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Neural network analysis of safe life of the oil and gas industrial structures

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Abstract

Purpose is to study safe life of industrial (metal) structures under long-time operation in the corrosive-active media of oil and gas wells with the help of neural network analysis.

Methods. The MATLAB system (MATrix LABoratory) was selected as the tool environment for interface modelling; the system is developed by Math Works Inc. and is a high-level programming language for technical computations. Of the three existing learning paradigms, we used the "with teacher" learning process, as we believed that a neural network had correct answers (network outputs) for each input example. The coefficients were adjusted so that the network gave answers being as close as possible to the known correct answers.

Findings. An artificial neural network has helped obtain a generalized diagram of the expected areas of high viscoplastic characteristics of carbon steels used to manufacture metal structures in the oil and gas industry. While applying the trained neural networks, generalized dependences of the corrosion rates of structural steels on the parameters of media with different concentrations of chlorine ions, sulphate ions, hydrogen sulphide, carbon dioxide, carbon dioxide, and oxygen ions were obtained; they were the basis to predict corrosion behaviour of steels.

Originality. For the first time, the possibility of applying neural network modelling to predict local corrosion damage of structural pipe steels has been shown in terms of the "steel 20 – oxygen and chloride-containing medium" system. For the first time, the technological possibility has been demonstrated to use neural network analysis for engineering predictive assessment of corrosion activity of binary systems of simulated solutions, which are most often found under industrial conditions of the oil and gas sector of the economy.

Practical implications. The proposed technology of using the neural network analysis will make it possible to expand a range of predicted values beyond experimental data, i.e. to predict the value of V_{cor} in very dilute or concentrated salt solutions within the acidified and neutral pH ranges. It should be noted that the error of the prediction results shown by the neural network will increase along with distancing from the scope of experimental data.

Keywords: *corrosion, crack resistance, ions, neuron, modelling, pitting*

1. Introduction

Main and industrial pipelines are the most cost-effective ways of oil and gas transportation in Ukraine. The system of gas and oil pipelines has entered a period of intensive aging and wear as evidenced by the technical condition analysis based on the data of diagnostics and technical examination of these objects [1]. Their resource depends on the characteristics of the material, deteriorating during operation, medium impact, operating conditions and modes, available initial defects and the ones formed during operation, etc. [1], [2].

It has been identified that due to metal corrosion, the national oil and gas industry occupies one of the first places among other industries [3], [4]. Corrosive destruction of oil and gas pipelines not only results in raw material losses but also causes great material losses for oil and gas companies and leads even to environmental pollution.

Therefore, analysis of the features of corrosion-mechanical damage and corrosion-hydrogen degradation of steel in the water-oil-gas medium is quite topical, being of high significance for the industry.

It is known that long-term operation of oil and gas equipment usually leads to the loss of initial mechanical properties. The reasons for this are both mechanical, i.e. cyclic loads, and aggressive influence of the working medium [5]. As identified in works [3]-[9], mechanical stresses increase linearly the rate of corrosion caused by thermodynamic instability and mechanical destruction of protective films, due to which anodic and cathodic processes increase.

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Oil and gas equipment often fails as a result of corrosive-mechanical, i.e. hydrosulphuric stress corrosion cracking (HSCC) or hydrogen-initiated destruction [5]-[8], which reduces significantly its efficiency, increases downtime and a share of repair costs in the total cost of production, and makes it difficult to meet the requirements for reliability and safety.

In the process of long-term operation, the pipeline material is exposed to the complex influence of corrosion and mechanical factors. Carbon steel used for the manufacture of pipes in the oil and gas industry is one of the important elements of the centralized transportation system for gas, oil, and petroleum products for the technological needs of production processes. Steel grade 20 (St 20) is a striking representative of such steel types; it has been widely used at oil and gas production enterprises for many years. It is known that corrosive aggressiveness of the technological mixture transported through the pipes (the mixture that is largely determined by the sulphur and hydrogen concentration) is of the greatest danger for the trouble-free operation of the pipeline network at such enterprises. It is a well-known fact that gases, i.e. hydrogen, influence greatly the mechanical properties of carbon steels [10]. In addition to the negative impact on the viscoplastic properties of steel, hydrogen contributes to the formation of residual defects in the form of pores, microcracks, hot and cold cracks, which reduce inevitably its performance, including resistance against corrosion and mechanical destruction. Thus, reduction of the hydrogen content in the metal is a necessary condition for increasing the viscoplastic properties, i.e. the impact toughness, which is largely responsible for the service life of a metal structure.

Analysis of the literature [3]-[11] indicates a great variety and a significant volume of information about the mechanisms, causes, factors, and conditions of corrosion destruction of metal structures, i.e. pipelines, operated for a long time in the corrosive-active media. The contradiction of such information complicates the development and use of effective anti-corrosion measures to increase the operational reliability of such structures. Nowadays, an important problem is the search for new methods to analyze the available information. Possibilities of its solution is the use of new information technologies, which constituent parts include intelligent means of processing the experimental results, i.e. such as artificial neural networks (ANN).

Currently, sequential computations are of most common use. However, they have depleted their technical capabilities, and the problem of developing parallel programming methods and creating parallel computers is extremely acute. Artificial neural networks (NN) as the most modern method for developing this area arose on the basis of knowledge about system functioning; it is an attempt to use processes to develop new technological solutions. The focus of neural network theory is on the models of parallel distributed processing, in which information is processed through the interaction of a large number of neurons, each transmitting excitation and inhibition signals to other neurons in the network [12].

The concept of information processing based on the principle of parallelism gives NN a special form of robustness (insensitivity to various deviations, inhomogeneities). While representing each property by a group of neurons, one can increase the network robustness. If computations are distributed among many neurons, a noisy or incomplete input signal can still be recognized.

However, it should be noted that the diversity, large volume of experimental material, and frequent uncertainty and contradiction of information regarding the viscoplastic characteristics of steels, obtained with the help of traditional methods, leads to the need to search for new, alternative methods of effective analysis. The task of estimating and forecasting the viscoplastic properties of steels is the key one in the general problem of managing the operational reliability of metal structures in the oil and gas industry.

