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THE USE OF NEURAL NETWORKS WITH BACKPROPAGATION OF ERROR IN THE PROBLEMS OF OIL AND GAS WELL ELECTROMETRY

Introduction. *The final step of electrometry (the main method of geophysical investigation of wells) is quantitative interpretation. Such an interpretation requires solving the ill-posed inverse problem of determining the geoelectrical parameters of the stratification of layers penetrated by the well.*

Problem Statement. *The need to solve inverse mathematical problems of electrometry of oil and gas wells presents the challenge of their instability. For electrical logging problems, there is no universal regularization method for effectively solving ill-posed inverse problems; for induction logging, the development of regularization methods is a technically complex task.*

Materials and Methods. *To solve the problem, various parameters and architectures of the neural network have been tested. A two-layer network with backpropagation of error has been selected.*

Purpose. *To demonstrate the possibility of effectively solving the inverse problem of electrometry (for both electrical and induction logging methods) using neural networks with backpropagation of error and a simple architecture.*

Results. *A neural network has been developed and trained (including the design of its structure and the computation of the corresponding training arrays) to determine the parameters of a three-layer formation penetrated by the well.*

Conclusions. *It has been shown that the problem of determining the radial (along the layer for vertical wells) distribution of resistivity can be effectively solved using neural networks with backpropagation of error and a simple architecture.*

Keywords: electrometry, oil and gas well, inverse problem, neural network, backpropagation of error.

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The solution of the inverse problem of well geophysical investigation (WGI) aims to answer the following key questions: where the useful fluid is located, how much of it is present, and at what rate it can be extracted [1—3]. The primary methods of WGI are electrometry techniques that include electrical logging (EL) and low-frequency induction logging (IL). However, solving the problems of quantitative interpretation of WGI data is complicated by the fact that these are, in essence, inverse mathematical problems that are generally ill-posed in the sense of Hadamard [2—3]. While regularization methods exist for IL problems to improve the accuracy of determining the vertical (along the wellbore) profile of specific electrical resistivity (SER), accurate determination for EL problems using conventional methods is not feasible. This is due to the inherently nonlinear nature of EL problems, whereas IL problems can be reduced to a Fredholm integral equation of the first kind (convolution type) through the application of regularization techniques [2—3].

The purpose of this research is to demonstrate the feasibility of effectively solving the inverse problem of electrometry (using both EL and IL methods) by employing neural networks (NNs). In this case, a neural network with backpropagation of error (NNBE) is applied [4].

The model of the studied reservoir is considered as a so-called five-layer structure [1—3], as shown in Fig. 1.

This is an axisymmetric model in which the layers, moving outward from the axis of symmetry (the wellbore axis), are arranged as follows: the first layer is the wellbore itself; the second layer is the mudcake; the third layer is the flushed zone (invaded by the filtrate of the drilling mud); the fourth layer is the transition zone; and the fifth layer is the uninvaded zone (the undisturbed reservoir formation). However, under most real-world conditions, including those typical for the Dnieper-Donets Basin [5], a three-layer model is commonly considered (Fig. 2). In this model, the flushed zone and the transition zone are combined into one, and the mudcake is neglected for both EL and IL methods (except for so-called micromethods that are not addressed in this study).

The wellbore diameter and the resistivity of the drilling mud are assumed to be known. This does not limit the capabilities of the method proposed in this paper, provided that the logging tool has a number of linearly independent measurements greater than the number of model parameters to be determined.

Thus, in the case of vertical wells, the problem is to determine the resistivity distribution along a

