Article citation info:
RYMARCZYK T, KŁOSOWSKI G. Application of neural reconstruction of tomographic images in the problem of reliability of flood protection facilities. Eksploatacja i Niezawodnosc – Maintenance and Reliability 2018; 20 (3): 425–434, http://dx.doi.org/10.17531/ein.2018.3.11.

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APPLICATION OF NEURAL RECONSTRUCTION OF TOMOGRAPHIC IMAGES IN THE PROBLEM OF RELIABILITY OF FLOOD PROTECTION FACILITIES

ZASTOSOWANIE NEURONOWEJ REKONSTRUKCJI OBRAZÓW TOMOGRAFICZNYCH W PROBLEMATYCE NIEZAWODNOŚCI ZABEZPIECZEŃ PRZECIWPOWODZIOWYCH*

The article presents an innovative concept of enhancing the flood embankments and landfills monitoring. The key advantage of such a solution is to obtain a more detailed distribution of components within a flood barrier. It leads to more early and sufficient threat detection, considering the exploitation of the building, thus - a vast enhancement of an embankment's performance. The method is based on implementing a neural system, composed of a number of parallelly-working neural networks. Each of them generate a singular point of final output view. By implementing such monitoring measures it is possible to successfully reconstruct two-and-three dimensional models of flood barriers and dams - including possible breaches and damages within its inner structure. An important advantage of such a solution is the possibility of replacing the systems that monitor hydrotechnical facilities pixel-by- pixel by neural imaging. The performed research leads to solving the problem of low resolution of such images. As this problem was of crucial value to tomographic imaging method, it was a main obstacle to the development of neural reconstruction method. Moreover, as the results may be obtained in real-time and at various levels, these new functionalities stand out in comparison to currently used methods for monitoring protective banks.

Keywords: *electric tomography, flood embankments and landfills, hydrotechnical facilities exploitation, neural networks, numerical methods.*

W artykule zaprezentowano nowatorską koncepcję usprawnienia monitoringu wałów i zapór przeciwpowodziowych. Główną przewagą nowego rozwiązania nad znanymi metodami jest uzyskanie dokładniejszego rozkładu komponentów wnętrza zapory, co zasadniczo przyczynia się do wczesnego i niezawodnego wykrycia zagrożeń związanych z eksploatacją tego typu budowli. Dzięki temu, zastosowanie nowej metody spowoduje wzrost niezawodności zabezpieczeń przeciwpowodziowych. W opisywanej metodzie założono wytrenowanie systemu neuronowego złożonego z wielu działających równolegle sieci neuronowych, z których każda generuje pojedynczy punkt obrazu wyjściowego. Powyższy sposób, uwzględniający jednoczesne zastosowanie wielu sieci neuronowych, umożliwia skuteczną realizację trudnych zagadnień rekonstrukcji obrazów dwu i trój-wymiarowych, w tym obrazowanie uszkodzeń i przecieków wnętrza zapór przeciwpowodziowych. Ważną zaletą prezentowanej metody jest możliwość zastąpienia obrazowaniem neuronowym wielu innych, obecnie stosowanych systemów, które monitorują budowle hydrotechniczne w sposób punktowy. Przeprowadzone badania umożliwiają rozwiązanie problemu niskiej rozdzielczości obrazów tomograficznych, co stanowi główną barierę rozwoju tych metod w odniesieniu do dużych budowli ziemnych. Poprawa rozdzielczości rekonstruowanych obrazów, a także możliwość ich uzyskiwania w różnych przekrojach w czasie rzeczywistym, są nowymi funkcjonalnościami, które wyróżniają obrazowanie neuronowe na tle obecnie stosowanych metod monitoringu wałów i zapór przeciwpowodziowych.

Słowa kluczowe: *tomografia elektryczna, zapory i wały przeciwpowodziowe, eksploatacja budowli hydrotechnicznych, sieci neuronowe, metody numeryczne.*

1. Introduction

The exploitation of flood defences - such as dams and flood banks - is of key value that heavily impacts the security of people, animals and plants that lay within the area of the object. There are two main types of issues that may appear as a result of improper exploitation of such pieces of infrastructure. The first threat is a physical damage of the embankment, which may result in a breach. The other is the leakage of such a structure - in case of reservoirs that contain fluid chemical compound waste it might lead to a vast range of contamination. Both types of breaches may result in [25]:

– endangering both people and animals' lives and cause an evacuation;
– closing public responsibility facilities, such as administration, hospitals or schools;
– increasing the possibility of epidemic, epizootic or epifitozic outbreaks;
– increasing the possibility of a plague of insects or rodents;
– destruction of stock and harvest in agricultural holdings (weakening the economical state of food industry, an increase of food supplies prices, a need to compensate the entrepreneurs who process and sell food);

(*) Tekst artykułu w polskiej wersji językowej dostępny w elektronicznym wydaniu kwartalnika na stronie ***www.ein.org.pl***

– destruction and damaging buildings (houses, utility buildings and public utility buildings);
– infrastructural damage (including roads, bridges, fly-overs, tunnels, dams, pumping stations, hydrotechnical devices, water mains and sewer networks-related devices);
– destruction in energy-production infrastructure - including generation, transmission and distribution of electricity and heating;
– disruptions in the functioning of communication and teleinformation systems;
– damage dealt to communication traction, accidents caused in industrial plants;
– malfunctioning of the fuel distribution system;
– possible increase in criminality as well as an increased number of common offenses (such as burglary, robberies, property destruction).

What is more, the penetration of chemical waste through embankments creates such hazards as the possibility of local environment contamination, as well as damage to installations and technical equipment. Also, it may cause a release of harmful substances and - consequently - a degradation of the natural environment.

Floods are considered to be natural disasters that cause particularly many tragedies [3, 7]. One of the means of ensuring the safety of flood-endangered areas near the flotation tailings landfills and rivers is to raise the flood embankments [18]. Considering the insufficient filtration capacity of the embankment, the high water level may cause leaks, which results in partial or complete destruction of the hydrotechnical building [19].

