Проведено відбір інформації для впорядкування теоретичних положень та розробки практичних рекомендацій щодо діагностичних обстежень системи протикорозійного захисту підземних металевих нафтогазових трубопроводів.

Сформовано множину інформативних параметрів для моделювання функціональних зв'язків та визначення поляризаційного потенціалу у системі "підземна металоконструкція – установка катодного захисту".

Для ділянки трубопроводу з урахуванням поляризаційного потенціалу на зовнішній поверхні запропоновано застосувати алгоритм прогнозування корозійного струму, підхід нелінійного програмування, а також нейронну мережу, що включає відповідні методи навчання. Сформовано тестуючу множину для оцінювання ефективності нейронної мережі.

Відзначена інформація є важливою для удосконалення апаратури дистанційного контролю металевих конструкцій нафтогазових підприємств, тобто методик коректного вимірювання та оцінювання постійних і змінних напруг та поляризаційного потенціалу на трубопроводі.

Розглянуто методи та алгоритми нейронних мереж, які застосовують для керування протикорозійним захистом підземних трубопроводів. Проведено дослідження ефективності штучних нейронних мереж, зокрема двошарової мережі прямого розповсюдження з функцією прогнозування ресурсу металевих труб. З використанням поляризаційного потенціалу виявлено здатність нейронних мереж виконувати недоступні для традиційної математики операції обробки, порівняння, класифікації образів, можливість самонавчання та самоорганізації стосовно підземних трубопроводів. Удосконалено кваліметричний критерій якості для ділянки трубопроводу з урахуванням оптимального діапазону поляризаційного потенціалу.

Розроблено метод прогнозування поляризаційного потенціалу установки катодного захисту і перехідного питомого опору ізоляційного покриття на поверхні підземної металоконструкції з використанням нейронної мережі. За результатами аналізу поляризаційного потенціалу і перехідного питомого опору конструкції розроблено методологію формування інформаційного забезпечення для методик деградації антикорозійного діелектричного покриття та металу на зовнішній поверхні підземної металоконструкції, а також для прогнозування її ресурсу

Ключові слова: нейронна мережа, підземні трубопроводи, поляризаційний потенціал, розподіл постійної напруги, нафтогазові підприємства

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DETECTION OF SPECIFIC FEATURES IN THE FUNCTIONING OF A SYSTEM FOR THE ANTI-CORROSION PROTECTION OF UNDERGROUND PIPELINES AT OIL AND GAS ENTERPRISES USING NEURAL NETWORKS

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1. Introduction

Analysis and monitoring of technical condition of underground metal pipelines (UMP) at oil and gas enterprises is important because the damage and destruction of the elements of structures in the process of operation can lead to dangerous and/or catastrophic consequences. That is why there is a large body of research and development for the implementation of intelligent monitoring systems that can control the life cycle of complex objects (specifically, UMP and plants of cathodic protection (PCP)). In the process of comprehensive analysis into the current state of the system "UMP – PCP", it is advisable to take into consideration the operating load and parameters that characterize their interactions with the environment.

Given the complexity of an object, it was found by experts estimations that it is advisable to analyze the system "UMP – PCP" with the help of neural networks. Here, the principle of using artificial neural networks (ANN) involves continuous and automatic control of defects and damages caused by adverse conditions during the operation of pipelines and metal structures. It is appropriate to analyze this type of complex systems with a large amount of damage (defects) using the ANN and take into consideration the elements of artificial intelligence of a certain level [1] in order to avoid errors in predicting operating conditions.

The relevance of the research into the system "UMP – PCP" is predetermined by three main factors. Firstly, it is appropriate to consider the "UMP – PCP" system as a complex integrated system taking into account the set of energy and kinetic parameters. This approach is problematic. Secondly, multi-layer ANN (at least with two perceptrons) were applied neither to the "UMP – PCP" system, nor to its components. Thirdly, it is problematic to choose the correct optimization approach for physically reasonable prediction of the resource of underground and surface elements of structures in contact with aggressive environment.

