

Determination of the Place Depressurization of Underground Pipelines in the Monitoring of Oil and Gas Enterprises



Volodymyr Yuzevych, Fedir Horbonos, Roman Rogalskyi, Iryna Yemchenko, Mykhailo Yasinskyi

Abstract: Analytical correlations of mathematical model that characterizes the processes of development of corrosive cavity on the surface of underground metallic pipeline are analysed. A pipeline in the environment of moist soil with solution of electrolyte is placed. In the top of cavity a crack appears and translates the system “underground pipeline (UP) – pumping station (PS)” in the state of depressurization. A new approach is proposed for diagnosing places of underground pipeline depressurization on the basis of two types of devices: pressure sensors and non-destructive testing devices, with the help of which we measure potentials and corrosion currents in surface defects. The presence of only pressure sensors makes it possible to set the coordinates of depressurization with a large error – 20...25%. Diagnosis of the pipeline only by devices BVS-K, VPP-M (at the first stage) allows to reveal surface defects. But this information is not enough for a qualitative experiment, as shown by the qualimetric quality criterion. Taking into account the pressure data in the second stage allows to determine which of the defects is the leakage point. A test example for the distance $L_1 = 6$ km from the pumping station of the pipeline is considered. The results of the experiment are used for the example and the growth time of the corrosion crack $t_* = 0.62$ year is established. On the basis of computational experiment the errors of estimating of crack growth time t_* and coordinates of the leakage points was established. They present 5...7%. Based on the method of neural networks, the main informative parameters for determining the places of depressurization on the surface of the underground pipe are estimated. A method for estimating the gas pressure change in the vicinity of the crack after depressurization of the pipeline was proposed. The principles of determining the limit values of the parameters of the system “pipeline – pumping station” taking into account the criteria of quality and strength of the metal are formulated.

Keywords: depressurization of gas pipelines, gas transportation enterprises, gas, corrosion, pressure sensors, neural network, non-destructive testing, anode current.

I. INTRODUCTION

The problem of ensuring high operational reliability of main underground pipelines (UP) is very important, as a significant part of it in many countries has been in operation for a long time and has largely exhausted its regulatory resources. The most important conditions for the operation of gas and oil transportation companies, which characterize their operational reliability, include the tightness of pipelines. Here it is necessary to emphasize the problem of tightness of the linear part (LP) of the UP [1, 2].

Depressurization of the pipe as a structural element of transport enterprises is accompanied by leakage and ignition of gas (oil, ammonia) [2, 3], accompanied by fires and explosions and often life-threatening [1].

The extent of environmental impact and the nature of combustion of gas and petroleum products depend on the following main factors [3]: 1) diameter of the pipeline (UP) and working pressure of gas (oil, ammonia); 2) soil density and properties of the root massif of the soil; 3) mutual placement (position) of the axes of the ends of the pipes.

By principal reason (over 50 %) of incidents (depressurization, accidents and failures) on UP is corrosion of the pipe metal [1, 4, 5]. If we start from theoretical positions and practical recommendations on the problem [1–5], then one of the urgent issues is to identify places of gas leakage (defects) from pipelines (UP). Pipelines can be placed in different environments, including sand, dry and wet soil. An important technical problem for them is to ensure rapid and high-quality elimination of defects [6].

Depressurization is often associated with the formation of a corrosive cavity [6, 7]. Over time, the cavity expands and its depth increases. At a certain value of depth at the top of the corrosion cavity comes the limit state and a crack is formed [7]. In that place there is a depressurization, which is accompanied by a change in gas concentration (decompression) inside the pipe in the vicinity of the defect.

II. LITERATURE REVIEW AND PROBLEM STATEMENT

The authors of the article [8] modeled the phenomenon of decompression of natural gas in pipelines and analyzed the process of initiating the destruction of the metal.

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But that work does not take into account the principles of fracture mechanics.

The thermodynamic properties of gas and the corresponding simple mathematical equations for modeling the two-phase behavior of gas in PT are discussed [9]. It has been suggested that the decompression of gas in gas pipelines is affected by heat flow, as well as longitudinal viscous cracks [9, 10].