As breakdowns lead to serious consequences, such technical facilities such as dams, embankments and other flood defences are equipped with various systems to increase their reliability. Embankment and dam exploitation systems include both adequate means of service as well as a code of operating activities designed as a set of strict procedures and instructions. This kind of guide set a universal standard which should be followed. These include, among others, tips regarding the frequency and method of inspections, tests, measurements and technical inspection of the facility, as well as a list of hydrotechnical building elements to be observed - along with a list of parameters that should be measured. The aforementioned registry constitute evidence of keeping constant observation, monitoring and measurements which are key elements of embankments and flood control dams. In most cases, flood protection security systems are extensive and vastly complex. They consist of many subsystems whose proper functioning affects the reliability of these objects. Typical subsystems included in embankments and flood control systems include hydrological protection systems, alarms, energy systems, mechanical water flow regulation systems and, as well as computer-aided decision support software.

In order to ensure effective monitoring of these systems, appropriate methods should be used. Computer-aided decision support systems play a special role in the integration of other pieces of software as well as decision-making automation. The latter consists of identifying and forecasting specific threats together with the probability of their occurrence. The final decision regarding the response to the results is always made by a human. Below, there are listed currently used monitoring methods - in the context of the Extraction Waste Treatment Facility Żelazny Most KGHM POLSKA MIEDŹ S.A. It is the largest hydrotechnical facility in Poland and one of the largest facilities of this type in the world. The monitoring methods used there can be divided into two groups: means related to the current behavior of the structure and its reliability, and those related to the impact of the structure on the surrounding natural environment. The first group includes the following monitoring methods: visual assessment of technical condition (direct observation carried out by employees), geodetic monitoring (detection of structural deformation by manual measurements with benchmarks and automatic using micromirrors), geotechnical monitoring (detection of anomalies in the geological structure of the native substrate embankments and reservoirs through deep drilling and pressure probes), hydrogeological monitoring (detection of anomalies which result in embankment leakage by observing piezometric pressures in piezometers installed in the waste mass, embankments and near and far foreground), seismic monitoring (detection of structural stability disturbances by means of accelerometers that are triggered each time they identify vibrations at a certain level), information systems for the analysis of large data sets (Big Data). The prevention on surrounding natural environment include hydrological monitoring (detecting leaks) and chemical monitoring (detection of contamination that affects groundwater).

The global trend of IT and communication technology development is reflected in the increase in the importance of IT flood protection systems. The extensive measurement systems provide a great deal of data collected from different points of flood defence. One of the main tasks of IT systems installed in hydrotechnical facilities is to create mathematical models based on the information provided. Currently used IT systems implement a wide variety of methods. The deterministic methods include the Fellenius one, which makes it possible to assess the degree of embankment stability by dividing the potential landslide mass into vertical blocks (belts). This method is also known as the Petterson-Fellenius or the Swedish method [4]. An example of a statistical quantitative method is the HST model (Hydrostatic-Season-Time). The empirical HST model is widely used for the analysis of various types of measurement data on flood embankments and dams [6]. Another group of methods used to improve the risk of flood barriers breach are probabilistic ones. It may be exemplified by the first order reliability method (FORM), by means of which the mode of longitudinal damage of a long embankment consisting of homogeneous soils can be examined [9]. In order to increase the reliability of earth structures, together with the FORM method the Hasofer-Lind reliability index can be applied [13]. Harmonic analysis is also one of the methods used in exploitation processes [11].

A frequent problem with flood dams is insufficient water filtration causing the so-called sub-penetration. In the literature one can find propositions of methods to calculate the probability that such phenomena will occur [15].

Another group of intelligent stochastic methods used by IT systems in order to increase the reliability of exploitation processes, including embankments and flood barriers, are heuristic methods based on fuzzy logic [14, 22, 24]. Less frequently used methods to obtain the same purpose are: integer linear programming [10], Support Vector Machine [17], non-linear criterion of shear stability [23], and artificial neural networks (ANN) [1, 8]. Currently, the main application area of ANN are predictive issues which aim at enhance exploitation processes by identifying [16] or classifying faults [26].

As previously mentioned, flood protection facilities belong to the category of hydrotechnical constructions. The analysis of procedures and rules of exploiting this type of objects allows to notice one of the main processes that ensure a proper course of operations, being observation of current behavior and phenomena detection. Due to their specificity, they may indicate irregularities threatening the safety of the building. Current methods of monitoring technical facilities such as flood banks and dams have, however, numerous disadvantages. The first of them are apparently high usage costs. Most of the currently used methods require the involvement of specialists, which means that labor is an important element of such expenses. In addition, the measurement systems require investments for repairs, maintenance, spare parts and materials that wear out. Also, an important disadvantage is usually a late threat detection. In the case of systems that are not a component of integrated IT systems, information about the threat reaches the relevant services within a few hours' delay. The delay depends on the frequency with which the readings of the measuring devices are included in the procedures. The effectiveness of monitoring methods that are by now implemented is also insufficient [4, 5]. Due to the point character of the measurements, there is a great uncertainty of the conclusions drawn on their basis. Probes and sensors placed in various places on the embankment do not give the possibility of obtaining full knowledge about its current state. There is a serious risk that defects appearing inside the flood dam (cracks, changes in the internal structure, changes in composition and density of the earth, etc.) will not be detected early enough to enable them to be corrected. In order to get the most complete knowledge about the technical condition of the facility, it is necessary to use many monitoring methods at the same time. In order to simplify the way of monitoring the facility and the application procedure, there is a clear need to develop one effective method, ensuring the speed and reliability of collecting, transferring and processing of information about existing threats. Most of the mentioned disadvantages would be eliminated if it was possible to develop a new method of technical condition assessment that would gather a current stream of data concerning differences in the internal structure of the flood defence. One of the potential methods to achieve this goal is electrical tomography [2, 12]. The tomography generates the image of the tested object interior. This method is mainly used in medicine and material engineering. The main obstacle of tomographic methods development in flood embankments and dams monitoring is the lack of appropriate technology that would provide a significant improvement in image resolution.

This article presents a new approach to the operational problem of object monitoring using neural imaging. Previous attempts to use artificial neural networks in electrical tomography have focused on the use of individual neural networks to process input signals into images. During the research, an improved method of neural tomographic reconstruction was developed. Its characteristic feature is the usage of a neural network system in which each network generates the color of a single pixel on the image grid. Thanks to the original architecture of the intelligent imaging system, a new functionality was obtained with reference to known tomographic methods, which consisted in increasing the resolution of cross-section images of scanned hydrotechnical objects.

