Сформовано множину визначальних параметрів для моделювання етапів розвитку поверхневого дефекту на зовнішній поверхні металевого трубопроводу з урахуванням втомної міцності.

Для ділянки трубопроводу з поверхневим дефектом запропоновано застосувати алгоритм прогнозування поляризаційного потенціалу з використанням засобів нейронної мережі. Сформовано методику функціонування тестуючої множини для оцінювання ефективності нейронної мережі, що включає відповідні методи навчання. За результатами аналізу взаємозв'язаних деформаційних та корозійних процесів розроблено елементи методології формування інформаційного забезпечення прогнозування ресурсу лінійної частини підземного металевого трубопроводу з урахуванням корозійної втоми.

Відомі результати оцінювання ресурсу підземного металевого трубопроводу (ПМТ) передбачали лінійний характер швидкості корозії. Відповідна інформація представлена в міжнародних та національних стандартах. Проведені в останній час експериментальні дослідження показали, що доцільно враховувати нелінійний характер швидкості корозії на зовнішній поверхні ПМТ.

Проведено обстеження ділянки ПМТ за допомогою вимірювача поляризаційного потенціалу (ВПП) у комплексі з безконтактним вимірювачем струму (БВС) і сформульовано принципи використання нейронної мережі для опрацювання результатів експерименту. Розглянуто конкретний приклад для ПМТ, в результаті аналізу якого з допомогою нейронної мережі для підземної труби (зі сталі 17Г1С) з корозійним дефектом на зовнішній поверхні проведено оцінювання ресурсу металу і виявлено нелінійність, величину якої характеризує відношення δ*=1,136.*

Запропоновано метод контролю і методики оцінювання поляризаційного потенціалу з допомогою нейронної мережі. Вони дозволяють фізично обґрунтовано та математично більш коректно на відміну від стандартних описати процедуру поширення корозійних дефектів у глибину труби.

Відзначена інформація є важливою для удосконалення методів контролю підземних металевих труб нафтогазових підприємств, зокрема, методик коректного вимірювання та оцінювання поляризаційних потенціалів та анодних струмів у дефектах ізоляційних покрить з урахуванням нелінійності інформативних параметрів

Ключові слова: підземні трубопроводи, нафтогазові підприємства, поверхневий дефект, поляризаційний потенціал, корозійна втома, нейронна мережа, ресурс металу

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FORMING THE TOOLSET FOR DEVELOPMENT OF A SYSTEM TO CONTROL QUALITY OF OPERATION OF UNDERGROUND PIPELINES BY OIL AND GAS ENTERPRISES WITH THE USE OF NEURAL NETWORKS

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1. Introduction

Assessment of quality of monitoring underground metal pipelines (BMP) in oil and gas industry relates to quality of functioning of their three defining components:

1) linear section (LS) (pipe metal);
2) compressor station (CS);
3) cathodic protection systems (CPS). The LS-CS-CPS system is rather complicated and it is expedient to use intelligent monitoring systems capable of processing large volumes of information for its control.

In the process of analysis of the LS-CS-CPS system, it is worth to take into consideration accumulation of defects and change of fatigue strength of metal during operation.

An important problem for the LS-CS-CPS system consists in stabilizing quality of the links between its components. In this context, artificial neural networks (ANNs) should be used to optimize working parameters of transportation of products, particularly gas, and minimize technological deviations during operation of pipelines and metal structures operated by oil and gas enterprises.

Information necessary for assessing pipeline quality can be established based on analysis of electrophysical parameters measured by a polarization potential meter (PPM) and a contactless current meter (CCM) [1].

Urgency of studying the LS-CS-CPS system service life is predetermined by 3 main factors. First, the LS-CS-CPS system should be considered as an involved composite system taking into consideration a multitude of electrophysical parameters and currents. Second, to optimize the LS-CS-CPS system, it is expedient to apply multilayer ANNs. Third, for correct forecast of service life of the underground pipelines contacting with ground electrolytes, correct strength criteria should be used taking into consideration loads and fatigue strength.

Known results of evaluation of BMP service life were obtained with assumption of linear nature of corrosion rate. Experimental studies have shown that it is advisable to take into consideration nonlinear nature of corrosion rate.

2. Literature review and problem statement

The problem of quality of underground metal pipelines is connected with efficiency of cathodic protection devices (CPD) as well as accuracy and reliability of information-measurement systems (IMS), in particular, relevant devices such as PPM, CCM [1]. Vibration of metal structure elements and influence of compressor stations were not taken into consideration in [1].

Implementation of measurements relates to diagnosis and monitoring of BMP taking into consideration parasitic and stray currents [2]. Background of stray currents is not separated in [1] as well. Therefore, negative effect of stray current background on quality of measurement of electrophysical parameters of the LS-CS-CPS system is disadvantage of studies [1, 2].

Protective coatings and cathodic protection devices are conventionally used to protect BMPs [3, 4]. Coating peeling is controlled by electrochemical (destructive) method [3]. It is assumed that coating efficiency is 97 %, that is, corrosion defects may appear on about 3 % of pipeline area [4].

A more up-to-date approach worth of application is related to a more qualitative CCM method which enables quick control of state of corrosion protection at various sections of underground pipelines and detection of insulation damage [5–7].

