Predicting the rate of underground corrosion of steel pipelines: A review

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Abstract

Estimation of the probable rate of corrosion of underground steel pipelines has long been a challenging problem for engineers and researchers and is still of importance. The complexity of solving this problem is due to a large number of influencing factors (the composition of the ground electrolyte, gas and solid phases of the soil), their constant daily and seasonal changes, the use of cathodic protection and protective polymer coatings. Another feature of the corrosion process is its probabilistic nature. Due to the complex nature of the phenomenon, several different approaches have been developed to predict its rate. This review deals with the factors that affect the formation and development of corrosion defects in underground pipelines and the various methods used to predict the corrosion of pipelines. The basis for predicting the growth rate of corrosion defects in the outer wall of underground pipelines are methods for predicting the corrosion rate of pipe steel in soils, which can be divided into qualitative and quantitative ones. Qualitative methods are mainly used to determine the degree of soil corrosion activity (scoring methods). Scoring methods create prerequisites for quantifying the corrosion rate of steels in soils. However, the currently existing quantitative models of underground corrosion take into account no more than two corrosion factors. Due to the imperfection of quantitative simulation of steel corrosion in soils, the methods for predicting the corrosion of the outer wall of pipelines are based on statistical processing of data obtained either in full-scale corrosion tests of pipe steel samples or during pipeline inspection. Models of various types (deterministic, probabilistic, and those created using machine learning) are presented and the criteria of their applicability are analyzed.

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1. Introduction

In many cases, the service life of underground steel structures such as pipelines, foundations, and tanks is determined by the corrosion rate of the outer wall of these structures in contact with the earth. The most common materials for underground structures, including the pipelines intended for various purposes, are low-carbon and low-alloy steels (hereinafter referred to as steels). The corrosion behavior of steels in soils or in model soil electrolytes has been examined by many researchers, and the results obtained were analyzed in a number of reviews published in the past decade [1–3]. However, the problem of reliable prediction of the service life of underground structures is far from being solved and remains a relevant issue. The difficulty of solving this problem is due, first of all, to the lack of generally accepted methods for the quantitative prediction of the rates of general and local corrosion of steels in soils during long-term operation of metal structures.

There are numerous factors that can affect the corrosion of underground steel structures, and not all factors can be taken into account in predictive models. Moreover, the corrosion of steels in natural environments (soil, atmosphere, natural waters) occurs under conditions of continuous changes in the physicochemical parameters of the corrosive environment. The thickness and barrier properties of the layer of corrosion products on the metal surface also vary over time. The operating parameters, such as the temperature and pressure of the product transported through pipelines, and the mode of their electrochemical protection may also change. A great risk of corrosion damage to a structure occurs when stray or induced currents from direct or alternating voltage sources flow in the soils. In the case of extended structures, primarily pipelines, macrogalvanic couples can form at the boundary of soils with different compositions or different degrees of aeration. The action of such couples is largely similar to that of stray currents from a constant voltage source. A significant hazard comes from corrosion due to waste products of microorganisms (biocorrosion), which, as a rule, occurs under the peeled-off insulating coating on pipelines.

Thus, the "pipeline-soil" corrosion system should be considered as an "ill-organized system" in which strictly deterministic cause-and-effect relationships between the process rate and numerous parameters that vary in time and space cannot be recognized. Hence, any predictive model of pipeline corrosion will be probabilistic in nature.

The development of a predictive model is based on a database, which consists of "corrosion effect – values of operating factors" sets. The mass loss of the metal or the depth of corrosion penetration or, in some cases, the area or geometric dimensions of the defect and the surface density of defects are used most often as the quantitative values of the corrosion effect.

To create a corrosion data base and to develop a predictive corrosion model, the most significant operating factors should be identified. For a practical application of the model, it is necessary that the number of these factors not be large and that their values (or the ranges in which these values vary) can be determined before or during the operation of the pipeline.

The purpose of this work is to provide a review of the existing predictive models for the corrosion of the external wall of underground pipelines. First, the factors affecting the formation and development of corrosion defects in underground steel structures, primarily pipelines, are considered. The types of steel corrosion such as stress corrosion cracking and biocorrosion are beyond the scope of this review since the prediction of these specific corrosion types requires a separate discussion.

2. Factors Affecting the Formation and Growth of Corrosion Defects in Underground Steel Pipelines

2.1. Corrosion of steel pipes in soil

Composition and structure of steel. Currently, it is believed that the composition and structure of steel are not the most significant factors in the soil corrosion of pipe steels. In the late 1950s, a research team of the Institute of Physical Chemistry of the USSR Academy of Sciences guided by N.D. Tomashov conducted field tests of carbon and low-alloy steels in six types of soil at the Zvenigorod corrosion station and on the route of the Moscow-Saratov gas pipeline, which was the first structure of this type in the USSR [4]. The mass losses of samples and the depths of corrosion defects were measured to determine the rates of general and pitting corrosion, and it was shown that the corrosion rate was determined by the type of soil rather than by the steel grade. The corrosion rates of individual steel samples and of a controlled section of the pipeline were found to be different, which was associated with the operation of differential aeration pairs. A conclusion important for practice was confirmed: in the case of extended objects, not the corrosive activity of the soil in general, but rather the corrosive activity of the soil at each specific section of the pipeline route is relevant.

Subsequently, models of the soil corrosion of carbon steel were developed without taking the steel chemical composition or structure into account [5]. In principle, the presence of alloying components can affect the protective properties of corrosion products and hence the corrosion inhibition coefficient over time during long-term exposure of pipe steel in the ground. In the case of a sufficiently low content of alloying components in pipe steel, one can expect that such an effect on the amount of metal mass loss will be insignificant, as it is observed in the case of atmospheric corrosion of carbon steels [6]. It was noted that the microstructure affected the liability of steels to local corrosion; in particular, microgalvanic couples can arise between inclusions of Mn oxides and the metal matrix [3], between ferrite and pearlite [7], and in the steel heat treatment zones [8]. On the other hand, the effect of the microstructure of pipe steels cannot be regarded as significant: a study of the corrosion behavior of 36 samples of various pipe steels in the associated fluid produced in an oil field (the concentration of Cl^- ions in this solution was 18.9 g/l) showed that the average rate of local corrosion of four groups of steels ranged from 4.5 to 6.0 mm/year [7]. It should be noted that the corrosion tests lasted only two weeks; therefore, the above values are corrosion rates at the initial stage of the process. The results of testing samples of Kh70 steel produced by KhTZ and Mannesman in three solutions simulating a ground electrolyte [9] showed that the size of the pits formed on both steels in the same solution differed only slightly.

Thus, no reliable experimental data are currently available which would enable a quantitative description of the effect of the chemical composition and structure of pipe steels on the rates of their general and pitting corrosion during long-term exposure in soils.

Residual stresses in the metal. It has now been reliably determined that the residual metal stresses affect the initiation and initial growth of corrosion cracks in pipe steel [10]. Residual stresses may affect the general and pitting corrosion of steels for several reasons:

– residual tensile stresses in the mechanical hardening layer accelerate the electrochemical dissolution of iron, including the region of cathodic potentials [11];
– residual stresses contribute to the hydrogenation of pipe steel [12], which in turn facilitates the formation of pits during cathodic or alternating polarization of pipe steel [13] and accelerates its anodic dissolution in pH-neutral electrolytes [14];
– the biofilm formed in the presence of sulfate-reducing bacteria in the zone of residual stresses of a metal is defective, which also favors the corrosion of pipe steels [12].

