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Modeling corrosion crack resistance of oil tanks using neural network analysis

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Abstract

Purpose. The research aims to study the influence of aggressive components on corrosion crack resistance of tank steels used in tank farms for long-term storage of oil and petroleum products using neural network analysis.

Methods. The MATLAB (MATrix LABoratory) system was chosen as the tool environment for interface modeling. It is a high-level programming language for technical calculations. Corrosion crack resistance testing of oil tanks was conducted on samples of 09G2S tank steel from dismantled tanks (with a service life of 5 and 10 years). The tests were performed in model environments at various NaCl concentrations and temperatures in accordance with the NACE standard on cylindrical samples with a diameter of 4 mm. During the research, neural network analysis, which is well suited for working with complex, non-linear dependences, was used to model the corrosion crack resistance of oil tanks. The neural network learns from the collected data, identifying complex correlations between input parameters and the probability of crack formation.

Findings. Using an artificial neural network, dependences of the corrosion crack resistance of oil tanks, in particular, the rates of local corrosion and the steel destruction process were obtained for any set of known parameters such as sodium chloride concentrations in the experimental medium. Using trained neural networks, generalized corrosion rate dependences of oil tanks on the parameters of environments with different sodium chloride concentrations were obtained, and based on them the corrosion behaviour of tank steel was predicted. Based on the results of neural network analysis, the residual service life of steel tanks for storing oil and petroleum products has been determined, taking into account actual operating conditions.

Originality. For the first time, neural network analysis has been used to model the corrosion crack resistance of oil tanks, which made it possible to obtain a neural model capable of predicting the corrosion resistance of steels depending on their chemical composition and the corrosion-active environment concentration. For the first time, an artificial neural network has been used to analyze and predict the remaining service life of steel tanks, allowing the remaining service life of oil tank steels to be predicted taking into account actual operating conditions, thereby reducing the risk of accidents.

Practical implications. The proposed technology for applying neural network analysis can be used to predict the crack resistance of new tanks, assess the remaining service life of oil tanks, and plan preventive maintenance and technical servicing of tanks.

Keywords: *tank, steel, corrosion, crack resistance, ions, neural network, modeling*

1. Introduction

Development of oil and gas fields is a key element of Ukraine's energy industry. This process covers a wide range of technologies related to the extraction, transportation and storage of oil and petroleum products, where steel tanks play a special role. However, continued exploitation of tanks in aggressive environments, such as those with high chloride ion and oxygen content, causes corrosion-mechanical damage, including hydrogen degradation and crack formation. These factors reduce the reliability and safety of equipment, creating a need for accurate methods of predicting their remaining service life. Steel tanks for oil storage can be used as technological, raw materials and commercial. The terms of their trouble-free operation vary and depend on the type of product being stored [1].

Tanks operating in static settling mode lose their bottom tightness in 3.0-3.5 years, with an average corrosion rate of 1-5 mm/year. Corrosion stimulants are hydrogen sulphide and tank bottom water containing dissolved oxygen and carbon dioxide.

Depending on the activity of different environments that come into contact with metal, different tank zones have their own specific nature and types of corrosion damage. Thus, the roof and upper rings corrode under the influence of the gaseous medium, moisture condensation on the walls of the tanks, H_2S and CO_2. Since the walls of the tank and the roof are constantly cooled, moisture condenses on them and a thin

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film is formed. The thinner this film is, the faster it becomes saturated with oxygen and the faster corrosion processes occur. Given the loads applied, the roofs of tanks fail much more often than the upper rings. The middle rings of the tank that come into contact with oil corrode less [1], [2].

It has been found that the most intense corrosion occurs in the lower part of the tank due to ingress of water into the system. Condensed water flowing down dissolves salts and other substances with oil, that is, it becomes mineralized and more aggressive [3], [4]. On the other hand, the presence of another non-polar phase – oil – in the liquid flowing down the wall of the tank promotes the rapid transfer of atmospheric oxygen through thin layers to the surface of the corroding material. Since the solubility of oxygen in hydrocarbons is 5-10 times higher than its solubility in water, during diffusion, oil releases part of the oxygen dissolved in it to water, contributing to its consistently high concentration in a thin film of condensing water. An increase in the concentration of oxygen and carbon dioxide in the thin layer of electrolyte accelerates the corrosion process. Deep corrosion damage in the form of pits, from which microcracks originate, form and develop under the influence of external and internal loads, are observed at the interface between two immiscible "electrolyte-oil" phases [5].

The metal of the tank bottom is heterogeneous in composition, and in the presence of electrolyte, individual parts of the sheets, having different potentials, form galvanic couples, which are sources of electrochemical bottom corrosion. The intensity of their destruction increases when hydrogen sulphide, carbon dioxide and chlorides are present in the tank bottom waters. Corrosion damage is exacerbated by elevated temperatures (up to 45°C) of oil and water contained in tanks. Mechanical impurities present in water and oil accelerate the corrosion process. Impurities entering the tank along with the liquid flow hit the bottom, thereby cleaning the metal surface of corrosion products and other deposits, thus providing access of aggressive environment to the metal, which means that in addition to corrosion damage, mechanical damage also occurs [3]-[7].