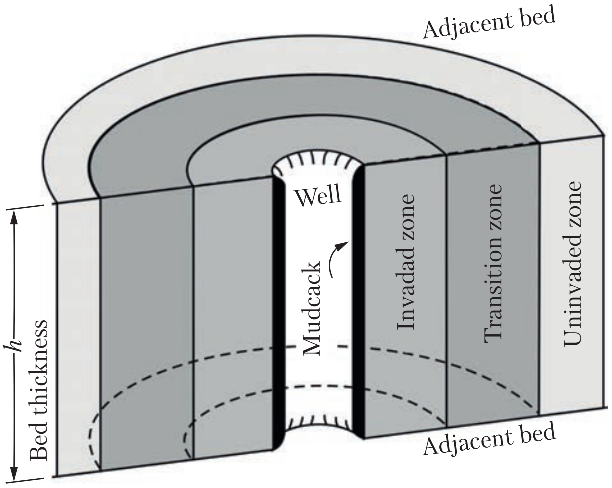

Fig. 1. Five-layer model

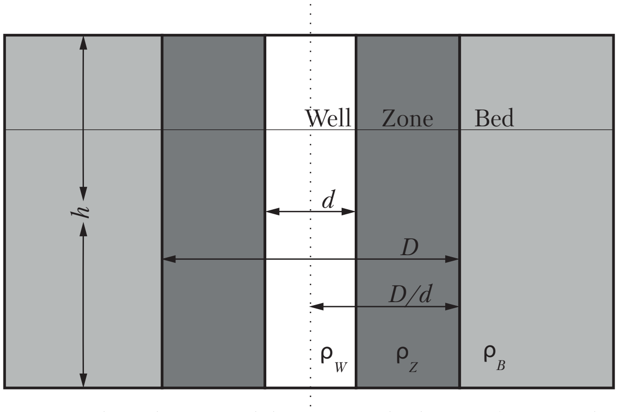

Fig. 2. Three-layer model of finite thickness (h): ρ_B is the specific resistivity of uninvaded part of the bed by the drilling mud filtrate (ρ_W is the specific resistivity of drilling mud (specific resistivity of the well)), ρ_Z is the specific resistivity of invaded zone of the filtrate of the drilling mud, D/d is the ratio of the diameter of the invaded zone to the nominal diameter of the well

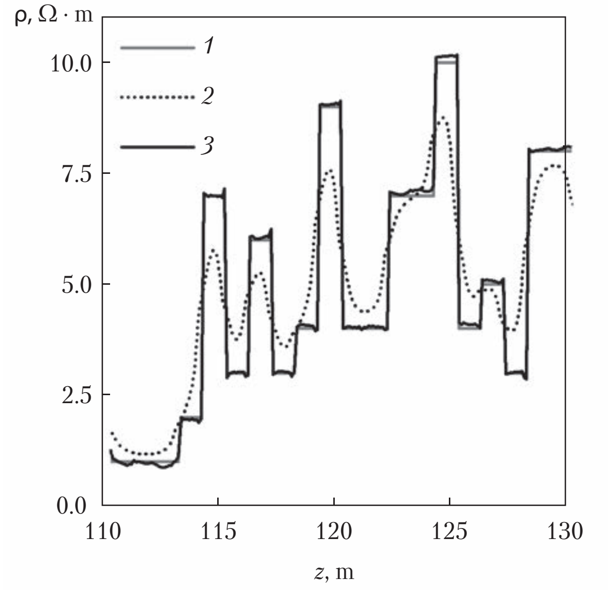

Fig. 3. Probe IL1.25: *1* — given specific resistivity; *2* — measured apparent resistivity; *3* — recovered specific resistivity

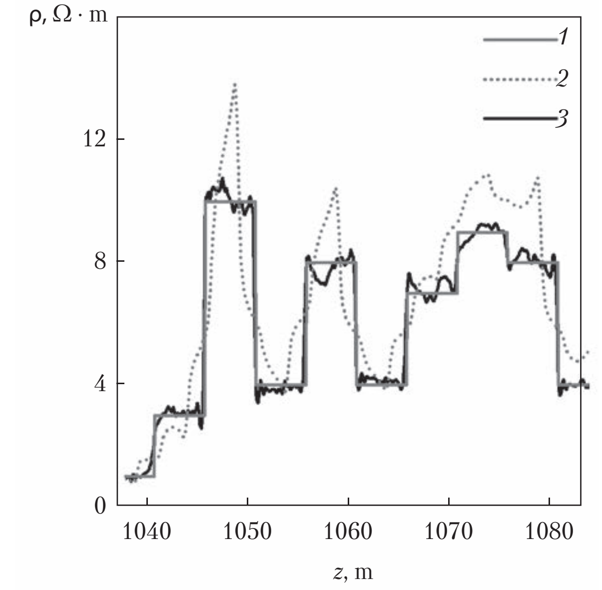

Fig. 4. Probe EL A2.0M0.5N: *1* — given specific resistivity; *2* — measured apparent resistivity; *3* — recovered specific resistivity

formation of finite thickness (which, for the three-layer model, means estimating the following parameters: the resistivity of the formation ρ_B, the resistivity of the flushed zone ρ_Z, and the ratio of the actual wellbore diameter to the bit diameter D/d. However, for formations of finite thickness, the measurements are significantly affected by the resistivity values of the adjacent layers (see Figs. 3—4). This greatly complicates the initial problem. In cases where formations are layered with thicknesses comparable to or smaller than the dimensions of the logging tools, the problem becomes two-dimensional.