Using ANN makes it possible to develop qualitatively new hardware and software tools that expand significantly the classes of problems to be solved and increase the efficiency of analysis and forecasting [13], [14].

Neural networks are developed and trained basing on a limited set of experimental data. It is required to obtain insufficient information for correct prediction of the corrosion behaviour of structural oil and gas industry steel of grade 20 in the media close to the neutral chloride ones. Neural systems must predict the speed of pitting deepening (local pits) based on any set of known parameters of the medium (sulphate ions, chloride ions, oxygen, hydrogen sulphide, temperature, pH etc.) and classify the corrosion medium state according to the predicted value of the corrosion rate [15]-[17].

Research on the degree of pipe wall damages by corrosion was reduced to determining the rate of local corrosion damage to the walls of industrial pipe structures after their 15-year operation in various operating conditions, which differ in the characteristics of the products in use. To compare, we used steel of the same brand from the reserve stock, i.e. the steel that was not in operation. More than 50 samples of steel pipes made of domestic carbon steel of grade 20 (DSTU 7806:2015) were studied.

The research was preceded by an analysis of the medium that is transported and causes corrosive destruction of pipe structures. The analysis helped select the research objects that operated in the conditions corresponding to different values of one of the variable concentrations (O_2, CI^-, SO_4^{2-}, HCO_3^-, H_2S, CO_2) while keeping the other two constant as well as when the concentration of two variables experienced certain changes (different variations) while maintaining the constancy of the third one. The limits of changes in the specified parameters were as follows: (pH 4.8-5.4; $t = 40$ºC); Cl^- 0-12000 mg/l; O_2 0-20 mg/l; SO_4^{2-} 0-25 mg/l, HCO_3^- 0-1200 mg/l, H_2S 0-12 mg/l, CO_2 0-30 mg/l. The selected modes of the pumped product made it possible to obtain data on the dependence of corrosion resistance of steels on the content in the mixture of each of the components included in its composition [8], [9], [18].

When selecting a method of assessing the degree of corrosion damage to steels as a function of the variables indicated above, we proceeded from the local nature of this destruction identified in papers [7], [19]. Thus, long-term observations have shown that there is a massive failure of pipelines in a number of fields due to local corrosion of the inner pipe surfaces. As a rule, through damages occur in the middle of horizontal rectilinear sections of pipelines [20].

After a visual examination of the steel samples affected by corrosion, an optical microscope "Neophot-32" was used to determine the depth of local damage with the help of double focusing. Pre-rejected samples with pronounced defects had the appearance of small cross-section pitting. 20-30 of the most expressive pittings were examined on each of the samples. After measuring the depth, the necessary number of the deepest ones was selected from 20-25 (usually ≈ 5-8); their average depth was taken as the maximum (h_{max}) [21], [22].

The actual rate of pitting deepening was used as the characteristic that limits the pipeline service life. The rate of pitting deepening in metal was determined by the formula $V_{max} = h_{max} / t$, where t is the total service life of a given section of the pipe structure [23]. The value of V_{max} was taken conventionally as the maximum rate of pitting deepening. As it turned out, the deviation of real h_{max} from their averaged values is not more than 7-10% [24].

The objective is to study the joint influence of hydrogen and sulphur on the viscoplastic characteristics of carbon steel using a neural network analysis of the experimental results.

To achieve the objective, it is necessary to construct neural network models to analyze the results of experimental studies and conduct a neural network analysis of the joint influence of sulphur and hydrogen on the viscoplastic characteristics of structural steel.

2. Research methodology

The MATLAB system was selected as the tool environment for interface modelling. The MATLAB system (MATrix LABoratory) was developed by specialists of Math Works, Inc. as a high-level programming language for technical computations. Modern versions of the MATLAB system are supplied to the information services market together with the Simulink extension package designed to model dynamic systems, which models consist of separate blocks (components). This package is a vivid representative of programmes created on the basis of the MATLAB system. One of these packages is Neural Networks, representing application programmes that contain tools to build neural networks and are based on the behaviour of a mathematical analogue of a neuron.

According to the practice of the NN method application (Fig. 1), it can be used for corrosion processes, being a set of corrosion-chemical characteristics of some metal and experience non-linear changes along with changes in the medium parameters (anion composition, medium concentration, temperature, pH, etc.).

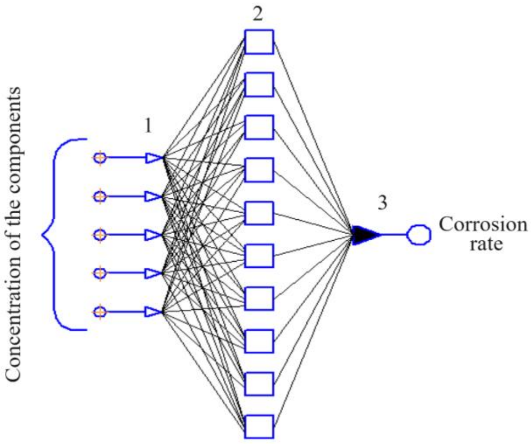

Figure 1. ANN structure to determine a corrosion rate. Designations: neuron layer 1 – input; 2 – hidden; 3 – output

The NN structure (Fig. 1) includes: a layer of neurons-receptors (input layer), which receives information from the outside; a layer of associative neurons (hidden), which functions were discussed earlier; a layer of output neurons that form the network's response to an external stimulus. In terms of the accepted terminology, NN of this type is called a perceptron with one hidden layer of neurons. Most of the applied works are related to the use of such networks, as they are the most studied ones. As a rule, one hidden layer is enough to solve the vast majority of problems.

To select the optimal number of neurons in the hidden NN layer, recommendations of the authors [25] were used, which made it possible to solve the issue of quick finding of the optimal NN structure. For the values of the V_{cor} parameter, 25 variants of the network were analyzed. While NN training, a set of experimental data was divided randomly into two subsets – training (70% of the data is used directly for training) and testing ones (30% of the data is used to control the NN ability to generalize information).

