1. Introduction

The main types of failure of underground metal pipelines (UMP) of oil-and-gas enterprises include [1, 2]:

1) mechanical failure of structural material;
2) corrosion as an arbitrary process of metal failure caused by electrochemical, chemical, biochemical interaction with the medium.
External factors of electrochemical corrosion of metal (of oil-and-gas enterprise UMP) include [1]:
1) acidity (alkalinity) of the soil that:
   a) is characterized by activity of hydrogen ions, composition and concentration of solutions;
   b) is determined by hydrogen exponent (pH) of the soil media;
2) temperature, pressure;
3) electrolyte flow rate;
4) contact with other metals, etc.

Hydrogen exponent (pH) of soil media is the most important of all above-mentioned technological factors which influences rate of corrosion failure of oil-and-gas enterprise UMPs [1–3]. The factors determining influence of corrosion activity of soils on the UMP metal show difficulty of diagnosing oil-and-gas enterprise UMPs in soil media. As is well known, the list of main factors includes [2, 4, 5]:
1) structure and granulometric composition of the soil;
2) composition of the soil electrolyte;
3) moisture content;
4) total acidity or alkalinity of the soil;
5) air permeability;
6) concentration of hydrogen ions;
7) oxidation-reduction (redox) potential;
8) electrical resistance of the soil;
9) bacteria.

Means of mathematical modeling and information technology should be applied to the “pipeline-coating” system and, accordingly, to forecasting service life of oil-and-gas enterprise UMPs using neural networks.

At the same time, the procedure of estimating the UMP hydrogen exponent as a significant characteristic of electrochemical metal corrosion on the pipe surface is of high importance. A concept of ensuring reliable and safe long-term operation of oil-and-gas enterprise UMPs taking into account hydrogen exponent (pH) of the soil contacting with the pipe metal is also important. The said concept includes:
1. Analysis of the results of non-destructive testing (NDT) of the UMP metal and replacement of worn pipeline sections according to the monitoring statistics available from the exploiting oil-and-gas enterprise.
2. Examination of oil-and-gas enterprise UMP sections using modern NDT methods and means, in particular, diagnosing pipelines by means of instruments such as a contactless current meter (CCM) and a polarization potential meter (PPM) enabling:
   1) early diagnosing of damage;
   2) identification of stress concentration zones (SCZ) as the main factors causing (or promoting) damage development.
3. Additional control is provided by conventional NDT means (ultrasonic diagnosing and X-ray control for identification, analysis and assessment of state) and study of mechanical properties and structure of the metal after digging prospect-holes at the oil-and-gas pipeline sections with detected SCZ.
4. For individual most stressed sections with detected SCZ remaining in operation, verification calculation of the structure elements is performed for determining service life taking into account nature of damages and conditions of wear of the pipeline metal.
5. The results of comprehensive study are summarized and measures to ensure reliability of the oil-and-gas enterprise pipelines are developed with drawing up a schedule of replacement of physically worn pipe sections most vulnerable to damage.

The proposed concept is based on assessment of a real service life of underground pipelines of oil-and-gas enterprises. This assessment combines exploitation experience (past damage statistics) and early prognostication of future damages using modern methods and means, in particular appropriate instruments such as PPM and CCM. The use of neural networks is also important here (that is, in the given diagnosing).

The study urgency is determined by two main factors. First, the “metal pipeline – coating” system should be considered as a complex system with its own features. This system includes a plurality of key parameters and information flows for simulation of the stages of sensing the external UMP taking into account pH of the soil contacting with the pipe metal. Secondly, for correct forecasting life of UMP contacting with the soil electrolyte, correct criteria of estimating pH on the surface of the oil-and-gas enterprise UMP should be used with application of a neural network.

It is clear from the aforesaid that the issue of diagnosing the of oil-and-gas enterprises UMPs operated in soil media based on current realities with application of neural networks is relevant and requires additional studies.

2. Literature review and problem statement

It was established that the issue of quality of underground metal pipelines is associated with the processes occurring at the “metal – coating” boundary.