Corrosion processes in a pipeline can be modeled taking into consideration electrophysical parameters and energy characteristics of interphase layers based on relations given in [7].

Principles of diagnosing complex systems operated by enterprises taking into consideration diagnostic value of information and risks are presented in [8]. A procedure for evaluating investment attractiveness of enterprises taking into consideration means of product control and quality criteria is presented in [9]. However, results of metrological examination of diagnostic devices are not presented in [8, 9].

A time-dependent model of propagation of corrosion defects using artificial neural networks was proposed for oil and gas pipelines, but its applicability was evaluated without taking into consideration data correction methods [10]. This model is formulated on the basis of defect parameters taken from inspection data and quantified by statistical analysis.

Main parameters of cathodic protection in three types (neutral, acidic, alkaline) of simulated soil media for a high-strength pipeline steel using technology of electrochemical impedance spectroscopy (EIS) in combination with polarization curves were studied in [11, 12].

Forecast of depth and length of corrosion defects which can be used for calculation of corrosion rate is proposed [12]. Results of corresponding studies can help pipeline operators forecast pipeline structure reliability in terms of probability of its failure and service life [11].

A method of using an intelligent software and hardware complex for monitoring systems of underground steel gas pipelines and a cathodic protection device with the use of databases and knowledge bases are proposed in [11].

Information on metrological characteristics of steel structures taking into consideration interphase layers and the corresponding procedure of their improvement with the help of neural networks is given in [10, 12]. However, these studies provide no description of influence of energy characteristics of interphase layers on corrosion processes occurring in defects in the metal surface.

Approximate formulas for assessing service life of underground pipelines if defects propagate from outer surface into the pipe wall are presented in [12]. However, the study does not take into consideration the wide range of variants of nonlinear nature of corrosion defect distribution. It is partially presented in [13].

As a result of analysis of studies [14, 15] with the help of artificial neural networks, it is possible to analyze information obtained in diagnostics of a pipeline section by means of PPM and CCM devices and predict service life of the metal pipe with the detected defect taking into consideration effect of metal corrosion fatigue.

Elements of a procedure for studying propagation of acoustic signals in pipelines have been developed in [16, 17], however, the possibility of detecting defects using electromagnetic waves has not been taken into consideration.

As it follows from above analysis, direction of solving the important problem of oil and gas enterprises associated with control of operation quality of their gas and oil transportation systems consists in substantiation of service life, in other words, evaluation of service life of underground metal pipelines taking into consideration fatigue life [18, 19] and information given in [20, 21].

3. The aim and objectives of the study

The study objective is evaluation of service life of underground metal pipelines operated by oil and gas enterprises with account for corrosion fatigue life using neural networks.

Achievement of this goal involves formulation of the following tasks:

– to conduct survey of sections of a underground metal pipeline with the help of a polarization potential meter and a contactless current meter and formulate principles of using neural networks in processing the experimental results;

– to improve quality criterion and use it for the BMP-CPD system;

– based on analysis of the results of BMP diagnosis, determine potentials along the pipeline section;

– using strength and quality criteria and a neural network, determine physical and chemical parameters that characterize rate of defect penetration in the outer surface of the pipeline taking into consideration corrosion fatigue.

4. Materials and methods used in studying medium impact on the state of underground pipelines

Let us consider a crack-like defect in the form of a cavity having a crack at its apex. The defect is in the outer surface of the pipeline as shown in Fig. 1

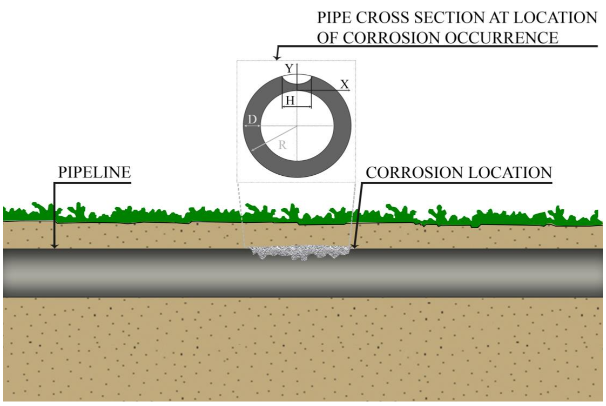

Fig. 1. Formation of a defect in the form of a cavity in the pipeline section

As can be seen from Fig. 1, pipe of the BMP is underground in a medium modeled as a soil electrolyte. Denote outer diameter of the pipe by D, thickness of the pipe wall by d, internal diameter by D-d [12]. Consider projection of the cavity on the XOY plane as a semi-elliptic crack with semi-axis dimensions c_T and a_T ($c_T>a_T$). The OY axis is directed along the pipe, OX axis is perpendicular to the pipe surface. The crack apex moves in the opposite direction relative to the OX axis. Origin of coordinates is at the crack apex.