While training the selected NN, all the data of the involved subset participated repeatedly in determining and changing their weights (importance) in the network. At the same time, the test subset data were not used in the procedure. Their main function is constant control of the NN ability to predict data that were not used in the training process. The training took place in several cycles, at each of which the error of the experimental data sets in the training and test subset was determined in relation to the results obtained using NN. We evaluated not only the absolute error value but also the tendency of its changes in the process of network training. The training was completed when the minimum number of errors was reached in the test subset. Selection of the learning algorithm was determined mainly by the speed of achievement and quality of the optimal parameters of the trained NN.

The developed NN determined the V_{cor} value based on a set of known parameters – concentration of chlorine ions, sulphate ions, carbon dioxide, carbon dioxide anions, hydrogen sulphide, and oxygen – and assessed the state of the corrosion system based on the predicted corrosion rate values. NN was implemented using the Statistica Neural Network package. The use of trained NNs helped obtain generalized dependences of the corrosion rates of structural steels on the solution parameters; they were also the basis to forecast the corrosion behaviour of steels.

Visual Basic was used to integrate the trained NNs into Excel in the form of programme modules that made it possible to analyze quickly large data sets and visualize the results of NN operation using standard means without developing a user interface and a data input-output system.

3. Results and discussion

Figures 2 and 3 show the data for pipe steel 20 operated for 15 years and steel that was not in operation in the media with different concentrations of chlorine ions, sulphate ions, hydrogen sulphide, carbon dioxide ions, carbon dioxide, and oxygen.

As it can be seen, in all cases, a change in the V_{cor} parameter is observed for the studied steels (at constant concentrations of other two impurities present in the mixture). At the same time, the value of V_{cor} is always lower for steel 20, which was not in operation, than for steels with a long service life. In our opinion, it is related to the metal degradation of pipe structures. It should be noted that an increase in oxygen concentration in the solution (Fig. 2c) leads to deepening of pitting, which is already noticeable when it increases from 2 to 6 mg/l. Along with a further increase in the content of this impurity, the V_{cor} growth becomes less steep.

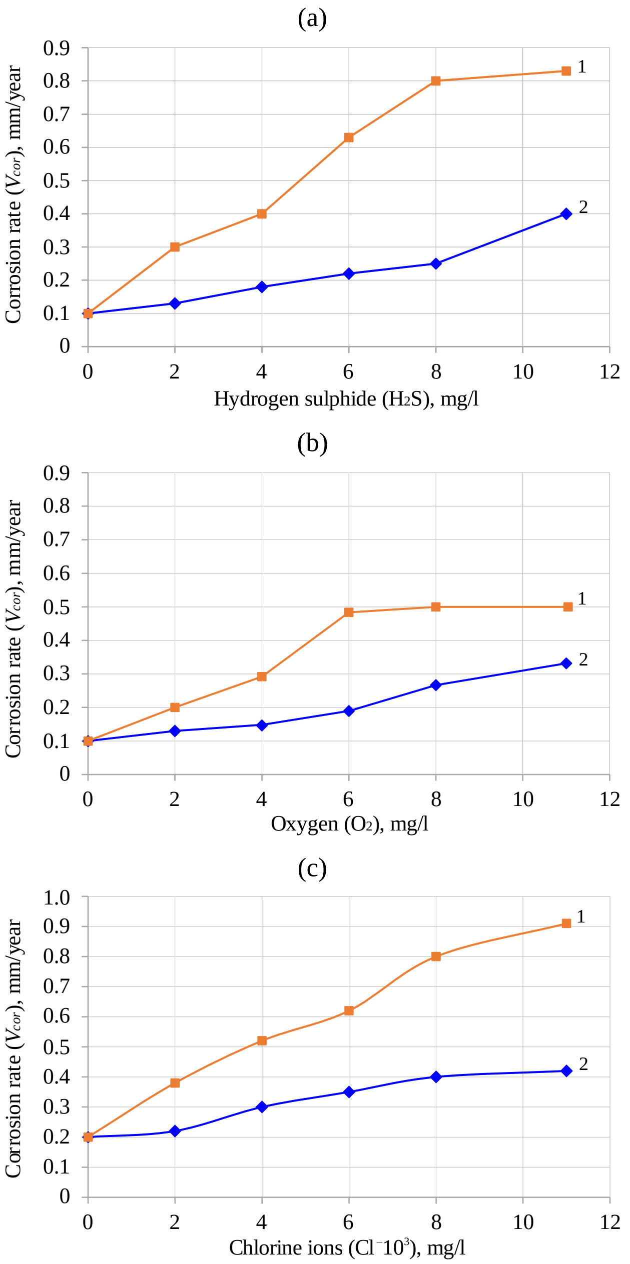

Figure 2. Effect of corrosion-active components of the simulated medium on the corrosion rate of test samples made of steel 20: (a) hydrogen sulphide; (b) oxygen; (c) chlorine ions; 1 – steel operated for 15 years; 2 – steel that was not in operation

