Computer assisted data analysis for predicting the protective potential of hull structures of ships and floating facilities

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Abstract. Nowadays, stress corrosion fracturing of hull structures of ships and floating facilities is a matter of concern. Considering the presence of the juvenile surface at the tips of local defects, some adjustment is required for parameters governing protection in the existing methods of protecting against stress corrosion damages. However experimental determination of the juvenile surface for all steels is impossible. This article deals with solving a problem of predicting the protective potential to prevent hull structures of ships and floating facilities against stress corrosion fracturing. The solving is performed by use of a computer assisted data analysis with intermediate prediction of reference parameters such as potential of steel with an oxide film on, and that of steel without any oxide film, for different steel grades and sea water salinities. The suggested approach allows improving quality of protective means of hull structures of ships and floating facilities against stress corrosion damages by stabilizing the cathodic polarization process, providing appropriate potential of the uncharged surface.

1. Introduction

Marine environment is aggressive to hull structures of ships and floating facilities fabricated of a wide range of shipbuilding steels of various chemical composition. Stress corrosion damages can lead to hull structures strength loss and buckling which will result in imminent wreck of ships/floating facilities. The above factors highlight the need for protecting those objects against corrosion, stress corrosion damages and marine growth. Cathodic protection is the most effective way to protect structures against stress corrosion damages. That is implemented by using current impressed on hull structures of ships and floating facilities immersed in sea water. Taking into account specific features of growing the crack or any other local defect, i.e. the presence of the juvenile surface at the crack tip, the protection potential value requires adjustment [1]. More precisely, as demonstrated in [2], in order to provide adequate protection of the underwater part of hull structures of ships and floating facilities, the potential values shall be considered not just for the steel with an oxide film on the surface, but also for that without any film, i.e. on the juvenile surface. However, the performance of laboratory-based experiments aimed at determination of those values for all steel grades and all possible salinities of sea water would be highly time-consuming, and the development of steels featuring a new chemical composition is not to be ruled out. With a view to optimizing determination of potential of steel without any oxide film, a suggestion is made to predict the potential of steel with an oxide film and that of steel without any oxide film for different steel grades and sea water salinities.
2. The use of a neural network in the simulation of corrosive processes

The software simulation provides a cost-effective and flexible environment to search and test research ideas. Even though a neural network-based solution could look like and behave as a conventional software, those are principally different since most neural network-based implementations will “learn” rather than be programmed, i.e. the network learns how to do a task instead of being directly programmed [3].

Let us consider basic approaches to the simulation of corrosion processes. Cathodic protection potential is simulated by a neural network of the following layout: input layer, two hidden layers and output layer. In that case, each network has different number of neurons in hidden layers. Experimental data were used to train the neural network [4]. The neural network analysis was used to estimate fracture toughness indices of welded joints of structural steel details. The neural network being used consists of three neurons, has two inputs and three outputs. The three neurons are combined in a single layer, i.e. the neural network is arranged as a single-layer perceptron. A unit step function is selected as the activation function of a neuron [5]. As mentioned in [6], the type of active constraint is suggested to determine prior to solving the service life problem, based on so far available relationship between the element’s damage type and the above listed factors, i.e. using a priori knowledge formalised in terms of artificial neuron networks. The use of a neural network in the computation algorithm of the corroded beam service life enables to considerably simplify the algorithm logic and as well avoid computation errors related to a wrong determination of the active constraint type [6]. The possibility of using artificial neuron networks is investigated to provide a pre-set computation precision of the beam service life while minimizing the number of calls of the finite element procedure [7]. The neural network model is used to compute a corroded plate with a hole [8], and in other corrosion investigations as well. However the above mentioned scientific experience has not addressed the presence of the juvenile surface, nor has taken that into account in neural network-based predicting, which confirms the relevance of the objective of neural network-based simulation of metal potential on the juvenile surface. Results of the laboratory investigations performed will be used for the neural network training.

3. Computer assisted data analysis for predicting the protective potential

The investigation objective is computer assisted data analysis for predicting the protective potential of hull structures of ships and floating facilities to protect those against stress corrosion damages, with intermediate prediction of reference parameters such as the potential of steel with an oxide film on, and that of steel without any oxide film, for different steel grades and seawater salinities.