Since corrosion fatigue is taken into consideration, consider that the crack increases its dimensions with the number of loading cycles N_C while retaining semi-elliptic shape [12]:

$$N_c = C_a \int_{ao}^{ac} \frac{da}{(\Delta K(a,\Delta a,\Delta\delta,K_1,pH_{tC},E_{tC},B_m(S)))^n},$$

$$N_{VC} = N_C / N_{C*}, \qquad (1)$$

where ao is the initial size of the macrocrack in the material; ac is critical size of the fatigue macrocrack; Δa is the quantum of destruction; $\Delta\delta$ is the peak-to-peak value of mechanical stresses; n, C_a are the constants characterizing the "material (steel)-medium" system; N_{C*} is the number of the base specimen loading cycles; N_{VC} is the relative number of loading cycles; K_1 is the stress intensity factor (SIF); pH_{tC} is hydrogen indicator of the medium; E_{tC} is the electrode potential of metal; $B_m(S)$ is parameters characterizing state of material surfaces, S, that are formed during fracture, $ao=d_*$ is the parameter in which d_* is the zone size before fracture [12].

Longevity of trouble-free operation (TFO) of BMP, T_S (that is the pipeline service life) can be estimated by formula [12] taking into consideration corrosion (anodic) current I_A

$$T_S = (h_{zm}(I_A) - h_{\max}) / I_A, \qquad (2)$$

where $h_{zm}(I_A)$, $h_{\max}$ are geometric dimensions of the variable defect and the defect of maximum permissible depth; I_A is anodic (corrosion) current, dimensionality of which is, in particular, 1 mm/year (1 mm/year ~0.8616 A/m^2).

For a qualitative analysis of propagation of fatigue cracks taking into consideration hardening, use the formula for analyzing the change of limit of the peak-to-peak value of SIF, ΔK_{th} [13]:

$$\Delta K_{th} = \Delta K_1 = E e_K \sqrt{2\pi p_{\min}}, \qquad (3)$$

where $p_{\min}$ is the critical radius of curvature of the crack nose which is determined by the Burgers vector; E is the Young's module; e_K is the actual residual deformation of metal after fracture.

The corrosion process takes place quite intensively at the crack apex and, therefore, to analyze in detail anodic dissolution of the metal, it is advisable to take into consideration the ratio that was introduced in [12]:

$$I_A = \frac{\alpha\cdot\chi\cdot\Delta\psi_{ak}}{\delta\cdot\ln(c/\delta)}\cdot\left(1+\beta_W\cdot\left(\frac{WPL-WPL0}{WPL0}\right)^S\right), \qquad (4)$$

where α is the angle at the apex of the surface defect (cracks); χ is electrical conductivity of electrolyte (particularly, soil); $\Delta\Psi_{ak}$ is the ohmic change of electric potential between anodic (A) and cathodic (C) sections; c, δ are effective depth and opening of the crack, respectively; β_W, S are empirical constants; WPL is surface energy of plastic deformation (SEPD) in a stressed state within the range of change of plastic strains, ε_P; $WPL0$ is SEPD under a condition when stress σ at the crack apex reaches boundary of yield strength σ_T of material. The ratio (4) is written for the crack apex, the anode A. Lateral surfaces of the defect (the crack) are the cathode K [12]. Elements of the procedure for estimating errors in basic parameters I_A, $\Delta\Psi_{ak}$ of formula (4) are presented in [22].

Interaction between the pipeline and the CPD system as well as transient specific resistance of the protective coating are taken into consideration.

Term PB_K of safe operation of the pipeline (gas pipeline) material with a damaged protective coating in a corrosive medium will be written as [12]:

$$PB_K = P_K w_K = K_W w_K P, PB = wP, P_K = K_W P, \qquad (5)$$

where PB is longevity of safe operation of the pipeline material in air; P, w are design and relative longevities of safe operation of the pipeline material in air, respectively; $K_W=K_W(N_C, N_K)$ are coefficients of influence of medium aggressivity on life span of the pipeline material; N_C, N_K are durabilities of the pipeline material in air and corrosive medium, respectively; P_K is durability of the pipeline material with a damaged protective coating.

An in-depth trained neural network was used in the study process. The in-depth trained neural networks correspond to a probabilistic generative model in which functions of several layers of hidden nodes are employed (Fig. 2). It can be considered as a composition of training modules forming each of the layers [23, 24].

The neural network is used for generative pre-training through the use of trained weight factors of initial weight factors. Reverse extension or other discriminating algorithms can be used for precise specification of these weight factors. This is particularly useful when available training data are limited since the weight factors with poorly set initial values can significantly interfere with effectiveness of the trained model. These pre-trained weight factors are in the scope of weight factors that are closer to the optimal weight factors than the randomly selected starting values. This ensures improved simulation procedure as well as faster convergence of the phase of accurate learning which is more appropriate than that given in [25].

During perceptron training, refined weight factors are taken according to the following equation:

$$\Delta w_{i,j}(t+1) = w_{i,j}(t) + \eta \frac{\partial \log(p(v))}{\partial w_{i,j}}, \quad (6)$$

where $p(v)$ is the probability of a visible vector set as follows:

$$p(v) = \frac{1}{Z}\sum_h e^{-E(v,h)}, \quad (7)$$

where Z is the statistical sum; $E(v, h)$ is the function of the so-called energy assigned to the neural network. The lower function shows that the neural network is in the desired configuration.