It has been revealed that the inter-repair period for tanks, storing oil containing aggressive components, is 2-5 years, and 9-11 years for tanks storing oil without aggressive components [5]-[8].

The actual service life of oil equipment is significantly lower than the prescribed depreciation period of 20 years. This is especially true for hydrogen sulphide-containing oil environments. The frequency and intensity of equipment failure are exacerbated by mechanical stresses [9].

Carbon and low-alloy steels used in the manufacture of tanks for storing oil and petroleum products are one of the most important elements of the centralized system for the extraction, transportation, storage and distribution of oil and petroleum products. As a rule, tanks store a water-oil-gas mixture with the following chemical composition (in mg/l): Ca_{2+} – 200-1000; Mg^{2+} – 40-300; K^+, Na^+ – 3000-8000; NH_4^+ – 30-70; Cl^- – 6500-14000; HCO_3^- – 70-950; $Fe_{(overall)}$ – 6-21; H_2S – 0.07-2,5; pH – 6.0-7.8; O_2 – 0.2-1.5; CO_2 – 10-200; SO_4^{2-} – 0.5-4.5. In this case, the content of mechanical impurities is 10-7000 mg/l; total mineralization is 6-38 mg/l; the bacterial content in the product stored in tanks is 6.0-102 ÷ 2.5-105 kl/cm^3. The average temperature of the mixture in the tanks is 40°C [10]-[12].

It has been determined that 65-70% of the total corrosion damage to tanks is caused by their internal corrosion, which is almost always local. Corrosion pits (pitting) have a funnel-shaped (often stepped) shape with a fairly large width-to-depth ratio and are covered with laminated growths of corrosion products several millimetres high. Growths have a shape similar to hemispherical, and are slightly offset relative to the pit in the direction of the mixture movement [13].

During the inspection of the tanks, it has been found that the mixture has an acidic reaction (pH 4-5), despite the maintenance of an alkaline water regime with a pH above 6.8 in the transportation and extraction system. The acidification effect of the environment inside the pit in case of carbon and low-alloy steel corrosion in a water-oil-gas environment, as well as iron corrosion in chloride-containing solutions, has been noted in a number of experiments [11]-[19]. This phenomenon is explained by the migration of Cl^- and SO_4^{2-} ions through corrosion products into the pit, which ensure electrical neutrality in its internal environment due to an increase in the concentration of Fe^{2+} ions formed during corrosion in the pit volume [16]. The hydrolysis of iron sulphates and chlorides leads, as experimentally proven, to a decrease in pH [17].

However, it should be noted that the diversity, large volume of experimental material and, most often, the uncertainty and inconsistency of information on corrosion damage obtained using traditional methods necessitates the search for new, alternative methods for its effective analysis. The tasks of assessing and predicting the corrosion behaviour of steels are key to the overall problem of managing the operational reliability of oil equipment and structures. The possibilities of their solution are the use of new information technologies, an integral part of which are intelligent information processing methods, such as artificial neural networks (ANNs). The use of ANNs makes it possible to create qualitatively new hardware and software tools that significantly expand the range of solvable tasks, thereby increasing the efficiency of analysis and prediction [16]-[19].

2. Research methods

The MATLAB system was selected as the tool environment for interface modeling. When using ANNs, it is important to configure the communication network architecture for effective performance of the given task, which is implemented during the training process. To develop a training process, it is first necessary to have an external environment model in which the neural network functions, and to know the information available to the network. Secondly, it is necessary to understand how to modify network parameters, which training rules govern the configuration process.

The advantage of the MATlAB system is its modification with the aim of solving various scientific-practical tasks. This system has an open architecture, which allows the programming language to be clearly applied to create convenient and clear visual-oriented means for analyzing, constructing and modeling systems. One of the packages in the current version of the MATLAB system is Neural Networks, which contains means for creating neural networks based on the behaviour of mathematical analysis of a neuron.

Of the three available training paradigms, the "supervised" training process was used, that is, it was assumed that the neural network (NN) has the correct answers (network outputs) for each input example. The responses (coefficients) are configured so that the network provides responses that are as close as possible to the known correct answers. The enhanced version of supervised training assumes that only the critical assessment of the correctness of the NN output is known, but not the correct output values themselves.

Each training algorithm is tailored to a network of a specific architecture and is designed for a limited class of tasks [20]. When it comes to storing oil-containing products, the main purpose is to ensure the necessary operational reliability of ground equipment. The main indicators here are the rate of local corrosion and the fracture energy of structural steels. This is particularly important for facilities that come into contact with oil extracted from fields at a late stage of exploitation, that is, from heavily water-logged formations.