The effect of residual stresses on the corrosion of pipe steels in soils (soil electrolytes) has not been studied sufficiently. Apparently, this effect would greatly depend on the exposure time of steel in a corrosive environment, since the direction and magnitude of residual stresses changes along the thickness of the pipe wall [15].

In the analysis of pipeline reliability, the magnitude of residual stresses and the size of a corrosion defect are often used as predictive model parameters (see, for example, [16, 17]). However, such models do not require establishing a relationship between the corrosion rate of the outer pipe wall and the magnitude of residual stresses.

Structure and granulometric composition of soil. The structure and granulometric composition of soil determine the conditions for water and gas exchange between the soil and the external environment and are indirect characteristics of the oxygen content in the soil. In addition, the type of soil (sand, clay, limestone, loess, marl, *etc*.) indirectly characterizes the soil moisture and the composition of the soil electrolyte. Early works suggested to estimate the corrosivity of a soil based on the content of sand, clay, limestone and humus (Rosebohm triangle) [5]. Of natural soils, peaty soils, lime-poor humus soils, and soils containing marl and sulfides, Jurassic marl, and shale soils are most corrosive. Soils contaminated with anthropogenic impurities are usually corrosive [5]. Some authors consider clayey soils to be the most hazardous due to their ability to absorb large amounts of water [2].

Soil humidity. Soil humidity primarily characterizes the area of contact between the steel surface and the soil electrolyte. With increasing humidity, the area of this contact increases, and the corrosion rate also increases. Once all the pores of the soil have been filled with water, a further increase in humidity can lead to a decrease in the corrosion rate due to a decrease in the rate of diffusion supply of oxygen to the metal surface [18].

Soil aeration. In neutral or alkaline soils, the electroreduction of oxygen is the main cathodic reaction in the corrosion of steels. In soils of the so-called backfill, the oxygen concentration is higher [2], which is one of the reasons for their higher corrosivity compared to natural soils.

Chemical composition of soil electrolyte. The parameters characterizing the composition of the soil electrolyte include the pH, buffer capacity (determined by titration with an alkali or acid), redox potential, concentrations of sulfide (bisulfide), chloride, sulfate, and carbonate (bicarbonate) anions, concentrations of magnesium and calcium cations, and the presence of carbon or coke components. Various qualitative estimates of the corrosivity of soil have been developed for various sets of these parameters [5, 19–24]. The most complete (score-based) estimation of soil corrosivity is presented in a standard [25].

Electric resistivity of soil. According to Russian and international standards [21, 25–27], the electric resistivity of soil (ρ) determines its corrosivity towards steels. This assessment is qualitative; a weak correlation between ρ of the soil and the corrosion rate of both steel samples and the outer wall of pipeline sections has been repeatedly noted [1, 28]. In the case of underfilm corrosion, that is, in the absence of the action of extended macropairs, assessing the corrosivity of the environment solely based on the ρ value of soil is clearly insufficient.

Mean cathodic current density [26]. This assessment of corrosivity is also qualitative. The basis for using this method for assessing the corrosivity of soil is that steel corrosion in soils usually occurs with oxygen depolarization, while the reduction of oxygen is limited by its diffusion transfer in the liquid phase of the soil [18]. The method does not take into account the possibility of cathodic reduction of weak organic acids that are present in ground waters. In addition, the values of cathodic currents may not match the oxygen reduction rate due to the reaction of reduction of iron oxides on the electrode surface or deaeration of the ground electrolyte by hydrogen gas released at the cathode. The oxygen concentration under a peeled-off coating is usually smaller than in the soil around the pipe. Despite the indicated drawbacks of this method for assessing the corrosivity of soil, the value of the cathodic current is the only quantity that can directly characterize the rate of oxygen reduction on steel in a soil.

The soil parameters such as its horizontal and vertical homogeneity [25] are of great importance for assessing the rate of steel corrosion in a through defect in the pipeline insulation but should not affect the rate of underfilm corrosion.

2.2. Corrosion of pipe steels under a peeled-off coating

As early as in the 1970s, a research team [29, 30] studied the rate of metal oxidation under free and adhered films. It was shown that on an isolated metal surface, the anodic reaction of metal ionization was inhibited more strongly than the cathodic processes. As a result, a corrosion current was generated in a pair composed of insulated and non-insulated metals; this increases the rate of destruction of the non-insulated electrode, which is the anode of the corrosion couple.

The use of pipeline cathodic protection stations added another component (long-term exposure to cathodic polarization), leading to adhesion failure in the pipe-coating system, *i.e.*, cathodic peeling. The phenomenon of cathodic peeling was thoroughly studied; one of the latest reviews of these studies is presented in [31].

Review [32] presents the results of the many years of explorations on the mechanism of external corrosion of underground pipelines under peeled coatings with or without through defects. Analysis of the published data showed that the majority of laboratory tests [33–47] were performed with delamination with a uniform gap. Actually, this parameter is constant only rarely and often varies in the longitudinal direction. In addition, the ionic current or oxygen diffusion through a permeable peeled coating was often not taken into account, either, with the exception of a few studies [48, 49].

In a later paper [50], a developed mathematical model was presented that made it possible to predict corrosion in a delamination with a through defect, while taking the factors listed above into account. The calculated corrosion rates were in good agreement with the results of laboratory experiments. The simulation results show that if a cathodic protection station operates, the pH of the underfilm electrolyte in the peeling area increases over time, whereas the corrosion rate decreases. In the absence of external polarization but in the presence of oxygen, the average pH value of the solution in the peeling zone decreases over time and the pH of the solution at the top of the crack becomes smaller than at the mouth of the defect. Acidification of the electrolyte under a peeled coating without cathodic polarization was also shown in [51]. It is noted [37, 52] that it is important to know the degree of corrosion of the pipe surface before insulation and before activation of cathodic polarization, since the corrosion products formed previously can significantly affect the corrosion rate under the peeled coating. The intensity of local anodic dissolution of the metal under such a "film," in the authors' opinion, may be due to the effect of surface heterogeneity, *i.e.*, the presence of mechanically stressed areas of the metal and galvanic couples emerging due to the partial reduction of corrosion products and local changes in the solution concentration due to the flow of cathodic current.

Under a peeled coating, an environment that is favorable for the growth of anaerobic microorganisms, in particular, sulfate-reducing bacteria, is created. The waste products of microorganisms change the composition of the underfilm electrolyte, usually increasing the concentrations of sulfide and carbonate-containing compounds [1, 53, 54].

Thus, the chemical composition of the liquid under a peeled coating may differ significantly from that of the soil electrolyte. However, practically acceptable (non-destructive) methods for determining the composition of the electrolyte under a coating are unavailable; therefore, in predictive models of pipeline corrosion, the properties of the soil or soil electrolyte are generally used as the input parameters.