The article [11] proposes elements of mathematical modeling in relation to the detection and localization of pipeline leaks, as well as a review of the causes and techniques of a technical nature. In this context, factors such as pipeline length, line pressure, type of gas (oil) flow, leakage rate and environmental sensitivity in the pipeline area are considered [11].

Based on the theory of natural gas transportation, taking into account the function of the leakage position, the discharge function, as well as the pressure test procedure, a mathematical model of leakage is proposed, which is related to the operation of pressure pipelines [12]. Variants of modeling [8–12] of physical processes concern one point of leakage of a substance (gas, oil) with UP.

A new model for detecting two gas leakage points in a pipeline has been proposed [13]. The model and the corresponding technique allow to detect leaks of the pipeline in real time, using the parameters of the flow of matter [13].

For the receipt of exact position of point of gas source on a pipeline the algorithm of localization of weighted average level is entered [14]. For control of depressurization take approach, that substantially promotes exactness of process of exposure of source of substance from pipelines artificial neural networks (ANN) [14, 15]. The corresponding results of calculations represent minimization of dilemma of difficult acceptance of decisions in relation to the coordinate of gas source on the surface of pipe [14].

In the context of analysis of the considered scientific articles [1–49] there is a problem of reliability of the underground pipeline systems. A problem is related to control of placing of places of gas (oil products) sources and with prognostication of their appearance taking into account intensity of corrosive processes.

III. THE AIM AND OBJECTIVES OF THE STUDY

The aim of the article is forming of theoretical positions and improvement of practical recommendations in relation to determination of the place depressurization of underground pipelines (in the monitoring of oil and gas enterprises) with the use of neural network (ANN). To the aim next tasks are related:

- to offer methodology of functioning of the new informatively-measuring system (IMS) for control of processes that accompany depressurization and decompression of the underground pipeline systems;
- to perfect methodology of control of depressurization of pipelines (in the monitoring of oil and gas enterprises).

In this article examine gas pipelines. But analogical methodology of researches relates to the oil pipelines.

IV. MATERIALS AND RESEARCH METHODS

Examine the system a metallic underground pipeline (UP) – pumping station (PS) with the streams of gas (oil). A metal

of pipeline is steel of high quality (for example L360QB). On a pipe gas (oil) passes in the conditions of internal high-pressure (Fig. 1).

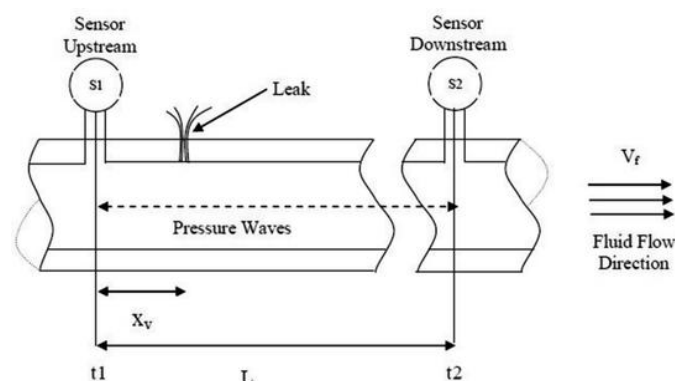


Fig. 1. An element of pipe with sensors (S1, S2) for measuring of pressure

Description of devices (as S1, S2) and standard methodologies for measuring of pressure in a pipeline is presented in the articles [16, 17]. As a result of experiments set, that determining the locations of depressurization with the use only of pressure sensors is characterized by the errors of order 10–20 %.

For reduction of error of determining the locations of depressurization will use the method of the non-contact current measurement (NCM) that gives an opportunity to carry out monitoring of the corrosive state of external surface of metal (UP) on the different areas of underground pipelines, and also to find out defects on a limit between a metal and soil in the places of the damaged isolation [18]. On a interface between a metal and soil moisture (water) can condense with cut-in salts (Fig. 2). Id est have a situation of contact of metal with solution of electrolyte.