Write the gradient function as follows:

$$\frac{\partial \log(p(v))}{\partial w_{i,j}}, \quad (8)$$

which takes a simplified form:

$$(v_i h_j)\text{data} - (v_i h_j)\text{model}, \quad (9)$$

where p is the average value relative to the distribution p. Let us use Gibbson's sampling. Gibbson's sampling is used to discard same numeric values of parameters in the database and organize data while working with the neural network.

Gibbson's sampling demonstrates the best forecast occurred following n steps (n=1 was set in the neural network). After n steps, sampling of data was made and used instead of expression $(v_i h_j)$ model.

The more detailed principle of the neural network operation is as follows:

1. Set the value of the training vector.
2. Clarify hidden functions (so-called hidden network nodes) for the data of visible nodes:

$$p\left(h_j = 1 \middle| V\right) = \partial\left(b_j + \sum_i v_i w_{i,j}\right), \quad (10)$$

where $\partial(\cdot)$ is a sigmoid function; b_j and h_j characterize shift.

3. Clarification of other hidden functions for the data of hidden nodes is done in parallel:

$$p(v_i = 1 \mid H) = \partial(a_i + \sum_j h_j w_{i,j}), \quad (11)$$

where a_i is shift of v_i.

4. Repeat clarification of hidden functions for data of rebuilt visible nodes using relation (11).
5. To construct the graph, refine weight coefficients (the weights to be set for the neural network input):

$$\Delta w_{i,j} \propto (v_i h_j)\text{data} - (v_i h_j)\text{reconstruction}. \quad (12)$$

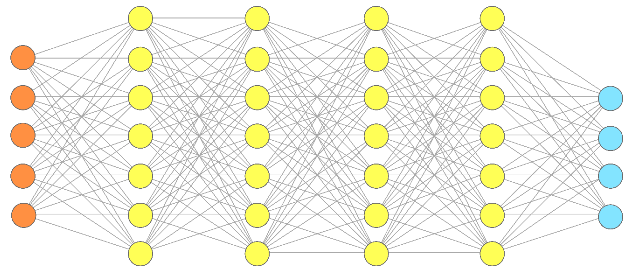

Fig. 2. Block diagram of forecasting using an in-depth trained neural network

Thus, the neural network is able to simulate virtually any complex function and the complexity of this function determines the number of hidden layers and the number of neurons in each of them [26]. Therefore, accuracy of forecast always depends on the appropriately and properly selected number of intermediate layers and corresponding neurons [27].

5. Quality criteria for an underground pipeline metal

Let us consider a product of the following type: $k_P = k_1 \cdot k_2 \cdot k_3$ [1]:

k_1: the coefficient of the BMP competitiveness;

k_2: the coefficient of the BMP reliability;

k_3: the coefficient characterizing strength p_S of the BMP metal.

In the same way as in [1], multiplicative quality criterion for the BMP section is presented as:

$$Z_1 = \prod_{i=1}^{m} k_i = k_1 \cdot k_2 \cdot k_3 \cdot k_4 \cdot k_5 \cdot k_6 \cdot k_7 \cdot k_8 \cdot k_9 \Rightarrow \max, \quad (13)$$

where $k_4(D_f)$, $k_5(n_Z, \Delta K_{th})$, $k_6(\sigma_{ve})$, $k_7(K_S)$, $k_8(T_S, N_C)$, $k_9(U_P)$ are the coefficients characterizing defectiveness D_f, strengthening n_Z, corrosion fatigue limit $\sigma_{ve}(N_C)$, the coating effect on corrosion resistance K_S, longevity of trouble-free operation T_S (service life) of the structure (pipe) taking into consideration N_C; observance of optimal range of polarization potential U_P.

Also, let us introduce the quality criterion Z_2 in the additive form similar to [1]:

$$\begin{aligned} Z_2 &= a_1 \cdot k_1 + a_2 \cdot k_2 + a_3 \cdot k_3 + a_4 \cdot k_4 + \\ &+ a_5 \cdot k_5 + a_6 \cdot k_6 + a_7 \cdot k_7 + a_8 \cdot k_8 + a_9 \cdot k_9 \Rightarrow \max, \end{aligned} \quad (14)$$

where a_j (j=1, 2, ..., 9) are the weight coefficients to be determined by expert estimation.

Here, in formulas (13), (14), unlike the study [1], $k_5(n_Z, \Delta K_{th})$ and $k_8(T_S, N_C)$ are taken into consideration depending on two parameters.

6. Results obtained in the study of cavity formation in a pipeline section

State of corrosion protection of pipeline sections was controlled with the help of CCM and PPM devices. Contactless measurement of currents is used during survey of conductive service lines (underground metal pipelines, cables, etc.) to determine distribution of current in the networks. On the basis of such measurements, damage to insulation coatings are found as well various defects formed in the outer surface of the underground pipelines are detected. Elements of the procedure for improving the regulatory framework for ordering monitoring of diagnosis of complex systems and improving quality of the results are presented in [28].

Using formulas (1)–(14), a comprehensive survey of the BMP section was carried out according to the procedures set forth in [5]. In accordance with these measurement results, locations of formation of corrosion defects (particularly cavities) were revealed as illustrated in Fig. 3 where distance is laid in the horizontal and polarization potential in the vertical. The procedure of estimation is partially presented in [1].