Neural network systems should reliably predict the corrosion-mechanical characteristics of metal: pitting corrosion rate, fatigue-corrosion strength, fracture energy – for any set of known environmental parameters (pH, corrosion-active anion concentration, product temperature) and the content of modifying additives in the metal, to classify the corrosion resistance of the material according to the specified corrosion-mechanical criteria.

The choice of NN structure (number of inputs and outputs on each neuron, interneuronal connections, etc.) capable of adequately reproducing the functional dependences of the researched process was based on our experience [21], [22].

Steel 09G2C in argon-deaerated borate buffer solutions (pH 3.8-4.0) with additives of 50-800 g/l NaCl was selected for the study of corrosion-electrochemical behavior. Before each experiment, the surface of the metal samples was mechanically ground, polished and degreased with ethyl alcohol. Potential-dynamic polarization curves of such samples were recorded in a deaerated model environment at a temperature of 40°C.

As quantitative criteria for assessing corrosion properties of the material were selected: local corrosion rate υ_{corr} ($g/m^2 \cdot h$) and steel destruction process A_{destr} (J), which contain complete information about the object [20], [23].

Analysis of experimental data showed that these two parameters can change most significantly depending on the content of modifiers in the metal and chlorine ions in the environment. For research, NN with two inputs and three outputs was used, and for each type of test (in air and in NaCl solution), their own NN was created. The structure of NN (Fig. 1) includes 1, 2, 3 – neurons; X_1, X_2 – input signals (NaCl concentration values in the model environment and the content of rare earth metals (REM) in metal, that is, NaCl and C_{REM}; W_{ij} – weight coefficients; Y_1, Y_2, Y_3 – output signals (criteria υ_{corr}, $A_{destr.}$).

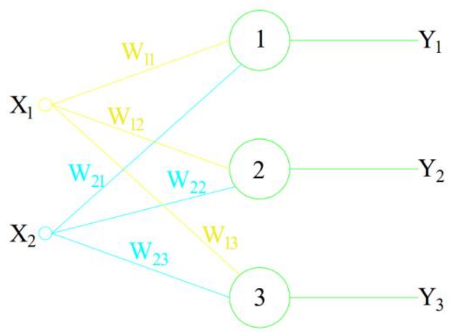

Figure 1. Structural scheme of a neural network

This type of NN in adopted terminology is referred to as a perceptron with one hidden layer of neurons. Most applied tasks are related to the use of this type of network, as they are the most studied and even a single hidden layer is sufficient to solve many tasks, particularly in the oil and gas industry.

The optimal number of neurons in the hidden NN layer was selected using a neurogenetic algorithm, which provides a quick search for the optimal NN structure [24], [25]. For each of the criteria examining the corrosion resistance of pipe steel, 25 network versions were analyzed. During the NN training process, the set of experimental data was randomly divided into two groups: teaching (70% of the data is used directly for training) and testing (30% of the data is used to control the NN's ability to generalize information).

During the NN training process, all data in the training subset repeatedly participated in the procedure of determining and changing their weight coefficients (significance) in the training network. In addition, the test subset data did not participate in such procedures, since their main purpose was to continuously monitor the NN's ability to predict data that is not used in the training process. The training process continued until the minimum error on the test subset was achieved, while assessing not only the absolute error value, but also the trend of its change during the network training process. The choice of training algorithm was determined mainly by the rate of achieving and quality of the optimal parameters of the trained NN.

The created neural network models determined the optimal values of υ_{corr} and A_{destr} for any set of known parameters – NaCl concentrations in model solutions and modifiers in metal, as well as the type of environment in which the research was conducted. The created NNs were implemented using the Statistica Neural Network package. Using trained NNs, generalized dependences of corrosion-mechanical characteristics of tank steel on the solution parameters and the chemical composition of steel were obtained, and based on them, a prediction of the material corrosion resistance was made [26], [27].

Using Visual Basic, trained NNs integrated software modules, which made it possible to quickly analyze large volumes of data and visually depict the NN work results by standard means without developing a user interface and data input/output system.

Thus, the neural networks used in this research consist of formal neurons, one of which is represented in Figure 2.

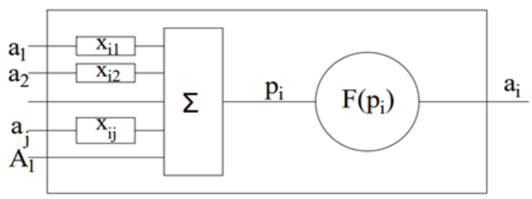

Figure 2. Formal neuron circuit: A_i – external input signals: a_j – input signals from other neurons; x_{ij} – interneuronal connections weight; Σ – neuron summation; $F(p_i)$ – nonlinear converter; a_i – neuron output signal

To perform the task of predicting steel properties, an error back-propagation algorithm, or double-functioning algorithm, was used, which is sufficiently flexible and copes well with similar tasks. Neural networks using a double-functioning algorithm are usually multilayer (between the first and last layers of neurons), and during training, information is sequentially passed through these layers. The errors obtained at the output are "driven" through the neural network backward, and the output signals are corrected.