Hence it is obvious that the relevance of the research is also caused by the fact that during development of algorithms of diagnosing UMP and designing improvements for the PCP based on the ANN, it is advisable to perform a selection of the ANN type.

2. Literature review and problem statement

At present, an acute problem of controlling and diagnosing the sites of an oil and gas complex (as potentially dangerous sites) by the object direction and the level of complexity arises in the practical context. Along with this, it was established that diagnostic examinations (or research) of the system of anticorrosive protection of underground metal pipelines (UMP) of oil and gas companies, especially with the use of neural networks, are becoming increasingly important today. At the same time, it was found that the information base for the research into the problem of predicting the resource of underground metal structures (oil and gas pipelines, ammonium pipelines) is formed by insufficiently substantiated results of decisions (conclusions) on the choice of optimization methods in the procedure of training an ANN [1, 2].

Thus, based on [1], approaches of stochastic optimization lead to large errors in prediction. Paper [2] does not highlight the approach to exploring complex systems (of the "UMP – PCP" type). The specified shortcomings [1, 2] lead to essential errors of prediction of time of learning.

It should be noted that the destruction of underground metal structures can be caused by many factors, such as the expiration of operation terms, occurrence of surface defects in the process of the plant manufacturing, mounting and operating, a change in operating loads and the influence of natural factors, accompanied by metal corrosion [3]. The specified work [3] does not take into account the possibility to consider the plant of cathodic protection (PCP) in the conjunction with UMP. Simulation of corrosion processes in a pipeline taking into account anodic currents, electrode potentials and energy characteristics of inter-phase layers can be conducted based on the relationships in article [4]. Article [4] does not take into consideration the possibilities of consideration of the plant of cathodic protection (PCP), specifically, polarization potential, in the conjunction with UMP.

To evaluate the resource of oil and gas pipelines, it is necessary to take into consideration the general principles of assessment of strength and durability of the elements of a structure, and the correspondent equipment was described in monograph [5]. However, it does not consider the procedure of modeling of corrosion processes [4] and approaches of correct measurement of polarization potential [6]. The appropriate diagnostic studies make it possible to estimate the levels of economic losses, loss of people's lives and environmental pollution [7]. However, the paper [7] does not contain the information on metrological research into specific devices. The information on metrological research into diagnostic systems, the quality and the possibility of their application for the sites of oil and gas industry is presented in article [8]. However, the methodology of analysis of the functional relationships for the "UMP – PCP" system was not highlighted in it.

An important problem of resource prediction for the system "UMP – PCP" is its complexity and large amount of functional parameters, which can negatively affect the quality of the prediction of resource piping systems. A general approach to the formation of a multiplicative quality criterion was provided in article [9]. However, it is applied to another type of transportation systems [9], not related to the transportation of gas and petroleum products.

The application of neural networks [10] taking into consideration the criteria of the type [9] makes it possible to develop the methodology for the analysis of functional connections for the system "UMP – PCP", enhance the quality of PCP, but does not give grounds to predict the resource of metal structures.

Methods of control and simulation, which are relevant to the systems of the "UMP – PCP" type are characterized by deviations, errors and uncertainty [11]. To overcome uncertainty during the formulation of optimum problems, related to the systems of corrosion control and evaluation of reliability of pipelines, it is advisable to predict the rate of metal corrosion based on the data about corrosive defects [11], along with the widely used deterministic and statistical methods. In addition, the results of [11] can be used to assess the maintenance aspects that can contribute to optimization of the future cost of pipelines maintenance, as well as create recommendations to reduce the number of accidents and catastrophes at oil and gas enterprises.

As a result, using ANN and taking into account the information from the above papers, it is possible to choose the optimal method for diagnosis, propose the necessary measuring devices, process a large amount of information obtained as a result of monitoring the "UMP – PCP" system, predict the physically substantiated resource of the corresponding systems ("UMP – PCP").

Thus, the results of analysis of the literature data and the existing practical problems of diagnosing the system "UMP – PCP" determine the directions of research, specifically, substantiation of the resource of the corresponding system.