2. Neural reconstruction of tomographic images

The neural reconstruction of tomographic images presented in this article is a new method aimed at increasing the resolution of images, and thus enhancing the flood protection monitoring effectiveness. The algorithm makes it possible to eliminate the main operational problems of hydrotechnical facilities connected with their monitoring. Tomography supported by a neural system gives new possibilities for surveillance. The presented concept create an accurate, three-dimensional image of the interior of a hydrotechnical building in real time. This is the key functionality that lessens the importance of maintaining the majority of existing subsystems of flood protection monitoring. Currently used monitoring systems (geodetic, geotechnical, hydrological, etc.) relate to obtaining point data regarding selected object parameters. Later on, obtained incomplete information is subject to analysis, both by IT systems and by specialists who perform the final assessment of the dam condition. Such an assessment process has major disadvantages resulting from measuring points, measurement errors, lack of real-time monitoring and subjectivism in evaluating the status of the subject technical object. The method depicted in this article is free from the above restrictions, as it results in obtaining sharp, colorful, three-dimensional images of the interior of the dams and flood dams bodies in high resolution and in real time. The obtained images are easy to analyze because they faithfully reproduce all changes taking place inside flood embankments and dams. Phenomena such as: cracks, changes in the structure of internal layers, moisture increase or density changes are immediately visible. The comparison of images recorded at regular intervals make it possible to determine the pace of changes that are taking place within the structure. This is a very valuable functionality because it provides a solid basis for making accurate and reliable predictions about the sources, directions of development, type and area of damage developing inside the building.

3. Neural system to reconstruct tomographic images - modelling

The presented solution is an improvement of the already known electrical tomography. A number of electrodes are placed in the body of the flood embankment. Then, a source of electric current with certain parameters (voltage, current, frequency, amplitude) is connected to different electrodes. The voltage values between the respective electrodes are read and recorded. The aforementioned voltage values are the input vector, on the basis of which the neural system generates images of the interior of the dam. It is assumed that the values of electric parameters read out from electrodes are closely dependent on the material from which the flood defence is made. Any changes in the internal structure of the dam caused by moisture, leakage, structure breakage, landslides and any other anomalies, are reflected in the values of the current-voltage parameters read from the electrodes. To confirm the above assumptions, a mechanism for converting electrical signals into high-resolution color images has been developed.

3.1. The means of data gathering

The real-life object of the research was the barrage of the Żelazny Most Flotation Wastes Depository located in the south-western part of Poland between Lubin and Głogów. The reservoir is located in a natural valley between moraine hills in the upper part of the Rudna river catchment. The management of the disposal facility is KGHM "Polska Miedź" S.A. Branch Hydrotechnical Plant in Rudna [21]. The "Żelazny Most" facility is intended for storing flotation waste from the Red Ore Enrichment Plants: Polkowice, Lubin and Rudna. Currently, it is the only place for depositing flotation waste from all mines. Due to the area occupied, the "Żelazny Most" landfill is one of the largest facilities of its kind in the world [20]. The total length of dams surrounding the reservoir is over 14 km. The total area of the landfill is 1410 ha. The height of the dams at the highest point reaches 55 m. The topographic model of the Żelazny Most reservoir is shown in Fig.1.

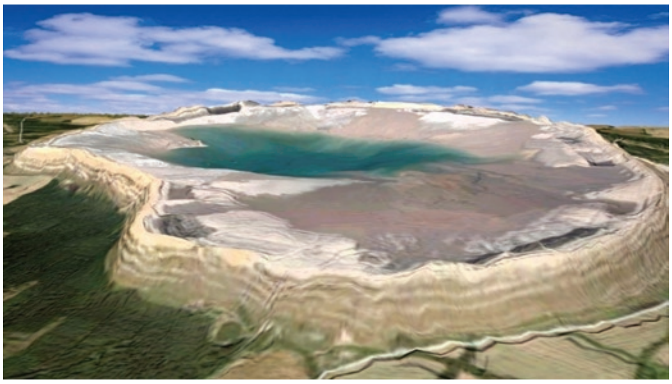


Fig. 1. Topological model of the Żelazny Most Flotation Wastes Depository

The facility has been equipped with various diagnostic and control-measurement systems, whose task is to ensure a high degree of reliability of the Żelazny Most reservoir. These include: drainage, systems for rapid and emergency dewatering of the basin, embankments and relief wells whose task is to reduce the water pressure in the soil of the ground. Around the „Żelazny Most" facility, constant surveillance is carried out on a regular basis. The monitoring concerns both surface and underground waters. The imperfection of currently used methods of monitoring is their punctuality. By using them, you cannot get cross-sectional images of the interior of the dam. Fig. 2 shows a photo of an earth embankment of the reservoir with visible elements of various measurement systems that provide point data enabling ongoing monitoring of the building.

Fig. 2. Surface of the earth embankment around the Żelazny Most reservoir

The key element of the neural system used to reconstruct tomographic images is a neural controller. Its task is to convert electrical signals into images. A proper set of training data was needed to implement the neural system. Due to the fact that it was not possible to download this type of data directly from the embankment of the Żelazny Most reservoir, a physical model of the flood embankment part was created in the laboratory conditions. By doing so, the examined features of the real object such as: dam material, geometry of shape, proportions of dimensions, water level in tank were reproduced. Thus, research data from many measuring cases was obtained. The data included sets (vectors) of current-voltage drops values and images of cross-sections of the barrier corresponding to these sets. Fig. 3 shows the earth model of a part of an embankment with the Electrical Impedance Tomography (EIT) system, which includes: electrode system, electronic voltage distribution module for individual electrodes and a module for recording results. The glass panes of the terrarium made it possible to observe the changes taking place in the mass of the earth embankment caused by seepage. Thanks to the possibility of observing the interior of the earth dam, it was possible to gather a large set of data containing vectors of electrical parameters and images assigned to these vectors.