2.3. Effect of process parameters on the corrosion rate of an underground pipeline

Gas pressure. Gas pressure is considered as a significant factors affecting the corrosion of pipe steel due to the mechanochemical (M-C) effect. The latter manifests itself in the acceleration of the anodic and/or cathodic reaction under the impact of tensile mechanical stresses. It was hypothesized that the thermodynamic activity of a metal increased under the impact of stress ε and its equilibrium potential E_0 shifts to more negative values [55]. If ε is proportional to the gas pressure P, the change in the equilibrium potential of the metal is described as:

$$\Delta E_0 = -\Delta P \cdot \frac{V_m}{zF} \tag{1}$$

where ΔP is the excess pressure, V_m is the molar volume of steel ($7.13 \cdot 10^{-6}$ m^3/mol), $z = 2$ is the charge of the iron ion, and F is the Faraday constant.

The shift in E_0 with an increase in ε from zero to the yield point is several mV, *i.e.*, it cannot lead to a significant acceleration of the anodic reaction on steels, as experiments confirm [56]. However, the layer of corrosion products may have a smaller strength than the yield strength of the metal, therefore, when the critical value of ε is reached, the layer of corrosion products should break and expose the steel surface. However, it has been shown that the iron carbonate layer formed on the surface of pipe steel in NS4 solution does not crack when a 582 MPa stress is applied [56]. As a result, the corrosion potential of steel does not change; a slight decrease in polarization resistance, *i.e.*, an increase in the corrosion rate is observed, which is explained by the deterioration of the barrier properties of the iron carbonate layer.

In the case of plastic deformation of steel, it is suggested to describe the value of ΔE_0 as [55]:

$$\Delta E_0 = -\frac{TR}{zF} \cdot \ln\left(\frac{\alpha \nu \varepsilon_p}{N_0} + 1\right) \tag{2}$$

while in the case of continuous elastic-plastic tension, as follows:

$$\Delta E_0 = -\Delta P_m \cdot \frac{V_m}{zF} - \frac{TR}{zF} \cdot \ln\left(\frac{\alpha \nu \varepsilon_p}{N_0} + 1\right) \tag{3}$$

where ΔP_m is the excess pressure during plastic deformation equal to 1/3 of the yield strength of steel, the coefficients are $\nu = 0.45$ and $\alpha = 1.67 \cdot 10^{11}$ cm^{-2}, $N_0 = 10^{-8}$ cm^{-2} is the initial density of dislocations before the plastic deformation, and ε_p is the plastic stress determined by elastic-plastic simulation.

The finite element method was used to determine the mechanical stresses arising upon formation of corrosion defects with various sizes, and the change in the potential and corrosion current due to the M-C effect was calculated [57, 58]. It was been experimentally shown that upon elastic M-C deformation, the effect was insignificant ($\Delta E \sim 2$ mV). Upon plastic deformation, a potential shift of 10 mV in the negative direction and an increase in the corrosion current by 2 μA/cm^2 are observed [57]. A galvanic couple emerges: the edges of the defect operate as the cathode, while the center of the defect operates as the anode. The calculation showed that for Kh100 steel and a defect with an initial depth of 2 mm and a width of 8 mm, the rate of iron dissolution in the center of the defect increases by 0.5 μA/cm^2 at the first moment of time, but after 20 years it should increase by 4 μA/cm^2 [59]. It has been noted that over time, the anodic zone of the galvanic couple narrows significantly (it is localized in the defect center), *i.e.*, the M-C effect should lead to the formation of a mechanical stress concentrator [57, 58].

Disadvantages of this model should be noted [57, 58]:

– only circumferential stresses of a pipeline are taken into account;
– the relationship between the anodic process rate and voltage is given by a semi-empirical expression that was obtained for the cathodic hydrogen evolution reaction;
– cathodic reduction of oxygen is not taken into account in the calculation of the corrosion rate;
– there is no experimental systematic verification of the predicted values of corrosion under the M-C effect, primarily in various types of soil electrolyte.

Thus, despite the progress in the quantitative description of the M-C effect, the statement [57, 58] that the growth of a corrosion defect with the time of pipeline operation can be well monitored using this model is clearly premature.

Gas temperature. Studies on the dependence of the corrosion rate of pipe steels on temperature are briefly reviewed in [60]. This dependence was usually studied in aqueous solutions or in soils with constant humidity [61]. Consequently, the effect of temperature on the life time of an electrolyte film on a metal surface was not taken into account. It can be assumed that the dependence of the corrosion rate of the pipe outer wall on its temperature passes through a maximum. The ascending branch of this dependence is associated with the acceleration of the corrosion process with increasing temperature, while the descending branch is associated with a decrease in the life time of the electrolyte film on the metal surface. In addition, the relationship between the temperatures of the gas and the pipe outer wall depends both on the design of the pipeline and on the conditions of heat exchange between the pipe and the external environment.

Given that the soil temperature changes over time (daily and seasonal variations), it seems appropriate to find correlations between corrosion and average annual temperatures of the operating area for pipelines with different types of coatings.

3. Methods for Predicting the Corrosion Rate of Steel in Soils

Estimation of the corrosion rate of steels in soils is the basis for predicting the growth rate of corrosion defects in the outer wall of underground pipelines. The methods for predicting underground corrosion of steel can be divided into qualitative and quantitative ones [2]. Qualitative methods determine the soil corrosivity but fail to provide a numerical value for the rate of steel corrosion. Quantitative methods make it possible to numerically estimate the expected rate of metal corrosion.

3.1. Qualitative methods (methods for estimating the corrosivity of soil)

The qualitative methods for estimating the corrosion of steels are primarily used to determine the corrosivity of soils based on a number of their properties (corrosivity factors). Qualitative models for assessing steel corrosion are often used in regulatory documents, for example, in [26], and determine the corrosivity of a soil based on 2 or 3 factors. However, the more factors the model takes into account to estimate the soil corrosivity, the higher its reliability should be.

The history of the development of qualitative models of underground corrosion is described in sufficient detail in [2]. Initially only one parameter, namely soil resistivity ρ, was used. The most widely used methods for estimating the corrosivity of soils based on the value of ρ suggested by the National Association of Corrosion Engineers (NACE) and the American Society for Testing and Materials (ASTM) are summarized in Table 1 [27, 62, 63].

Table 1. Estimation of the corrosivity of soil based on the value of its electrical resistivity according to NACE and ASTM methods.

Soil resistivity, Ohm·cm	NACE	ASTM
>10000	Insignificant influence	Very weakly corrosive
5001–10000	Weakly corrosive	Weakly corrosive
2001–5000	Weakly corrosive	Moderately corrosive
1001–2000	Moderately corrosive	Strongly corrosive
501–1000	Corrosive	Extremely corrosive
0–500	Very corrosive	Extremely corrosive

To rank soils according to corrosivity, the value of the redox potential [64] or the pH of the soil aqueous extract [65] were also used. Subsequently, two parameters were introduced to assess soil corrosivity: soil resistivity and pH of the water extract (Table 2) [21].