The advantage of the backpropagation idea is that it makes it possible to estimate errors for neurons in hidden layers. Known errors made by neurons in the output layer arise from still unknown errors made by neurons in hidden layers. The greater the synaptic connection value between the hidden layer neuron and the output neuron, the stronger the error of the first affects the error of the second. Therefore, the error estimate for hidden layer elements can be obtained as the weighted sum of errors for subsequent layers. During training, information propagates from lower layers to higher ones, and error estimates made by the network propagate backward, as reflected in the name of the method [28].

A simple version of one of the best modern neural network algorithms (2nd generation) is a double-functioning algorithm, an improved version of which is used in the "Model" program. The program is integrated into Microsoft Excel spreadsheets, and one of its advantages is the ability to use the resources of this package, including optimization tools. The double-functioning algorithm is described by the following equations – functioning of neural network neurons:

$$a_i^{k+1} = \frac{p_i^k}{\left(a + \left|p_i^k\right|\right)}; \quad (1)$$

$$p_i^k = \sum x_{ij} a_j^k + A_i^k, \quad (2)$$

where:

a_i – the state of the output neurons (output data);
k – cycle number of the neural network operation;
i – neuron number;
a – constant;
a_j – the state of other neurons;
x_{ij} – interneuronal connections;
A – state of neural network inputs (output data);
j – neuron input number.

Rule for modifying connections during network training:

$$x_{ij}^{m+1} = x_{ij}^m + \Delta x_{ij}^m \Delta t, \quad (3)$$

where:

m – adaptation cycle number;
Δt – modification step.

$$\Delta x_{ij}^m = -\sum_{k=0}^{p} \Delta_i^k a_j^k, \quad (4)$$

where Δ_i for all k is calculated as:

$$\Delta_i^{k-1} = \frac{\left(\sum x_{ij}\Delta_j^k + \frac{\partial H}{\partial a_i^k}\right)\left(1 - \left|a_i^k\right|\right)^2}{a}. \quad (5)$$

Target function for a neural network:

$$H = \frac{1}{2}\sum_{i,k}\left(a_i^k - \delta_i^k\right)^2, \quad (6)$$

where:

δ_i – required neuron condition.

The described procedure is iterative and terminates after achieving the necessary accuracy of solving the task or after the time allocated for the neural network training has elapsed [29].

3. Results and discussion

A set of experimental data (υ_{corr}, A_{destr} of 09G2S tank steel with varying content of yttrium, cerium, zirconium, barium and calcium micro-additives in environments with different NaCl concentrations and using different test methods), given in Tables 1-3, were obtained in a limited range of conditions for full-scale analysis of dependences of corrosion-mechanical characteristics on solution parameters and the chemical composition of steels. Only the presence of distinctly nonlinear links between variables is obvious.

Table 1. Destruction of steels with modifying microadditives in NACE environment

Steel designation	Destruction in the air			Destruction in NACE environment		
	Neural network prediction	Experiment	ε, %	Neural network prediction	Experiment	ε, %
Steel 09G2S	4.46	4.15	6.95	1.32	1.25	5.30
Ts1	4.27	4.21	1.41	2.62	2.49	4.96
Ts2	4.40	4.33	1.41	3.86	3.68	4.66
Ts3	4.70	4.62	1.70	4.25	3.99	6.12
B1	4.49	4.43	1.66	2.94	1.82	3.81
B2	4.82	4.79	1.62	2.20	2.03	5.46
B3	0.73	5.63	1.75	2.98	2.86	7.00
I1	4.93	4.82	2.23	2.20	2.06	6.36
I2	5.95	5.76	3.19	3.22	2.98	7.45
I3	6.62	6.45	2.56	4.05	3.80	6.17
S1	5.18	5.01	3.28	2.70	2.52	6.67
S2	6.39	6.18	3.29	3.66	3.53	3.55
S3	7.50	7.12	5.06	4.29	4.02	6.29
K1	4.49	4.32	3.79	1.79	1.66	7.26
K2	5.02	4.83	3.79	2.22	2.16	2.70
K3	5.49	5.22	4.92	2.98	2.78	6.71

Table 2. Destruction of steels with modifying microadditives in NaCl environment

Steel designation	Destruction in the air			Destruction in NaCl environment		
	Neural network prediction	Experiment	ε, %	Neural network prediction	Experiment	ε, %
Steel 09G2S	0.073	0.068	6.85	0.055	0.052	5.17
Ts1	0.045	0.042	2.17	0.0347	0.034	2.02
Ts2	0.020	0.018	10.0	0.032	0.029	10.0
Ts3	0.0089	0.085	4.49	0.022	0.023	4.35
B1	0.0453	0.044	2.87	0.034	0.0333	2.94
B2	0.0342	0.033	3.51	0.0263	0.025	4.94
B3	0.0195	0.018	7.69	0.128	0.014	9.09
I1	0.0362	0.035	3.32	0.264	0.028	5.71
I2	0.0218	0.020	8.26	0.154	0.014	9.09
I3	0.011	0.010	9.09	0.0050	0.0048	4.00
S1	0.043	0.042	2.33	0.033	0.032	3.03
S2	0.0188	0.018	4.26	0.0127	0.012	5.51
S3	0.0083	0.008	3.61	0.0070	0.0072	2.78
K1	0.042	0.043	2.33	0.0351	0.034	3.13
K2	0.0316	0.031	1.90	0.024	0.0022	8.33
K3	0.0212	0.020	5.66	0.0144	0.013	5.72