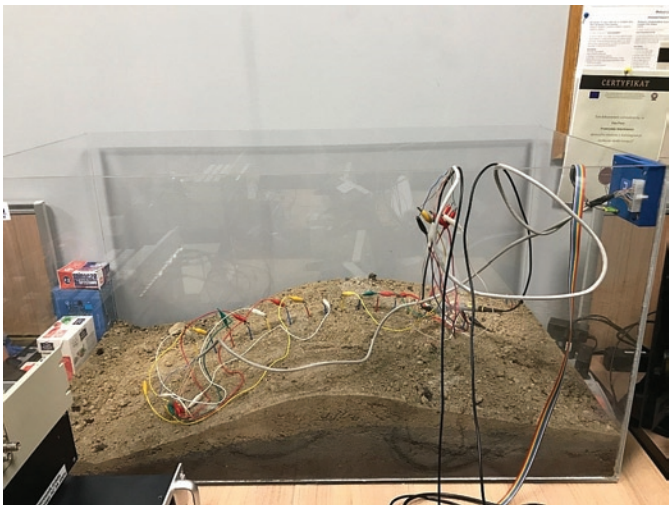


Fig. 3. The physical model of the Żelazny Most reservoir dam

In the dam model, 16 electrodes were placed to cover the entire embankment width. As a result, by placing rows of electrodes spaced apart at equal distances, the entire length of the barrier can be covered with the EIT system. The arrangement of the rows of electrodes in the dam is presented in Fig. 4.

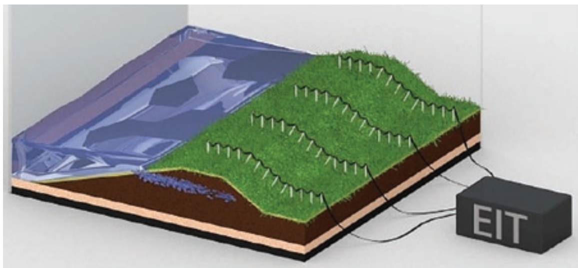


Fig. 4. Scheme of the flood embankment with the electrodes placed on it

3.2. The concept of the neural system

The neural system of tomographic image reconstruction is the original concept of a system that contains many neural networks. When run in parallel, they generate an image consisting of single points. Each of the output image points is the effect of an independent, separately trained neural network. By using this method, two-dimensional (2D) and three-dimensional (3D) images are generated. From the point of view of the mechanism of creating the output image, the difference between 2D and 3D images depends on the number of pixels that make up a single image. In the case of 3D images, these points are vastly more numerous than in the case of 2D images.

As mentioned before, the EIT system that was touched upon consisted of a set of 16 electrodes, which generated 208 voltage drops during each measurement. The measurements read thanks to the electrodes placed in the body of embankment, made it possible to determine the conductivity of the tested object, which is variable depending on such factors as e.g. moisture level, heterogeneity of the structure or the type of soil. The illustrated cross-section of the embankment has been divided into a grid of pixels generated as triangular elements by means of the finite element method. In the case of 2D imaging, the pixel grid of the initial image counted 2012 points, while in the case of a three-dimensional image a spatial grid of 17869 points was used. The first case is presented in Fig. 5. In the upper part of the drawing, the locations of the electrodes are marked. The 3D case is presented in Fig. 6. The density of the grid points around the electrodes serves to more accurately reflect the changes taking place inside the depicted flood bank.

Fig. 7 and 8 present the method of operation of a neural system that converts electrical signals from electrodes into 2D and 3D images. The input vector contains 208 measuring cases (1). Each single measurement case corresponds to a certain amount of voltage drop for a given pair of electrodes.

$$U = [\alpha_1, \alpha_2, \alpha_3, \ldots, \alpha_{208}]^T \tag{1}$$

The U vector is the input vector for all artificial neural networks (ANN) included in the neural system.

The design of the neural model was based on the following assumptions:

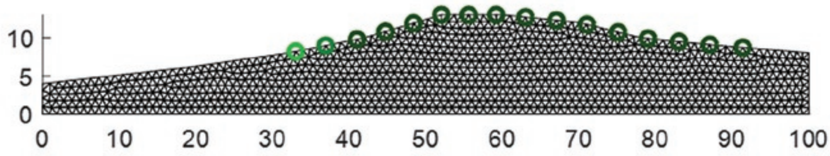


Fig. 5. Grid of the output 2D image of the flood barrier section (counting 2012 points)

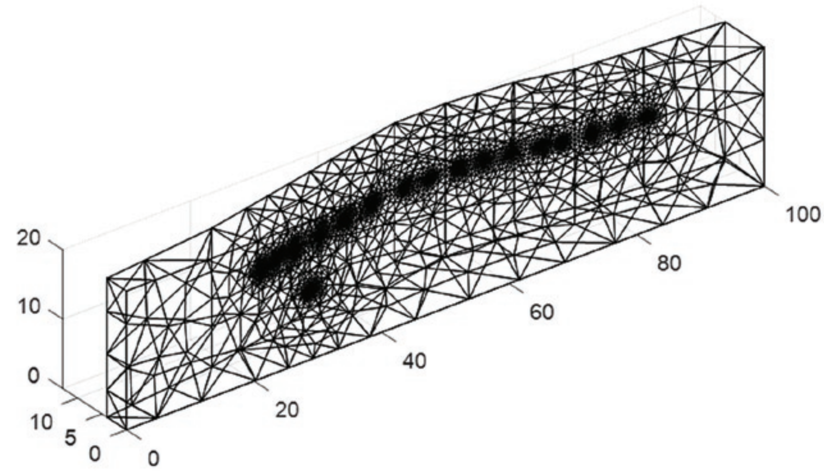


Fig. 6. Grid of the output 3D image of the flood barrier section (counting 17869 points)

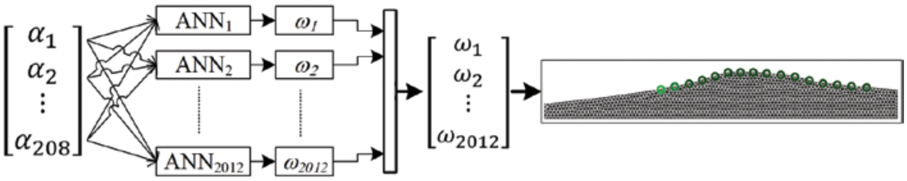


Fig. 7. A mathematical neural model for converting electrical signals into 2D images