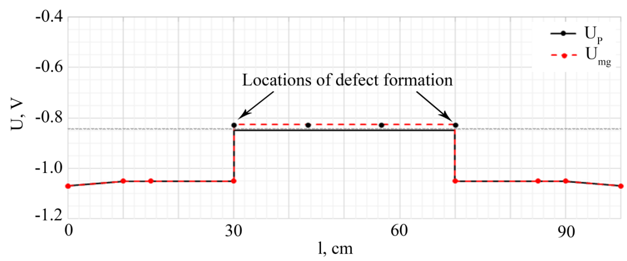

Fig. 3. A pipeline section with corrosion defects in the pipe surface (distance in mm is shown in the horizontal, potential in V is shown in the vertical)

At the first stage, diagnosis of the terrain from space was conducted. To make presentation more visual, a map with a view from the space where the defect was detected is shown in Fig. 4.

Fig. 4. Location of the surveyed BMP section shown in a space photograph

At the second stage, the pipeline was diagnosed with non-destructive testing devices (PPM and CCM). During a more detailed analysis of the pipeline, a defect with total length of about 40 cm was detected (Fig. 3). This defect was not protected by cathodic protection device. The defect propagation was observed during five years.

In contrast to standard methods, the proposed control method and procedures for estimating the polarization potential with the aid of a neural network make it possible to physically substantiate and mathematically more correctly describe the process of propagation of corrosion defects in the depth of the pipe wall. In particular, the range of estimation of the average value of density of corrosion current in the coating defects was constricted by approximately 50–70 %.

Protective potential in the defect zone is less than −0.85 V, therefore, there was corrosion dissolution of metal. It was established that the most intense anode (corrosion) dissolution was at the ends.

7. Result of the neural network forecast for the pipeline section with a defect formed

With the help of an in-depth trained neural network, data of the past five years were loaded and average value for the current year shown in the graph was found (Fig. 3). Forecast of the situation regarding formation of a corrosion defect with propagation rate about 0.13 mm/year in the current year was made.

To estimate the defect depth h_{cr} and width L_T, use relation [12]:

$$h_{cr} = h + c_{cr} = d - L_T \sqrt{0{,}1785 \frac{p_{cr}}{\sigma_b}},$$

$$h_{cr} = d\sqrt{\frac{L_T}{D}} \left(1 - \frac{p_{cr}(D-2d)}{2K_K K_S \sigma_b d}\right),$$

$$L_T \Rightarrow L_{cr} = \frac{1}{\pi}\left(\frac{8d}{p_{cr}D}\right)^2 K_C^2, \quad K_S = 1 + \frac{h+c}{d}\sqrt{\frac{L_T}{D}}, \qquad (15)$$

where K_K is the coefficient of crack sensitivity; c_{cr} is critical crack depth; K_S is the coefficient which takes into consideration change in the pipe thickness in the defective section of the pipeline; K_C is the parameter of cracking resistance determined experimentally by known mechanical test methods; p_{cr} is critical internal pressure (gas) in the pipeline.

Width L_T of the crack was determined experimentally and used to establish depth h_{cr}.

Similar experimental studies were carried out with 17G1S grade steel specimens in a medium simulating soil electrolyte.

Based on the model relations (1) to (15), a set of key parameters for simulation of stages of the defect propagation in the outer surface of the pipeline was formed taking into consideration fatigue strength.

Input data and the neural network forecast for the pipeline section where the defect was detected are given in Fig. 5.

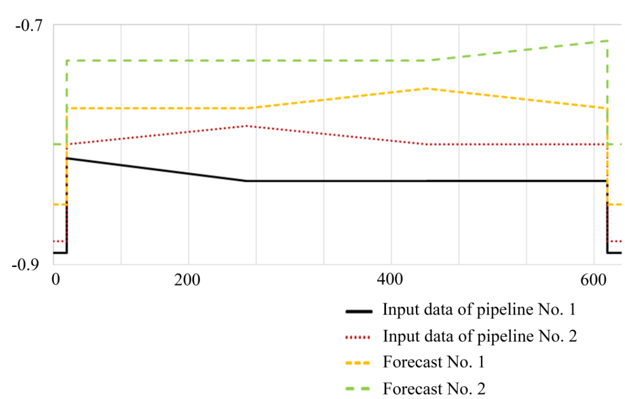

Fig. 5. Graph with input data and the neural network forecasts (distance in mm is shown in the horizontal, potential in V is shown in the vertical)

The graph of forecast No. 1 of corrosion formation according to the input data is given in Fig. 6.

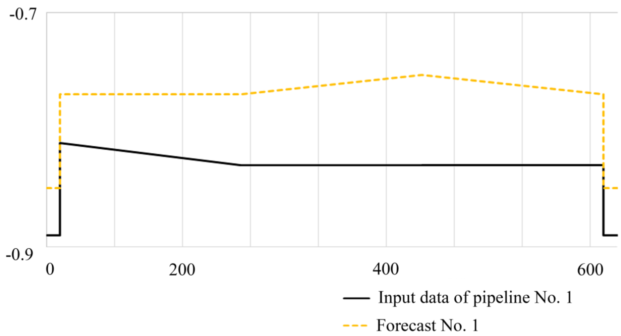

Fig. 6. Forecast No. 1 of the neural network (distance in mm is shown in the horizontal, potential in V is shown in the vertical)

It was established that corrosion leads to defect propagation by 0.39 mm in the pipeline section where the defect was formed.