Sour, alkaline and neutral soils are the main types of natural soils [1]. It was noted in [2, 3] that electrolytic composition of the soil medium significantly influences rate of growth of defects such as cracks in the pipe steel. Specifically, it was proven in [4, 5] that many factors influence the process of soil corrosion of underground metal structures, namely, water content, chemical composition and pH value of the medium, electrical resistance, soil type, salinity, noise, porosity, etc. Some processes involved are associated with hydrogen [6]. However, there is no systemic orientation and applied nature of the study in this area was not considered in [4, 5] which significantly limits possibilities for effective engineering and making technological decisions concerning the problem.

At the same time, it is worth noting that basic principles of diagnosing complex systems for enterprises (considering the diagnostic value of information and risks) are presented in [7, 8].

It was established that in order to solve the problem of qualitative assessment of underground metal pipelines of oil-and-gas enterprises, it is necessary that:
1) diagnosing of the UMP operated in corresponding types of soil media (acidic, alkaline, and neutral) was conducted [1]:
   2) relevant investment projects (decisions) of modernization and reconstruction were implemented which would be prospective for further studies in this direction [9, 10].

As regards diagnosing UMPs in corresponding types of soil media, properties of the coating (a thin film) on the metal surface and their potential features are important. In particular, the metal surface is usually characterized by electric potentials as well as certain values of re-passivating potentials [6]. Disadvantage of study [6] consists in that it did
not present a concrete procedure for evaluating connection of the polarization potential with characteristics of defects on the outside surface of the metal pipe.

Also, it should be noted that the quality criterion for UMPs of oil-and-gas enterprises was presented in [8]. However, the study does not show impact of chemical composition of the soil electrolyte as well as moisture content and total acidity or alkalinity of the soil on the UMP quality. A positive fact in this regard consists in that a toolkit for assessing investment projects of enterprises and quality criteria was presented in [9, 10].

In this context, it has been established that the method of contactless measurement of currents and potentials is currently used for pipeline probing [8]. This makes it possible to promptly control corrosion protection of UMP and find locations of corrosion defects [11, 12].

It has been found out that simulation of corrosion processes in pipelines taking into account electrophysical parameters and energy characteristics of interphase layers can be carried out based on the relations given in [13, 14]. However, connection between energy characteristics of interphase layers and electric currents and potentials in the vicinity of the pit nose in the metal surface was not described in [13, 14]. A connection of energy characteristics of interphase layers with electric currents and potentials on a flat defect-free metal surface was fragmentally presented in [15].

Elements of nonlinear nature of corrosion defect propagation from the outside surface contacting with soil electrolyte in the depth of the pipe wall are presented in scientific articles [16, 17]. Specifically, a probabilistic approach to structural analysis of the processes occurring in UMP was proposed in [17]. However, features of connection of the processes taking place in a pipeline with electrical currents and potentials in the vicinity of the pit nose in the metal surface was not described in [13, 14]. A connection of energy characteristics of interphase layers with electric currents and potentials on a flat defect-free metal surface was fragmentally presented in [15].

Proceeding from the results obtained in preliminary studies [15, 17], it was proven that the processes characteristic of the "pipeline – cathodic protection system (CPS)" system can be analyzed with the help of neural networks (NN). However, the studies [15, 17] did not describe the procedure of NN application to the "pipeline – dielectric coating" system.

Examples of evaluating service life of UMPs with taking into account fatigue life are given in [18, 19]. Proceeding from the results obtained in [20, 21], elements of solution of the problem of controlling quality of gas-and-oil transportation system operation were formed with the help of probabilistic approach and NN.

The results of analysis of [22, 23] show that due to application of NN, it is possible to analyze the information obtained in diagnosing a coated pipeline section with the help of CCM and PPM instruments and predict service life of a UMP with detected defects taking into account value of the pipe surface pH and the effect of corrosion fatigue in the metal in conditions of electrochemical corrosion.

Substantiation of evaluation of service life of a UMP taking into account fatigue life and the processes occurring in the "UMP – soil medium" system is one of the main problems of oil-and-gas enterprises in controlling quality of operation of oil-and-gas transportation systems. All this, in view of expediency and importance of this problem solution, has predetermined the study objective and tasks.