3. The aim and objectives of the study

The aim of this research is to form theoretical positions and to develop practical recommendations for diagnostic examinations of the system of anticorrosive protection of underground metal pipelines (UMP) at oil and gas enterprises using neural networks for establishing physically substantiated operation terms (resources) of UMP.

To achieve the set aim of research, the following tasks were defined:

– to carry out the examination of the pipeline sections (UMP) with the help of the non-destructive control equipment VPP-M (the device controls parameters of the state of anticorrosive protection of pipeline sections);

– based on the results of diagnosing the "UMP – PCP" system and modeling the processes of propagation of defects in metal pipes, to determine the potentials between metal and electrode of comparison (ECOM), which correspond to direct and alternating currents, as well as the distribution of polarization potential along the section of the structure element;

– using the quality criteria and the neural network, to describe the process of the change of polarization potential of the PCP and transitional specific resistance of the insulating coating on the surface of an underground metal structure and on this basis to determine physical-chemical parameters that characterize physically reasonable operation terms (resource) of the UMP.

4. Materials and methods to study the influence of environment on the state of underground pipelines

The problems of predicting the states of metal and dielectric coatings have recently acquired special relevance in the field of diagnosis of underground metal pipelines (UMP) of oil and gas enterprises. The shortcomings of the "classic" methods of prediction of pipelines are:

– the absence in the model of the objects and processes of the views on the structure and the system of relationships of the real object, which introduces subjectivity in the selection of both the model and its structure;

– difficulty of constructing the models of objects and processes, provided that the data are stored in different time series and (or) have temporal shifts in relation to each other;

– insufficient accuracy of prediction;

– considerable sensitivity of the obtained results regarding the information and (or) noisy information;

– significant uncertainty of estimation of parameters while processing a large volume of information;

– dependence of results of the forecast on the analyst's qualification in a particular subject area.

In this situation for a pipeline section, taking into consideration polarization potential, it is advisable to apply neural networks with the prediction algorithm that includes a well-developed methodology of structural modeling of direct and alternating voltages and methods of learning, based on the well-developed theory of nonlinear programming [11, 12]. The main criterion of the UMP protection is considered to be the difference of potentials between metal and environment, which is called polarization potential (PP) [6].

The problem of predicting the resource an underground metal pipeline refers to a class of the problems of time series prediction of type (1):

$$|(t_1,\ldots,t_{i+k\text{-}1})-t_{i+k}| \qquad (1)$$

that is, there is time series $\{t_1, t_2, t_n\}$ of statistical data (parameters of the "UMP – PCP" system), directly related to polarization potential [6]. From the dataset, we choose the initial and the final value $t_1,\ldots, t_n$.

Function $f(t_1,\ldots, t_n)$, $k\leq n$, is constructed to meet the conditions (1).

Function f (the range of its values) is a "successful" (in a certain sense) prediction of value t_{i+k} by the value of the time window $\{t_1,\ldots, t_{i+k-1}\}$. Since the prediction quality criterion can be different, it is not discussed in this case. The ultimate goal of the optimization problem of information ordering for the "UMP – CPC" system is its use for the prediction of unknown values t_{n+1}, t_{n+2},.... In this case it is assumed that if a "successful" prediction is found for a large number of time windows, it also remains partially "successful" for a small number of time windows that are beyond the boundaries of the known values.

Fig. 1 shows the algorithm for calculating the values for the predicted function. Each node at the network accepts at the input a set of output values of the previous network layer and transmits the calculation result to the following layer, so that a_k^t is the coefficient of relation with the i-th node (L–1) of the i-th layer or with the k-th node of the i-th layer, and $y^{L-1}=f\left(a_i^{L-1}\right)$ is the calculation result in node number i of layer number L–1.