In the course of forecast No. 2 by the neural network according to the input data, a decrease in polarization potential was observed. This decrease in potential characterizes corrosion propagation. The corresponding graph is shown in Fig. 7.

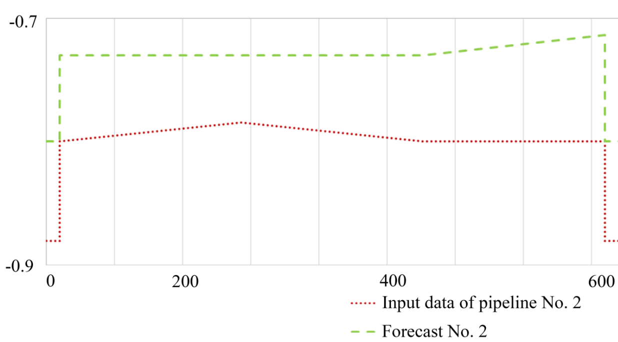

Fig. 7. Forecast No. 2 of the neural network (distance in mm is shown in the horizontal, potential in V is shown in the vertical)

Initial value of corrosion rate (Fig. 7) was 0.13 mm/year. The forecast made by the neural network (forecast No. 1) has shown that the cavity has propagated in depth by 0.39 mm at the left end of the defective region during three years. The forecast No. 2 has shown that the cavity has propagated in depth by 0.43 mm at the right end during the same period. Thus, forecasts No. 1 and No. 2 show an uneven (nonlinear) character of corrosion rate.

8. Discussion of results obtained in studying the system of protection of pipelines operated by oil and gas enterprises with the help of a neural network

Based on analysis of graphic dependences and modeling results (Fig. 3–7) obtained in the study, it was established that corrosion rate decreased with time (approximately by 10 % in the case for the right end of the unprotected BMP section). At the same time, polarization potential decreased in an absolute magnitude.

Proceeding from the study results, it can be stated that corrosion rate obtained in forecasting with the aid of a neural network corresponds to a rather "successful" result. Forecast of the neural network concerned the operating pipeline section of length L=40 cm which contained places where corrosion occurred. Forecast No. 1 has shown distribution of polarization potential, U_V, for the left end and, accordingly, forecast No. 2 has shown U_V distribution at the right end of the unprotected BMP section. The neural network has allowed us to establish that the average value of the rate of metal (steel) corrosion in the surface of the underground pipe in locations of coating defects was roughly in the range of 0.13÷0.15 mm/year.

Drawback of the testing set consists in the fact that it is insufficiently volumetric. Besides, taking into consideration this initial testing set, the neural network functioned as a "hidden calculation layer" during training which imposed certain limitations on the corresponding results of forecast of the pipe service life.

For an example, consider a concrete situation for a underground pipe made of 17G1S steel grade. The specified initial dimensions of the pipe and cavities, ultimate strength of metal, effect of corrosion fatigue, initial corrosion rate in the coating defect and other parameters useful in solving problems of diagnosing the corrosion process were taken into consideration. In particular, pressure inside the pipe p=5.5 MPa (≈55 atm), thickness of the pipe wall d=10 mm, the pipe diameter D=2R=0.76 m; initial cavity depth h=3 mm. Critical crack depth c_{kp}=3 mm. Critical situation (pipe destruction) occurs when effective size of the defect (h+c) reaches depth of h+c=6 mm. In this case, mechanical stresses at the crack apex reach critical value which, according to the criterion of maximum normal stresses, corresponds to the condition of destruction, that is, ultimate strength $\sigma_b \approx 510$ MPa. Criterion of quality (13) was taken for estimation of polarization potential shifts and the factor of safety was taken to be 1.43. Effect of corrosion fatigue has been taken into account based on consideration of known experimental data for 17G1S grade steel [12].

Critical defect depth meets the condition of 0.6d and the time to reach this crack depth depends on initial corrosion rate of 0.14 mm/yr and characteristics of vibration caused by compressor stations. Vibration causes deviations of mechanical parameters associated with fatigue strength. Corrosion rate decreases with time. It was confirmed by means of modeling, that is, on the basis of relations (1) to (15). This fact was substantiated physically and confirmed experimentally since corrosion products move away with time from the top of the defect at a lower speed. If initial corrosion rate i_{a0}=0.14 mm/yr, then the metal tube lifetime (that is, the time when the crack achieves critical depth h+c=6 mm) in this particular example is approximately τ=21.4 years. Since the corrosion process is nonlinear, the time of crack propagation, that is, service life of the metal pipe, is τ_L=24.3 years ($\delta=\tau_L/\tau$=1.136).

The considered example confirms the possibility and usefulness of simulation of corrosion processes occurring in underground pipelines with the help of a neural network. Based on the obtained results, it is possible to estimate service life of pipelines and take into consideration such phenomenon as corrosion fatigue as well as nonlinear effects.