Table 3. Corrosion properties of 09G2S steel in model environments with NaCl

Corrosion rate, $g/m^2 \cdot h$																	
Experiment						Neural network prediction						ε, %					
Environment I with NaCl, g/l			Environment II with NaCl, g/l			Environment I with NaCl, g/l			Environment II with NaCl, g/l			Environment I with NaCl, g/l			Environment II with NaCl, g/l		
50	100	200	50	100	200	50	100	200	50	100	200	50	100	200	50	100	200
0.052	0.074	0.082	0.031	0.052	0.059	0.056	0.079	0.086	0.033	0.054	0.064	7.14	6.33	4.65	6.1	2.99	7.81

Note: Table shows the average values of experimental measurement results and predictive data from neural network analysis. Value variations do not exceed ± 1%

Given that the structure and methods of NN training are not determined by the nature of the studied object characteristics, but depend on the amount of experimental data submitted to the NN inputs, the optimal number of neurons in the hidden layer, and the complexity of the studied process, the errors of training and testing the selected NN structure are different for each of the two criteria analyzed (Table 4).

Table 4. Optimal NN parameters for predicting characteristic potentials and NN error during training and testing

Criteria for network output properties	υ_{corr}	A_{destr}
Number of neurons in the network	4	6
Network training error	0.0051	0.0201
Network testing error	0.00289	0.0220
Training algorithm	MLS	DCG
Number of training cycles	315	295

Note: MLS – method of least squares; DCG – conjugate gradient descent

The mean-square errors of training and testing are 0.5-2.9 and 0.2-2.2%, respectively, which indicates good training ability of NNs and their ability to predict the value of each of the assessed criteria with a rather small error. As an example, Figures 3 and 4 show the results of NN training for E_{corr} and A_{destr}.

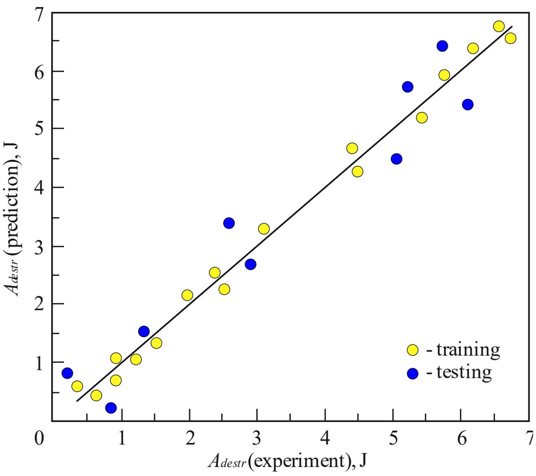

Figure 3. Dependence of the E_{corr} values predicted by trained NN on experimental values

Data analysis shows that the better trained the neural network is, the closer the experimental and neural network predicted values of E_{corr} and A_{estr} are, that is, their correlation curve should be located at an angle of 45° to the coordinate axes.

When assessing the influence of each input parameter (NaCl content in solution and concentration of modifiers in metal) on the prediction quality, the degree of deterioration in NN performance in its absence served as the criterion for factor significance. This approach is acceptable in our case, where there is no mutual influence of input parameters [30].

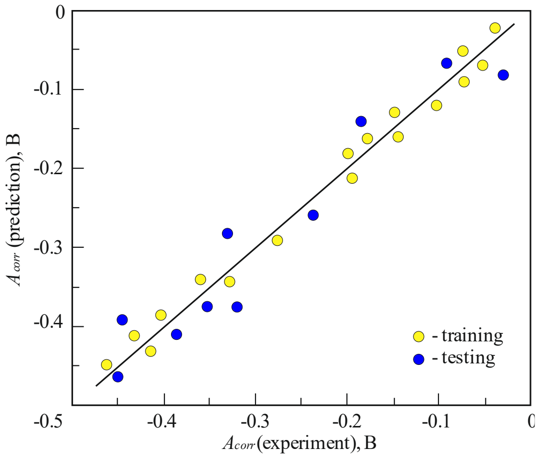

Figure 4. Dependence of the A_{destr} values predicted by trained NN on experimental values

To automatically recognize a variable and assess its importance in the scope of training and testing subsets, the well-known computer-based parameters were used, such as Rank, Error and Ratio. The main parameter for assessing recognition quality – Error – is expressed as a percentage (or fraction) and is calculated as follows:

$$\Delta = \frac{N - N^*}{N} \cdot 100, \%, \quad (7)$$

where:

Δ – recognition error;

N – number of recognized samples;

N^* – number of samples identified correctly.