3. The aim and objectives of the study

The study objective was to evaluate hydrogen exponent (pH) on the surface of underground metal pipelines exploited by oil-and-gas enterprises in conditions of electrochemical corrosion using a neural network.

To achieve the objective, the following tasks were set:
– conduct examination of 17G1S steel specimens placed in soil media of various types using a polarization potential meter and a contactless current meter and formulate principles of NN application to processing of experimental results;
– improve the quality criterion for the “UMP-coating” system taking into account characteristics of the corroding soil medium;
– using the initial conditions as well as the developed NN, propose variants of assessment of the UMP hydrogen exponent and corresponding probabilistic parameters characterizing features of the outside surface of the pipeline metal at the boundary with the soil electrolyte.

4. Materials and methods used in studying the influence of soil medium on technical condition of underground metal pipelines

Because of the high level of wear of components of the gas transportation system (GTS) and imperfection of state control over its safety, an increase in the number of emergencies (accidents and failures) on the GTS was observed in recent years. The following information is given for reference. According to analytical materials, average depreciation of the gas transportation system of Ukraine exceeds 60 %. Almost 20 thousand kilometers of main gas pipelines (from total 33.25 thousand km) in Ukraine are operated for more than 33 years. Up to 29 % of Ukrainian gas pipelines have already exhausted their depreciation period [15].

It was established that the conventional approach to maintaining efficiency of the UMPs of oil-and-gas enterprises cannot ensure the GTS reliability and safety because of their large length and different technical condition of individual sections. Therefore, the main strategy for ensuring high reliability of main systems consists in operation and repair “at the actual state”, that is, transition to a selective “point” repair of elements and sections according to the results of diagnosis of many kilometers of pipelines. For this purpose, diagnostic instruments are used. They are working on the electromagnetic field principle [15].

Let us consider an UMP pipe made of 17G1S steel. The pipe is buried. The corrosive medium features presence of soil electrolyte as shown in Fig. 1. Outside diameter of the pipe is D, wall thickness is t, inside diameter is D – d. Presence of coating deformation and peeling is possible in some places. The gaps in those places may create voids filled with aqueous solution of soil electrolyte. Consequently, under the influence of moisture, corrosion defects such as pitting and cracking are formed. Over time, pitting extends into the depth of the metal under the effect of soil electrolyte.

The neural network (for the “pipeline-coating system”) is capable of solving the problems of cluster analysis and image classification and also makes it possible to process data without prior spectral transformation by using discrete counts of information signals. Taking into account [24, 25], this type of neural network allows it to dynamically extend its own
base of knowledge of possible types of defects in controlled objects (pipelines) in their operation.

![Fig. 1. Schematic representation of types of soil media: A – acid medium; B – neutral medium; C – alkaline medium](image)

It is necessary to point out the network feature: both matrices of weight coefficients (W and Y) are united into one matrix W. Components of the input vectors X are experimental data normalized in the interval [0, 1]: \( X = x_1, x_2, ..., x_m \), and X [0, 1]. The F2 recognition layer contains neurons storing information about the class base.

At the beginning of the neural network learning process, each class \( j \) is set to an inactive initial state. A matrix of weight coefficients, W, is located between the input and the recognition layer. All its elements (weight coefficients) are first initialized by units, that is, \( w_{ij} = 1 \) for \( i = 1, 2, ..., n \) and \( j = 1, 2, ..., m \) (the index \( i \) corresponds to the element of the input vector, and the index \( j \) corresponds to the neuron (the class number) of the recognition layer). The following parameters are also set in the network:

\[
y_j = \frac{X \cap W_j}{a + |W_j|} \tag{1}
\]

where \( a \) is the parameter of choice \( a > 0 \), which determines the class choice at the time of classification; \( n \) [0, 1] is the correction factor that significantly influences speed of the neural network; \( p \) [0, 1] is the coefficient of sensitivity of the classifier or the level of similarity of the input and reference signals governing the process of forming the classes of signals.