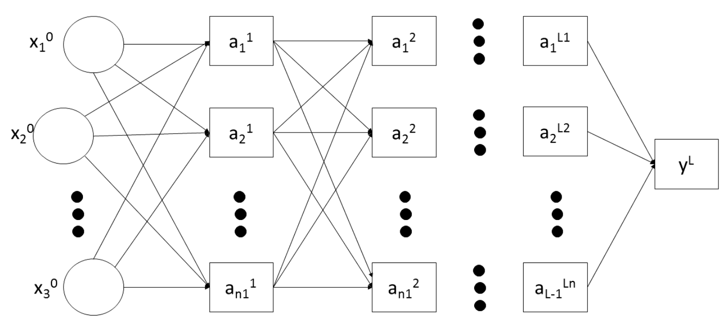

Fig. 1. Block-diagram of the prediction function to calculate parameters of the "UMP – CPC" system using a neural network

A neural network is a homogeneous composition of layers of elementary solvers [13]. From the side of the prediction function alone, it does not matter at all from which interval one takes values: [0; 1] or [–1; 1]. It is common to take the range [0; 1], but according to the results of the computational experiment, it was found that in some cases the choice of range of [–1; 1] is a more appropriate [14].

Because the numerical values of the time series elements can vary continuously (on the section), the entire network should be steady in continuous mode to implement function f_0 by all arguments. That is why it is considered undesirable for a node (of the elemental calculator) to enter the "saturation" mode, that is, getting of a_i^L to the point where $f'\left(a_i^L\right)$ – the first derivative – is quite small.

Since we consider the completely defined functions that characterize the "UMP – PCP" system, it means that a_i^L should not greatly deviate from initial values.

Consider restrictions $a^-\leq a_i^L\leq a^+$, $\left|a^-\right|=\left|a^+\right|$. If $\left|a^+\right|$ is small enough value, $f(x)$ is quite accurately approximated by a linear function.

Neural network learning is the process of finding such relation coefficients, according to which the neural network implements a "successful" prediction function [15].

Because the network implements a continuous function, with its help, it is possible to predict value $f(x)$ using normalized series, as well as transformed ones, help to predict the value of $f(x)$ using the normalized series, as well as converted one, for example, when all values are decreased by k times [15, 16].

5. The criterion of quality for an underground pipeline

Consider the product of the type of $k_P=k_1\times k_2\times k_3$ [3, 9]:

k_1 is the coefficient of commercial gain;

k_2 is the coefficient of competitiveness level (competitive ability) of the UMP;

k_3 is the coefficient of reliability of UMP.

Similar to papers [3, 9], we will present the multiplicative qualimetric criterion of quality for the UMP section as follows:

$$Z_1=\prod_{i=1}^{m} k_i = k_1 \cdot k_2 \cdot k_3 \cdot k_4 \cdot k_5 \cdot k_6 \cdot k_7 \cdot k_8 \cdot k_9 \Rightarrow \max, \quad (2)$$

where $k_4(D_f)$, $k_5(p_S)$, $k_6(\sigma_{ve})$, $k_7(K_S)$, $k_8(T_S)$, $k_9(U_P)$ are the coefficients which characterize defectivity D_f, strength p_S, boundary of corrosive fatigue $\sigma_{ve}(N_P)$, influence of the coating on corrosive resistance K_S, period of fault-free operation T_S (resource) of a structure (pipe); keeping to an optimal range of polarization potential U_P.

We will also introduce quality criterion Z_2 in additive form, similarly to [3]:

$$Z_2 = a_1 \cdot k_1 + a_2 \cdot k_2 + a_3 \cdot k_3 + a_4 \cdot k_4 + a_5 \cdot k_5 + a_6 \cdot k_6 + a_7 \cdot k_7 + a_8 \cdot k_8 + a_9 \cdot k_9 \Rightarrow \max, \quad (3)$$

where a_j (j=1, 2, ..., 9) are the weight factors determined by the expert method.

In contrast to paper [3], we took into account $k_9(U_P)$ and, respectively, polarization potential U_p.

According to current standards for a steel pipe in the ground, polarization potential (PP) U_P must be in the range from –0.85 V to 1.15 V relative to the copper-sulphate reference electrode [6]. An important problem of electrochemical protection is to control PP on the outer surface of a pipeline, which can contact with a ground electrolyte, and to order the investment system [7].