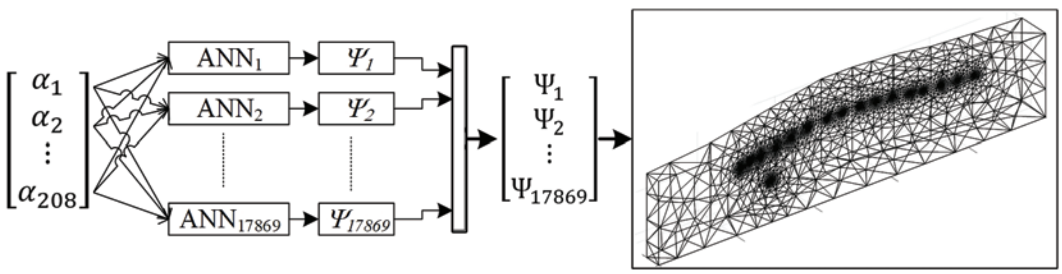


Fig. 8. A mathematical neural model for converting electrical signals into 3D images

1. Each point of the output image is generated by a separate artificial neural network with 208 voltage drop values. The output of each of the neural networks is a single real number corresponding to the conductivity value of a single element of the reconstructed image (in the visual form represented by the appropriate color of the assumed scale of conductivity).
2. A mutual relationship between individual points of the output image is assumed. Therefore, any neural network that generates the value of a single image element can be trained independently, with randomly generated initial weights and biases.
3. Neural networks assigned to elements of the output image can solve both classification and regression problems. In the case of a classification issue, the generated image may be monochrome or have several colors / shades. Then the classifier assigns a given pixel to a specific color. If the network implements the regression problem, the output generates a real number, corresponding to the conductivity value of the given element. This type of imaging is the most desirable, but this network layout is the most difficult to train. Neural systems described in this paper deal with regression issues.

During the research, many trials were carried out, taking into account various configurations of the neural multi-layered perceptron. In particular, variants were analyzed taking into account changes in the following factors affecting the efficiency of the neural system: selection of network training algorithm, number of hidden layers and number of neurons in each layer of the network, parameters of the perceptron (learning factor, maximum number of incorrect validations, momentum and others). The possibility of using new solutions in the field of convolutional neural networks (CNN) was also analyzed. The research results showed that CNN networks are ineffective in this case due to insufficient data input - especially in comparison to the high resolution of the output image.

Due to the large amount of data and the need to train several thousand neural networks (for the 3D model), the implementation of the above concept required the use of fast algorithms including parallel computations and computers with high computing power.

3.3. Training process of the selected neural network

The analysis of the training process for the selected neural network included in the neural system for the reconstruction of the 2D image is presented below. In this case, the complete neural system counted 2012 separately trained ANNs. Due to the large number of networks, in this study it is impossible to present the learning process of all artificial neural networks.

Fig. 9 presents a diagram of the used model of the neural network. The network has 208 inputs, 10 neurons in the hidden layer and 1 neuron in the output layer. The hidden layer uses a logistic transfer function. In the output layer, the transfer function is linear.

Table 1 presents the results of training one neural network, selected randomly from the system integrating 2012 networks. Presented network generates on the output a single pixel of the output image. The total number of cases used in the network training process was 10442. All cases were randomly divided into 3 sets: training, validation and

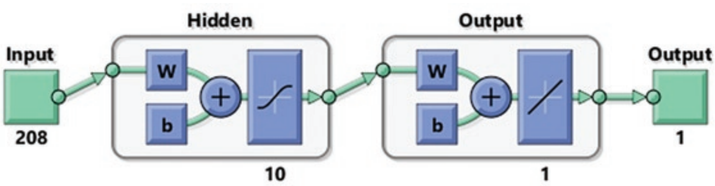


Fig. 9. A neural network model that generates a single point of the output image

Table 1. The division of data into sets and results of the training process

Division of the data set	The number of cases in a given set	Mean Squared Error (MSE)	Regression (R)
Learning set (70%)	7310	$1.35760 \cdot 10^{-3}$	0.997303
Validation set (15%)	1566	$5.84343 \cdot 10^{-3}$	0.988642
Test set (15%)	1566	$6.88341 \cdot 10^{-3}$	0.987701

test in the following proportions: 70%, 15%, 15%. The validation set was used to determine the moment of stopping the training process. It is used to verify the quality of the obtained network. The training process ends when the gradient change dynamics approaches zero.

The Mean Squared Error (MSE) reflects the mean square difference between the outputs and the reference values. The lower the MSE values, the better. Zero MSE means no error. The training set was burdened with the lowest learning error, which is the most common and correct situation. The low MSE error of the training set results from the fact that the weight of the network is best adapted to the training cases. The highest medium-squared error (MSE) of $6.88341 \cdot 10^{-3}$ occurred with reference to the test set. A slightly smaller MSE error of $5.84343 \cdot 10^{-3}$ was recorded for the validation set. The smallest error was noted in relation to the training set.

Another analyzed network quality indicator was the regression of R. R = 1 means full compliance of the outputs with the patterns, while R = 0 means the lack of connections between them. The regression coefficient merit for all three sets was very high, close to 1. This proves the high ability of the network to knowledge generalization (that is, the correct conversion of input data to output information not only for the training set).

The results obtained as a result of checking the network on the test set are the most reliable indicator of the effectiveness of a given network, because cases from this set do not participate in the learning process. Good MSE and R indices for the test and validation test indicate lack of overtraining.

Fig. 10 presents correlation diagrams of the considered network. As you can see the difference beyond the reference lines is noticeable, however the number of cases away from the reference line is not large. This is evidenced by the overlapping correlation lines for all considered sets: the training, validation and test sets, and collectively (for all three sets).

Fig. 11 presents the mean square error (MSE) diagrams recorded during the network training process. MSE values are low. The relatively regular shape of the lines (no large fluctuations) indicates the lack of overfitting and thus the high efficiency of the developed system of tomographic reconstruction of the image. The hyperbolic shape of the curves indicates a sufficient number of training cases. The chart marks the thirtieth epoch (iteration) on which the learning of the network was completed. This is the iteration in which the MSE error of the validation set has reached its minimum.