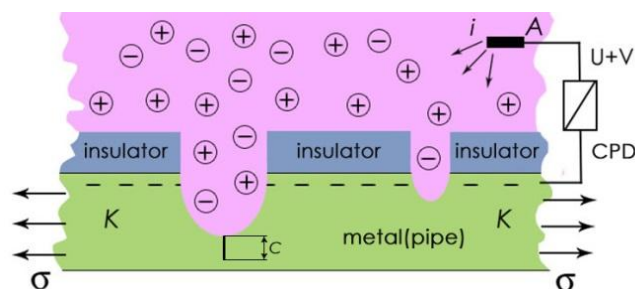


Fig. 2. Element of pipe with surface corrosive defects [45]

On Fig. 2 c is a depth of crack; σ – mechanical tension.

The example of corrosive defects is presented on Fig. 2 in the places of peeling of a protective covering (insulator) from a metal. A metal of pipeline is in the conditions of cathode defence and connected to the cathode of K . The system of cathode defence is illustrated on figure by cathode (K), CPD (cathode protection device), anode (A); U, V are constant and variable differences of electric potentials.

Surface corrosive defects (cavities) are potentially dangerous (Fig. 2). In the process of modeling take into account the complex structure of cavity (pitting) (Fig. 3), where I is a resistance layer, II is the nonsaturated solution of electrolyte, $\vec{\xi}(t), \vec{r}(t)$ are radiuses, $\alpha(t), \Sigma(t)$ are surfaces, t is time.

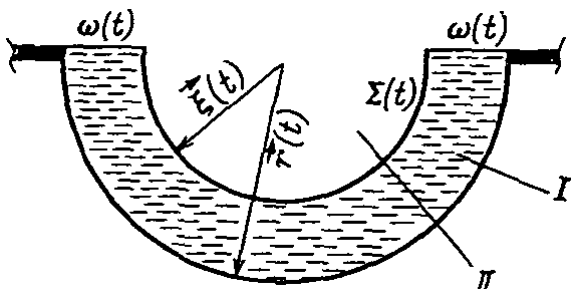


Fig. 3. Model of hemispheric cavity (pitting)

On Fig. 3 radiuses $\vec{\xi}(t)$, $\vec{r}(t)$ and surfaces $\omega(t)$, $\Sigma(t)$ limit a resistance layer (RL). There is the saturated solution of electrolyte in RL.

For control of interface layers of metal of pipeline use the devices of BVS-K (noncontact measuring device of currents) and VPP-M (measuring device of polarization potential) [18, 19]. System of pressure sensors and devices of BVS-K and VPP-M form the new informatively-measuring system (IMS) for determining the locations of pipeline depressurization (UP) (Fig. 4).



Fig. 4. Diagnostic inspections and monitoring of corrosion protection of underground pipelines*

*Note: applicant and patent holder **Karpenko Physico-mechanical Institute of the NAS of Ukraine**, Ukraine; <http://uapatents.com/>

V. RESEARCH RESULTS AND DISCUSSION

5.1. Results of diagnostics of corrosive processes of underground pipelines in the monitoring system of oil and gas enterprises

In the article [1] the method of leak gas location is offered for a pipeline with the use of touch-controls for pressure measuring (in particular, $S1$, $S2$ on Fig. 1).

Block diagram of the new informatively-measuring system (IMS) and corresponding technology of system monitoring “underground pipeline (UP) – pumping station (PS)” is presented on Fig. 5.