To take into account the various factors affecting the steel corrosion rate in more comprehensively, methods for assessing soils based on score scales have been developed. In this case, each soil parameter has a weight that depends on the degree of its effect on corrosion. The following approaches have been developed:

– AWWA C105 scale, which takes into account the humidity and resistivity of the soil, redox potential, pH of the water extract and the concentration of sulfide in it [22, 23];
– DVGW technique [66];
– DIN 50 929[25] standard, which improves the DVGW procedure;
– tabular method for assessing the soil corrosivity from Dechema [67].

Table 2. Corrosivity of soil as a function of pH and electrical resistivity in accordance with EN 12501-2:2003 [21].

pH	Soil resistivity, Ohm·cm	Corrosion level
<3.5	Any	High
3.5–4.5	<4500	High
	>4500	Above average
4.5–5.5	<4500	High
	4500–5000	Above average
	>5000	Average
5.5–6.0	<1000	High
	1000–5000	Above average
	5000–10000	Average
	>10000	Below average
6.0–9.5	<1000	High
	1000–3000	Above average
	3000–10000	Average
	10000–20000	Below average
	>20000	Low

The latter two methods [25, 67] estimate the soil corrosivity using 12 parameters (Table 3).

Table 3. Variables considered in the Dechema Soil Corrosivity Table [67] and in the standard [25].

Parameter No.	Parameter name and unit of measurement
1	Soil type
2	Electric resistance, Ohm
3	Water content, %
4	pH
5	Buffer capacity
6	Content of sulfides, mg/kg
7	Content of neutral salts, mol/kg
8	Content of sulfates, mol/kg

Parameter No.	Parameter name and unit of measurement
9	Presence of ground waters
10	Horizontal homogeneity
11	Vertical homogeneity
12	Redox potential

The AWWA C-105 method for estimating the corrosivity of soil was used in an attempt to develop a "design decision" model [68]. The essence of this model is that, based on the score of soil corrosivity, methods of anti-corrosion protection are suggested (type of insulating coating, need for cathodic protection).

Thus, as knowledge about the mechanism of underground corrosion of steel and the factors that affect it accumulated, qualitative methods evolved [2]. In the beginning, one or more variables that were believed to be most important were taken into account in assessing the corrosivity of soil. Later, it was understood that the corrosion rate is determined by a multitude of factors and their combinations. The score scale made it possible to improve methods for ranking soils by corrosivity, and in some cases created prerequisites for a quantitative estimation of corrosion rates. For example, based on the data from the standard [25], a model [69] was developed that made it possible to estimate the uniform corrosion rate and the maximum pit depth based on the values of the parameters presented in Table 3.

3.2. Quantitative methods for estimating the corrosion losses of pipe steel

Corrosion damage to steels in soils is usually estimated by two values: the metal mass loss and the maximum depth of the corrosion pits. Accordingly, the rates of conditionally uniform corrosion and corrosion penetration (pit growth) are calculated. Most methods for the quantitative estimation of the rates of the two types of corrosion are based on the results of field tests of steel samples or on data from diagnostic inspections of pipelines and other underground structures.

In [1], a brief historical overview of the results of inspections of pipeline sections laid in soils with varying corrosivity [70–73] is presented; however, the most complete studies of steel corrosion in various types of soils were carried on request from the US National Bureau of Standards in the period from 1922 to 1947 [74, 75]. As part of this program, thousands of samples (mostly pipes) of various grades of steel were buried at 47 locations in the United States territory for up to 17 years. Throughout the test period, samples were extracted to determine the mass loss and the maximum pit depth. These data made it possible to determine the rates of uniform and local corrosion of steel over various periods of time. The final report by M. Romanoff [75] presented the relationship between the corrosion rate and the properties of soils: the rates of both general and local corrosion were found to decrease with time according to a power law.

We agree with the conclusion [2] that Romanoff made a revolution in the field of underground corrosion of steel, and the majority of subsequent studies only confirmed the conclusions and recommendations made [75].

The data contained in [75] were re-analyzed in [76]. A number of drawbacks of that study [75] were noted, including:

- the statistical documentation of the test results is insufficient;
- the differences in different soil horizons at the same test location were not taken into account;
- the seasonal and annual variation in some parameters (temperature, precipitation, *etc.*) were not taken into account;
- samples could be placed in the ground at different depths due to the lack of a uniform method for test preparation;
- non-representative values were used for some variables, for example, their average value was taken for past periods of time rather than for the test period;
- many soil properties were measured in the laboratory rather than at the test site, due to which the soil humidity, the amount of carbon dioxide and oxygen, and the solution pH could change;
- full chemical analysis was completed at only 26 of the original 47 test sites;
- possible changes in soil characteristics during the test period were not taken into account.

Despite these limitations, the data obtained over 70 years ago are still in use today. Moreover, according to [2], Romanoff's tables [75] are the most representative quantitative method that takes into account the largest number of soil properties that affect the corrosion of steels. The quantitative models developed later take into account one or two factors of soil corrosivity. For example, in [77], the rate of underground corrosion of steel was determined using the pH values and the minimum resistivity of soil. In [78], a statistical model was suggested to calculate the rate of corrosion loss of steel (V, mm/year):

$$V = 25.4\cdot(0.000761\cdot[\mathrm{Cl}] + 2.52\cdot\mathrm{pH} - 17.2) \tag{4}$$

where [Cl] is the concentration of chloride ions (ppm) in the soil water extract.

In the opinion of the authors of [79], the loss of thickness due to corrosion (mm) of a pile after 35 years of operation in soils of any type can be estimated as

$$25.4\cdot(1.2964\cdot\mathrm{pH} + 0.0025\cdot[\mathrm{Cl}]) \tag{5}$$

or

$$25.4\cdot(1.5616\cdot\mathrm{pH}), \tag{6}$$

i.e., the pH of the soil electrolyte is the main corrosive factor.

Subsequent studies were carried out to predict and quantitatively estimate the corrosion of underground structures, primarily pipelines. An overview of the results of those works is presented in Section 4.

Thus, at present no quantitative model is available that would predict the rate of uniform corrosion (or weight loss) of steel taking into account all the corrosion factors used as the basis for the qualitative estimation of soil corrosivity.

4. Methods for the Quantitative Estimation of the Rate of Underground Corrosion of Pipelines

The models of underground pipeline corrosion differ both in the set of parameters taken into account and the methods applied for predicting the corrosion rate. These models primarily predict the rate of local corrosion that is most hazardous in pipeline operation. Models can be divided into semi-empirical, probabilistic, and machine learning models.

4.1. Semi-empirical models

Constant corrosion penetration rate model

This model sets a constant rate of corrosion penetration on the outer pipe wall in accordance with the NACE recommendation (0.4 mm/year) [80]. The model does not take into account the properties of the soil around the pipe and the design features of the pipeline. This model is a limiting case of linear models in which the defect growth rate does not depend on the age and depth of the corrosion defect [81].

Model of changes in the corrosion defect depth according to a linear law

This model assumes a linear dependence of the depth of the corrosion defect on time [82]:

$$d(t)=d_0+v\Delta t, \tag{7}$$

where $d(t)$ is the corrosion defect depth at time t, Δt is the time interval during which the corrosion process occurs, d_0 is the initial depth of the defect, and v is the corrosion rate.