A concrete example was considered and analyzed. Due to application of a neural network to estimation of service life of metal of an actual pipe made of 17G1S grade steel with a corrosion defect in the outer pipe surface, this analysis has revealed nonlinearity characterized by magnitude of δ=1.136. Specified initial dimensions of the pipe and cavity, ultimate strength of the metal, effect of corrosion fatigue, initial rate of corrosion in the coating defect and other parameters useful for solving the problems of diagnosing the corrosion process were taken into consideration.

9. Conclusions

1. Inspection of underground metal pipeline sections was conducted with the aid of a polarization potential meter together with a contactless current meter and principles of using neural networks for processing experimental results were formulated. In simulation of physical-chemical processes occurring in the pipeline, its interaction with the cathodic protection device system as well as transient specific resistance of the insulating coating were taken into consideration.

2. In view of varying threshold peak-to-peak value of stress intensity factor, quality criterion was defined more clearly and used for the “underground metal pipeline-corrosion protection device” system.

3. Based on analysis of the results obtained in diagnosis of the underground metal pipeline, potentials were measured in a pipeline section. The proposed control method and procedures for estimating polarization potentials with the aid of neural networks make it possible to describe the process of corrosion defect propagation in the depth of the pipe wall. This description is physically substantiated and mathematically more correct in contrast to standard descriptions. In particular, the range of estimation of the average value of corrosion current density in coating defects was constricted by approximately 50–70 %.

4. With the help of a neural network, a concrete example was considered and analyzed for metal of an actual pipe of 17G1S grade steel with a corrosion defect in the outer surface. This analysis has resulted in estimation of the metal service life and revealed nonlinearity characterized by magnitude of δ=1.136.

References

1. 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 / Lozovan V., Dzhala R., Skrynkovskyy R., Yuzevych V. // Eastern-European Journal of Enterprise Technologies. 2019. Vol. 1, Issue 5 (97). P. 20–27. doi: https://doi.org/10.15587/1729-4061.2019.154999
2. Analysis of Stray Current Induced by Cathodic Protection on Steel- Framed Masonry Structures / Wu Y-Y., Lambert P., Mangat P., O’Flaherty F. J. // The Open Corrosion Journal. 2011. Vol. 4, Issue 1. P. 34–39. doi: https://doi.org/10.2174/1876503301104010034
3. Farzaneh A., Jaber N., Jamshid M. An Electrochemical Measurement for Evaluating the Cathodic Disbondment of Buried Pipeline Coatings under Cathodic Protection // Iranian Journal of Chemistry and Chemical Engineering. 2015. Vol. 34, Issue 2. P. 83–91. URL: http://www.ijcce.ac.ir/article_14100.html
4. Merzah A. S., Ateeq A. A., Mustafa A. A. An Experimental Investigation of Impressed Current Cathodic Protection system (ICCP) In Basra Soil // International Journal of Scientific & Engineering Research. 2017. Vol. 8, Issue 7. P. 1311–1314. URL: https://www.ijser.org/researchpaper/An-Experimental-Investigation-of-Impressed-Current-Cathodic-Protection-system-ICCP-In-Basra-Soil.pdf
5. An artificial neural network modeling for pipeline corrosion growth prediction / Din M. M., Ithnin N., Zain A. M., Noor N. M., Siraj M. M., Rasol R. M. // ARPN Journal of Engineering and Applied Sciences. 2015. Vol. 10, Issue 2. P. 512–519. URL: http://www.arpnjournals.com/jeas/research_papers/rp_2015/jeas_0215_1484.pdf
6. Cathodic Protection of X100 Pipeline Steel in Simulated Soil Solution / Chen Y., Wang Z., Wang X., Song X., Xu C. // International Journal of Electrochemical Science. 2018. Vol. 13. P. 9642–9653. doi: https://doi.org/10.20964/2018.10.23
7. Yuzevych V. M., Dzhala R. M., Koman B. P. Analysis of Metal Corrosion under Conditions of Mechanical Impacts and Aggressive Environments // METALLOFIZIKA I NOVEISHIE TEKHNOLOGII. 2018. Vol. 39, Issue 12. P. 1655–1667. doi: https://doi.org/10.15407/mfint.39.12.1655
8. Yuzevych V., Klyuvak O., Skrynkovskyy R. Diagnostics of the system of interaction between the government and business in terms of public e-procurement // Economic Annals-XXI. 2016. Vol. 160, Issue 7-8. P. 39–44. doi: https://doi.org/10.21003/ea.v160-08
9. Skrynkovskyi R. Investment attractiveness evaluation technique for machine-building enterprises // Actual Problems of Economics. 2008. Issue 7. P. 228–240. URL: http://www.scopus.com/inward/record.url?eid=2-s2.0-77952681437&partnerID=MN8TOARS
10. Lozovan V., Yuzevych V. Neural network as a mean for metal constructions performance enhancement by accounting the interfacial layers // Measuring equipment and metrology. 2017. Vol. 78. P. 48–54. URL: http://science.lpnu.ua/istcmtm/all-volumes-and-issues/volume-78-2017/neural-networks-means-improving-metrological
11. Intelligent Analysis of Data Systems for Defects in Underground Gas Pipeline / Yuzevych V., Skrynkovskyy R., Koman B. // 2018 IEEE Second International Conference on Data Stream Mining & Processing (DSMP). 2018. doi: https://doi.org/10.1109/dsmp.2018.8478560
12. Mykyychuk M., Yuzevych L. Quality control of underground pipelines in view of corrosion fatigue, durability and regulatory documents // Measuring equipment and metrology. 2017. Vol. 78. P. 101–107. URL: http://science.lpnu.ua/istcmtm/all-volumes-and-issues/volume-78-2017/control-underground-gas-pipelines-quality-taking
13. Chonghua Y., Minggao Y. A calculation of the threshold stress intensity range for fatigue crack propagation in metals // Fatigue & Fracture of Engineering Materials and Structures. 1980. Vol. 3, Issue 2. P. 189–192. doi: https://doi.org/10.1111/j.1460-2695.1980.tb01113.x
14. Hinton G. E., Osindero S., Teh Y.-W. A Fast Learning Algorithm for Deep Belief Nets // Neural Computation. 2006. Vol. 18, Issue 7. P. 1527–1554. doi: https://doi.org/10.1162/neco.2006.18.7.1527