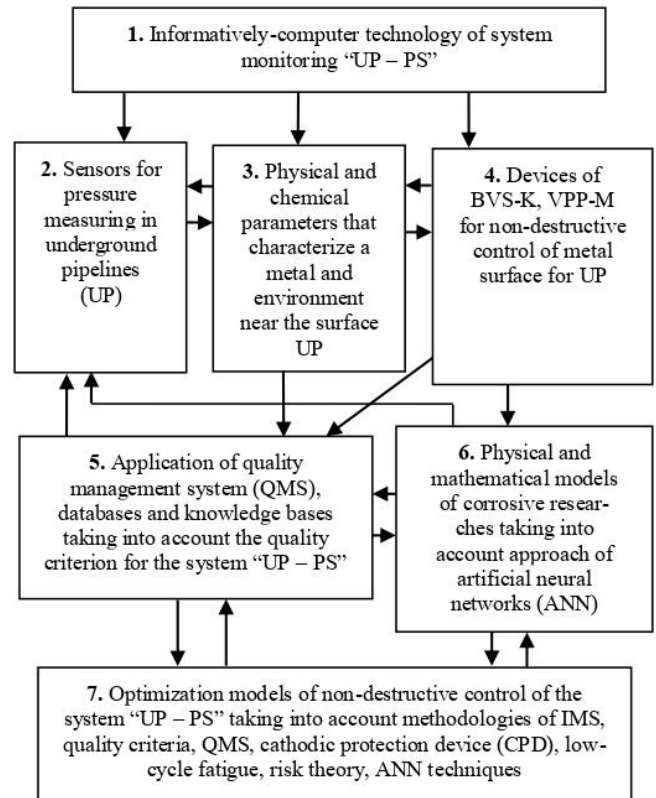


Fig. 5. Block diagram of informatively-computer technology for underground pipelines (UP) taking into account the informatively-measuring system (2, 3, 4) for control of corrosive processes

Scheme on Fig. 5 contains 7 blocks from which blocks 2, 3, 4 answer the new informatively-measuring system (IMS) for realization of measuring. Blocks 5, 6, 7 are the basis of the information processing system received by sensors and non-destructive control devices (IMS). Methodologies of functioning of blocks 5, 6, 7 are partially described in articles [20, 21].

For pressure sensors using a barometric formula we obtain the dependence of gas pressure p on the concentration of his molecules [1]:

$$p = nkT, \tag{1}$$

where n is the number of gas molecules per unit volume; k is the Boltzmann constant; T – absolute temperature.

Here, thanks to the procedure of measuring the gas concentration in different points by formula (1), we determine the pressure distribution field p around the source. It was found out, that the concentration of gas is most exactly determined using spectral analysis methods [1].

The indicated method can be applied to UP. UP can be accommodated in different environments, in particular, in soil with the different degree of humidity.

It should be noted that for UP portable motion of porous environment (soil) is practically absent. Thus differential equation of point source (probable place of depressurization) is reduced to the Laplace equation in the form of formula (2) [1]:

$$\zeta \nabla^2 p^2 = -\frac{f}{\rho \beta^*}, \quad \nabla^2 = \frac{\partial^2}{\partial x^2} + \frac{\partial^2}{\partial y^2} + \frac{\partial^2}{\partial z^2}, \quad (2)$$

where ζ is coefficient of piezoelectric conductivity of the external porous environment (soil), $\left(\zeta = \frac{k}{\mu \beta^*}\right) \text{ m/s}^2$; k is the permeability of the porous medium, m^2 ; μ is absolute viscosity of the environment, $\text{Pa}\cdot\text{s}$; $\beta^* = m\beta_p + \beta_c m$ – consolidated coefficient of volume elasticity; β_p, β_c – coefficient of volumetric elasticity of liquid and solid soil particles, respectively; m – porosity of the environment; ∇^2 – Laplace operator; f is the function of the internal source, $\text{km} / (\text{m}^3 \cdot \text{c})$.

For the estimation of f we use the relationship (3) [1]:

$$f(x, y, z) = \lim_{\substack{\Delta V \rightarrow 0 \\ \Delta t \rightarrow 0}} \frac{\Delta G}{\Delta V \Delta t} \quad (3)$$

where ΔV is volume change; G is compression energy of the porous environment (soil).

Let initial pressure in all points infinite planar porous environment identical and p_0 equals. Let in a point with coordinates (x_0, y_0, z_0) there is a constantly operating source of intensity of q ($\text{kg}/(\text{m}\cdot\text{s})$) [1]. Then the function of f has the form (4) [2]:

$$f = q\delta(x - x_0)\delta(y - y_0)\delta(z - z_0), \quad (4)$$

where $\delta(x - x_0), \delta(y - y_0), \delta(z - z_0)$ – Dirac delta function (δ function).

Taking into account (4), equation (2) has the form of relationship (5):

$$\frac{\partial^2 u}{\partial x^2} + \frac{\partial^2 u}{\partial y^2} + \frac{\partial^2 u}{\partial z^2} = \delta(x - x_0)\delta(y - y_0)\delta(z - z_0), \quad (5)$$

where $u = p^2(x, y, z)$.