6. Results of studying the pipeline at a certain section with the help of VPP-M equipment

The state of anticorrosive protection of pipeline sections was controlled using the equipment (devices) CMC-K and VPP-M [6]. Contact-free measurements of currents (CMC) are used in the course of studying current conductive communications (underground metal pipes, cables, etc.) to determine the current distribution in communication network. Based on these measurements, we detect damages to insulating coverings, unauthorized connections and control the state of anticorrosive protection in order to prevent road accidents and to ensure reliability of operation [6].

With the help of digital devices VPP, direct and alternating electric voltages are measured and U_P**,** are determined, while VPP-M is improved compared with VPP and allows determining the geographic coordinates for pipelines based on GPS with memory and interface [6].

Simultaneous measurement of a constant difference of potentials and alternating electric voltage on the ground surface enables conducting a search for damages to UMP insulation using the known methods of transverse gradient and the Pearson method [6]. According to measurements of polarization potential, the state of electrochemical protection is controlled and corrosion spots on the surface of metal structures are detected.

Equipment BPP-M makes it possible to determine transitional specific resistance of insulating coating R_{in} for each interval within length Δl_n between the points of measurements of currents of UMP [6]:

$$R_{in}=\frac{U_{in}}{i_n}, \quad (4)$$

where the density of constant component of the current of cathode protection i_n in the n-th interval of length and surface square S_n (of cross-section) takes the value:

$$i_n=\frac{\Delta I_n}{S_n}=\frac{\Delta J_n}{\pi D\times \Delta l_n \times k_n}, \quad (5)$$

where ΔJ_n is the difference of measurements of a variable current component at the ends of an underground pipeline section (UMP); D is the pipeline diameter; k_n is the number of research experiments.

A drop of potential on the insulating coating of UMP [6]:

$$U_i=U_{MG}-U_{GG}-U_P=V_{MG}/k_P-U_{GG},$$

$$k_P=V_{GG}/U_{GG}, \quad (6)$$

where k_P is the coefficient of harmonics of alternating current, which flows into the pipeline on the given section, it is determined by the ratio of alternating V_{GG} and direct U_{GG} voltages in the ground transversally to the road; U_{MG} and V_{MG} are the voltages between metal and comparison electrode (ECOM), measured at direct and alternating currents, respectively.

A voltage drop in ground U_G will be equal to the measured difference of potentials U_{GG} between a comparison electrode and an auxiliary electrode, if distance x between the electrodes was selected taking into consideration depth of lying h and pipeline diameter D:

$$x=h\sqrt{\left(\frac{4h}{D}-2\right)}. \quad (7)$$

Using formulas (1) to (7), we conducted comprehensive examination of the pipeline sections (UMP) using the methodologies of paper [6] and measuring results are shown in Fig. 2. During processing the results of measurements of currents and potentials, we used equal sections between the points of measurement (Fig. 2–5).

In this research option, information in Fig. 2–4 is auxiliary and makes it possible to optimize the procedure of the experiment. The variant of output experimental data are shown in paper [17]. After a year of pipeline operation, a similar experiment was conducted based on [17], and the distribution of direct voltage “pipe – ground” U_{MG} was obtained (Fig. 5). Distribution of polarization potential U_P along the UMP was determined taking into consideration (6) and procedures of papers [1–11, 17, 18]. In the diagram (Fig. 5), the horizontal straight line (U=0.85 V) allows estimating boundary potentials U_{MG} and separating the pipe area l=177÷212 m, which undergoes corrosive dissolution. The corresponding information is testing for performing optimization calculations using a neural network.

For better visualization, the maps with the 3D view and the map with the view from space were demonstrated (Fig. 6).