The Error parameter shows an NN error when certain input parameter is excluded from its structure. Excluding the most important input parameters naturally generates the largest prediction error, thereby indicating a deterioration in the NN performance.

The Ratio parameter shows the ratio between the Error parameter and the NN error when all input parameters are included in its structure, that is, it is equal to the NN error increase multiplicity when a certain input parameter is excluded from its structure. Thus, if the Ratio parameter is ≤ 1, then the considered input parameter at least does not influence the training quality, and if it is >1, then it does influence it, and the greater the Ratio, the more significant the influence.

The Rank parameter ranks the input parameters in order of importance based on the Error parameter value (Table 5). Analysis of the data given in Table 5 shows that the corrosion behaviour of tank steels is most strongly influenced by chloride concentration (at an approximately constant pH of 4.0) and much less by the content of REM modifiers and dense elements from rare earth metals in steels. In this case, both input parameters significantly influence on the fracture energy, with the concentration of chlorine ions having the greatest influence.

Table 5. The influence of the chlorine-containing solution concentration and modifying additive on the corrosion-mechanical characteristics of 09G2S steel

Parameters	Input variables			
	Training		Testing	
	REM content	Cl^- concentration	REM content	Cl^- concentration
Corrosion potential				
Rank	2	1	2	1
Error	0.059	0.164	0.034	0.126
Ratio	8.235	23.433	1.122	3.568
Corrosion rate				
Rank	2	1	2	1
Error	0.024	0.0953	0.012	0.073
Ratio	1.404	6.436	0.422	6.474
Fracture energy				
Rank	2	1	2	1
Error	0.039	0.073	0.030	0.045
Ratio	1.294	2.344	2.465	3.010

The trained NNs were used for predicting E_{corr}, υ_{corr} and A_{destr} both within the range of experimentally tested input parameters (Tables 3, 4) and beyond it (Fig. 5).

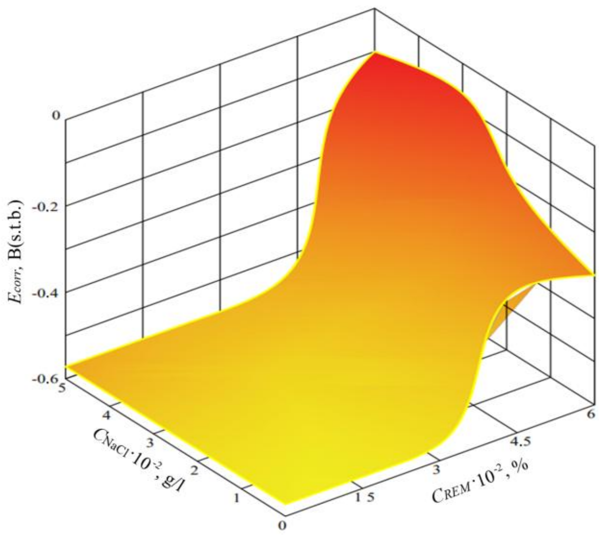

Figure 5. Dependence of the E_{corr} parameter predicted by NN on the concentration of chloride environments and the content of REM modifiers in steel (s.t.b. – static bending test)

As can be seen in Figure 5, the E_{corr} parameter is complexly dependent on the chloride concentration in the environment and the content of REM in the metal, but some general patterns are evident. Thus, at an REM content of less than 0.02%, E_{corr} is quite negative, increases slightly with a decrease in C_{REM}, and is practically independent of the chloride anion concentration. In the analyzed range of C_{REM} changes under constant conditions of E_{corr} deaeration, steel dissolves actively.

In a small range of C_{REM} content growth (0.02-0.045%), the E_{corr} parameter of steel (due to its passivation) shifts sharply in a positive direction and, in the area of passivity, begins to depend on the concentration of chloride ions.

The data presented in Figure 6 show that at low REM contents in metal (< 0.03%), the pitting corrosion rate is high in almost the entire range of chlorine ion concentration changes in the environment, only at C_{REM} > 0.03% and C_{NaCl} < 100-150 g/l in oil fields and oil refineries.

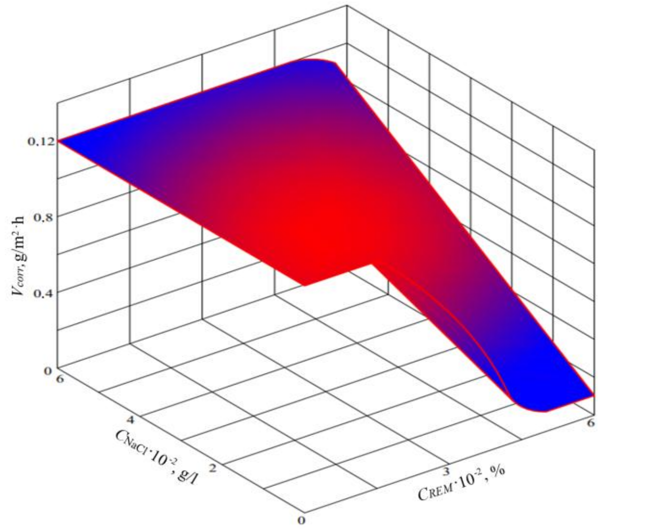

Figure 6. Dependence of the υ_{corr} parameter predicted by NN on the concentration of chloride environments and the content of the REM modifier in steel

A similar pattern is observed in Figure 7, which shows the dependence of A_{destr} on C_{REM} and C_{NaCl} concentrations.