Table 1. **The Structure of NN Training Data**

ρ_Z	ρ_B	D/d	ρ_1	ρ_2	...
...	...	...	...	...	...
6.60693	0.2884	6	4.00596	6.2271	...
6.60693	0.2884	8	4.05827	6.69085	...
6.60693	0.2884	10	4.08602	6.97078	...
6.60693	0.302	0	0.437	0.29079	...
6.60693	0.302	2	3.38531	3.22457	...
6.60693	0.302	4	3.86985	5.27074	...
6.60693	0.302	6	4.00626	6.22999	...
6.60693	0.302	8	4.05842	6.69248	...
6.60693	0.302	10	4.0861	6.97163	...
6.60693	0.31623	0	0.44902	0.30473	...
6.60693	0.31623	2	3.38742	3.23547	...
...	...	...	...	...	...

To simplify it, the following approach is used: the two-dimensional problem is divided into two one-dimensional problems (along the well axis and along each formation layer). The first task aims to minimize the influence of adjacent formations (the so-called shoulder effect) so that the measurements taken opposite the target layer can be considered as if the formation had infinite thickness. By analogy with the method of variable separation in solving partial differential equations, this approach is referred to as factorization.

Thus, we first eliminate the shoulder effect for each of the investigated formations, and then, for each layer, we determine its radial geoelectrical

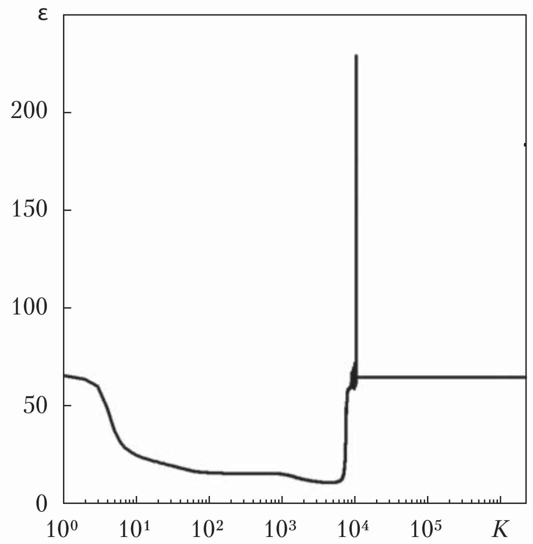

Fig. 5. Dependence of the training error on the number of epochs. $N_2 = 3$

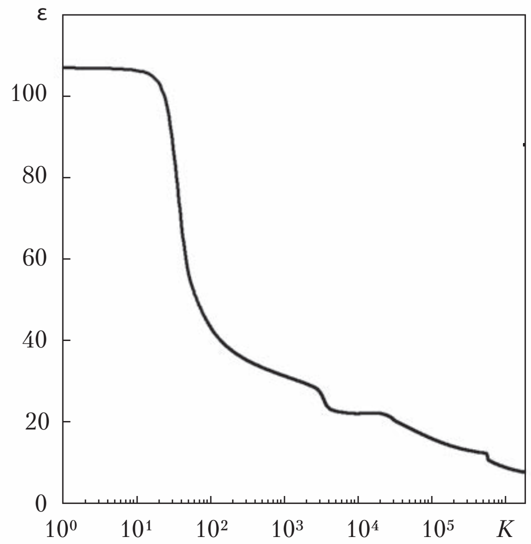

Fig. 6. Dependence of the training error on the number of epochs. $N_2 = 1$

parameters under the assumption that it has an infinite thickness, with the adjacent formations no longer influencing the measurement of apparent resistivity across from it. To solve this problem effectively, one may use regularization or NNBE methods for induction logging, and NNBE for electrical logging.

Examples of using NNBE are shown in Figs. 3—4 for well-known logging tools: an electrical logging sonde (A2.0M0.5M) and an induction logging sonde (IL1.25) [6]. Such an approach makes it possible to establish the vertical resolution of the overall solution. In this case, for both EL and IL problems, neural networks of simple architecture with two hidden layers have been used.

To solve the second one-dimensional problem, we also have employed the NNBE method.

Thus, once the problem of determining the resistivity along the wellbore axis is considered solved (for each sonde of the multi-sonde logging tool), it becomes necessary to determine the radial parameters of each formation. We have used NNBE for this purpose.

