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IMPROVING THE DIAGNOSTICS OF UNDERGROUND PIPELINES AT OIL-AND-GAS ENTERPRISES BASED ON DETERMINING HYDROGEN EXPONENT (PH) OF THE SOIL MEDIA APPLYING NEURAL NETWORKS

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Сформовано множину визначальних параметрів та інформаційних потоків для моделювання етапів зондування зовнішньої поверхні підземного металевого трубопроводу (ПМТ) з урахуванням водневого показника (ВП) ґрунту, який контактує з металом труби.

Проведено обстеження зразків сталі 17Г1С, поміщених у кислі, лужні та нейтральні середовища. Обстеження здійснено за допомогою вимірювача поляризаційного потенціалу у комплексі з безконтактним вимірювачем струму. Сформульовано принципи використання нейронної мережі (НМ) для опрацювання результатів експерименту. Розроблено базу даних, яка відповідає початковим умовам для контролю ВП ґрунту на межі з металом в реальних умовах.

Запропоновано елементи оптимізаційного підходу щодо оцінювання ВП ПМТ з покриттям у ґрунтовому середовищі. В основі підходу лежить мультиплікативний кваліметричний критерій якості для ділянки ПМТ з урахуванням двох груп коефіцієнтів. Перша група коефіцієнтів стосується внутрішніх коефіцієнтів і характеризує метал трубопроводу, а друга – зовнішнього середовища (ґрунтового електроліту). Запропоновано елементи оптимізаційного підходу щодо оцінювання ВП трубопроводу з покриттям у ґрунтовому середовищі.

Представлено НМ для системи "трубопровід – покриття", яка:

1) здатна сприяти розв'язуванні задачі кластерного аналізу і класифікації образів;

2) дозволяє виконувати обробку даних без попереднього спектрального перетворення, оперуючи з дискретними відліками інформаційних сигналів.

Запропонований тип НМ дозволяє їй динамічно розширювати власну базу знань про можливі типи дефектів контрольованих об'єктів (трубопроводів) у процесі роботи. З допомогою НМ для ПМТ (зі сталі 17Г1С) проведено оцінювання ВП ґрунту для трьох ситуацій.

Відзначена інформація є важливою для удосконалення методів контролю ПМТ нафтогазових підприємств, зокрема, методик коректного оцінювання густини анодного струму у дефектах металу з урахуванням нелінійного характеру інформативних параметрів

Ключові слова: підземні трубопроводи, нафтогазові підприємства, корозійні струми, поляризаційний потенціал, водневий показник, нейронна мережа

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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 measured by means of instruments of CCM type were not reflected in studies like [16–18].

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 in 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 d, 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.

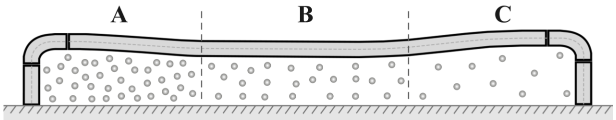

Fig. 1. Schematic representation of types of soil media: A — acid medium; B — neutral medium; C — alkaline medium

It is necessary to point out the network feature: both matrices of weight coefficients (W and V) are united into one matrix W. Components of the input vectors X are experimental data normalized in the interval [0, 1]: $X=\{x_1, x_2, \ldots, x_m\}$, 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 $i=1, 2, \ldots, n$ and $j=1, 2, \ldots, m$ (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:

$$y_j=\frac{\left|X\cap W_j\right|}{a+\left|W_j\right|}, \tag{1}$$

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; ∩ 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

$$\left(y_k\right): y_k=\max_j\left(y_j\right).$$

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:

$$W_J(t+1)=\eta\left[X\cap W_j(t)\right]+(1+\eta)W_j(t), \tag{2}$$

where t is the number of the current learning stage; η 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: $X\cap Y=\min(X,Y)$, that is, for a certain

$$x_i\le y_i=\min\left(x_i,y_i\right)=x_i.$$

Thus, provided that $w_{k,i}\ge x_i$ for all $i=1, n$, and at $X\notin W_k$, the comparison operation results in:

$$\frac{\left|X\cap W_k\right|}{|X|}=\frac{|X|}{|X|}=1, \tag{3}$$

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 $x_i\le y_i$:

$$x_i\cup y_i=\max\left(x_i,y_i\right)=y_i.$$

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

$$p^*=\frac{\left|\left(X\cup W_k\right)-\left(X\cap W_k\right)\right|}{|X|}. \tag{4}$$

At $w_{k,j}=x_i$ (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 $p^*\le 1-p$ 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.

