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AN EXAMPLE OF THE APPLICATION OF NEURAL NETWORKS OF A SIMPLE ARCHITECTURE TO UNFOCUSED WELL ELECTROMETRY PROBES

Abstract. *An effective method of finding stable solutions of inverse problems of electric and induction logging along the well is proposed, which allows avoiding the influence of the resistance values of the neighboring formations on the determination of the geoelectrical parameters of the object under study. A highly efficient method was proposed for solving such an unstable inverse problem. This method is based on the application of a neural network with inverse error propagation of a simple architecture. Namely three-layer. The mathematical statement of the problem is given, both the topology of the neural network and all its parameters are described in detail. In the course of the numerical experiment, they were selected as optimal. The process of building a base for training a neural network is described in detail. Namely, how each of the examples of the learning base is built by solving a direct problem. With this cut parameter, the training for each example is chosen arbitrarily, which guarantees a comprehensive range for training the neural network. The number of examples in the training base is one hundred thousand examples. As the activation function, the sigmoid is chosen due to the fact that it is differentiable everywhere. The results of testing the written program are given. The learning rate was estimated to obtain the required small error. It is shown that this approach is stably convergent. For testing, the parameters of the layers of the cut, which are inherent to the geophysical parameters of the cuts of the Dnipro-Donetsk depression, were chosen. A complex of lateral logging sounding was chosen as the electrical logging equipment. Four-probe low-frequency induction logging equipment was chosen as induction logging equipment. Examples for induction and electrical logging are given separately. The obtained results are analyzed in detail. Ways of further improvement of the obtained neural network and its use for other problems of geophysics are given.*

Keywords: *geophysical exploration of wells, resistivity, oil and gas wells, Shoulder effect, inverse problem, vertical resolution.*

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1. Introduction. The solution of most mathematical inverse problems faces the problem of stability. Inverse problems of electrometry are no exception [1]. Consider the problem of establishing the electrical specific resistivity (SR) of a layer of finite thickness (in the presence of axial symmetry of the problem), which is part of the layering opened by a vertical well. Fig. 1-4 shows a comparison of the SP and the measured apparent resistivity (AR) inherent in the conditions of the Dnipro-Donetsk basin [2]. It is clear that the measurement of the AR, $\tilde{\rho}(z)$ at a single point with the z coordinate (the depth along the axis of the well in the cylindrical coordinate system) will be affected by the SR values in some vicinity of the measurement point proportional to the length of the probe.

It should be noted that the use of NN in the tasks of geophysics and in particular the geophysical investigation of wells is not new [3, 4]. However, the author is not aware of the use of such an approach for unfocused probes. A two-layer NN will be used in the work. Well-known works are devoted to the use of NN of complex architecture (deep learning) to solve the problem of modeling (prediction) of logging data (solving a direct problem).

The aim of the work is to create a method that eliminates the influence of neighboring layers (shoulder effect) on the determination of geoelectrical parameters of the studied object by using neural networks (NN) of simple architecture.

2. Shoulder effect. For the task of low-frequency induction logging (IL), the electric specific conductivity (SC) σ and the apparent conductivity (AC) $\tilde{\tilde{\sigma}}$ (inverse of the SR and AR values) are related by the equation:

$$\tilde{\sigma}(z) = \int g(z - z`)\sigma(z`)dz`, \quad (1)$$

where g is the so-called geometric factor of the probe [5]. The problem of solving such a Fredholm equation of the first kind of the convolution type is incorrectly posed according to Hadamard and, accordingly, is unstable [1].

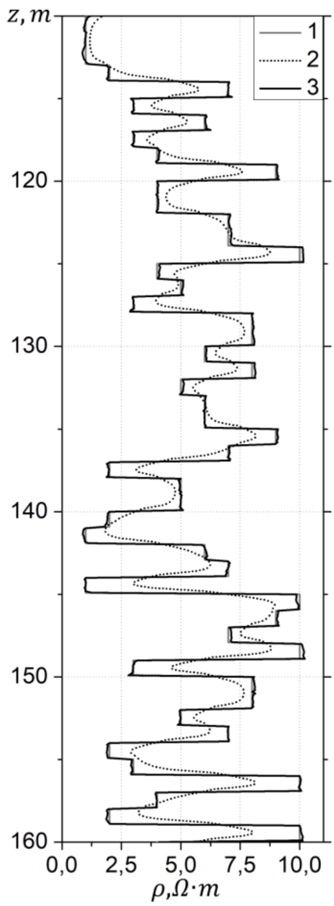

Fig. 1. Probe IL1.25. Code of the curves: 1 – given SR, 2 – measured AR, 3 – recovered SR