Boundary condition $u_{(-\infty, +\infty)} = u_0 = p_0^2$ [2].

The general solution of the Laplace equation is given by Green's formula [1] and we obtain relation (6):

$$u(x, y, z) = p^2(x, y, z) = \frac{1}{2\pi} \int \int_{-\infty}^{\infty} \frac{z}{\left[(x - \xi)^2 + (y - \eta)^2 + z^2\right]^{3/2}} f(\xi, \eta) d\xi d\eta, \quad (6)$$

where ξ, η coordinates of the point where the gas concentration was measured.

Defining the values of coordinates x, y, z in formula (6), we determine the values of the function u , according to which we build isobars in the soil and, accordingly, we obtain the coordinates of a point on the outer surface of the pipeline. At that point, the probable source of gas pollution or the place of depressurization of the gas pipeline is located.

For the section of the underground metal pipeline, taking into account the procedure of sounding the system using IMS (2, 3, 4) (Fig. 5), it is advisable to use artificial neural networks (ANN) similarly to articles using acoustic technologies [22, 23].

As a neural network will realize a continuous goal function, then with her help methodology of prognostication of value of potentials is offered in the special areas on the surfaces of pipeline, in that the broken condition in relation to polarization potential (PP) of U_p [18, 24].

From corrosion consider the witness value of difference of potentials the basic criterion of defence of pipeline between a metal and ground electrolyte, that is named polarization potential [18, 24].

A task over of prognostication of resource of underground metallic pipeline is brought to the optimization task with the use of neural networks, methods of computer modeling [21, 25], and also to the criterion of quality for the system “UP – cathodic protection device (CPD)” [5, 20].

Like as in article [7] will use the criterion of strength, and also criterion of quality for the UP linear section, that will give in the form (7) [5, 26]:

$$Z_1 = \beta_1 k_1 \cdot k_2 \cdot k_3 + \beta_2 \prod_{i=4}^9 k_i, \quad (7)$$

where k_1 is the coefficient of UP reliability; k_2 is the coefficient of reliability of sensors for pressure measuring; $k_3 = k_3(T_S, N_C)$ – 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); $k_4, k_5, k_6, k_7, k_8, k_9$ – 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.

Coefficients k_1, k_3 depend on the following information parameters, namely [5]: 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; K_S is the coating effect on corrosion resistance; T_S 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.

A criterion (7) differs from analogical in the articles [5, 26], as new interpretation of coefficient of k_2 is entered.

As a result of corrosive process depth of h cave grows. In course of time in the top of cave after the action of mechanical tensions σ_{yy} there is a crack of depth of c (Fig. 1 and Fig. 6) [7].

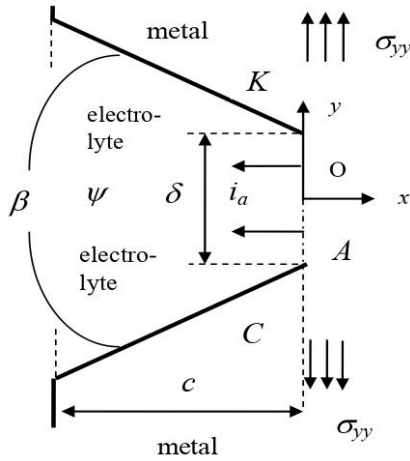


Fig. 6. Scheme of crack tip (i_a is anode current)

For estimate the current density in the crack tip we use the generalized Kaeshe relation type [7]:

$$I_a = I_0 \cdot \left(\exp\left(\frac{DE}{a}\right) \right) \cdot (1 + \beta_w \cdot W_{PL}); \quad I_0 = \frac{\alpha \cdot \chi \cdot \Delta\psi_{ak}}{\delta \cdot \ln((h+c)/\delta)} \quad (8)$$

where a is the Tafel parameter of the anode metal dissolution process; $DE = U_p - E_a$; I_0 , U_p – corrosion current density and the potential of cathode protection of metal; I_a , E_a – is the anode current density and the anode potential for metal; $I_a = i_a/S$; S – the cross-sectional area of the conductor through which the electric current passes; δ – crack opening; α is the angle at the crack tip; χ is the electrical conductivity of the electrolyte; $\Delta\psi_{ak}$ is the ohmic change of potential between the anode and cathode parts (anode – top, cathode – crack sides); $h+c$ – total depth of defect (pitting and crack); W_{PL} is the energy of plastic deformation per unit of surface; β_w is the empirical coefficient.