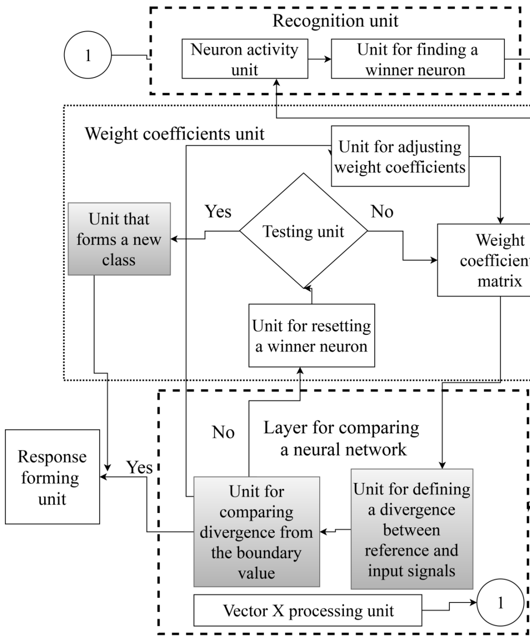

Fig. 2. Block diagram of the neural network

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.

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

Let us consider a product of $k_P=k_1\times k_2\times k_3$ type in the same way as in [8]:

– k_1 is the coefficient of UMP reliability;

– k_2 is the coefficient characterizing strength p_S of the UMP metal;

– $k_3=k_3(T_S, N_C)$ 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 qualimetric quality criterion for the UMP section in the improved form:

$$Z_1=\beta_1 k_1\cdot k_2\cdot k_3+\beta_2\prod_{i=4}^{9}k_i, \qquad (5)$$

where k_4, k_5, k_6, k_7, k_8, k_9 are the coefficients characterizing the corrosive medium (soil), respectively:

– k_4 is the structure and granulometric composition;

– k_5 is chemical composition of the soil electrolyte and concentration of hydrogen ions;

– k_6 is moisture content and oxidation-reduction (redox) potential;

– k_7 is total acidity or alkalinity of the soil;

– k_8 is air permeability;

– k_9 is electrical resistance;

– β_1, β_2 are weight coefficients.

It is worth noting here that coefficients k_i (i=1, 2, ..., 9) are conventionally divided into 2 groups. The first (1) group of internal coefficients k_1, k_2, k_3 characterizes the pipeline metal. The second (2) group of coefficients k_4, ..., k_9 refers to the external medium, that is, the soil electrolyte.

Coefficients k_1, k_2, k_3 depend on the following information parameters, namely:

– D_f – defectiveness of the metal surface layers;

– n_Z is strengthening of the pipe metal;

– $\sigma_{ve}(N_C)$ is the limit of corrosion fatigue (N_C is the number of deformation cycles to the structure failure);

– K_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_p is compliance with the optimal range of the polarization potential. That is:

$$k_i\cdot=k_i\left(D_f, n_Z, \sigma_{ve}, K_S, T_S, N_C, U_P\right),\ \ i=1,\ 2,\ 3. \qquad (6)$$

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

$$Z_2=a_1\cdot k_1+a_2\cdot k_2+a_3\cdot k_3+a_4\cdot k_4+a_5\cdot k_5+$$
$$+a_6\cdot k_6+a_7\cdot k_7+a_8\cdot k_8+a_9\cdot k_9\Rightarrow \max, \qquad (7)$$

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

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

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.

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 φ_p=–0.83 V, that is, 20 mV less than the limit potential φ_{p*}=–0.85 V [11]. Consequently, electrochemical corrosion on the surface of the specimens will be adequate because condition for protection is $|\varphi_{P*}|$>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 $|\Delta\varphi_{P*}|\approx 0.02$ V. There was no information in [11] about the medium pH and to assess deviations of polarization potential, $|\Delta\varphi_P|$, actual values of φ_P 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.