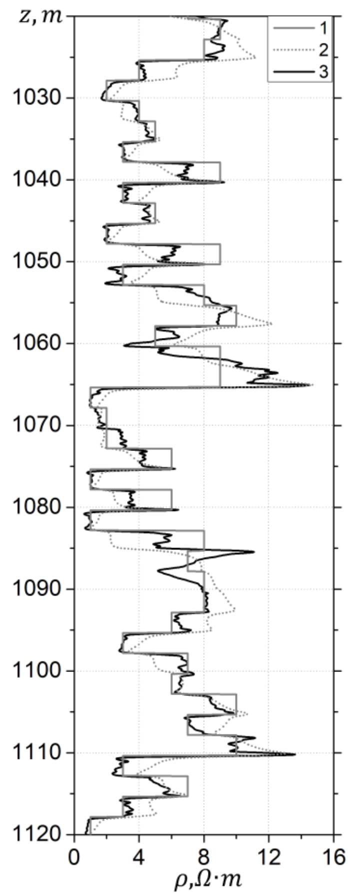

Fig. 2. Probe EL A2.0M0.5N. Code of the curves: 1 – given SR, 2 – measured AR, 3 – recovered SR

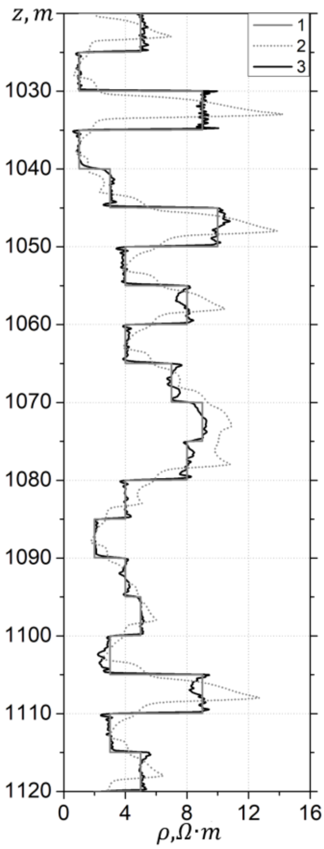

Fig. 3. Probe EL A2.0M0.5N. Code of the curves: 1 – given SR, 2 – measured AR, 3 – recovered SR

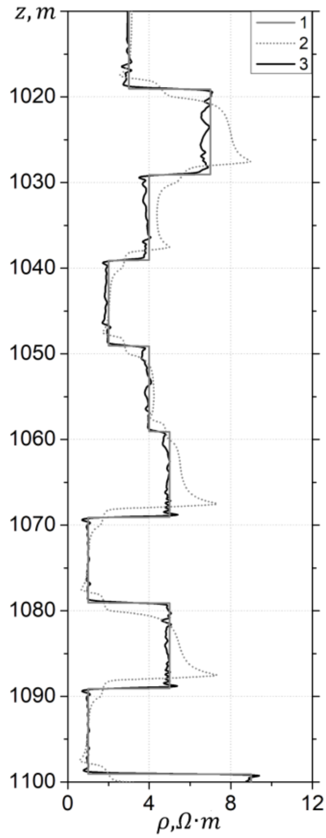

Fig. 4. Probe EL A2.0M0.5N. Code of the curves: 1 – given SR, 2 – measured AR, 3 – recovered SR

The sought values of SC are determined through the measured values of AC, which in turn depend on the values of AC at some interval (determined by the form of function g). Therefore, the determination of the AC value at some point is influenced by the measurement values at the neighboring ones. This phenomenon is called "Shoulder effect". The problem of electrical logging (EL) is generally nonlinear and does not have an integral description of the type of the given equation (1), but the Shoulder effect is also present in it.