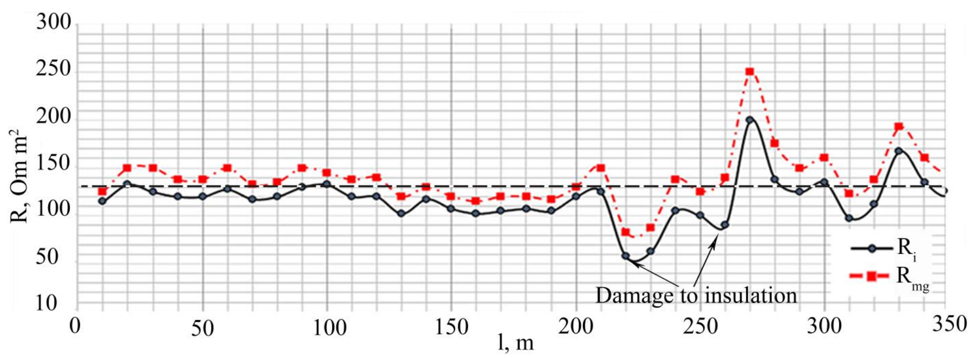

Fig. 2. Distribution of transitional resistance "pipe – ground" R_{MG} (l) and insulation resistance R_i(2)

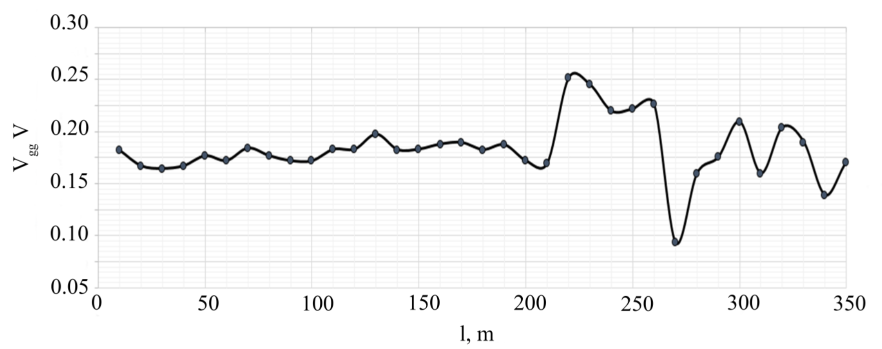

Fig. 3. Distribution of alternating voltage "ground – ground" V_{GG} (l)

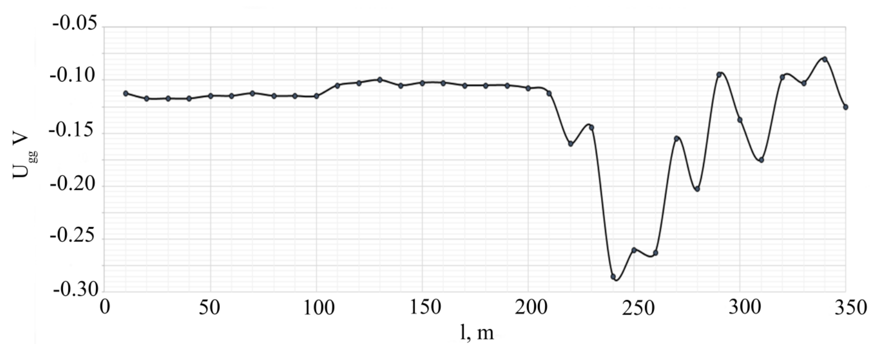

Fig. 4. Distribution of direct voltage "ground – ground" U_{GG} (l) – gradient of potential

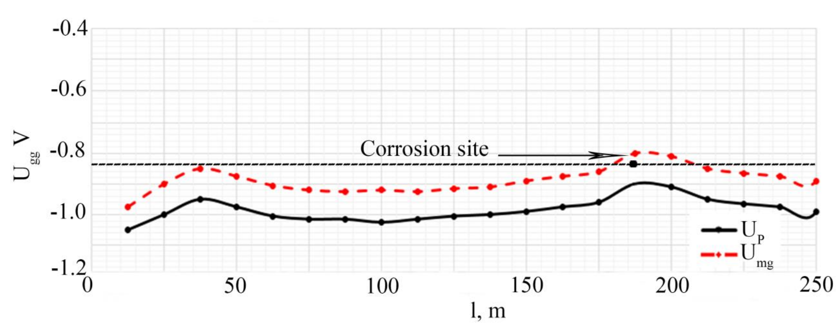

Fig. 5. Distribution of direct voltage "pipe – ground" U_{MG} and polarization potential U_P along UMP

Mistaken decisions, such as false failure (when an object is in order, but control shows the deviation from the norm, i.e. defect) are possible in the course of research into control of the pipelines state. These errors (of the first kind) are usually not particularly important, because it is possible to check the existence of a defect. In contrast, an undetected failure, undetected defect (error of the second kind) can cause damage and emergency, which is very important for the operation of the system "UMP – PCP". Such errors for the contact method are possible when the results of measurements of potentials at the points of a route are missing (due to the local nature of this control). Comprehensive use of VPP-M makes it possible to reduce the probability of errors and increase the reliability of results of control. The method of prediction using the neural network was proposed for more detailed proofs.