The corrosion rate is usually determined using at least two sets of pipeline inspection data [83]:

$$v=\frac{d(t_2)-d(t_1)}{t_2-t_1}, \tag{8}$$

where $d(t_1)$ is the defect depth at time t_1, and $d(t_2)$ is the defect depth at time t_2.

Model of nonlinear change in corrosion penetration depth

This model is based on the power-law dependence of $d(t)$ on time, which was established as a result of field tests of samples of various steels [75]:

$$d(t)=kt^n \tag{9}$$

where k and n are parameters determined by the characteristics of the soil and pipeline.

Then, over several decades, attempts were made to improve the power-law model by finding a relationship between the coefficients k and n and soil properties. It was assumed that the value of n depends on the degree of soil aeration: in well-aerated soils $n=1/6$, and n increases with a decrease in oxygen concentration and can take values of 1/3, 1/2, and 2/3 [84].

Based on Romanoff's data, empirical dependences of the k and n values (Equation 9) on soil parameters was found [85]:

$$\begin{cases} k = 5.74\cdot(9.9-\text{pH}),\ \text{pH}<6.8 \\ k = 5.05\cdot(2\text{pH}-10.3),\ \text{pH}>7.2 \end{cases} \tag{10}$$

$$n = A_1\theta + A_2CL + A_3 \tag{11}$$

In Equation 11, θ is the soil moisture, CL is the clay content, while the A_i constants ($i=1, 2, 3$) depend on the degree of soil aeration.

Kajiyama and Koyama [72] investigated the relationship between soil characteristics and pitting depth in an underground pipeline and noted a significant correlation between the maximum pit depth and the values of pH, specific gravity of soil, and pipe-to-ground potential. In [73], a regression model was suggested that included 20 variables:

$$d_{\max}(t) = \exp\left(\alpha_0 + \sum\nolimits_{j=1}^{p}\alpha_j x_j\right)\cdot t^{\mathrm{b}} \tag{12}$$

Equation 12 includes both the quantities typically used to characterize soil corrosivity (soil type and its electrical resistance, pH of the water extract and the content of salt anions in it, redox potential, *etc.*), and the parameters that were not previously available in qualitative models, such as: the color of the soil, the difference between the layer of cut soil and loose soil, the residue from the evaporation of the soil extract, the pH of the soil oxidized with H_2O_2, and other factors). The use of such "unusual" parameters in a quantitative model cannot be considered sufficiently justified.

J.M. Race *et al.* [86] suggested a quantitative model for assessing pipeline corrosion rates that takes into account the coating type, coating condition, coating age, cathodic protection effectiveness (availability and maintenance), soil type, tabulated corrosion rates for specific soils, and quality of inspections. This is the first model to take into account a coating and cathodic protection for estimating corrosion damage. This model also takes into account the effect of the technology applied to inspect a pipeline.

One of the most popular models based on Equation 9 is the model suggested in [87]. It takes into account the time before the destruction of the protective polymer coating and the onset of corrosion t_{ini}:

$$d(t) = k(t-t_{\text{ini}})^n \tag{13}$$

The pit growth rate is determined as:

$$v(t) = kn(t-t_{\text{ini}})^{n-1} \tag{14}$$

This model was developed using a database obtained over 3 years of observations on pipelines in various types of soils [88]. The latter were combined into 3 groups: clay, loam, and sandy loam. The collected database consists of 259 data sets. The data set includes the maximum pit depth (any corrosion defect whose diameter did not exceed the doubled pipe wall thickness was regarded as a pit), exposure time, type of coating, pipe-to-ground potential, and soil properties: redox potential, pH, soil resistivity, water content, soil density, along with the chloride, bicarbonate, and sulfate content. Pitting was determined on a pipeline without insulation and with 4 types of coatings. Statistical analysis of the database was carried out using the multivariate regression method, while the *k* and *n* constants in Equation 13 were obtained as the sum of the factor values multiplied by the "weighting" coefficients. It was found that the *k* coefficient is a function of the redox potential, soil resistance, pH, and anion concentrations; the *n* exponent depends on the ground-to-pipe potential, water content, soil density, and type of coating. The "weighting" coefficients for each type of soil and those common for all soils were obtained.

Some researchers suggested alternative functional dependences of the pit growth depth on time, in particular, the following equation was suggested [89]:

$$d_{\max}(t) = v_{\mathrm{p}} \cdot t + \frac{(v_0 - v_{\mathrm{p}})}{q_0} \cdot \left[1 - \exp(-q_0 \cdot t)\right] \tag{15}$$

where v_0 and v_{p} are the initial (at $t = 0$) and long-term pit growth rates, respectively, and q_0 is the regression constant. The long-term rate v_{p} is the minimum average rate of pit growth; in the suggested model, only v_{p} depends on the properties of the corrosive system, namely the pH value, soil resistance, redox potential, and pipe-to-ground potential. In the opinion of the authors [89], the model has removed the shortcomings of power-law models and makes it possible to describe the growth of corrosion defects with greater accuracy, even over a long period of time. However, it should be noted that this model does not take into account many factors that affect the corrosion of underground pipelines.

Based on an analysis of various empirical models, it has been shown that the growth of pit depth is highly nonlinear, and regression constants depending on various factors, including soil properties and environmental parameters, have a significant impact on the accuracy of the model in predicting pit depth [90]. However, standard methods, such as linear and nonlinear regression, cannot provide accurate results due to the stochastic nature of localized corrosion of underground pipelines.

4.2. Probabilistic models

Since local pipeline corrosion is a stochastic process, when models are built, it is necessary to take into account the possibility that defects grow at different rates. When models are used, assumptions are made about the statistical homogeneity of the data and the constancy of the operating conditions. Any systematic change in operating conditions, temperature, or environmental properties can impair the reliability of probabilistic models [91].

Probabilistic methods do not contradict the deterministic approach but complement it, since these methods make it possible to predict not only the maximum pit depth, but also the distribution of pit depths in a selected section of the pipeline after a certain time interval. Predicting the pit depth distributions is critical in the development of reliability and risk models for pipeline inspection and maintenance planning. For example, the pipeline reliability index (R) can be calculated [92, 93]. A decrease in the R value to an acceptable level of reliability indicates the need for a diagnostic inspection of the pipeline section. If the distribution of pit depths ($f(x)$) at time (t) and the probability distribution of the pit growth rate ($g(v)$) are known, the change in R over time (t+δ) is determined as [92, 93]:

$$R(t+\delta)=1-\int_{\text{pwt}}^{\infty}\int_{0}^{\infty} g(v)\,f(x-v\delta)\,dv\,dx\,, \qquad (16)$$

where pwt is the pipeline wall thickness.

Pipeline reliability decreases with increasing mean and variance of the pit corrosion rate distribution [93]. Thus, a probabilistic pipeline corrosion model should predict the distribution of pit growth rates. Let us now consider the most popular models of local pipeline corrosion developed using various statistical methods.

Monte Carlo method

The Monte Carlo method (MCM) is a well-known probabilistic parametric method for studying random processes. MCM in the "classical" sense is used to analyze uncertainties in deterministic calculations, since it provides a distribution that describes the probability of alternative possible values with respect to the point of interest [91]. The main limitation of this model is that the mathematical model of the process under study must be solved dozens of times, and this requires a long computational time [94]. The discrete random numbers generated in this model are used to determine previous corrosion rates (*CR*s). Figure 1 shows a scheme for generating discrete random numbers using MCM [94].