In contrast to [7], in (8) there is U_p – cathodic protection potential of metal.

For modeling we use the results of measurements of currents near the PS (Table 1), which are presented in the range $L = 0 \dots 12$ km.

Table 1. Anode current density I_a depending on the distance L from the pumping station (PS)

Distance L , km	Anode current density I_a , A/m ²
0	20,7
3	17,2
6	15,0
9	13,3
12	12,0

This is because the maximum number of accidents is observed at a distance of $0 \dots 20$ km from PS [27].

Based on the analysis of the data, it can be seen (Table 1) that with distance from PS the anode current density decreases nonlinearly.

5.2. Discussion of the results of the study of the distribution of corrosion current densities and pressure in the pipeline (in the monitoring of oil and gas enterprises) for providing of safe exploitation

Consider the example of accident prediction for the pipeline on the data on the physical and geometric characteristics of UT, as well as on the information of the IBC (Fig. 5).

The corresponding situation is schematically shown in Fig. 7, where there are two PS (Station A and Station B, $L \approx 100$ km – distance between PS).

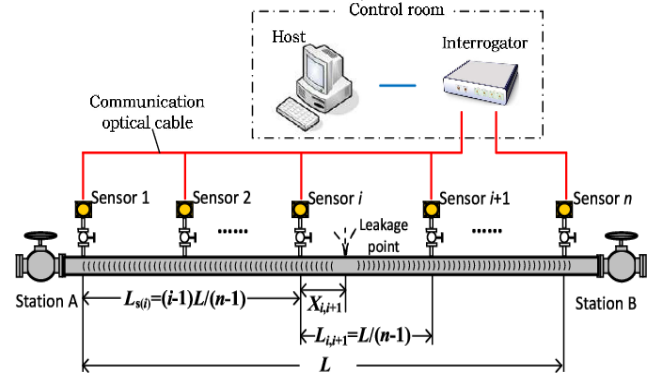


Fig. 7. Linear section of the pipeline between two pumping stations (PS)*

*Note: <http://doi.org/10.5281/zenodo.3829900>

Consider a test example. For example, use the information in Table 1, in particular, the value of the current density I_a for $L_1 = 6$ km (from Station A, Fig 7).

Based on the relations (1)–(8) and the strength criteria [7], the crack growth time and leakage point were determined using a neural network (ANN):

$$\begin{aligned} T_0 &= 293 \text{ K}; D = 1200 \text{ mm}; d = 16 \text{ mm}; \\ I_{a0} &= 15,0 \text{ A/m}^2; I_{az} = 3,0 \text{ A/m}^2; \\ U_K &= 0,95 \text{ V}; \sigma_T = 360 \text{ MPa}; \\ H = h+c &= 8,1 \text{ mm}; t_* = 0,62 \text{ year}; \\ L_1 &= 6 \text{ km}; L_2 = 46 \text{ km}. \end{aligned} \quad (9)$$

In relationships (9) H is the maximum possible depth of the defect at a distance $L_1 = 6$ km from PS. At this point, with the help of BVS-K, VPP-M (Fig. 8), a defect was detected. For this defect, the forecast gives $t_* = 0.62$ year (defect growth time). $L_2 = 46$ km – distance from the station (Station B), where the leakage point was detected.

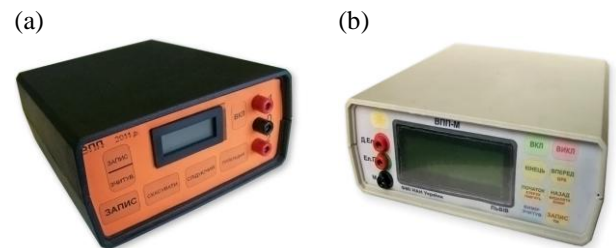


Fig. 8. Digital instruments for measuring constant and alternating electric voltages and determining the polarization potential: (a) – VPP, (b) – VPP-M*

*Note: Pat. 52293 Ukraine, IPC (2009) G 01 V 3/00, C 23 F 13/00. Device for determining the location and measurement of potential of underground pipelines / R. Dzhala, B. Verbenets; applicant and patent holder **Karpenko Physico-mechanical Institute of the NAS of Ukraine**, Ukraine. – No. u2010 00756; stated. 26.01.2010; Positive decision 08.06.2010; published Aug 25, 2010, Bul. No. 16.