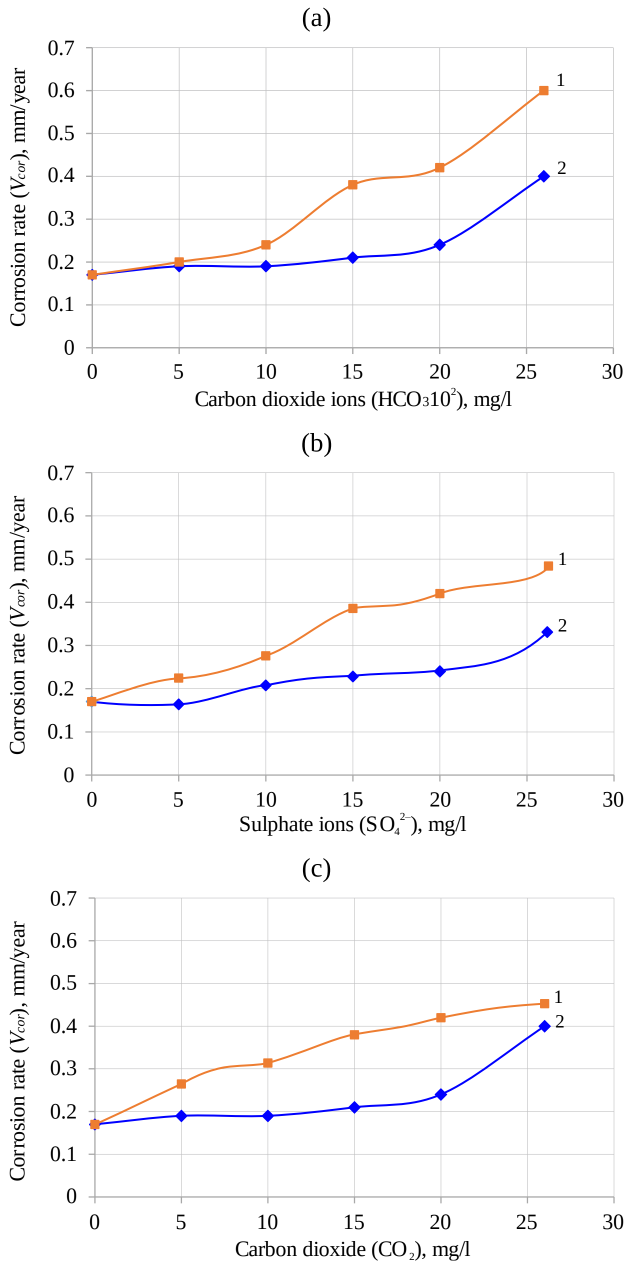

Figure 3. Effect of corrosion-active components of the simulated medium on the corrosion rate of test samples made of steel 20: (a) carbon dioxide ions; (b) sulphate ions; (c) carbon dioxide; 1 – steel operated for 15 years; 2 – steel that was not in operation

To assess the complex effect on V_{cor} of the studied components, it was necessary to use NN analysis. The structure and methods of NN training are not determined by the nature of the analyzed data but depend on the number of experimental results and the complexity of the learning process. As an example, Figure 4 shows some results of NN training for V_{cor}.

The better the NN is trained, the closer the experimental and network-predicted values of V_{cor} are, i.e. the curve of dependence on the former should be located at an angle of 45 degrees to the coordinate axes. When evaluating the influence of each of the input parameters (concentration of oxygen, hydrogen sulphide, oxygen dioxide and anions Cl^-, HCO_3^-, SO_4^{2-}) on the quality of the factor significance forecast, a degree of deterioration of the NN in case of its absence was used.

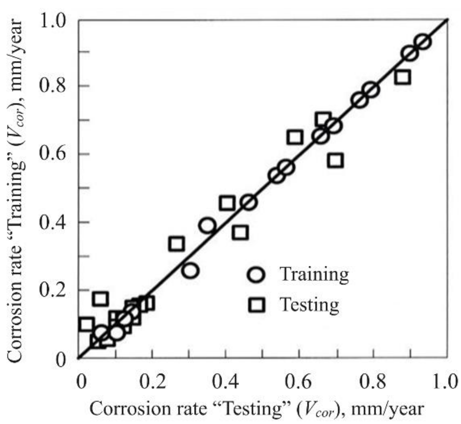

Figure 4. Graphic dependence of the V_{cor} values predicted by the trained NN on the experimental and observation values

This approach is suitable for the current case, when there is no mutual influence of the input parameters [26]-[29].

The sensitivity of each variable of the training and testing subsets was evaluated by three parameters – "Rank", "Error", and "Ratio". The main parameter – "Error"– shows the NN error when a certain input parameter and its structure are excluded. The exception of the most important input parameters generates naturally the largest forecasting error, indicating the NN deterioration. The "Ratio" parameter shows the ratio between the "Error" parameter and the NN error when all input parameters are included in its structure, i.e. it is equal to the growth rate of the NN error excluding a certain input parameter from its structure. If the "Ratio" parameter is 1, the input parameter under consideration at least does not affect the quality of learning; if it is > 1, then it affects. Moreover, the higher the "Ratio" is, the more significant the effect is. The "Rank" parameter ranks the importance of the input parameters by the value of the "Error" parameter.

As an example, Table 1 shows the data obtained for the ternary system: "concentration of oxygen, sulphate ions, and chlorine ions", from which it can be seen that the chlorine ion concentration has the strongest effect on V_{cor}, and the concentration of sulphate ions is much weaker.

Table 1. Effect of the components of a simulated solution on the corrosion rate V_{cor} of pipe steel 20

Parameter	Input parameters					
	training			testing		
	concentration					
	Cl^-	SO_4^{2-}	O_2	Cl^-	SO_4^{2-}	O_2
Rank	1	3	2	1	3	2
Error	0.193	0.051	0.087	0.174	0.032	0.065
Ratio	18.31	2.72	9.34	15.56	1.13	6.67

Thus, the most significant input parameter for the analyzed indicator V_{cor} is concentration in the chloride solution.

For the computer experiments, the NN structure was selected with its subsequent training, and the optimal number of neurons in the hidden layer, which allowed optimizing the errors of the selected-structure NN training and testing. A combined gradient descent method was used as the learning algorithm, making it possible to obtain root mean square errors of testing and learning of 1.7-5.5 and 0.9-4.2%, respectively. That indicates good NN training and its ability to predict a pitting corrosion rate value with a sufficiently small error.

The trained neural networks were used to predict V_{cor} both within the experimentally tested input parameters and beyond them. As one can see from Figure 5, V depends largely on the concentration of chlorine and sulphate anions, hydrogen sulphide, carbon dioxide, carbon dioxide ions, and oxygen. Nevertheless, it is possible to trace some regularities.