To determine the class \( k \) which includes the input parameter (vector) \( X \), the degree of activation of neurons (1) is determined initially:

where \( X \) is the input vector; \( W_j \) is the vector of the weight coefficients of the neuron \( j \) reflecting the standard in the neural network memory; \( a \) is the parameter that represents the class choice during classification; \( \cap \) is the operator of intersection of two fuzzy sets (the operator of fuzzy AND); \( |M| \) is the \( L_2 \)-norm of the vector in the Euclidean space.

In this case, the input vector \( X \) belongs to the class \( y_j \) for which the degree of activation is maximal

\( \{y_j\}: y_j = \max \{y_j\} \).

In cases where two classes have the same maximum activation value, a class with a reference signal having the lowest index is selected. This ensures allocation of neurons of the recognition layer F2 to each class of the input signals in a sequence 1, 2, ..., \( n \).

During execution of this criterion, the process of adaptation (modification) of weight coefficients is activated. Otherwise, the search for an alternative class continues in the layer of recognition or a new neuron is selected to form a new class of input signals. The vector of the weight coefficients is corrected according to the rule:

\[
W_j(t+1) = \eta \frac{X \cap W_j(t)}{a + |W_j(t)|} + (1 - \eta) W_j(t), \tag{2}
\]

where \( t \) is the number of the current learning stage; \( \eta \) is the coefficient determining speed of learning the neural network.

Classical architecture of the network is sensitive to the order of presentation of input vectors during operation. This drawback manifests itself during implementation of the second phase (the phase of comparison) in the F1 layer and is associated with the operator of fuzzy AND. In the mathematical representation, this operator functions as follows:

\[
x_i \leq y_j = \min(x_i, y_j) = x_i.
\]

Thus, provided that \( w_{ik} > x_i \) for all \( i = 1, n \), and at \( X \in W_i \), the comparison operation results in:

\[
\frac{|X \cap W_i|}{|X|} = 1, \tag{3}
\]

which in turn will not activate the reset signal and the vector will be classified incorrectly. To solve the above drawback, the classical architecture and the network operation algorithm were modified. To this end, the operator of the fuzzy OR was additionally used

\[
\cup: X \cup Y = \max(X, Y),
\]

that is, the following will take place at a certain \( x_i \leq y_j \):

\[x_i \cup y_j = \max(x_i, y_j) = y_j.\]

The degree of discrepancy between the input vector \( X \) and the reference image \( W_j \) in the database of the neural network is determined in a modified network in the comparison layer at the second phase:

\[
p^* = \left| \frac{X \cap W_j - (X \cap W_j)}{|X|} \right| \tag{4}
\]

At \( w_{ik} = x_i \) (for all \( i = 1, n \)), \( p^* = 0 \) and it will grow in proportion to the increase in discrepancy between the two signals. Activity of the winning neuron will be reduced if the condition \( p^* < 1 - p \) is not met (\( p \) is the coefficient of the classifier sensitivity). This approach gives independence from the order of presentation of input vectors and the modified neural network can be used to solve the problems of nonstandard diagnosing of pipelines. Fig. 2 shows a block diagram of the implemented modified neural network in which the blocks added to the classical implementation are highlighted.

Novelty of the neural network (Fig. 2) consists in the fact that the proposed method makes it possible to reduce the time of learning the ANN and, unlike the other methods, includes algorithms and methods of NN with many criteria, not with one. Taking into account alternative approaches to NN formation [26, 27], this is an advantage provided that this NN is sufficiently loaded with data from the database. With this method, it is possible to display forecasting graphs in a percentage dependence and add various criteria during forecasting the processes. At the same time, the proposed approach to NN formation is characterized by a novelty consisting in the fact that the winning neuron unit is used at the first stage of forecasting the neural network. At the second stage of forecasting, the data are compared using two blocks: response formation unit and the winning neuron unit as
shown in the diagram. In the final version, the results of the two blocks are compared and the best result of the forecast is output.