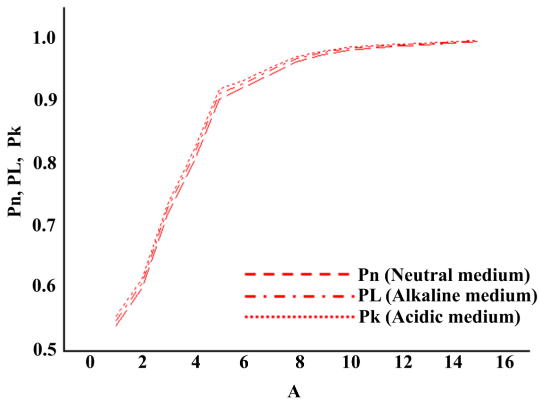

Fig. 3. Information on the degree of protection $P=1-1/g$ in the conditions of cathodic protection of 17G1S steel against external media having various pH values ($1\leq A\leq 14$; Pn⇒pH=6.9; PL⇒pH=11.0; Pk⇒pH=3.5)

In Fig. 3, $A=i_p/i_{cor}$ is the relative polarization current; i_p, i_{cor} are densities of polarization and corrosion currents, respectively; $g=i_{cor}/i_a$ is the coefficient of corrosion inhibition; i_a, i_k are densities of anode and cathode currents; $i_p=i_k-i_a$.

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 $g\equiv i_{cor}/i_a$ was determined. Errors in parameters A, P, g did not exceed 5 % for the range of $A=1\div 14$.

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 metal pipe with application of a neural network.

Let us consider a project to control pH of the soil medium near the outside surface of a metal underground pipe. To optimize the procedure of pH control, the quality functional $J(P_k, FB(P_k))$ [12] was used taking into account the coefficient of sensitivity β_R and feedback:

$$J\left(P_k, FB\left(P_k\right)\right)=\int_{t_0}^{t_k} f\left(\bar{y}, \bar{u}, \bar{s}, \beta_R\right) \mathrm{d}t \Rightarrow \text{opt}, \tag{8}$$

where:

$\bar{y}$ is the vector of specified impacts on the pipeline ($y_j(t)$ are the components of the $\bar{y}$ vector (determining parameters of the USGP (underground steel gas pipelines) system and coating)) which is characterized by the k_i coefficients included in correlations (5)–(7) ($j=1, 2, ..., n$);

$\bar{u}$ is the vector of information flow controls;

$\bar{s}$ is the vector of indeterminate perturbations;

P_k is the information flow ($k=1, 2, ..., m$);

m is the total number of information flows, P_k, considered in this project (pH control in a concrete place on the surface of the underground pipe);

$[t_0, t_k]$ is the time interval in which the process is considered (formation of optimal values of the parameters corresponding to P_k);

$f\left(\bar{y}, \bar{u}, \bar{s}, \beta\right)$ is the function reflecting the project quality;

β_R is the coefficient of sensitivity;

$FB(P_k)$ is the function characterizing feed-back between the flows P_k and the project environment taking into account the sensitivity β_R coefficient and expert opinions;

opt is the optimization symbol.

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 β_R and the feedback.

To implement the above processes of the project (pH control), we have proposed to use the intellectual forecasting system of control of technological processes united in a single information complex similar to that in [11]. At the same time, we have recommended that the information complex and the equipment for measuring constant and alternating voltages and determination of the polarization potential be combined in a single information space.

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.

Currents and potentials are the main informative parameters in the initial conditions (that is, those in Fig. 3). They were experimentally established according to the approach described in [11]. Actual currents and voltages were compared with analogous parameters in initial conditions (i. e., with the data in Fig. 3) and pH was determined for the actual point on the surface of the underground pipe taking into account relations (5)–(8) and applying the neural network. This is the essence of novelty since pH of the medium is determined by the NDT method with the help of PPM and CCM instruments. In this case, 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.

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).

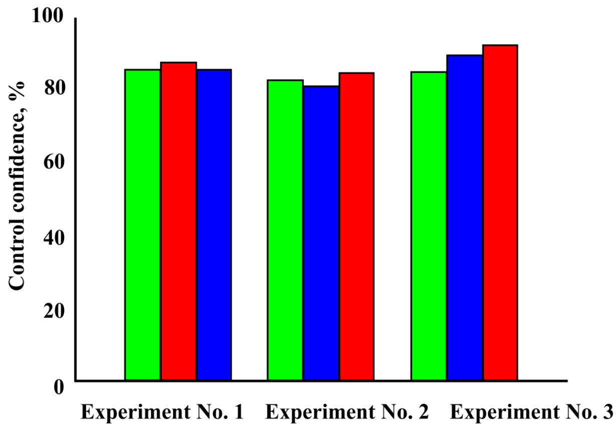

Fig. 4. Control confidence for the pipeline section (the green column on the left corresponds to the neutral medium, the red column in the middle corresponds to the alkaline and the blue column on the right corresponds to the acidic medium)