Thus, it follows from the data in Figure 5a that along with an increase in the concentrations of Cl^- to $6 \cdot 10^3$ mg/l and H_2S to 4-5 mg/l, the rate of local (pitting) corrosion increases sharply with the following steady increase to the values of $V = 0.8\text{-}1.0$ mm/year. The same trend is observed for the mixture containing O_2 and Cl^-: with O_2 increase in the simulated solution from 2 to 6 mg/l, the values of V grow sharply to 0.4-0.5 mm/year, after which V increases smoothly up to the values of 0.6 mm/year and more (Fig. 5b). At the same time, an increase in the content of Cl^- in this mixture from 2 to $7 \cdot 10^3$ causes a sharp growth in V, after which the corrosion rate increases gradually.

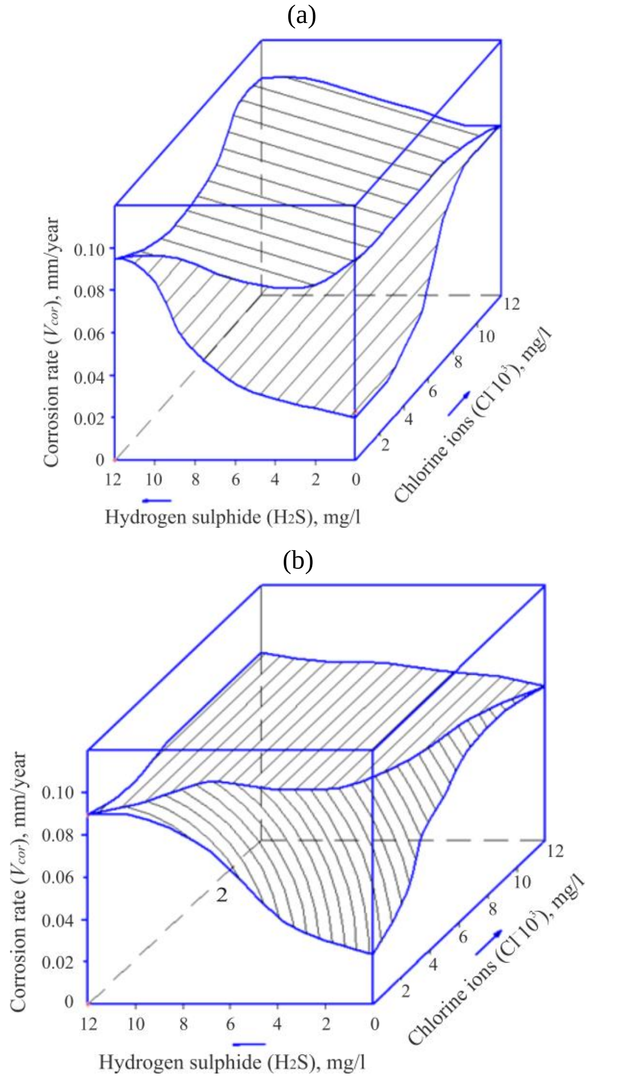

Figure 5. Corrosion activity of binary model systems while contacting with structural steel 20, which was in operation: (a) $H_2S – Cl^-$; (b) $H_2S – HCO_3^-$

The data in Figure 5a, b show the growth of corrosion damage to samples of pipe steel in a mixture consisting of O_2 and SO_4^{2-} anions. Oxygen (up to 7 mg/l) and sulphate anions (up to 6 mg/l) exert the greatest simultaneous influence on the corrosion rate. Exceeding the indicated concentration limits of O_2 and SO_4^{2-} anions leads to an increase in V values, but not so significantly.

In general, from the analysis of the data shown in Figure 6, it follows that the greatest degree of pitting corrosion is caused by binary mixtures $H_2S – HCO_3^-$, $H_2S – Cl^-$, $Cl^- – SO_4^{2-}$, $HCO_3^- – SO_4^{2-}$.

The mixtures, including concentrations of O_2 and CO_2 components, showed less corrosive-aggressive ability, which is confirmed by literature data [27], [28] and many observations from the practice of operating industrial structures in zones of oil, gas, and gas condensate fields with different corrosive activity.

The trained ANNs has helped analyze how the concentrations of sulphate anion, chlorine anion, carbon dioxide anion, hydrogen sulphide, oxygen, and carbon dioxide interact with each other from the viewpoint of a complex effect on the corrosion resistance indicator of structural steels, including those placed outside the scope of experiments.

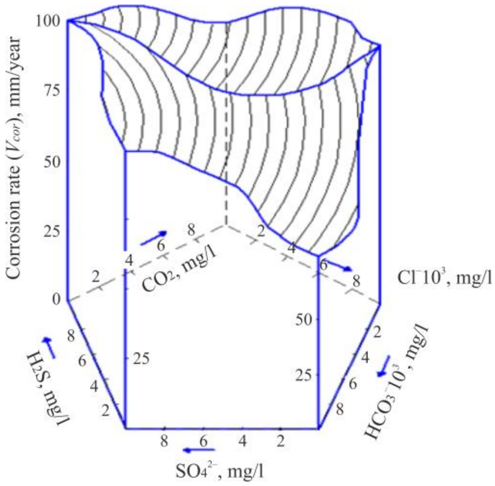

Figure 6. Local corrosion of industrial steel 20, which was not in operation, when interacting with a multi-component corrosion-active simulated medium

To identify which type of corrosion resistance corresponds to the specified medium conditions, it was necessary to use trained neural network models to obtain sets of dependencies $V_{cor} = f(K_1; K_2)$ and determine the lines of intersection of these dependencies for different, pre-selected critical values of the V_{cor} indicator. These lines will determine the limits of states in relation to the corrosion resistance of structural steels of industrial use. Here, the K_1 and K_2 parameters represent a concentration of the components of the studied binary systems.

Analysis of the results obtained with the help of neural network modelling made it possible to obtain generalized diagrams of predicted areas of corrosion resistance of low-carbon structural steels in the media close to neutral chloride ones containing hydrogen sulphide, oxygen, and oxygen dioxide (Fig. 6 and 7).