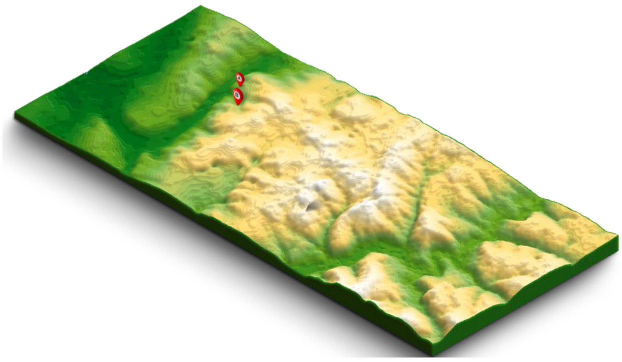

Fig. 6. Location of the examination area of UMP over the 3d relief

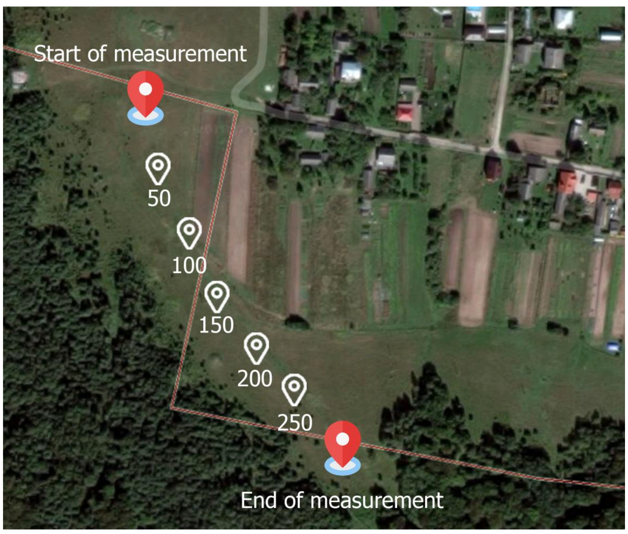

Fig. 7. Location of the examination area of UMP in the photograph from space

7. Results of prediction with the help of a neural network for a pipeline section

With the help of the neural network with the prediction function $f(x_1,..., x_n)$, we predicted the situation regarding potentials of the U_{MG} type and polarization potential U_P along the underground pipeline (UP) on the pipeline section of the length of 250 m (Fig. 8). The place (l≈190 m, prediction No. 1, i. e., prediction for a year ahead), where the corrosion process can occur, was found on the given section (Fig. 8).

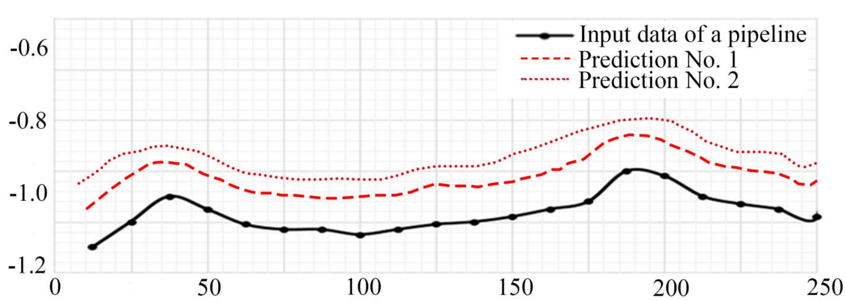

Fig. 8. Diagram of prediction of potentials of U_{MG} type along the UP with the help of the neural network taking into consideration the process of corrosion

If prediction dependence 1 for U_{MG} (prediction No. 1, first year of prediction) is shifted on average by 0.06 V, dependence 2 (prediction No. 2, second year of prediction) is shifted on average by 0.05 V) in comparison with the result of prediction 1. Thus, prediction 2 indicates the non-uniform character of corrosion rate.