To reach the stated objective, use is made of a multifactor neural network incorporating eight (8) neurons such as water salinity, %; carbon content in steel, %; manganese content in steel, %; chrome content in steel, %; silicon content in steel, %; nickel content in steel, %; copper content in steel, %; titanium content in steel, %. The output layer incorporates two neurons, i.e. the potential of steel with an oxide film on it, mV, and the potential of steel without any oxide film, mV. The numerical experiment is performed by using the following types of neural networks:

- Generalized Regression Neural Network (GRNN) is a sub-class of Bayes networks, where a core approximation is used for the regression [9].
- Linear neural network is a network without any intermediate layers, which in its output layer incorporates just linear elements. Weights correspond to the matrix elements, while thresholds correspond to the translation vector components. On the run, the network actually multiplies the vector of inputs by the weight matrix, and then adds the vector obtained on the translation vector. Simulation is performed by approximation of the discriminant or regression function by means of a hyperplane. For that hyperplane, a globally optimal location is found by relatively “simple” computations [9].
- Radial Basic Neural Network is a network with the intermediate layer of radial elements, and the output layer of linear elements [9].

The neural network training was supported by results of laboratory investigations performed in a test solution of sea water varied in salinity for shipbuilding steel grades St3, 09G2, 10CrSN, 20Cr13 and
Let us consider results predicted by the Generalized Regression Neural Network of reference parameters such as the potential of steel with an oxide film on, and that of steel without any oxide film.

The following numerical values are indicated along the X-axis (Figure 1): 1 – potential of steel 12Cr18N10T with an oxide film, mV; 2 – potential of steel 12Cr18N10T without any oxide film, mV; 3 – potential of steel St3 with an oxide film, mV; 4 – potential of steel St3 without any oxide film, mV; 5 – potential of steel 09G2 with an oxide film, mV; 6 – potential of steel 09G2 without any oxide film, mV; 7 – potential of steel 20Cr13 with an oxide film, mV; 8 – potential of steel 20Cr13 without any oxide film, mV; 9 – potential of steel 10CrSND with an oxide film, mV; 10 – potential of steel 10CrSND without any oxide film, mV. The red line splits the diagram into two domains. The lower domain is most interesting. All the results pertaining to that domain are allowable, i.e. the relative error is within 5%.

At a first approximation, numerical simulation results suggest that most correctly operating neuron networks are the following ones: Generalized Regression Neural Network with a bias of 10; linear neuron network (7 of the 10); radial basic neural network (6 of the 10); radial basic zero-error neural network (6 of the 10) [10].

However the relative error goes beyond the peak error in predicting the potential of corrosion resistant steels. With a view to improving prediction quality, it was decided to perform a second approximation simulation by sub-dividing the training set based on the degree of corrosion resistivity of steels as follows: non-corrosion resistant carbon- and alloy steels: grades St3, 09G2, 10CrSND; corrosion resistant steels: grades 20Cr13 and 12Cr18N10T.

Potential prediction results obtained for carbon- and alloy steels showed the following: for the Generalized Regression Neural Network with a bias of 10, 5 of the 6 results are allowable, with the unsatisfactory result going just slightly beyond the allowable limit; the linear neural network (6 of the 6); the radial basic neural network with a minimal number of neurons (5 of the 6); the radial basic zero-
error neural network (5 of the 6). Therefore, the linear neural network provides the highest potential prediction precision, i.e. 100% of the results stay within the peak relative error limit. However other types of neuron networks also provide a reasonable precision yielding 83% of results not-extended beyond the limit.

Results of the potential prediction for corrosion resistant steels show the following: for the Generalized Regression Neural Network with a bias of 10, allowable are 4 of the 6 results; the linear neural network (3 of the 6); the radial basic neural network with a minimal number of neurons (4 of the 6); the radial basic zero-error neural network (3 of the 6).

Based on the results, the highest potential prediction precision is provided by the Generalized Regression Neural Network and by the radial basic neural network with a minimal number of neurons. Thus, the training set sub-division based on the degree of corrosion resistivity of steels resulted in 13…20% increase of the potential predicting precision [10]. However the potential predicting precision for corrosion resistant steels was not higher than 58%.

Adding Cr, Al, Si to steel composition will build up the steel resistance to corrosion. Those elements will form a continuous hard oxide film and increase its electrode potential. Al, Si would enhance steel embrittlement and therefore are used less frequently than chrome. Chrome tends to increase steel hardenability thereby making it stronger. Steel with more than 12% Cr content will become resistant to corrosion due to a sharp increase in its electrode potential, with formation of a dense protective film of Cr2O3 on the surface. Such steel is resistant to atmospheric corrosion, as well as corrosion in a number of acids, alkali and salts. In addition to chrome, some other elements, more often nickel to enhance corrosion resistance, improve mechanical properties and formation of a single-phase structure, are incorporated in corrosion resistant steel compositions. Corrosion resistance improves with the increase of chrome content.