First, it is necessary to prepare a training dataset. Each training example consists of a correspondence between the input data (fed into the neural network) and the expected output data (that represent the solution).

This dataset consists of two parts. The first (larger) part is the training set that is used directly for training the network. The second (smaller) part is the validation set that is used to verify the network's performance; its examples are not used during training.

To construct such a dataset, a lookup table (see Table 1) is generated over the full possible range of values for the parameters ρ_B, ρ_Z, and D/d. Each line of the table corresponds to one training example, where ρ_i denotes the apparent resistivity measured by each sonde in the multi-sonde logging tool.

To build the table, the direct problem has been repeatedly solved using an accurate mathematical modeling method [7].

A total of 375,000 examples have been calculated for the ranges of resistivity values ρ_B and ρ_Z from 10^{-2} to 10^3 Ohm · m, and for discrete values of the geometric parameter: $D/d = 0, 2, 4, 6, 8$, or 10. A two-layer neural network has been used. The input to the network consists of the apparent resistivity values from the sondes; therefore, the number of input neurons equals the number of sondes in the tool. The first hidden layer consists of N_1

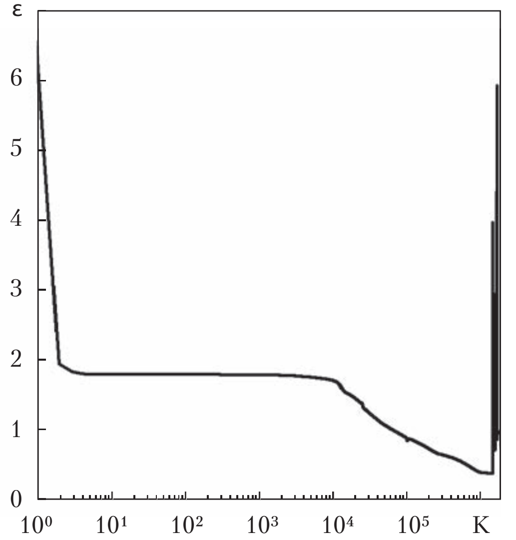

Fig. 7. Dependence of the training error on the number of epochs. $N_2 = 2$

Table 2. **Examples of Solving the Installation Problem of *D/d***

ρ_Z	ρ_B	D/d	D/d'
1.04	10.47	0	0.14
		2	2.3
		4	4.32
		6	6.2
		8	8.41
		10	9.76
2.63	23.98	0	0.02
		2	1.82
		4	3.78
		6	5.83
		8	7.78
		10	9.96
7.58	69.18	0	0.02
		2	1.99
		4	3.99
		6	5.81
		8	7.95
		10	9.99

neurons, and the second layer consists of N_2 neurons, which equals the number of output parameters of the network. For the considered model, the initial value $N_2 = 3$ is set, corresponding to the number of parameters to be estimated. The number of epochs K is selected based on the required accuracy of the solution (which depends on the training error ε). The learning rate i set to 0.5, the activation function is the sigmoid function, and the initial synaptic weights are randomized.

As a starting point, a fixed value of $K = 2 \cdot 10^6$ is assumed.

Figure 5 shows the training error as a function of the number of epochs. As seen, the error function is non-monotonically decreasing, as expected for a convergent method, and reaches a minimum. The neural network has been tested both at this number of epochs and at other values — yet in all cases, the solution deviated significantly from the expected one. Moreover, even a qualitative correlation between the input and output data — expected as a consequence of the physical relationship between the geoelectrical parameters of the model and the corresponding apparent resistivity measurements — has not been established.

A similar evaluation has been performed for various network architectures: different numbers of neurons in the hidden layers, different numbers of training epochs, and even for a three-layer network with varying parameters. In all cases, the results have been unsatisfactory. This may be attributed to the fact that the expected outputs differ qualitatively in physical nature (see Table 1): the first two parameters represent resistivity values, while the third is a dimensionless quantity.

During the learning, testing, and analysis of the results, it has been confirmed that the effectiveness of using neural networks strongly depends on the design of the training dataset. Although the architecture and parameters of the network also play a significant role, it has been shown that increasing the number of hidden layers does not lead to substantial improvement in the outcome.

An alternative approach has been then employed. Two separate problems have been solved: the first involved the determination of ρ_B and ρ_Z, and the second — of D/d. For the first neural network, $N_2 = 2$; for the second, $N_2 = 1$.

