., Yin, D., & Wen, J. (2012). Sensitivity analysis of groundwater level in Jinci Spring Basin (China) based on artificial neural network modeling. *Hydrogeology Journal, 20*(4), 727–738. http://dx.doi.org/10.1007/s10040-012-0843-5.

Oh, H. J., & Lee, S. (2011). Integration of ground subsidence hazard maps of abandoned coal mines in Samcheok, Korea. *International Journal of Coal Geology, 86*(1), 58–72. http://dx.doi.org/10.1016/j.coal.2010.11.009.

Osowski, S. (2006). *Sieci neuronowe do przetwarzania informacji (wyd. II) [Neural networks for information processing* (2nd edition). Warszawa: Oficyna Wydawnicza PW.

Park, I., Choi, J., Jin Lee, M., & Lee, S. (2012). Application of an adaptive neuro-fuzzy inference system to ground subsidence hazard mapping. *Computers & Geosciences, 48*, 228–238. http://dx.doi.org/10.1016/j.cageo.2012.01.005.

Pawluś, D. (2007). Prognozowanie osiadań powierzchni terenu przy użyciu sieci neuronowych [Prediction of surface subsidence using neural networks]. *Górnictwo i Geoinżynieria, 31*(3), 329–335.

Subbaiah, R. (2011). A review of models for predicting soil water dynamics during trickle irrigation. *Irrigation Science, 31*(3), 225–258. http://dx.doi.org/10.1007/s00271-011-0309-x.

Tadeusiewicz, R. (1993). *Sieci neuronowe* [*Neural networks*]. Warszawa: Akademicka Oficyna Wydawnicza RM. Seria Problemy Współczesnej Nauki i Techniki. Informatyka.

Tadeusiewicz, R. (2013). *Biocybernetyka: metodologiczne podstawy dla inżynierii biomedycznej* [*Biocybernetics: methodological basis for biomedical engineering*]. Warszawa: Wydawnictwo Naukowe PWN.

Witkowski, W. T. (2014). Review of computational models using to subsidence prediction due to fluid withdrawal. In 15. *Geokinematischer Tag, 15. und 16. Mai 2014, Freiberg* (pp. 117–127).

Xia-Ting, F., Young Jia, W., & Jian Guo, Y. (1996). A Neural Network Model for Real-time Roof Pressure Prediction on Coal Mines. *International Journal of Rock Mechanics and Mining Sciences, 33*(6), 647–653.

Yang, W., & Xia, X. (2013). Prediction of mining subsidence under thin bedrocks and thick unconsolidated layers based on field measurement and artificial neural networks. *Computers & Geosciences, 52*, 199–203. http://dx.doi.org/10.1016/j.cageo.2012.10.017.

Zhang, H., Liu, L., & Liu, H. (2011). Mountain ground movement prediction caused by mining based on BP-neural network. *Journal of Coal Science and Engineering(China), 17*(1), 12–15. http://dx.doi.org/10.1007/s12404-011-0103-7.

Zhu, L., Gong, H., Li, X., Li, Y., Su, X., & Guo, G. (2013). Comprehensive analysis and artificial intelligent simulation of land subsidence of Beijing, China. *Chinese Geographical Science, 23*(2), 237–248. http://dx.doi.org/10.1007/s11769-013-0589-6.