Since corrosion resistance is influenced by the presence of an alloying element, i.e. chrome, the relationship between chrome content and potential of sea-water-immersed steel both with a surface (oxide) film and without it was investigated.

Therefore, with a view to decreasing the relative error, a third approximation simulation used two sets classified based on the chrome content in steel, i.e. carbon- and low alloy steels St3, 09G2; and chrome steels 20Cr13, 10CrSND and 12Cr18N10T [10].

Potential prediction results obtained for carbon- and low alloy steels showed the following: for the Generalized Regression Neural Network with a bias of 10, allowable are 6 of the 6 results; the linear neural network (6 of the 6); the radial basic neural network with a minimal number of neurons (6 of the 6); the radial basic zero-error neural network (5 of the 6, with the unsatisfactory result going just slightly beyond the allowable limit).

Potential prediction results obtained for chrome steels showed the following best combination of steel grades and neural network types:

- for steel grade 12Cr18N10T, the allowable results are provided by the Generalized Regression Neural Network with a bias of 10;
- for steel grade 20Cr13, the allowable results are provided by the radial basic neural network with a minimal number of neurons at $G = \text{newrb}(A, Z, 0.00)$;
- for steel grade 10CrSND, the allowable results are provided by the radial basic zero-error neural network at $G = \text{newrbe}(A, Z, 100)$, and by the linear neural network.

The Generalized Regression Neural Network with a bias of 10, the linear neural network, the radial basic neural network with a minimal number of neurons provide the highest potential predicting precision for carbon- and low alloy steels, i.e. 100% of results stay within the peak relative error limit. However the radial basic zero-error neural network provides a reasonable precision as well, with a single unsatisfactory result going just slightly beyond the allowable limit.

It follows that the below listed neural networks are recommended to use for the respective steels to provide a highest potential predicting precision for chrome steels:

- the radial basic zero-error neural network, or the linear neural network – for high alloy steels with lower than 5% chrome content;
• the radial basic neural network with a minimal number of neurons - for steels with 5 through 15% chrome content;
• the Generalized Regression Neural Network – for high alloy steels with higher than 15% chrome content.

Thereby we obtain the reference parameters, i.e. the potential of steel with an oxide film on it, and that of steel without any oxide film. Protective potential which will provide an uncharged steel surface on the juvenile surface (i.e. the surface without any oxide film at the tips of local defects) shall be predicted for the correct functioning of the cathodic protection to prevent hull structures of ships and floating facilities against stress corrosion damages. The values of the uncharged surface potentials for various chrome content shipbuilding steels with an oxide film were obtained by Professor Yu.G. Ozhiganov [11].

A series of laboratory experiments was conducted to obtain the values of potential for shipbuilding steels on the juvenile surface (without any oxide film) in cathodic polarization. A minimal value of $\lg(i)$, which corresponds to the polarization current $I = 0 \text{ mA}$, was obtained in potentiodynamic studies while changing the current from anodic to cathodic. This value is actually the corrosion potential value. Results of the studies show that this value tends to change depending on the presence of an oxide film of the shipbuilding steel. We have obtained differences between the potential with an oxide film and potential without any oxide film on shipbuilding steels St3, 09G2, 10CrSND, 20Cr13 and 12Cr18N10T. Therefore, to predict the protective potential, the code was modified by adding a formula which will adjust the uncharged surface potential value, obtained by Professor Yu.G. Ozhiganov, by the value of the difference of the corrosion potential with an oxide film and that without one obtained in the studies.

4. Conclusion
The suggested approach allows improving the quality of cathodic protection of hull structures of ships and floating facilities against stress corrosion damages and preventing the propagation of local damages by means of selecting appropriate protective potential considering the juvenile surface. That is based on computer assisted data analysis to predict the protective potential of hull structures of ships and floating facilities against stress corrosion damages with intermediate prediction of reference parameters such as potential of steel with an oxide film on it, and potential of steel without any oxide film for different steel grades and sea water salinities by use of several types of neuron networks. The main features of such protection are as follows: suppression of anion- and cation adsorption; prevention of steel fracturing; stabilization of cathodic polarization with providing appropriate potential of the uncharged surface where there is no steel surface charge with respect to sea water and thereby the electrostatic adsorption is being deferred. There is establishment of conditions for a specific adsorption without the occurrence of Rehbinder effect to restore surface strength.

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