Figure 6 presents the training error as a function of the number of epochs for the problem of determining only D/d, and Table 2 provides a sample of the results for three groups of examples (taken from the validation portion of the dataset), where the parameters ρ_B and ρ_Z remain constant within each group, and only the expected value of D/d varies (D/d' denotes the obtained value). The maximum error in these examples does not exceed 15%. This maximum error has been reported at low values of the formation parameters and decreases as the parameter increases.

Figure 7 shows the training error as a function of the number of epochs for the problem of determining ρ_B and ρ_Z, and Table 3 provides a sample of results for three groups of examples, similar to Table 2 ($\rho_{B'}$ and $\rho_{Z'}$ denote the obtained values).

The maximum error has been observed only for the lowest values of parameter ρ_Z (up to approximately 50%) and parameter ρ_B (20%, at most). For other orders of magnitude, the error does not exceed 12—15%.

The relatively high error for low parameter values can be attributed to the use of the sigmoid activation function that only asymptotically approaches the extreme points of its definition range. This issue can be mitigated by adjusting the parameter definition range or by modifying the normalization coefficients of the training examples prior to network training.

All software used in this study has been independently developed by the author, in Delphi.

Table 3. **Examples of Solving the Installation Problem of ρ_Z and ρ_B**

D/d	ρ_Z	ρ_Z'	ρ_B	ρ_B'
0	1.04	1.53	10.47	11.38
2		1.54		11.43
4		1.58		11.89
6		1.63		12.32
8		1.60		12.03
10		1.52		11.20
0	2.63	2.95	23.98	26.53
2		2.85		25.42
4		2.92		26.15
6		2.98		26.72
8		2.95		26.33
10		2.83		25.05
0	7.58	7.04	69.18	69.51
2		6.96		68.75
4		6.94		68.57
6		6.89		67.74
8		6.90		67.32
10		6.94		67.67

Based on the obtained and demonstrated examples, it can be concluded that the problem of determining the radial distribution of resistivity (along the formation for vertical wells) has been effectively solved using a neural network with backpropagation of error.

This effective solution is enabled by the prior solution of the problem of determining the vertical resistivity profile along the wellbore for each individual logging tool employed.

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ЗАСТОСУВАННЯ НЕЙРОННИХ МЕРЕЖ ЗІ ЗВОРОТНИМ РОЗПОВСЮДЖЕННЯМ ПОМИЛКИ В ЗАДАЧАХ ЕЛЕКТРОМЕТРІЇ НАФТОГАЗОВИХ СВЕРДЛОВИН

Вступ. Кінцевим кроком електрометрії як основного методу геофізичного дослідження свердловин є кількісна інтерпретація, яка вимагає розв'язання нестійкої оберненої задачі визначення геоелектричних параметрів нашарування пластів, розкритих свердловиною.

Проблематика. Необхідність розв'язувати обернені математичні задачі електрометрії нафтогазових свердловин супроводжується проблемою їхньої нестійкості. Для задач електричного каротажу не існує універсального регуляризаційного методу ефективного розв'язання нестійких обернених задач, створення регуляризаційних методів є технічно складним завданням.

Мета. Продемонструвати можливість ефективного розв'язання оберненої задачі електрометрії (як методами електричного, так й індукційного каротажу) за допомогою використання нейронних мереж зі зворотним розповсюдженням похибки простої архітектури.

Матеріали й методи. Для розв'язання поставленої задачі шляхом випробовування різних параметрів та архітектури нейронної мережі було обрано двошарову мережу із зворотнім поширенням помилки.

Результати. Створено та навчено нейронну мережу (із розробкою структури та обчисленням відповідних масивів її навчання) для визначення становлення параметрів тришарового пласта, розкритого свердловиною. Це дозволило встановлювати радіальні геоелектричні параметри продуктивних пластів-колекторів і визначати їхні фільтраційні характеристики при подальшій кількісній інтерпретації.

Висновки. Показано, що задача визначення радіального (вздовж пласта для вертикальних свердловин) розподілу питомого електричного опору може бути ефективно розв'язана за використання нейронних мереж із оберненим розповсюдженням помилки простої архітектури. Створено ефективний інструмент для надання швидкої та точної відповіді на головні питання замовника геофізичних робіт: де саме і в якій кількості знаходиться корисний флюїд.

Ключові слова: електрометрія, нафтогазова свердловина, обернена задача, нейронна мережа, зворотне розповсюдження похибки.