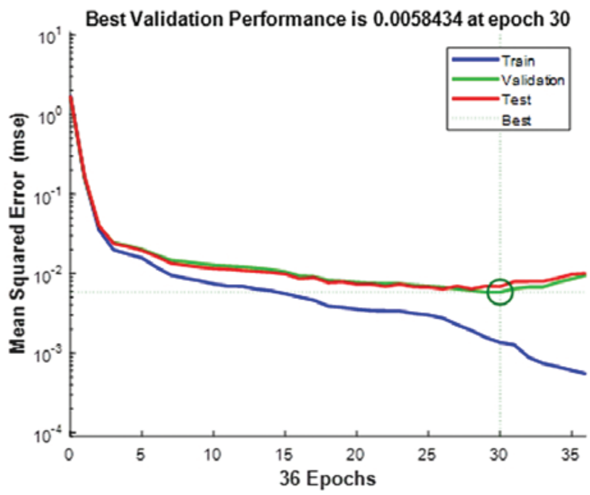


Fig. 11. MSE error charts for the training, validation and test sets

Fig. 12 presents a histogram of errors (differences) between the values generated by the network and the patterns. Each vertical bar indicates the number of deviations from the reference value. As you can see, the largest number of deviations are very small errors, with values close to zero. The shape of the histogram is similar to the normal distribution curve. This fact also confirms the high quality of the received solution.

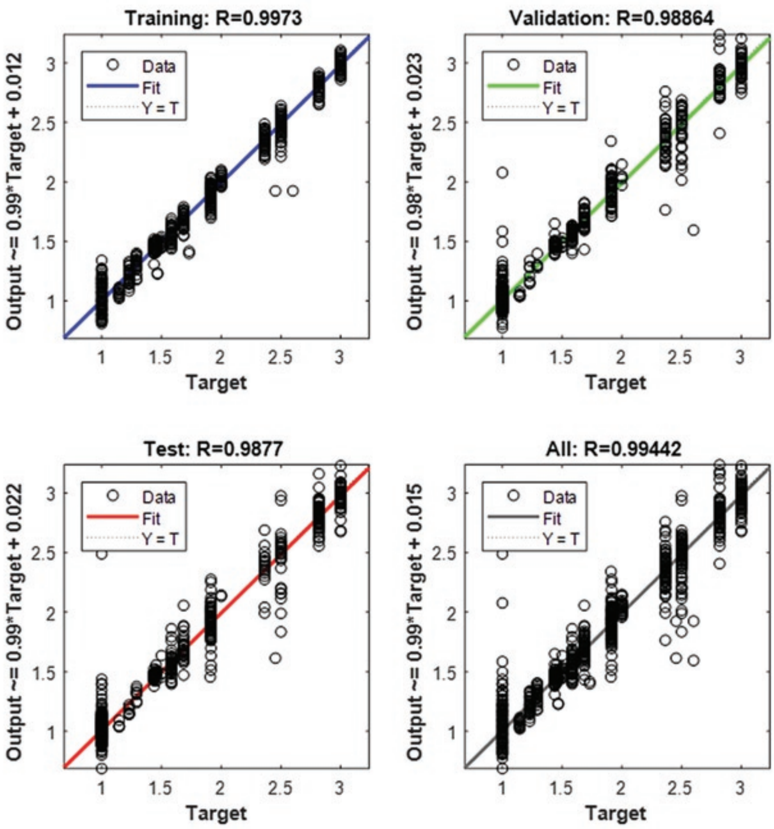


Fig. 10. Correlation diagrams of a neural network

4. Results of research on the neural system of reconstructing tomographic images

As part of the research work, two neural models of tomographic image reconstruction systems have been developed. The first model realized the issues of flat (2D) imaging, while the second model generated spatial (3D) images. This chapter presents the effects of both neural network systems.

In Table 2a in two columns, the patterns and reconstructed images generated by the 2D controller are summarized. Table 2b presents a graphical representation of differences in the values of individual pixels between the reference images and reconstructed images presented in

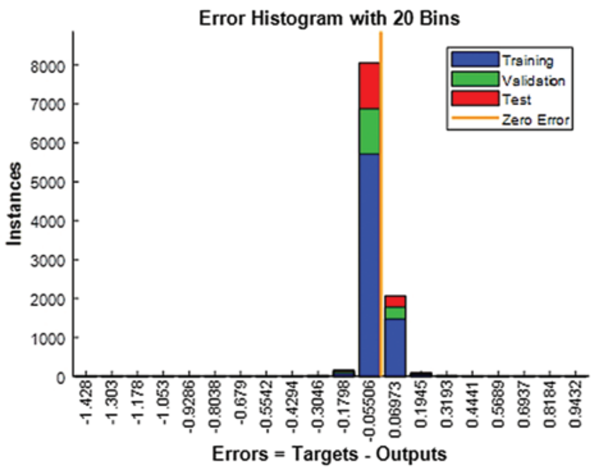


Fig. 12. Histogram of network error learning process

Table 2a. Results of 2D imaging

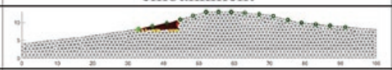
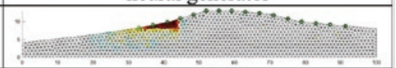
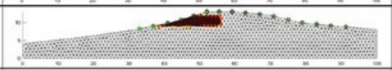
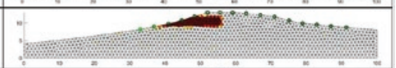
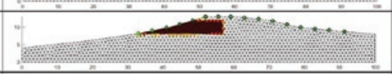
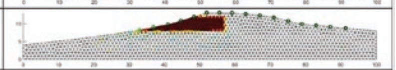
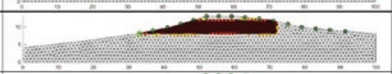
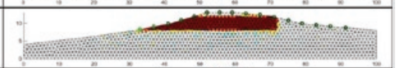
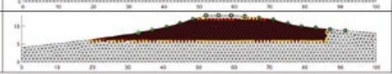
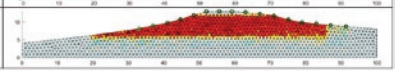
ID	The cross-sectional patterns of the flood embankment	The images reconstructed by using a neural generator
1		
2		
3		
4		
5		