Let us consider a product of $\kappa_p = \kappa_1 \times \kappa_2 \times \kappa_3$ type in the same way as in [8]:
- $\kappa_1$ is the coefficient of UMP reliability;
- $\kappa_2$ is the coefficient characterizing strength $p_s$ of the UMP metal;
- $\kappa_3 = \kappa_3(T_s, N_C)$ is the coefficient characterizing the term of trouble-free operation, $T_s$, (i.e., service life) of the structure (pipe) taking into account $N_C$ ($N_C$ is the number of loading cycles, that is, the base of tests for resistance to corrosion fatigue).

In the same way as in [8], represent the multiplicative qualitative criterion for the UMP section in the improved form:

$$Z_i = \beta_1 \kappa_1 \cdot \beta_2 \kappa_2 \cdot \beta_3 \prod_{k=4}^{9} \kappa_k,$$

(5)

where $\kappa_4, \kappa_5, \kappa_6, \kappa_7, \kappa_8, \kappa_9$ are the coefficients characterizing the corrosive medium (soil), respectively:
- $\kappa_4$ is the structure and granulometric composition;
- $\kappa_5$ is chemical composition of the soil electrolyte and concentration of hydrogen ions;
- $\kappa_6$ is moisture content and oxidation-reduction (redox) potential;
- $\kappa_7$ is total acidity or alkalinity of the soil;
- $\kappa_8$ is air permeability;
- $\kappa_9$ is electrical resistance;
- $\beta_1, \beta_2$ are weight coefficients.

It is worth noting here that coefficients $\kappa_i$ ($i=1, 2, \ldots, 9$) are conventionally divided into 2 groups. The first (1) group of internal coefficients $\kappa_1, \kappa_2, \kappa_3$ characterizes the pipeline metal. The second (2) group of coefficients $\kappa_4, \kappa_5, \kappa_6, \kappa_7, \kappa_8, \kappa_9$ refers to the external medium, that is, the soil electrolyte.

Coefficients $\kappa_1, \kappa_2, \kappa_3$ depend on the following information parameters, namely:
- $D_j$ = defectiveness of the metal surface layers;
- $\nu_j$ = strengthening of the pipe metal;
- $\sigma_{\nu}, (N_C)$ is the limit of corrosion fatigue $(N_C$ is the number of deformation cycles to the structure failure);
- $S$ is the coating effect on corrosion resistance;
- $T_s$ (of the service life) is the term of trouble-free operation; $T_s$ (service life) of the structure (pipe), taking into account $N_C$;
- $U_{ij}$ is compliance with the optimal range of the polarization potential. That is:

$$k_i = k_i\{D_j, \nu_j, \sigma_{\nu}, K_s, T_s, N_C, U_{ij}\}, \quad i = 1, 2, 3.$$

(6)

Let us also introduce quality criterion $Z_2$ in the additive form similar to [8]:

$$Z_2 = a_1 \kappa_1 + a_2 \kappa_2 + a_3 \kappa_3 + a_4 \kappa_4 + a_5 \kappa_5 + a_6 \kappa_6 + a_7 \kappa_7 + a_8 \kappa_8 + a_9 \kappa_9 \rightarrow \max,$$

(7)

where $a_j$ ($j=1, 2, \ldots, 9$) are weight coefficients assessed by the expert method.

In the first approximation, choose: $a_1 = a_2 = \ldots = a_9 = 1/9$; $\beta_1 = \beta_2 = 0.5$.

Thus, relations (5)–(7) are the basis of an optimization approach to assessment of the hydrogen exponent (pH) for a coated pipeline placed in a soil medium under conditions of electrochemical corrosion.

5. Quality criterion for a metal of underground pipelines of oil-and-gas enterprises

Thus, due to the use of the neural network, in the event of appearance of new data in the system memory, a new class is formed which will correspond to the given object (a coated pipeline) and corrective setting-up of the neural network classifier is made. That is, it is possible to learn the system in the control process and there is no need to generate a large number of reference specimens for initial set-up of the system.

6. The results obtained in forecasting service life of underground pipelines in various soil media using neural networks

Let us monitor state of a pipeline in alkaline, neutral, and acidic media with the help of CCM and PPM instruments. Contactless current measurements are used in examination of electrically conductive lines (underground metal pipelines, cables, etc.) to determine current distribution in the line networks. Probability of defects formed on the outside surface of the underground pipeline is established on the basis of such measurements.