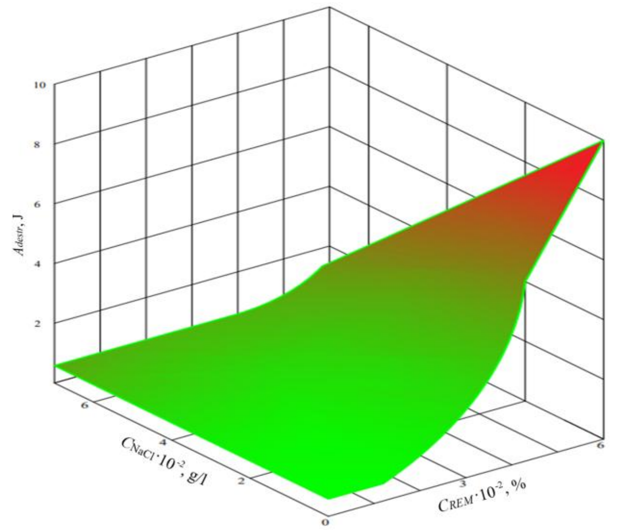

Figure 7. Dependence of the A_{destr} parameter predicted by NN on the concentration of chloride environments and the content of the REM modifier in steel

Figure 7 shows that with a low content of modifiers in metal (≤ 0.03%), the fracture energy of the test samples placed in a solution containing chlorine ions is characterized by low values, which indicates a weak resistance of the metal to corrosion-mechanical destruction. The introduction of REM modifiers in an amount of (0.03-0.06%) contributes to an increase in the corrosion-mechanical resistance of metal even in environments containing a significant (more than 150-200 g/l) NaCl amount, which is consistent with the results obtained by many scientists in the field of corrosion.

Thus, the obtained NNs made it possible to analyze how the criteria for the properties of the studied tank steels correlate with each other, and to determine the state of the corrosion system when the characteristics of the environment change, including those outside the scope of the experimental area.

To determine to which type of corrosion process certain environmental conditions correspond, depending on the degree of economical modification of REM steel, it was necessary to obtain sets of dependences $\upsilon_{corr} = f(C_{NaCl}, C_{REM})$, using trained NN. The intersection lines between areas with different corrosion rates will determine the boundaries of the corrosion system states.

The results obtained using neural modeling are presented in Figure 8, which shows four areas of corrosion state of steel exploited in a chlorine environment.

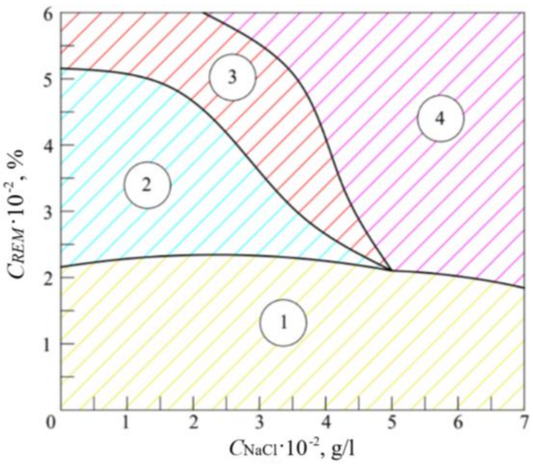

Figure 8. Areas of corrosion state of 09G2S pipe steel in close to neutral conditions predicted by NN: 1 – active dissolution; 2 – persistent passivity; 3 – non-persistent passivity; 4 – pitting corrosion

The data obtained are of great practical importance, in particular: when carbon and low-alloy steels are used in corrosion-active chlorine-containing environments typical of many oil fields in Ukraine, even significant concentrations of chlorine ions will not cause local corrosion of steels. In addition, the dependences shown in Figure 8 allow, without conducting time-consuming experimental studies, to qualitatively predict the corrosion behaviour of steel in specific solutions.

A trained neural network allows predicting the values of important factors beyond the range of experimental data, in particular, υ_{corr} and A_{destr} for any set of known parameters – NaCl concentrations. However, it should be noted that the accuracy of predictions will decrease if the values deviate from those used to train the model.

The uniqueness of the neural network is in its ability to clearly determine the corrosion-mechanical characteristics of metal, the rate of pitting corrosion, fatigue-corrosion strength, as well as to identify situations where corrosion occurs, leading to metal weakening.