Table 2b. Differences in 2D imaging results

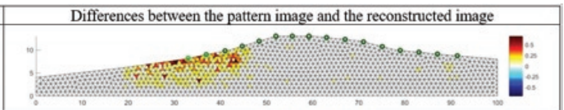
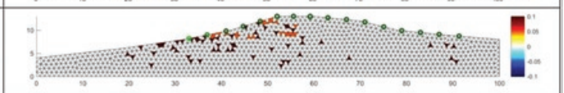
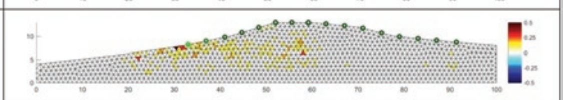
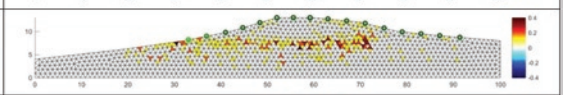
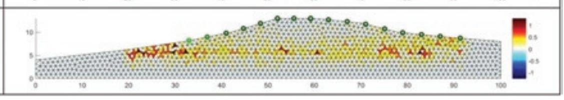
ID	Differences between the pattern image and the reconstructed image
1	
2	
3	
4	
5	

Table 2a. The color scale in the illustrations in Table 2b reflects differences in the conductivity between the elements of the reference images and the elements of the reconstructed images.

In Table 3a, the patterns and reconstructed images generated by the 3D controller are compared in a similar way. Table 3b presents a graphical representation of differences in the values of individual pixels between spatial model images and reconstructed images presented in Table 3a.

As in Table 2b, the color scale in the illustrations in Table 3b reflects differences in conductivity between the elements of the reference images and the elements of the reconstructed images.

When analyzing table 2a, it can be seen that the resulting images accurately represent the shapes and colors of the reference images. In the case of the 2D model, the numerical values of the pixels of the reference image were real numbers belonging to the range from 1 to 3. From Table 2b, the values of errors of images reconstructed with respect to their patterns can be read. You can see that most pixels on the grid do not contain errors (no color). In the case of deviations greater than zero, most errors do not exceed 0.2.

Table 3a presents a comparative analysis of reconstructed 3D images. High accuracy of mappings for all five presented cases is also visible here. The spatial grid of the 3D model has as many as 17869 points. The numerical values of the pixels of the reference image were real numbers that belong to the range from 1 to 2. Table 3b shows the values of errors of images reconstructed with respect to their patterns. Most pixels on the grid do not contain errors (no color). As in the 2D model, non-zero deviations in most cases do not exceed 0.2.

5. Conclusion

The article presents the original concept of a neural system for the reconstruction of tomographic images. The effectiveness of the method has been verified based on the conditions of the "Żelazny Most" Flotation Wastes Depository. Taking into account the key structural features of the Żelazny Most technical facility, a physical model of the flood embankment part was developed. The above model was equipped with an electrode system and the necessary tomography devices (EIT), which enabled the execution of many measurements of electrical quantities and the allocation of cross-sections of the investigated embankment model to those sizes. The data obtained in this way was used to train the neural network system. An innovative feature of the solution is the separate training of a large number of neural networks in the amount corresponding to the resolution of the reconstructed image mesh. During the laboratory experiments two models of reconstruction of tomographic images were developed - flat (2D) and spatial (3D). The obtained results indicate that the presented method of neural imaging can be effective both in the case of two- and three-dimensional reconstruction. The application of a system of many separate neural networks operating simultaneously to depict the cross-section of the embankment damage enabled the generation of exact mappings of the given patterns. The quality of these mappings is sufficient to correctly identify the nature of threats, as well as to assess the rate of changes taking place inside the flood embankment.

Taking into account the possibility of taking measurements at regular intervals, the rate of leakage spreading can be easily determined. The above information enables not only a accurate diagnosis useful for determining the embankment's reliability level, but also an effective forecast of the moment of the coming disaster. Thanks to information obtained by the use of neural imaging system, it is possible to appropriately plan actions to prevent damage to flood protection facilities.

Acknowledgment

The authors would like to thank the authorities and employees of the Institute of Mathematics, Maria Curie-Skłodowska University, Lublin, Poland for sharing supercomputing resources.