8. Discussion of results of studying the system of anticorrosive protection of underground pipelines at oil and gas enterprises using neural networks

Based on an analysis of graphic dependences and modeling results obtained by the analysis of literature data, it was found that over time corrosion rate decreases (in this case approximately by 17 %).

Based on the research results, it is possible to argue on that the corrosion rate during prediction with the help of the neural network corresponds to a fairly "successful" result. The prediction of neural network was related to the pipeline operation section of the length of L=250 m with the place where corrosion occur. Prediction No. 1 illustrates potentials U_{MG} for the first year and, accordingly, prediction No. 2 illustrates potentials U_{MG} for the second year. The neural network allowed us to establish that the average value of metal (steel) corrosion rate on the surface of an underground pipe in defects of the coating occurs approximately in the range of 0.13–0.15 mm/year (unlike standard procedures according to monograph [5], for which a wider range 0.12–0.16 mm/year is more characteristic in a similar case).

The proposed qualimetric criterion (2) has the advantages over the existing ones [3, 9], because it takes into consideration polarization potential and allows more proper statement of the optimization problems for setting cathodic protection (SCP).

Based on the information about the control of anti-corrosive protection of the underground metal pipeline (UMP) by the equipment (devices) BVS-K and VPP-M [6, 17], a testing set for the evaluation of effectiveness of a neural network was formed.

The disadvantage of the test set is that it is not voluminous enough. In addition, the neural network taking into consideration this initial test of set functions as a "black box" during learning, which imposes some limitations on corresponding results regarding the pipe resource prediction.

The conducted research is continuation of earlier studies, specifically [6, 17, 19], and has the prospects for improvement of metrological methods for correct determining currents and voltages in the field of diagnostic studies and non-destructive remote control of the system "UMP – PCP" with the equipment BVS-K and VPP-M.

Along with this, it is worth noting that in papers [20, 21], the need and prospects for non-destructive diagnosis of underground metal pipelines using acoustic signals was highlighted. The advantage of the methodology and of the devices, which use the principle of electromagnetic waves [6, 17, 19], is obvious, because it is associated with the length of probe waves and geometric dimensions of defects (cracks) on the outer surface of an underground metal structure. The specified methodology for express control [6, 17, 19] makes it possible to detect defects on the surface of an underground metal pipe of smaller dimensions.

The proposed qualimetric criterion of type (2), (3) can be also used to organize the information about enhancing effectiveness of interaction between the system of cathodic protection (CPS) and compressor stations.

9. Conclusions

1. An analysis of the results of contact-free measurements of currents and voltages, obtained as a result of monitoring the pipeline sections using devices of non-destructive control BVS-K and VPP-M, was performed. Owing to these devices, transitional resistance of the insulating coating was determined and the appropriate test set for the evaluation of the effectiveness of a neural network was formed.

2. We formed a set of informative physical and chemical parameters for determining the polarization potential in the system "underground metal pipeline (UMP) – plant of cathodic protection (PCP)". Informative parameters based on energy characteristics of inter-phase layers, voltage and corrosive currents bands correspond to the method of probing metal structures by means of electromagnetic waves.

3. The method for the prediction of polarization potential of PCP and the transitional specific resistance of the insulating coating on the surface of an underground metal structure using the optimization criterion and neural network was developed. According to the results of analysis of polarization potential of the PCP and transitional specific resistance, we developed informational support for procedures describing the degradation of anti-corrosive dielectric coating and metal on the outer surface of an underground metal structure, as well as for the prediction of resource of the "UMP – PCP" system. The appropriate method and procedures for the evaluation of physical and chemical parameters, unlike the standard ones, make it possible to describe in a physically-substantiated way and mathematically correctly the procedure of propagation of corrosive defects into the depth of a pipe, as well as to narrow down the range of estimation of the mean value of corrosive current in defects of the coating approximately by 50 %.

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