Experimental studies were carried out and the degree of protection $P$ of specimens of 17G1S steel in various media was assessed on their basis. This study was conducted at a condition that the protective potential on the UMP surface is $\phi_{P} = -0.83$ V, that is, 20 mV less than the limit potential $\phi_{lim} = -0.85$ V [11]. Consequently, electrochemical corrosion on the surface of the specimens will be adequate because condition for protection is $|\phi_{P}| > 0.85$ V.

The measurement results are given for three types of external media (acidic, neutral, alkaline) and illustrated
in Fig. 3. Unlike [11], this study considered three types of media (sour, neutral, alkaline) under the condition of $|\Delta p|$=0.02 V. There was no information in [11] about the medium pH and to assess deviations of polarization potential, $|\Delta p|$, actual values of $\varphi$ were determined (measured) in the section of the defective tube.

The horizontal axis in Fig. 3 was used for relative polarization current, $A$, and the vertical axes for the degree of steel protection, $P$, to build curves for the three media in which the study was conducted.

$\Delta$Fig. 3. Information on the degree of protection $P=1-1/g$ in the conditions of cathodic protection of 17G1S steel against external media having various pH values ($1 \leq A \leq 14$; $P_0 \Rightarrow$ pH=6.9; $P_L \Rightarrow$ pH=11.0; $P_K \Rightarrow$ pH=3.5)

In Fig. 3, $A=1/i_{o} / i_{w}$ is the relative polarization current; $i_p$, $i_{w}$ are densities of polarization and corrosion currents, respectively; $g = i_{o} / i_{w}$ is the coefficient of corrosion inhibition; $i_p$, $i_c$ are densities of anode and cathode currents; $i_p = i_c - i_o$. Data in Fig. 3 correspond to a one-year period of recording corrosion dissolution of 17G1S steel specimens in three types of media. Fig. 3 characterizes the base of real information data (initial conditions) for further measurements. According to the data in Fig. 3, the coefficient of corrosion inhibition $g=i_{o} / i_{w}$ was determined. Errors in parameters $A$, $P$, $g$ did not exceed 5% for the range of $A=1$–$14$.

Taking into account the information given in [11], a procedure was proposed for controlling the hydrogen exponent (pH) of a corrosive medium on the surface of an underground pipe. To implement the above processes of the project (pH control), the quality functional (8) taking into account sensitivity $\beta_k$ and the feedback.

Improvement of the procedure for quality assessment and hence the procedure novelty is related to the fact that the quality criterion for the "UMP-coating" system (5)–(7) is supplemented with the quality functional (8) taking into account sensitivity $\beta_k$ and the feedback.

Application of the developed neural network presented above makes it possible to describe the procedure of propagation of corrosion defects in the depth of the pipe wall physically substantiated and mathematically more correct in contrast to the standard procedure. To do this, it is necessary to know pH of the soil medium outside the pipe.

The results obtained with application of the neural network and relations (1)–(8) are presented in Fig. 4. Study 1 corresponds to some point on the surface of the underground pipe. Study 2 corresponds to a point located at a distance of 5 m from the first point and Study 3 corresponds to a point located at a distance of 10 m from the first point. Actual currents and voltages measured by means of CCM and PPM instruments are the main informative parameters for determining pH of the medium in the given point on the underground pipeline surface.

Reliability of control of the medium pH determined according to the procedure described in [28, 29] was entered on the ordinate axis (Fig. 4). The green column on the left corresponds to a neutral medium, the red column in the middle corresponds to the alkaline medium and the blue column on the right corresponds to the acidic medium. Hence, information on the alkaline, neutral and acidic media obtained in Studies 1, 2 and 3 was presented in Fig. 4. The conclusion regarding the medium type in this point of the pipe was drawn based on the maximum value of control reliability,
that is, one of the three columns. As a result, the following pH values were obtained: pH$_1$=4 (sour), pH$_2$=10.2 (neutral), pH$_3$=12.1 (alkaline).