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 since the experimental results correspond to the condition $|\Delta\varphi_{P*}|\approx 0.02$ V (potential deviation $|\Delta\varphi_{P*}|$ may differ). However, polarization currents can be calculated for arbitrary physically possible values of $\Delta\varphi_{P*}$ 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 β_R 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

1. Carvalho, M. L. (2014). Corrosion of copper alloys in natural seawater: effects of hydrodynamics and pH. Analytical chemistry. Université Pierre et Marie Curie - Paris VI. Available at: https://tel.archives-ouvertes.fr/tel-01207012/document
2. Arriba-Rodriguez, L., Villanueva-Balsera, J., Ortega-Fernandez, F., Rodriguez-Perez, F. (2018). Methods to Evaluate Corrosion in Buried Steel Structures: A Review. Metals, 8 (5), 334. doi: https://doi.org/10.3390/met8050334
3. Marshakov, A. I., Ignatenko, V. E., Bogdanov, R. I., Arabey, A. B. (2014). Effect of electrolyte composition on crack growth rate in pipeline steel. Corrosion Science, 83, 209–216. doi: https://doi.org/10.1016/j.corsci.2014.02.012
4. Liu, Z. Y., Li, X. G., Du, C. W., Zhai, G. L., Cheng, Y. F. (2008). Stress corrosion cracking behavior of X70 pipe steel in an acidic soil environment. Corrosion Science, 50 (8), 2251–2257. doi: https://doi.org/10.1016/j.corsci.2008.05.011
5. Fu, J., Pei, F., Zhu, Z., Tan, Z., Tian, X., Mao, R., Wang, L. (2013). Influence of moisture on corrosion behaviour of steel ground rods in mildly desertified soil. Anti-Corrosion Methods and Materials, 60 (3), 148–152. doi: https://doi.org/10.1108/00035591311315346
6. Kakooei, S., Taheri, H., Che Ismail, M., Dolati, A. (2012). Corrosion Investigation of Pipeline Steel in Hydrogen Sulfide Containing Solutions. Journal of Applied Sciences, 12 (23), 2454–2458. doi: https://doi.org/10.3923/jas.2012.2454.2458
7. Yuzevych, V., Klyuvak, O., Skrynkovskyy, R. (2016). Diagnostics of the system of interaction between the government and business in terms of public e-procurement. Economic Annals-XXI, 160 (7-8), 39–44. doi: https://doi.org/10.21003/ea.v160-08
8. Lozovan, V., Dzhala, R., Skrynkovskyy, R., Yuzevych, V. (2019). 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. Eastern-European Journal of Enterprise Technologies, 1 (5 (97)), 20–27. doi: https://doi.org/10.15587/1729-4061.2019.154999
9. Skrynkovskyi, R. M. (2011). Methodical approaches to economic estimation of investment attractiveness of machine-building enterprises for portfolio investors. Actual Problems of Economics, 118 (4), 177–186. Available at: http://www.scopus.com/inward/record.url?eid=2-s2.0-84930489016&partnerID=MN8TOARS
10. Skrynkovskyi, R. (2008). Investment attractiveness evaluation technique for machine-building enterprises. Actual Problems of Economics, 7 (85), 228–240.
11. Lozovan, V., Skrynkovskyy, R., Yuzevych, V., Yasinskyi, M., Pawlowski, G. (2019). 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. Eastern-European Journal of Enterprise Technologies, 2 (5 (98)), 41–48. doi: https://doi.org/10.15587/1729-4061.2019.161484
12. Yuzevych, V., Skrynkovskyy, R., Koman, B. (2018). Intelligent Analysis of Data Systems for Defects in Underground Gas Pipeline. 2018 IEEE Second International Conference on Data Stream Mining & Processing (DSMP). doi: https://doi.org/10.1109/dsmp.2018.8478560
13. Din, M. M., Ithnin, N., Zain, A. M., Noor, N. M., Siraj, M. M., Rasol, R. M. (2015). An artificial neural network modeling for pipeline corrosion growth prediction. ARPN Journal of Engineering and Applied Sciences, 10 (2), 512–519. Available at: http://www.arpnjournals.com/jeas/research_papers/rp_2015/jeas_0215_1484.pdf
14. Chen, Y., Wang, Z., Wang, X., Song, X., Xu, C. (2018). Cathodic Protection of X100 Pipeline Steel in Simulated Soil Solution. International Journal of Electrochemical Science, 13, 9642–9653. doi: https://doi.org/10.20964/2018.10.23
15. Lozovan, V., Yuzevych, V. (2017). Neural networks as a means of improving the metrological characteristics of metal structures, taking interphase layers into account. Measuring Equipment and Metrology, 78, 48–54. doi: https://doi.org/10.23939/istcmtm2017.78.048
16. Guo, H., Tian, Y., Shen, H., Liu, X., Chen, Y. (2016). Study on the Electrochemical Corrosion and Scale Growth of Ductile Iron in Water Distribution System. International Journal of Electrochemical Science, 11, 6993–7010, doi: https://doi.org/10.20964/2016.08.03
17. Frankel, G. S. (1998). Pitting Corrosion of Metals. Journal of The Electrochemical Society, 145 (6), 2186. doi: https://doi.org/10.1149/1.1838615
18. Chonghua, Y., Minggao, Y. (1980). A Calculation of the Threshold Stress Intensity Range for Fatigue Crack Propagation in Metals. Fatigue & Fracture of Engineering Materials and Structures, 3 (2), 189–192. doi: https://doi.org/10.1111/j.1460-2695.1980.tb01113.x
19. Kazemi Eilaki, N., Sanayee Mogahdam, S., Ghasemi, A., Abotorab, H. (2018). Corrosion Reliability Assessment of Underground Water Transmission Pipelines by IHS Algorithm. International Journal of Reliability, Risk and Safety: Theory and Application, 1 (1), 45–51. doi: ttps://doi.org/10.30699/ijrrs.1.45
20. Sinha, S. K., Pandey, M. D. (2002). Probabilistic Neural Network for Reliability Assessment of Oil and Gas Pipelines. Computer-Aided Civil and Infrastructure Engineering, 17 (5), 320–329. doi: https://doi.org/10.1111/1467-8667.00279