Thanks to the dependences obtained, it is possible to effectively predict the corrosion characteristics of tank steel in specific operating conditions without conducting additional complex and time-consuming studies, using only neural network modeling.

It should be noted that further research and training of artificial neural networks will allow expanding the boundaries of factor prediction beyond the range of experimental data, in particular, predicting the values of negative indicators of tank steel that influence their corrosion-mechanical characteristics, especially for steels exploited in aggressive environment. Such studies will help to identify hidden and complex for analysis relationships.

4. Conclusions

For the first time, an attempt was made to create and train a neural network based on a set of experimental data in order to obtain missing information for the accurate determination of the corrosion-mechanical characteristics of tank steels exploited in aggressive environments.

Research has shown that hydrogen, sulphur and oxygen have a negative influence on the viscous-plastic properties of metal, which determine the crack resistance of pipe structures at oil and gas enterprises.

It has been proven that modeling the corrosion properties of materials using neural network is an effective tool for analyzing and summarizing experimental data on corrosion under the influence of many factors and insufficient information.

For the first time, the technological possibility has been demonstrated of using neural network analysis to assess the corrosion activity at a low concentration chlorine-containing solution and modifying additives on the corrosion-mechanical characteristics of 09G2S steel.

Research has shown that, given a small number of possible situations, the neural network modeling method can be used to determine and predict the influence of chlorine-containing solution and modifying additive on the corrosion-mechanical properties of tank steel.

Author contributions

Conceptualization: AM; Data curation: YV, SM, YN; Funding acquisition: AA; Investigation: AM; Methodology: YV: Project administration: SM; Resources: AM; Validation: MR; Visualization: YN; Writing – original draft: YV, AM; Writing – review & editing: YV, SM, AM. All authors have read and agreed to the published version of the manuscript.

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Conflicts of interest

The authors declare no conflict of interest.

Data availability statement

The original contributions presented in the study are included in the article, further inquiries can be directed to the corresponding author.

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Моделювання корозійної тріщиностійкості нафтових резервуарів за допомогою нейромережевого аналізу

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Мета. Дослідження впливу агресивних компонентів на корозійну тріщиностійкість резервуарних сталей, що використовуються в товарних парках для зберігання нафти та нафтопродуктів протягом тривалого періоду, за допомогою нейромережевого аналізу.

Методика. Як інструментальне середовище для моделювання інтерфейсу була вибрана система MATLAB (MATrix LABoratory – матрична лабораторія), що представляє собою мову програмування високого рівня для технічних обчислень. Дослідження корозійної тріщиностійкості нафтових резервуарів проводилося на зразках резервуарної сталі 09Г2С із демонтованих резервуарів (термін експлуатації яких 5 і 10 років). Дослідження виконувалися у модельних середовищах при різних концентраціях NaCl та температурах за стандартом NACE на циліндричних зразках діаметром 4 мм. При виконанні досліджень застосовувався нейромережевий аналіз для моделювання корозійної тріщиностійкості нафтових резервуарів, що добре підходять для роботи зі складними, нелінійними залежностями. Нейромережа навчається на зібраних даних, виявляючи складні залежності між вхідними параметрами та ймовірністю утворення тріщин.

Результати. За допомогою штучної нейронної мережі були отримані залежності корозійної тріщиностійкості нафтових резервуарів, зокрема, швидкості локальної корозії та процесу руйнування сталі, для будь-якого набору відомих параметрів – концентрацій хлориду натрію в експериментальному середовищі. Із використанням навчених нейронних мереж були отримані узагальнені залежності швидкості корозії нафтових резервуарів від параметрів середовищ з різними концентраціями хлориду натрію і на їх основі був виконаний прогноз корозійної поведінки резервуарної сталі. Визначено, на основі результатів нейромережевого аналізу, залишковий ресурс експлуатації сталевих резервуарів для зберігання нафти та нафтопродуктів з урахуванням реальних умов експлуатації.

Наукова новизна. Вперше застосовано нейромережевий аналіз для моделювання корозійної тріщиностійкості нафтових резервуарів, що дало змогу отримати нейронну модель, здатну прогнозувати корозійну стійкість сталей залежно від їхнього хімічного складу та концентрації корозійно-активного середовища. Вперше застосовано штучну нейронну мережу для аналізу та прогнозування залишкового ресурсу сталевих резервуарів, що дозволяє прогнозувати залишковий ресурс резервуарних сталей нафтового призначення з урахуванням реальних умов експлуатації, зменшуючи ризик аварій.

Практична значимість. Запропонована технологія застосування нейромережевого аналізу може використовуватися для прогнозування тріщиностійкості нових резервуарів, оцінки залишкового ресурсу експлуатації нафтових резервуарів, а також для планування профілактичного та технічного обслуговування резервуарів.

Ключові слова: *резервуар, сталь, корозія, тріщиностійкість, іони, нейрона мережа, моделювання*

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