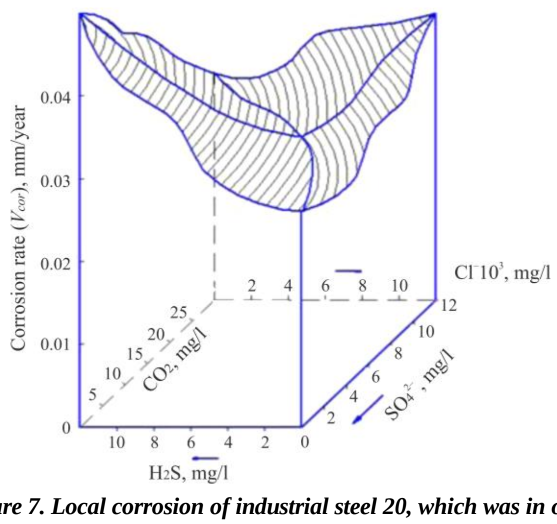

Figure 7. Local corrosion of industrial steel 20, which was in operation, when interacting with a multi-component corrosion-active model medium ($H_2S – O_2 – Cl^- – SO_4^{2-} – HCO_3^-$)

The data shown in Figures 6 and 7 made it possible to rank the ingredients of the simulated solutions by corrosion activity in the following order (as the corrosion activity increases): $CO_2 – O_2 – SO_4^{2-} – HCO_3^- – Cl^- – H_2S$. It helped also determine the most corrosively active ternary systems of simulated solutions, i.e.: $H_2S – Cl^- – HCO_3^-$; $H_2S – Cl^- – SO_4^{2-}$; $H_2S – Cl^- – O_2$; $H_2S – HCO_3^- – SO_4^{2-}$; $Cl^- – HCO_3^- – SO_4^{2-}$ and binary: $H_2S – Cl^-$; $H_2S – HCO_3^-$; $H_2S – SO_4^{2-}$; $Cl^- – HCO_3^-$ and $Cl^- – SO_4^{2-}$.

The analysis of the given data (Figs. 6 and 7) shows that NN allowed determining unambiguously the areas of corrosion behaviour of steel and demonstrated the tendency to pitting corrosion in solutions with different concentrations of active anions and dissolved gases. The obtained results made it possible to draw conclusions about the water-chemical regimes, which do have negative effect on the design term of the accident-free service of industrial metal structures, being 12-15 years with a pipe wall thickness of 8-12 mm. When adopting this indicator, the maximum rate of pitting deepening should not exceed 0.1-0.2 mm/year (otherwise, the pipe wall reduction will exceed half of the thickness, which is not permissible according to design standards). While operating tubular steel 20 in real chemically active media, the corrosion behaviour will be very sensitive even to slight changes in the concentration of chlorine and sulphate ions, while the effect of changes in the oxygen and carbon dioxide content in the solution is not so great. Thus, basing on the data obtained during the experiments, we can conclude the following: to eliminate the premature failure of metal structures, it is necessary to limit the concentrations of SO_4^{2-}, Cl^-, HCO_3^-, H_2S, CO_2 and O_2 in the corrosion-active mixtures at a level not higher, respectively (mg/l): 6-8; 6000-8000; 200-300; 1.5-2; 8-10; 4-6. At the same time, it should be noted that the given indicators refer only to pipe materials that do not contain macrodefects and non-metallic impurities such as sulphides, in terms of which the growth rate of local sources of corrosion steel damage increases sharply. Relying on the dependencies similar to those shown in the diagram (Figs. 6 and 7), it is possible, to predict qualitatively the corrosion behaviour of pipe steel in a specific case, without performing time-consuming auxiliary studies.

It should be emphasized that the results shown in the diagrams of Figures 6 and 7 are in agreement with many known corrosion cases of metal structures made of carbon and low-alloy steels and operated in natural and industrial chlorine-containing media, typical of the oil and gas industry. The trained NN helps expand a range of predicted values of significant factors beyond the limits of the experimental data, i.e. to predict the value of V_{cor} in very dilute or concentrated salt solutions in acidified and neutral pH areas. It should be highlighted that the error of the NN forecast results will grow along with the distancing from the scope of data of the experimental results.

The ANN uniqueness is in the ability to determine unambiguously the area of high viscoplastic properties of pipe carbon steel and show in which cases it is prone to a decrease in resistance to microcrack formation due to metal weakening and how this process is affected jointly by hydrogen and sulphur. When using grade 20 carbon structural steel at the enterprises of oil and gas and machine-building industries, the tendency to embrittlement and destruction will be significant with an increased content of sulphur and hydrogen in the metal, even despite the relatively low content of harmful impurities of sulphur (0.030-0.045%) and hydrogen $(5\text{-}15)\cdot10^{-4}$ %.

The obtained dependencies make it possible to use neural network modelling for qualitative prediction of the mechanical crack resistance of pipe steel in specific operating conditions, without conducting additional complex and time-consuming research.

It should be noted that further ANN study and training will help expand a range of predicted values of factors beyond the limits of the experimental data, i.e. to predict the values of viscosity and plasticity indicators of steels, which are responsible for crack resistance of steels containing such elements as sulphur and hydrogen. We consider that ANN will reveal the hidden and difficult-to-analyze connections.

4. Conclusions

For the first time, the authors has made an attempt to develop and train ANN based on a limited selection of the experimental data to obtain missing information for correct determination and engineering prediction of the viscoplastic properties of steels in a wide range of changes in chemical elements.

The research has resulted in the identified negative influence of hydrogen, sulphur, and oxygen on the viscoplastic characteristics of metal, which are responsible for crack resistance of pipe structures at oil and gas enterprises.

It has been proved that modelling of the processes of corrosion resistance by a neural network is an effective tool to analyze and generalize the experimental data during corrosion in terms of numerous factors and lack of information.

For the first time, the technological possibility to use neural network analysis for engineering assessment of corrosion activity of binary solution systems, which are found most often in the industrial conditions of the oil and gas sector, has been demonstrated.