21. Pandey, M. D. (1998). Probabilistic models for condition assessment of oil and gas pipelines. NDT & E International, 31 (5), 349–358. doi: https://doi.org/10.1016/s0963-8695(98)00003-6
22. Hinton, G. E., Osindero, S., Teh, Y.-W. (2006). A Fast Learning Algorithm for Deep Belief Nets. Neural Computation, 18 (7), 1527–1554. doi: https://doi.org/10.1162/neco.2006.18.7.1527
23. Ossai, C. I., Boswell, B., Davies, I. J. (2015). Pipeline failures in corrosive environments – A conceptual analysis of trends and effects. Engineering Failure Analysis, 53, 36–58. doi: https://doi.org/10.1016/j.engfailanal.2015.03.004
24. Mitchell, M. R., Link, R. E., Jiang, Q. (2010). Study of Underground Oil-Gas Pipeline Corrosion Pits Estimation Based on MFL Inspection Method. Journal of Testing and Evaluation, 38 (2), 102467. doi: https://doi.org/10.1520/jte102467
25. Colorado-Garrido, D., Ortega-Toledo, D. M., Hernández, J. A., González-Rodríguez, J. G., Uruchurtu, J. (2008). Neural networks for Nyquist plots prediction during corrosion inhibition of a pipeline steel. Journal of Solid State Electrochemistry, 13 (11), 1715–1722. doi: https://doi.org/10.1007/s10008-008-0728-7
26. Srivastava, N., Hinton, G., Krizhevsky, A., Sutskever, I., Salakhutdinov, R. (2014). Dropout: a simple way to prevent neural networks from overfitting. Journal of Machine Learning Research, 15, 1929–1958. Available at: http://jmlr.org/papers/volume15/srivastava14a.old/srivastava14a.pdf
27. Kenny, E. D., Paredes, R. S. C., de Lacerda, L. A., Sica, Y. C., de Souza, G. P., Lázaris, J. (2009). Artificial neural network corrosion modeling for metals in an equatorial climate. Corrosion Science, 51 (10), 2266–2278. doi: https://doi.org/10.1016/j.corsci.2009.06.004
28. Zhang, S., Zhou, W. (2013). System reliability of corroding pipelines considering stochastic process-based models for defect growth and internal pressure. International Journal of Pressure Vessels and Piping, 111-112, 120–130. doi: https://doi.org/10.1016/j.ijpvp.2013.06.002
29. Witek, M. (2016). Gas transmission pipeline failure probability estimation and defect repairs activities based on in-line inspection data. Engineering Failure Analysis, 70, 255–272. doi: https://doi.org/10.1016/j.engfailanal.2016.09.001