3. Formulation of the problem. A method of finding a stable solution to the problem of determining the SR based on the data of the measurement of the AR for IL and EL will be proposed. In both cases, we will look for the value of SR itself (since SR and AR are related as $\sigma = \rho^{-1}$). For both problems (EL and IL), we need to solve the problem of finding ρ_i at each point z_i of some interval if we know:

$$\tilde{\rho}_{z_i}\left(\rho_{z_{i-m}}, \dots, \rho_{z_i}, \dots, \rho_{z_{i+m}}\right), \tag{2}$$

where the coordinate indices are simply the numbers of an ordered set of measurement points (the measurement along the well is not continuous and is performed with a discrete step Δz). That is, we use an approximation model where the SR is a piecewise continuous function along the well and within each interval of thickness Δz, the SR values do not change.

4. Architecture and education of NN. In fact, (2) means that the direct problem is the search for the mapping of SR values into one AR value. However, we need to set another mapping (inverted):

$$\tilde{\rho}_{z_{i-m}}, \dots, \tilde{\rho}_{z_i}, \dots, \tilde{\rho}_{z_{i+m}} \to \rho_{z_i}. \quad (3)$$

We will use this type of connection for learning NN with backpropagation of the error [6]. We have [1, 7] a reliable tool for calculating mapping (3). That is, according to known values of AR at some interval $(2m+1)\cdot\Delta z$ we need to determine the AR in its center.

For each example, we will model the AR curves for the interval of the well cut which consists of a sequence of layers the SR of which we set as a constant (within each layer) but random value for each of them (if the SR of neighboring layers defined in this way coincide, then we in fact, we have one layer of permanent SR but twice as thick).

Therefore, the SR value of each of the well cut of the selected interval will change randomly for each NN training example within the range of SR values of the field in which the geophysical wells are surveyed (see fig. 3, 4, curve 1).

Thus, we have for each training example of our NN an "interval-measurement point" correspondence. The construction of NN training examples in this way was significantly simplified by using our own software for modeling EL and IL.

We will use the sigmoid ${e^x}/{e^x+1}$ whose values are limited to the interval (0,1) as the activation function of all neurons of our NN. The choice of sigmoid is due to the need for continuous differentiability of the activation function for using the method of backpropagation of the error. Accordingly, taking into account the limited range of possible sigmoid values before the learning process, we normalize the input data (AR values) and output data (SR values) for each example.

The following NN parameters were chosen: two-layer, the activation function is sigmoid, the learning step is 0.5, the number of epochs is fixed and equal to 20,000, the number of training examples was 100,000 (both for IL and EL problems). The number of neurons in each layer was chosen separately for IR and EC problems.

5. NN check, results. It should be emphasized that the examples are given for unfocused probes. This just demonstrates the possibilities of using NN for more complex tasks. Indeed, joining the complex of geophysical logging focused down probes of electric logging or induction significantly improve the vertical resolution of the method as a whole. This stage of the research did not include the assessment of the possibilities of using NN for solving inverse solutions of focused problems. To solve such problems, where both unfocused and focused probes are used at the same time, it was solved at one time, but under the condition that the layers adjacent to the studied layer have the same resistance and are of semi-unsheared thickness. War conditions do not allow references to authors from the aggressor country.

As it is generally accepted to check the quality of training of NN, we set the input data to examples that were not used during training and compare what the NN gives at the output and what it should have given.

Consider the IL problem. According to the value of the length of the interval (12.1 m) on which the data for the examples of NM training were calculated and the size of the recording step (0.1 m), the number of NN input data is 121, the number of neurons in the first hidden layer is 20, the number of neurons in the second hidden layer (corresponds to the number of output signals) – 1. That is, synopses connect: the input data layer and the first hidden layer and the first and second hidden layers. The value at the output of the second hidden layer is the value of the NN output signal.

In fig. 1 shows the results for the I1.25 probe [5] (where the number means the distance between the generating and receiving coils and thus it determines the vertical resolution of the method). It turned out that for layers with a thickness of 1 meter (less than the length of the probe), the SR according to the proposed method is set almost perfectly from the point of view of the generally accepted requirements of well-logging (determining the boundaries of each layer, determining the value of its SR with an error of no more than 10%). For the EL problem (recording step 0.05 m), the length of the interval on which the data for the NN training examples was calculated was 10.05 m. Therefore, the number of input signals is 201. The number of neurons of the first hidden layer was chosen to be 30, and the number of neurons of the second was 1.