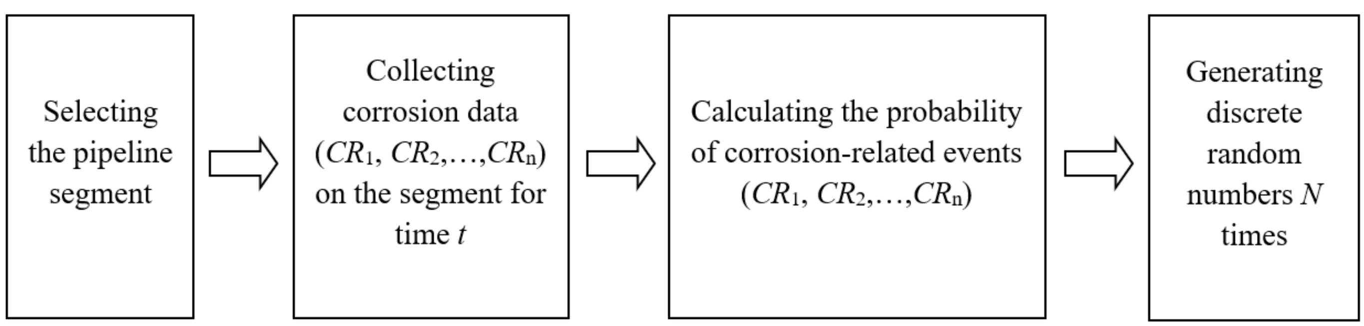

Figure 1. Scheme of the generation of random numbers using MCM [93].

In [95], using data on the distribution of defect depths and the time of their initiation, MCM was applied to estimate the corrosion rate in underground pipelines. To obtain this result, random numbers were used and entered into the MCM algorithm based on a linear growth model. The results were very sensitive to the time of corrosion onset. Testing the model on real data provided a value of 0.15–0.275 mm/year, while according to [96], the corrosion rate was 0.4 mm/year.

In [93], the MCM was used to assess the probability distributions of the maximum depth of pits and their growth rates according to the power law (Equations 13, 14). Empirical equations obtained on the basis of the Velazquez database [88] and relating the k and n coefficients in Equations 13, 14 with soil parameters and type of coating were used. The maximum pit growth rates in soils of all categories (0.087 mm/year) obtained with a confidence probability of 80% are also significantly smaller than the value recommended by NACE [96]. This disagreement is explained [93] by the fact that the NACE recommendations are based on the results of field tests of steel samples without cathodic protection, while the Velazquez' DB was obtained on pipelines under real operating conditions, *i.e.*, with insulating coatings and under cathodic protection. Good agreement was obtained between the predicted distribution of pit depths along an 82 km pipeline section and the pit depths measured during in-line inspection of this section.

Markov model

The general concepts and examples of Markov models of pipeline degradation are presented in a monograph [97]. A model for the growth of many single independent corrosion defects was suggested, which is based on a time-continuous Markov pure birth process [97, 98]. Subsequently, this model was modified, and pitting corrosion of pipelines was considered as a time-continuous inhomogeneous linear growth of the Markov pure birth process [99], while the transition probability function of the process was found by comparing the stochastic average value of the pit depth with the average value obtained from simulations using MCM [93]. This yielded a relationship between the pit depth distribution function and soil parameters, which determine the index n and the time of the onset of pitting [99].

If the pipe wall thickness is divided into N sections (for example, 0.1 mm in size), the depth of defects can be converted into Markov state units, and the distribution of defect depth can be represented in terms of the probability that $P_m(t_0)$ is in a state equal to or less than m at time t_0. Using Equation 17, we can calculate the probability that the defect is in state M ($M \geq m$) at time $t = t_0 + \delta t$ [99]:

$$P_M(t) = \sum_{m=1}^{M} P_m(t_0) \frac{(M-1)!}{(M-m)!(m-1)!} \left(\frac{t_0 - t_{\text{ini}}}{t - t_{\text{ini}}} \right)^{nm} \left[1 - \left(\frac{t_0 - t_{\text{ini}}}{t - t_{\text{ini}}} \right)^{n} \right]^{M-m} \quad (17)$$

In Equation 17, t_{ini} and n determine the nonlinear time variation of the corrosion defect depth on an underground pipeline according to Equation 13, while t_0 corresponds to the observation time $P_m(t_0)$ or the time of the first inspection. Not only the mean value but also the shape and dispersion of the distribution of defect depths depend on the age and depth of the defect.

The equation derived in [99] describes the distribution of pit growth rates. This distribution also depends on both the size and age of corrosion defects, and this dependence reflects the nonlinear nature of the corrosion process in underground pipelines.

Some authors, for example, [92, 100], also suggested probabilistic models based on Markov processes to assess the rate of pit growth during the operation of underground pipelines. According to [91], Markov models are more practically useful than other probabilistic models of pipeline pitting corrosion.

A few other probabilistic pitting corrosion models are described in [83, 91], such as time-dependent generalized extreme value distribution (GEVD) model, time-independent GEVD (TI-GEVD) model, gamma process, and the model of Brownian motion with shift. Depending on the type of corrosion data available, different models are applied to estimate corrosion rates. Since each model has its own advantages and limitations (Table 4), several deterministic and probabilistic models or a combination thereof are used to estimate the corrosion rate of pipelines [91].

Table 4. Advantages and limitations of various models for estimating the corrosion rate of pipelines [91].

Corrosion estimation model	Advantages	Limitations
Constant rate model	Deterministic model Easy to use	Constant corrosion rate
Model of varying the depth of a corrosion defect according to a linear law	Deterministic model Easy to use	Two sets of pipeline survey data are required
Model of nonlinear variation in defect depth	Deterministic model Composition of soil and type of insulation are taken into account	Two sets of pipeline survey data are required
Markov model	The continuous time approach is used The non-uniform linear growth or pure birth approach is used	Probabilistic model The initial distribution of defect depth and soil-pipe parameters is required
Monte Carlo simulation	Analysis of uncertainty of deterministic calculation Does not require complex analysis	Long computational time Complex equations
Generalized extreme value distribution (GEVD). Time dependence	Prediction of defect distribution by depth Results are comparable to a linear or Markov model	Probabilistic model Applicable to various types of soil Complex equations

Corrosion estimation model	Advantages	Limitations
Time-independent GEVD model (TI-GEVD)	Prediction of defect distribution by depth	Probabilistic model Complex equations
Gamma process	Possibility of mathematical analysis Monotonically increasing	Probabilistic model Complex equations
Model of Brownian motion with shift	Corrosion is considered as a random process The measurement error can be taken into account	Probabilistic model Complex equations

It should be noted that the development of probabilistic models continued lately, in particular, a model based on a geometric Brownian bridge has been suggested [101], and estimating the corrosion rate of underground pipelines using machine learning methods is becoming increasingly popular.