According to the analysis of the results of training in terms of a small volume of all possible situations, the method of neural network modelling can be used to determine and predict the viscoplastic properties of the pipe material, which experience non-symbate (non-linear) changes under the influence of elements of the chemical composition of steel.

Author contributions

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

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Conflicts of interests

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.

References

[1] Makarenko, V., & Shatilo, S. (1999). Increasing desulphurisation of the metal of welded joints in oil pipelines. *Welding International*, *13*(12), 991-995. https://doi.org/10.1080/09507119909452086

[2] Radkevych, O., P’yasets’kyi, O., & Vasylenko, I. (2000). Corrosion-mechanical resistance of pipe steel in hydrogen-sulfide containing media. *Materials Science*, *36*(3), 425-430. https://doi.org/10.1007/bf02769606

[3] Martinez, F., Briones, F., Villarroel, M., & Vera, R. (2018). Effect of atmospheric corrosion on the mechanical properties of SAE 1020 structural steel. *Materials (Basel)*, *11*(4), 591. https://doi.org/10.3390/ma11040591

[4] Raffik, M., & Salleh, S. (2017). Effect of heat-treatment on the hardness and mechanical properties of boron alloyed steel. *MATEC Web of Conference*, *90*, 01014. https://doi.org/10.1051/matecconf/20179001014

[5] Makarenko, V., Vynnykov, Yu., & Manhura, A. (2020). Investigation of the mechanical properties of pipes for long-term cooling systems. *International Conference on Building Innovations*, *73*, 151-160. https://doi.org/10.1007/978-3-030-42939-3_17

[6] Zhou, F., Dai, J., Gao, J., Zhou, Q., & Li, L. (2020). The X80 pipeline steel produced by a novel ultra fast cooling process. *Journal of Physics: Conference Series*, *1676*, 012102. https://doi.org/10.1088/1742-6596/1676/1/012102

[7] Prifiharni, S., Sugandi, M., Pasaribu, R., Sunardi, S., & Mabruri, E. (2019). Investigation of corrosion rate on the modified 410 martensitic stainless steel in tempered condition. *IOP Conference Series: Materials Science and Engineering*, *541*, 012001. https://doi.org/10.1088/1757-899X/541/1/012001

[8] Makarenko, V., Manhura, A., & Makarenko, I. (2020) Calculation method of safe operation resource evaluation of metal constructions for oil and gas purpose. *Proceedings of the 2nd International Conference on Building Innovations*, *73*, 641-649. https://doi.org/10.1007/978-3-030-42939-3_63

[9] Vynnykov, Y., Kharchenko, M., Manhura, S., Aniskin, A., Hajiyev, M., & Manhura, A. (2022). Analysis of corrosion fatigue steel strength of pump rods for oil wells. *Mining of Mineral Deposits*, *16*(3), 31-37. https://doi.org/10.33271/mining16.03.031

[10] Figueredo, R., Oliveira, M., Paula, L., Acciari, H., & Codaro, E. (2018). A comparative study of hydrogen-induced cracking resistances of API 5L B and X52MS carbon steels. *International Journal of Corrosion*, *2018*, 1604507. https://doi.org/10.1155/2018/1604507

[11] Ismail, N., Khatif, N., Kecik, M., & Shaharudin, M. (2016). The effect of heat treatment on the hardness and impact properties of medium carbon steel. *IOP Conference Series: Materials Science and Engineering*, *114*, 012108. https://doi.org/10.1088/1757-899X/114/1/012108

[12] Yuzevych, L., Yankovska, L., Sopilnyk, L., Yuzevych, V., Skrynkovskyy, R., Koman, B., Yasinska-Damri, L., Heorhiadi, N., Dzhala, R., & Yasinskyi, M. (2019). Improvement of the toolset for diagnosing underground pipelines of oil and gas enterprises considering changes in internal working pressure. *Eastern-European Journal of Enterprise Technologies*, *6*(5(102)), 23-29. https://doi.org/10.15587/1729-4061.2019.184247

[13] El May, M., Saintier, N., Palin-Luc, T., Devos, O., & Brucelle, O. (2018). Modelling of corrosion fatigue crack initiation on martensitic stainless steel in high cycle fatigue regime. *Corrosion Science*, *133*, 397-405. https://doi.org/10.1016/j.corsci.2018.01.034

[14] Gopalaswami, N., Liu, Y., Laboureur, D.M., Zhang, B., & Mannan, M. (2019). Experimental study on propane jet fire hazards: Comparison of main geometrical features with empirical models. *Journal of Loss Prevention in the Process Industries*, *41*, 365-375. https://doi.org/10.1016/j.jlp.2016.02.003

[15] Hu, J., Du, L., Xie, H., Gao, X., & Misra, R. (2014). Microstructure and mechanical properties of TMCP heavy plate microalloyed steel. *Materials Science and Engineering: A*, *607*, 122-131. https://doi.org/10.1016/j.msea.2014.03.133

[16] Wang, X., Yuan, G., Zhao, J., & Wang, G. (2020). Microstructure and strengthening/toughening mechanisms of heavy gauge pipeline steel processed by ultrafast cooling. *Metals*, *10*(10), 1323. https://doi.org/10.3390/met10101323

[17] Qin, M., Li, J., Chen, S., & Qu, Y. (2016). Experimental study on stress corrosion crack propagation rate of FV520B in carbon dioxide and hydrogen sulfide solution. *Results in Physics*, *6*, 365-372. https://doi.org/10.1016/j.rinp.2016.06.012

[18] Yuzevych, V., Dzhala, R., & Koman, B. (2018). Analysis of metal corrosion under conditions of mechanical impacts and aggressive environments. *Metallofizika i Novitni Tekhnologii*, *39*(12), 1655-1667. https://doi.org/10.15407/mfint.39.12.1655

[19] Zulkifli, F., Ali, N., Yusof, M., Khairul, W., Rahamathullah, R., Isa, M., & Wan Nik, W. (2017). The effect of concentration of Lawsonia inermis as a corrosion inhibitor for aluminum alloy in seawater. *Advances in Physical Chemistry*, *2017*, 8521623. https://doi.org/10.1155/2017/8521623