Relationships (1)–(8) and information about the anode current in surface defects (table 1) are the basis of a new mathematical model for modeling the behavior of surface defects on the surface of UP and the stages of their development using a neural network. The dangerous area initially looks like a spot. Then the stain in the process of corrosion and self-organization turns into a cavity (pitting) [28]. At a determined size of a cavity in its top there is a crack and will be a depressurization (Fig. 7).

Based on relations (1)–(8) using neural networks, data were obtained for two partial examples, which correspond to two special points ($L_1=6$ km; $L_2= 46$ km).

The depressurization phenomenon will correspond to the limit values of two informative parameters $u(x,y,z)$, Z_l . They ($u(x,y,z)$, Z_l) characterize the critical situation of gas leakage and are determined from relations (6) and (7).

The presence of only pressure sensors (Fig. 7) makes it possible to set the coordinates of depressurization with a large error – 20... 26 % ($\delta_{PS}=23$ %). Diagnosis of the pipeline only by devices BVS-K, VPP-M (at the first stage) allows to reveal surface defects. But this information is not enough for a qualitative experiment, as shown by the qualimetric quality criterion (7). Taking into account the pressure data in the second stage allows you to determine which of the defects is the leakage point.

The presence of a resistive layer (Fig. 3) of the cavity (pitting) leads to a nonlinear change in the depth of the defect, which is described by relation (8) [27]. Based on the computational experiment and neural networks, the error in estimating the coordinates of points L_1 and L_2 , which is 5... 7% ($\delta_{LS}=6$ %), was established.

The presence of resistive layer of cavity (pitting) (Fig. 3) leads to a nonlinear change of defect depth. This dependence is described by correlation (8). Analogical correlation is presented in [27].

On the basis of computational experiment and neural networks the errors of parameter of $T_S=t_*$ (pipeline resource) and coordinates of leakage points of L_1 and L_2 are estimated and they approximately take the values $\delta_L \approx 5...7$ % ($\delta_{LS} \approx 6$ %).

Thus, on the basis of test example (9) as a result of diagnosing the pipeline by a new method (pressure sensors and non-destructive testing devices BVS-K, VPP-M) obtained a higher quality of leakage point control, in particular:

$$\begin{aligned} \delta_L &\approx 5...7\%; \quad \delta_{LS} \approx 6\%; \\ \Delta_{PL} &= \delta_{PS} - \delta_{LS} = 17\%; \\ \delta_{PS}/\delta_{LS} &\approx 3,8. \end{aligned} \quad (10)$$

Indicated parameters of the type Δ_{PL} , δ_{PS}/δ_L may be the characteristics of a new method of pipeline control (pressure sensors and non-destructive testing devices BVS-K, VPP-M) compared to the method based on only pressure sensors.

VI. CONCLUSION

According to the results of the study such conclusions and recommendations have been formulated [1–49]:

1. An analysis and ground of the analytical correlations characterizing gas leaks and the quality of the “underground pipeline – pumping station” system was realized.

2. A set of informative parameters for determining the location of gas depressurization on the surface of the

underground metal pipe and an expression for estimating the change in gas pressure after the formation of a through crack.

3. A new approach to diagnosing places of depressurization of the pipeline with the help of: pressure sensors and non-destructive testing devices (BVS-K, VPP-M), with which we measure the pressure, potentials and corrosion currents.

4. The new neural network method of prognostication of the stages of development of corrosive cavity (pitting) has been developed. A method describes motion of pitting, appearance of crack in the top of pitting, the transition of the crack to a critical state and depressurization of the pipeline based on information obtained from the use of information and measurement system (IMS), id est pressure sensor systems and non-destructive testing devices (BVS-K, VPP-M).

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