4.3. Machine learning methods

Lately, with the development of data storage capabilities and increasing the computing power available for solving various problems in the field of corrosion, researchers are increasingly interested in smart algorithms such as machine learning. Machine learning makes it possible to eliminate writing detailed instructions. Instead, an algorithm is specified to independently find solutions through integrated use of statistical data, from which patterns are derived and on the basis of which a prediction is made.

Machine learning models are based on using databases. Currently, the databases most often used in the field of underground corrosion research are those of Romanoff [75] and Velazquez [88].

To estimate the reliability of model predictions, the following statistical criteria are used most often:

– mean square error (MSE):

$$\mathrm{MSE}(x,y)=\frac{1}{N}\sum_{\mathrm{i}=1}^{N}(x_{\mathrm{i}}-y_{\mathrm{i}})^2\,, \tag{18}$$

where x_i and y_i are the experimental and predicted values of the target parameter, respectively, and N is the number of objects in the database. The closer to zero the MSE value, the better the model;

– root of mean square error (RMSE):

$$\mathrm{RMSE}(x,y)=\sqrt{\frac{1}{N}\sum_{\mathrm{i}=1}^{N}(x_{\mathrm{i}}-y_{\mathrm{i}})^2} \tag{19}$$

RMSE is the square root of MSE. The square root is introduced to ensure that the error scale is the same as the scale of the target parameter;

– coefficient of determination R^2:

$$R^2 = 1 - \frac{\mathrm{MSE}(x, y)}{\mathrm{MSE}(x, x_{\mathrm{av}})}, \tag{20}$$

where x_{av} is the average of experimental values. R^2 is the ratio of the MSE of the developed model relative to the mean value. The value of R^2 lies in the range from 1 to 0. The R^2 value of an ideal model tends to 1, while a model corresponding to the average value yields an R^2 value equal to zero;

– mean absolute error (MAE):

$$\mathrm{MAE}(x, y) = \frac{1}{N}\sum_{\mathrm{i}=1}^{N}\left|x_{\mathrm{i}} - y_{\mathrm{i}}\right|. \tag{21}$$

The smaller the MAE, the smaller error the model makes in its prediction.

Xiang and Zhou [102] developed a non-parametric Bayesian network (NPBN) model to predict the corrosion depth of underground pipelines using the pipeline operating time and soil properties. The model was created on the basis of the Velazquez database. NPBN uses Gaussian coupling to determine the relationship between the distribution of pit depth and the operating time of the pipeline in conjunction with soil parameters. The results show that the predicted mean pit depths generally agree well with the corresponding field measurements, and more than 95% of the measured depths fall between the 5th and 95th percentiles of the predicted pit depth distribution.

In [103], based on Romanoff's database, a model for predicting the depth of a defect was developed using spectral analysis of Bayesian regression. The relationship between the input parameters of the model and the response (pit depth) was presented in a semi-parametric way. Incomplete records and outliers from the original data were removed, and the data were normalized to the mean value. The initial information was divided into numerical and categorical. The complexity of the effect of the selected factors on the growth of defect depth was solved by assuming that this effect can be described by a continuous function. The resulting model is then a weighted sum of individual functions, namely functions dependent on exposure time; presence of drainage; pipeline depth; mass percentage of sand, sediment, clay, colloidal particles, and suspended particles in the soil; average temperature; amount of precipitation; soil moisture in volume percent; resistance, porosity, soil density; volume shrinkage; and pH of the soil electrolyte.

The R^2 value for the actual and predicted values of the defect depth was 0.871. The developed model makes it possible to quantify the uncertainty of the initial data and predict the depth of corrosion pitting.

Some studies focused on the use of hybrid and metaheuristic algorithms [104]. Ben Seghier *et al.* [105] presented three hybrid algorithms based on the Velazquez database, which combined the support vector regression (SVR) with particle swarm [106, 107], genetic [108], and firefly [109] algorithms to predict the maximum pitting corrosion depth. The hybrid SVR-firefly algorithm was reported to be superior to all the other algorithms (RMSE was 0.2909). The authors compared the reliability of machine learning models and regression models from [87] (Equation 13) and [92] (Equation 15). All machine learning methods showed the best results (see Table 5).

The next study by the same authors [110] provided a description of six different types of machine learning models for predicting the maximum pitting depth (artificial neural network (ANN), M5 Tree (M5Tree), multivariate adaptive regression splines (MARS), locally weighted polynomials (LWP), Kriging model (KR), and extreme learning machines (ELM)). The models were trained on eight different combinations of features from the Velazquez database. It was found that to improve the prediction accuracy, one has to use all 11 parameters of the pipeline-soil corrosion system in the Velazquez database. In this case, the Kriging model turned out to be the most reliable with RMSE=1.15683 and MAE=0.91 mm. The models were also estimated using the global performance indicator (GPI), which makes it possible to analyze and rank machine learning models based on a single statistical parameter:

$$GPI = \sum_{j=1}^{11} \alpha_j \left(I_j^{\text{med}} - I_{i,j}^{\text{med}} \right) \qquad (22)$$

where I_j^{med} is the scaled value of the median of the j-th indicator (in total, 11 indicators were used in this study), $I_{i,j}^{\text{med}}$ is the scaled value of the j-th indicator for the i-th model (6 models in this work). According to [111], α_j is a coefficient that is considered the same for all statistical indicators, with the exception of the coefficient of determination R^2 ($j=-1$). The machine learning model with the best performance is the one with the highest GPI. Based on the GPI values, the Kriging and M5Tree models are identified as the best with values of 2.53 and 0.91, respectively.

In [112], based on the Velazquez database, deep learning models (the “generalization” model and the “generalization-memorization” model) were developed that made it possible to predict the maximum pit depth in underground gas pipelines. A specific feature of the generalization model is that all the neurons of one level are connected with all the neurons of the next level. The generalization-memorization model is characterized by returning all or some of the data from the last hidden layer back to the input. The root means square error in predicting pitting depth on the test database was 0.0037 mm. Since the accuracy of measuring the pitting depth in the database used does not exceed 0.01 mm, then, according to [112], the prediction error of the model is smaller than the experimental data measurement accuracy. The authors also compared the developed models with three models presented in [105].

J. Du *et al.* [90] suggested “theory-guided automatic machine learning” (Tg-AML) to predict the maximum pitting corrosion depth in a pipeline. The Velazquez database was also used as the data source. At the first stage, several new characteristic indicators were constructed.

The new indicators were constructed taking into account some published relationships between the soil parameters. The relationship between the redox potential, *RP*, and the pH value was presented as follows [113]:

$$RP = \frac{k_B \times T^* \times \ln 10}{2e} \times (r_{\mathrm{H}_2} - 2\mathrm{pH}) \tag{23}$$

where k_B is the Boltzmann constant, e is the elementary charge, T^* is the absolute temperature, and r_{H_2} is the reciprocal of the thermodynamic activity of molecular hydrogen.

The relationship between the water content *WC* and soil resistance ρ can be expressed as [114]:

$$WC = a \cdot \rho^b \tag{24}$$

where a and b depend on the soil type.