15. Hornik K., Stinchcombe M., White H. Multilayer feedforward networks are universal approximators // Neural Networks. 1989. Vol. 2, Issue 5. P. 359–366. doi: https://doi.org/10.1016/0893-6080(89)90020-8
16. Saifullin E. R., Izmailova E. V., Ziganshin S. G. Methods of Leak Search from Pipeline for Acoustic Signal Analysis // Indian Journal of Science and Technology. 2017. Vol. 10, Issue 1. doi: https://doi.org/10.17485/ijst/2017/v10i1/109953
17. Sanchez-Amaya J. M., Cottis R. A., Botana F. J. Shot noise and statistical parameters for the estimation of corrosion mechanisms // Corrosion Science. 2005. Vol. 47, Issue 12. P. 3280–3299. doi: https://doi.org/10.1016/j.corsci.2005.05.047
18. Theory and Application of Magnetic Flux Leakage Pipeline Detection / Shi Y., Zhang C., Li R., Cai M., Jia G. // Sensors. 2015. Vol. 15, Issue 12. P. 31036–31055. doi: https://doi.org/10.3390/s151229845
19. Mitchell M. R., Link R. E., Jiang Q. Study of Underground Oil-Gas Pipeline Corrosion Pits Estimation Based on MFL Inspection Method // Journal of Testing and Evaluation. 2010. Vol. 38, Issue 2. P. 250–253. doi: https://doi.org/10.1520/jte102467
20. Parkins R. N. Predictive approaches to stress corrosion cracking failure // Corrosion Science. 1980. Vol. 20, Issue 2. P. 147–166. doi: https://doi.org/10.1016/0010-938x(80)90128-6
21. Parkins R. N. The application of stress corrosion crack growth kinetics to predicting lifetimes of structures // Corrosion Science. 1989. Vol. 29, Issue 8. P. 1019–1038. doi: https://doi.org/10.1016/0010-938x(89)90091-7
22. Klapper H. S., Goellner J., Heyn A. The influence of the cathodic process on the interpretation of electrochemical noise signals arising from pitting corrosion of stainless steels // Corrosion Science. 2010. Vol. 52, Issue 4. P. 1362–1372. doi: https://doi.org/10.1016/j.corsci.2009.12.021
23. Neural networks for Nyquist plots prediction during corrosion inhibition of a pipeline steel / Colorado-Garrido D., Ortega-Toledo D. M., Hernández J. A., González-Rodríguez J. G., Uruchurtu J. // Journal of Solid State Electrochemistry. 2009. Vol. 13, Issue 11. P. 1715–1722. doi: https://doi.org/10.1007/s10008-008-0728-7
24. Artificial neural network corrosion modeling for metals in an equatorial climate / Kenny E. D., Paredes R. S. C., de Lacerda L. A., Sica Y. C., de Souza G. P., Lázaris J. // Corrosion Science. 2009. Vol. 51, Issue 10. P. 2266–2278. doi: https://doi.org/10.1016/j.corsci.2009.06.004
25. Reddy N. S. Neural Networks Model for Predicting Corrosion Depth in Steels // Indian Journal of Advances in Chemical Science. 2014. Vol. 2, Issue 3. P. 204–207. URL: https://www.ijacskros.com/artcles/IJACS-M98.pdf
26. Schmidhuber J. Deep learning in neural networks: An overview // Neural Networks. 2015. Vol. 61. P. 85–117. doi: https://doi.org/10.1016/j.neunet.2014.09.003
27. Schmidhuber J. Discovering Neural Nets with Low Kolmogorov Complexity and High Generalization Capability // Neural Networks. 1997. Vol. 10, Issue 5. P. 857–873. doi: https://doi.org/10.1016/s0893-6080(96)00127-x
28. Standardization and quality management in next-generation sequencing / Endrullat C., Glökler J., Franke P., Frohme M. // Applied & Translational Genomics. 2016. Vol. 10. P. 2–9. doi: https://doi.org/10.1016/j.atg.2016.06.001