Table 3a. 3D imaging results

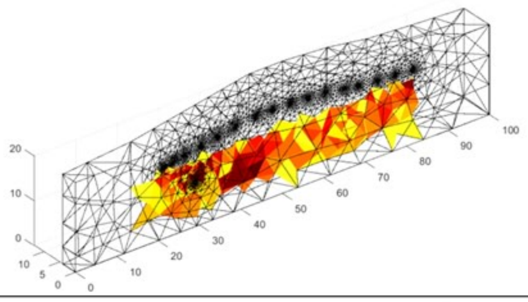
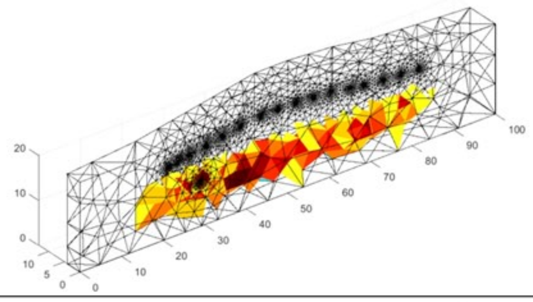
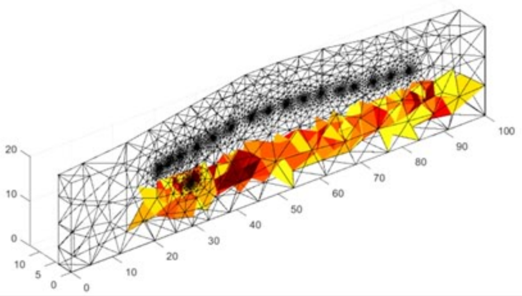
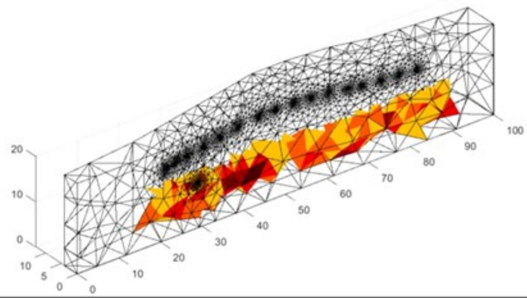
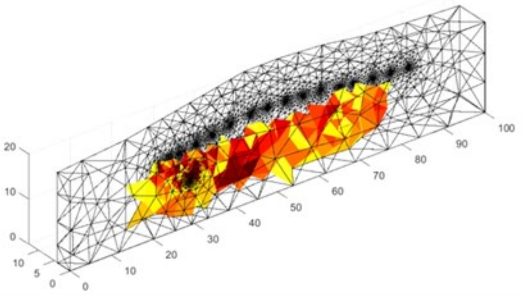
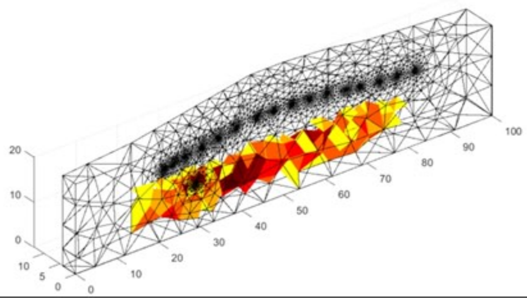
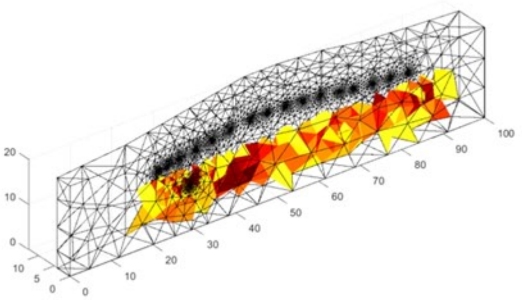
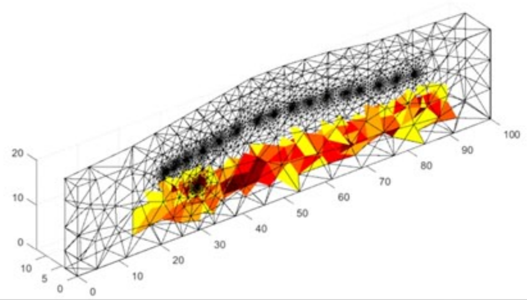
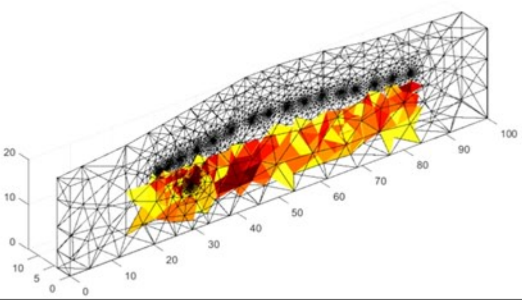
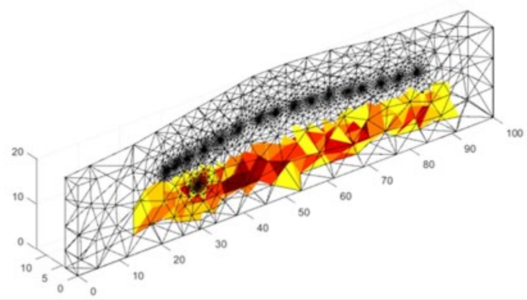
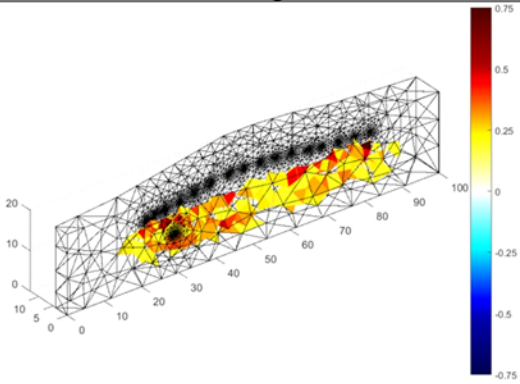
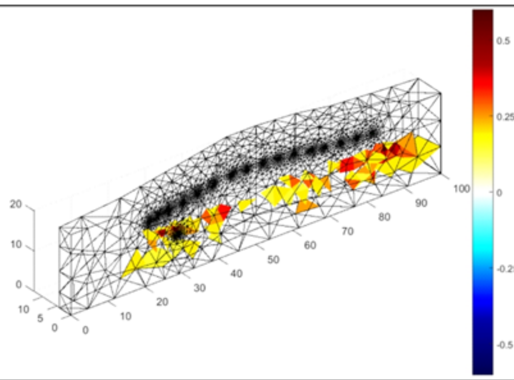
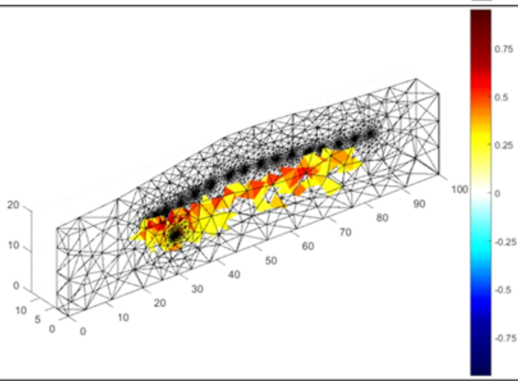
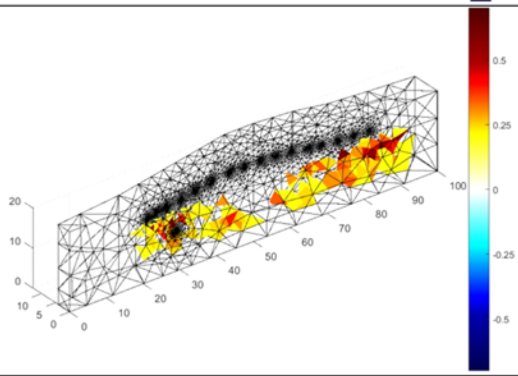
ID	The cross-sectional patterns of the flood embankment	The images reconstructed by using a neural generator
1		
2		
3		
4		
5		

Table 3b. Differences in 3D imaging results

ID	Differences between the pattern image and the reconstructed image
1	
2	
3	
4	

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