It was established with the help of the data presented in Fig. 4 and corresponding calculation results that when the system of non-destructive testing was applied in determining pH at the pipeline section on the basis of the developed neural network, control reliability was more than 90%.

7. Discussion of results obtained in the study of diagnosis of underground pipelines in soil media using neural networks

Based on the analysis of graphical dependences (Fig. 3, 4) obtained in the studies, character of acidity (alkaline, acidic, or acidic media) and numerical values of pH were established in Studies 1, 2, and 3.

Actual currents and voltages were compared with analogous parameters in initial conditions (that is, with the information corresponding to Fig. 3) and pH for the actual point on the surface of the underground pipe was established taking into account correlations (5)–(8) and applying the neural network. This is illustrated in Fig. 4. This is the essence of novelty since pH of the medium was determined by the non-destructive method using PPM and CCM instruments and the model correlations (1)–(8). Due to this fact, it is not necessary to excavate ground near the pipe (which can be at a depth of up to 3 m) to determine the medium pH.

Disadvantage of the corresponding initial conditions (Fig. 3) in the context of the polarization potential and currents consists in that the database is not sufficiently voluminous so the experimental results correspond to the condition $|\Delta \varphi_o|=0.02$ V (potential deviation $|\Delta \varphi_o|$ may differ). However, polarization currents can be calculated for arbitrary physically possible values of $\Delta \varphi_o$ with the help of known electrochemical relations.

Advantage of the proposed method of pH assessment consists in that it is non-destructive. Its application is gainful as there is no need to excavate ground near the underground pipe. The destructive electrometric method of pH assessment ensures accuracy within 5±17%. The proposed method provides similar accuracy of pH assessment in electrolytic medium within the range of 7±16%.

The considered example confirms the possibility and usefulness of simulation of corrosion processes in underground pipelines of oil-and-gas enterprises with application of a neural network. On the basis of analysis of the obtained results (Fig. 3, 4) which can be considered as an example of implementation of the new mathematical model (1)–(8) and the new method of non-destructive testing, pH of the medium can be assessed.

A concrete example was considered. As a result of its analysis, pH of the soil electrolyte was assessed using a neural network for a concrete pipe (17G1S steel) with a corrosion defect in the outer surface (Fig. 4). The specified initial conditions were taken into account (Fig. 3).

In the future, it is also necessary to take into account initial rate of corrosion in the place of coating defects which depends on the polarization potential and other parameters, in particular, temperature and mechanical stresses. Their consideration is useful for solving the problems of the corrosion process diagnosing.

8. Conclusions

1. Assessment of connection between the degree of protection of 17G1S steel specimens placed in acid, alkaline and neutral ground media and the relative polarization current was performed with the help of a polarization potential meter and a contactless current meter in conditions of cathodic protection. The corresponding volume of data characterized the base of actual information parameters (initial conditions for currents and voltages) which were used for further measurements of the medium pH at the boundary between the metal and the soil electrolyte.

2. The quality criterion for the “UMP-coating” system has been improved taking into account characteristics of corrosive soil medium. Novelty of the quality criterion consists in that unlike the known analogous variants, the coefficients $k_i$ characterizing the “pipeline-substrate” system were divided into two groups. The first group of internal coefficients characterizes the metal pipeline. The second group of coefficients refers to the external medium, that is, the soil electrolyte and their content is new. Improvement of the quality assessment procedure and, accordingly, the novelty relate to the fact that the quality criterion for the “UMP-coating” system was supplemented with a quality functional taking into account sensitivity $\beta_i$ and the feedback.

3. Probabilistic parameters describing characteristics of the outside surface of the metal pipe and the corresponding variants of pH of the underground metal pipeline were assessed based on the proposed method of non-destructive testing using initial conditions as well as the proposed neural network. The results of pH assessment can be used in future to determine service life of the underground metal pipelines.

It is worth to note that the combined application of the method for determining the medium pH and the neural network is promising for detecting defects on the surface of the underground metal pipes and assessment of the trends in their development over time (according to the monitoring data).
References