In fig. 2-4 show the results (Fig. 2 for stratification of layers 2.5 m thick; Fig. 3 – 5 m thick; Fig. 4 – 10 m thick) for the known A2M0.5N probe (the first digit is the distance between the current electrode and the first measuring electrode, the second digit is the distance between the measuring electrodes) [7], which is included in the complex of standard electrometry of wells used in Ukraine [2].

For the layer thickness of 2.5 m, the boundaries of each of them are determined precisely, but it was not possible to determine the SR even qualitatively. For layer thicknesses of 5 m and 10 m, the SR is installed almost perfectly according to the proposed method.

6. Discussion. The results obtained in a similar way for three-layer NN do not differ significantly from those obtained for two-layer NN except for an increase in training time.

Thus, knowing the vertical profile of the SR for each probe of the multi-probe complex, we can also determine its radial SR distribution with an accuracy that corresponds to the accuracy of the proposed method. Since the use of NN is essentially a method of approximation, we, having a very diverse base of learning using random, have created a reliable method of approximation. Since we did not have examples of unstable solutions in the basis (the solution of the direct problem), then such a solution (already the inverse problem) turned out to be stable.

The greater accuracy of setting the vertical profile for IL tasks than for EL problems is a consequence of a more accurate qualitative coincidence of the measurement curves AR with the SR curves, which must be restored. But the achieved accuracy of establishing the SR of layers comparable to two lengths of the probes is more than high.

The choice of examples selected for learning NN is definitely decisive.

7. Conclusions. The possibilities of using NN to solve the problems of increasing the vertical spatial ability of unfocused probes are demonstrated. It is shown what vertical resolution can be achieved for such probes using only two-layer neural networks.

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ПРИКЛАД ВИКОРИСТАННЯ НЕЙРОННИХ МЕРЕЖ ПРОСТОЇ АРХІТЕКТУРИ ДЛЯ НЕ СФОКУСОВАНИХ ЗОНДІВ ЕЛЕКТРИЧНОГО КАРОТАЖУ

Анотація. Запропоновано ефективний метод знаходження стійких розв'язків обернених задач електричного та індукційного каротажу вздовж свердловини, який дозволяє уникнути впливу значень опору сусідніх пластів на визначення геоелектричних параметрів досліджуваного об'єкта. Для розв’язання такої нестійкої оберненої задачі було запропоновано високоефективний метод. Такий метод заснований на застосуванні нейронної мережі з оберненим розповсюдженням похибки простої архітектури. А саме тришарової. Дано математичну постановку задачі, детально описано як топологію нейронної мережі, так і всі її параметри. В ході числового експерименту вони обрані оптимальними. Детально описано процес побудови бази для навчання нейронної мережі. А саме як за допомогою розв’язання прямої задачі будується кожен з прикладів бази навчання. При цьому параметри розрізу для кожного прикладу навчання обираються довільним чином, що гарантує всеохоплюючий діапазон для навчання нейронної мережі. Кількість прикладів в базі навчання складає сто тисяч прикладів. В якості функції активації обрано сигмоїду через те, що вона всюди диференційована. Наведено результати тестування написаної програми. Оцінена швидкість навчання для отримання необхідної малої похибки. Показано, що такий підхід є стабільно збіжним. Для тестування обрано параметри пластів розрізу, що притаманні геофізичним параметрам розрізів Дніпровсько-Донецької западини. В якості апаратури електричного каротажу обрано комплекс бокового каротажного зондування. В якості апаратури індукційного каротажу обрано чотиризондову апаратуру низькочастотного індукційного каротажу. Наведено окремо приклади для індукційного та електричного каротажу. Детально проаналізовано отримані результати. Наведено шляхи подальшого вдосконалення отриманої нейронної мережі та використання її для інших задач геофізики.

Ключові слова: геофізичне досліження свердловин, питомий опір, нафтогазові свердловини, обернена задача, вертикальна роздільна здатність.

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