[20] Makarenko, V., Manhura, S., Kharchenko, M., Melnikov, O., & Manhura, A. (2021). Study of corrosion and mechanical resistance of structural pipe steels of long-term operation in hydrogen sulfur containing. *Materials Science Forum*, *1045*, 203-211. https://doi.org/10.4028/www.scientific.net/MSF.1045.203

[21] Colorado-Garrido, D., Ortega-Toledo, D., Hernández, J., González-Rodríguez, J., & Uruchurtu, J. (2008). Neural networks for Nyquist plots prediction during corrosion inhibition of a pipeline steel. *Journal of Solid State Electrochemistry*, *13*(11), 1715-1722. https://doi.org/10.1007/s10008-008-0728-7

[22] Liao, K., Yao, Q., Wu, X., & Jia, W. (2012). Numerical corrosion rate prediction method for direct assessment of wet gas gathering pipelines internal corrosion. *Energies*, *5*(10), 3892-3907. https://doi.org/10.3390/en5103892

[23] Zhang, K., Shen, Y., Palulli, R., Ghobadian, A., Nouri, J., & Duwig, C. (2023). Combustion characteristics of steam-diluted decomposed ammonia in multiple-nozzle direct injection burner. *International Journal of Hydrogen Energy*, *48*(42), 16083-16099. https://doi.org/10.1016/j.ijhydene.2023.01.091

[24] Bukhamseen, N.Y., & Ertekin, T. (2017). The use of artificial neural networks to quantify the effect of formation damage on well production response. *SPE Kingdom of Saudi Arabia Annual Technical Symposium and Exhibition*, SPE-188094-MS. https://doi.org/10.2118/188094-MS

[25] Allegrini, E., Vadenbo, C., Boldrin, A., & Astrup, T. (2015). Life cycle assessment of resource recovery from municipal solid waste incineration bottom ash. *Journal of Environmental Management*, *151*, 132-143. https://doi.org/10.1016/j.jenvman.2014.11.032

[26] Esmaeili, A., Elahifar, B., Fruhwirth, R., & Thonhauser, G. (2012). ROP modeling using neural network and drill string vibration data. *SPE Kuwait International Petroleum Conference and Exhibition*, 1-13. https://doi.org/10.2118/163330

[27] Lozovan, V., Dzhala, R., Skrynkovskyy, R., & Yuzevych, V. (2019). Detection of specific features in the functioning of a system for the anticorrosion protection of underground pipelines at oil and gas enterprises using neural networks. *Eastern-European Journal of Enterprise Technologies*, *1*(5(97)), 20-27. https://doi.org/10.15587/1729-4061.2019.154999

[28] Lozovan, V., Skrynkovskyy, R., Yuzevych, V., Yasinskyi, M., & Pawlowski, G. (2019). Forming the toolset for development of a system to control quality of operation of underground pipelines by oil and gas enterprises with the use of neural networks. *Eastern-European Journal of Enterprise Technologies*, *2*(5(98)), 41-48. https://doi.org/10.15587/1729-4061.2019.161484

[29] Alloush, R., Elkatatny, S., Mohmoud, M., Moussa, T., Ali, A., & Abdulraheem, A. (2017). Estimation of geomechanical failure parameters from well logs using artificial intelligence techniques. *Kuwait Oil & Gas Show and Conference*, *9*(10), 165-177 https://doi.org/10.2118/187625-MS

Нейромережевий аналіз безпечного ресурсу промислових конструкцій нафтогазового призначення

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Мета. Дослідження безпечного ресурсу промислових (металевих) конструкцій, які тривалий період часу експлуатуються у корозійно-активних середовищах нафтогазових свердловин, за допомогою нейромережевого аналізу.

Методика. В якості інструментального середовища для моделювання інтерфейсу була вибрана система MATLAB (MATrix LABoratory – матрична лабораторія), яка розроблена спеціалістами Math Works Inc і представляє собою мову програмування високого рівня для технічних обчислень. Із існуючих трьох парадигм навчання, нами використовувався процес навчання “з вчителем”, тобто вважали, що нейрона мережа володіє правильними відповідями (виходами мережі) на кожний вхідний приклад. Коефіцієнти налаштовувалися так, щоб мережа давала відповіді, як можна більш близькі до відомих правильних відповідей.

Результати. За допомогою штучної нейронної мережі отримана узагальнена діаграма передбачуваних областей високих в’язкопластичних характеристик вуглецевих сталей, що використовуються для виготовлення металоконструкцій у нафтогазовій промисловості. З використанням навчених нейронних мереж були отримані узагальнені залежності швидкостей корозії конструкційних сталей від параметрів середовищ з різними концентраціями хлор-іонів, сульфат-іонів, сірководню, іонів вуглекислоти, двоокису вуглецю та кисню і на їх основі був виконаний прогноз корозійної поведінки сталей.

Наукова новизна. На прикладі системи “сталь 20 – хлоркисеньвмісне середовище” вперше показана можливість застосування нейромережевого моделювання для прогнозування локальних корозійних ушкоджень конструкційних трубних сталей. Вперше показана технологічна можливість використання нейромережевого аналізу для інженерної прогнозної оцінки корозійної активності бінарних систем модельних розчинів, які найбільш часто зустрічаються у промислових умовах нафтогазового сектору економіки.

Практична значимість. Запропонована технологія застосування нейромережевого аналізу дозволить розширити діапазон передбачуваних значень за межами експериментальних даних, зокрема, прогнозувати значення $V_{кор}$ в дуже розбавлених чи концентрованих розчинах солей в підкислених і нейтральних межах pH. Слід відмітити, що помилка результатів прогнозу, що видається нейронною мережею, буде збільшуватися по мірі віддалення від простору експериментальних даних.

Ключові слова: *корозія, тріщиностійкість, іони, нейрон, моделювання, пітінг*

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