The relationship between ρ and *BD* can be presented as [114, 115]:

$$\log \rho = \alpha + \beta_{\mathrm{DC}} DC + \beta_{\mathrm{DS}} DS \tag{25}$$

$$DC = \frac{BD_{\mathrm{natural}}}{BD_{\mathrm{ref}}} \times 100 \tag{26}$$

where *DC* is the degree of compaction, *BD* is the bulk density, and *DS* is the degree of saturation.

Next, based on correlation analysis, seven different subsets of input parameters were developed, which included various combinations of values from the main set.

The strongest relationship of indicators with the target variable based on statistical parameters (mutual information coefficient [116] and Pearson's coefficient) was exhibited by the set that contained all the 11 indicators from the original Velazquez database and 7 constructed indicators ($RP \cdot$pH, $WC \cdot \rho$, $WC \cdot BD$, $\rho \cdot BD$, ln(k), n, and PM).

Algorithms such as decision tree regression DTR, support vector regression SVR, random forest regression RFR, gradient boosting GBR, extreme gradient boosting XGB, and artificial neutron network ANN were used to develop the models. The logarithm of the maximum pit depth was used as the target parameter. Once a suitable subset of characteristics was obtained, a Tg-AML maximum pit depth prediction model was established, which is an ensemble of the tested algorithms. The results show that the suggested model provides better accuracy and efficiency than the other models (RMSE = 0.288 mm, MAE = 0.174 mm). Moreover, nearly all statistical criteria of all the models studied improved after adding the seven additional parameters.

It should be noted that when using the original (according to the Velazquez database) parameters at the input and the same model (any one), it was the prediction of the logarithm of the maximum pit depth that yielded the smaller error.

Table 5 provides information about the indicators of the considered models that use machine learning methods. It should be noted that it is difficult to compare these models with each other since they were obtained and tested on different databases. However, the results of those works which compared machine learning methods and regression models show the superiority of the former (Table 5). Moreover, ensemble models consisting of a combination of various algorithms perform well. Thus, machine learning methods make it possible to obtain the most accurate prediction of the intensity of local corrosion of underground pipelines.

Table 5. Indicators of the machine learning models considered.

Source	Database	Target parameter	Tested models	Best model	Statistical parameters
[86]	Velazquez database	D_{max}	Nonlinear regression	Nonlinear regression	MAE=1.2165 mm, RMSE=2.3153 mm, MSE=1.1311 mm (according to data of [104])
[91]	Velazquez database	D_{max}	Nonlinear regression	Nonlinear regression	MAE=4.8449 mm, RMSE=5.8525 mm, MSE=37.2137 mm (according to data of [104])
[101]	Velazquez database	Relationship between the distribution of piting depth and the age of the pipeline in conjunction with soil parameters	Non-parametric Bayesian network (NPBN)	Non-parametric Bayesian network (NPBN)	more than 95% of actual pitting depths are in the range from 5 to 95 percentiles of the predicted pitting depth distribution
[102]	Romanoff database	D_{max}	Spectral analysis of Bayesian regression	Spectral analysis of Bayesian regression	R^2=0.871
[104]	Velazquez database	D_{max}	Method of support vector regression (SVR) with particle swarm, genetic, and firefly algorithms	Hybrid SVR-firefly algorithm	MAE=0.2359 mm, RMSE=0.2909 mm, MSE=0.5588 mm

Source	Database	Target parameter	Tested models	Best model	Statistical parameters
[109]	Velazquez database	D_{max}	6 ML models: ANN, M5 Tree, MARS, LWP, Kriging (KR), and Extreme Learning Machines (ELM)	Difficult to choose the most reliable model. The lowest MAE value corresponds to the Kriging model.	GPI=2.53 for the Kriging model GPI=0.91 for the M5Tree model
[111]	Velazquez database	D_{max}	Generalization model and generalization-memorization model	Generalization model	MSE=0.0037 mm, RMSE=0.061 mm, MAE=0.0591 mm
[112]	Velazquez database	$\log D_{max}$	DTR, SVR, RFR, GBR, XGB, ANN	TG-AML model. Algorithm not specified	RMSE=0.288 mm, MAE=0.174 mm

Conclusion

Predicting the corrosion rate of the outer wall of underground pipelines is an urgent task both at the design stage and during the operation of pipelines. The complexity of solving this problem is due to the following reasons:

– the electrochemical process of corrosion of pipe steels in soils is affected by numerous factors since the soil electrolyte is a multicomponent system, the composition of which depends both on the amount of water in the soil (its moisture content) and on the chemical compositions of the gas and solid phases of the soil;
– corrosion of pipe steels occurs under continuous changes in the physical and chemical parameters of the corrosive environment, associated primarily with daily and seasonal variations in the environmental parameters;
– the duration of pipeline operation and its design features, primarily the type of insulating coating and cathodic protection mode, strongly affect its corrosion state;
– local (pitting) corrosion of steels is a stochastic process; therefore, pipeline corrosion has a probabilistic nature, too.

The factors affecting the formation and development of corrosion defects in underground pipelines and various methods for predicting pipeline corrosion are reviewed above. The prediction of the growth rate of corrosion defects in the outer wall of underground pipelines is based on methods for predicting the corrosion rate of pipe steel in soils, which can be divided into qualitative and quantitative ones. Qualitative methods are used primarily to determine the corrosivity of soils. The most reliable qualitative methods are the methods for assessing the corrosivity of soils which are based on point scales and take into account the degree of influence of various soil properties on the corrosion of steels. Scoring methods are included in a number of standards, for example, DIN 50929 (part 3) [25], according to which the corrosivity of soil is estimated using 12 parameters. Scoring methods form a basis for the quantitative assessment of the corrosion rate of steels in soils. However, the currently existing quantitative models of underground corrosion take into account no more than 2 corrosion factors, for example, the pH value and concentration of chloride ions in the water extract of the soil or the pH and electrical resistance of the soil.

Due to the imperfection of quantitative modeling of steel corrosion in soils, methods for predicting the corrosion of the outer wall of pipelines are based on statistical treatment of data obtained either in field tests of the corrosion of pipe steel samples (for example, the Romanoff database [74]) or during pipeline inspection (for example, the Velazquez database [87]). Models of underground pipeline corrosion vary in the way they use to predict corrosion rates, including deterministic, probabilistic ones, and machine learning.

Deterministic models based on correlation-regression data analysis predict changes in the maximum depth of a corrosion defect, assuming that the growth rate of the defect is constant or decreases over time. In the latter case, the linear or power-law dependence of the corrosion rate on time is used most often. Some deterministic models relate the pit growth rate to soil properties, pipe-to-ground potential, and pipeline coating type.

Probabilistic models complement the deterministic ones since they can predict not only the maximum pit depth, but also the distribution of pit depths in a selected section of a pipeline after a certain time interval. The Monte Carlo method and the mathematical apparatus of Markov processes are most widely used for the development of probabilistic models, but other methods for studying the stochastic process of local corrosion were also applied. Since each model has advantages and limitations of its own, it is recommended to use a combination of several deterministic and probabilistic models in predicting pipeline corrosion rates.

In recent years, machine learning models have become widespread due to the accumulation of large databases and an increase in computer performance. These types of models are trained on real data and can produce more accurate predictions than deterministic and probabilistic models. In addition, machine learning models can be combined into ensembles, which enhances prediction accuracy.

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