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STEEL POTENTIAL PREDICTING USING THE NEURAL NETWORK

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Abstract

Neural network modeling is widely used for research in various fields of science, including the study of corrosion processes, durability of corrosive structures, as well as in predicting the steel potential under cathodic protection.
The paper describes the conducted numerical experiment of predicting the steel potential with oxide film and without the oxide film for various kinds of steel and salinity using several types of neural networks. Laboratory results of steels St3, 09G2, 10CrSND, 20Cr13 and 12Cr18N10T are used for training the neural network. The most effective neural network to set a problem is defined based on the allowable relative the numerical experiment error, which satisfies 70% of the results. The next step the quality improving of steel potential predicting is performed by splitting the training sample based on the corrosion resistance of steel.
Thus high performance neural network for predicting the potential with oxide film and the potential without the oxide film was determined for various steel.

INTRODUCTION

The marine environment affects aggressively on the steel structures of ships and ocean technology funds, so grows the need for modeling of corrosion processes and systems of protection against corrosion and mechanical damage to prevent accidents in the strategically important objects.

In modern ocean vessels and structures to prevent corrosion destruction is recommended to install cathodic protection system. It is necessary to provide protection against corrosion and cracking in steel local defects. Taking into account the specifics of a crack or any other local defect, namely the presence of juvenile surface of the crack tip, the protective value of the potential need to adjust in order to ensure full protection of designs [1-2].

Materials designs ships and facilities represent the extensive list of carbon, alloy and stainless steels. Conducting a pilot study to determine two potentials (with and without oxide film) for all kinds of steels is almost impossible. The best solution is the use of neural network modeling.

Computer simulation provides enough cheap and flexible environment for research and testing research ideas. Although the decision on the basis of neural network may look and behave like normal software, they are different in principle, since most implementations based on neural networks "learn" and not programmed: the network learns to perform the task, and is programmed directly. The most neural networks are used when it is impossible to write a suitable program. [3]

Scientists are just beginning to use neural networks for modeling of corrosion processes. In the articles [4-8] are described the concept of the neural networks in studies of corrosion processes and durability of corrosive structures, and in predicting potential steel with cathodic protection. However, the aforesaid scientific experience does not consider the presence of the juvenile and the surface does not take it into account in predicting neural network [9].

METHODS OF THE NUMERICAL EXPERIMENT

We pose the following purpose of the experiment: the capacity of prediction of steel with an oxide film and the building of steel without the oxide film for various kinds of steel and salinity.

For this goal we use multifactor neural network structure shown in Fig.1.

The input layer consists of eight neurons: salinity, ‰; the carbon content in steel,%; the manganese content in steel,%; chromium content in steel,%; Si content in steel,%; nickel content in steel,%; the copper content in

steel,%; titanium content in steel,%.

The output layer comprises two neurons: potential steel oxide film mV; potential-free steel oxide film mV.

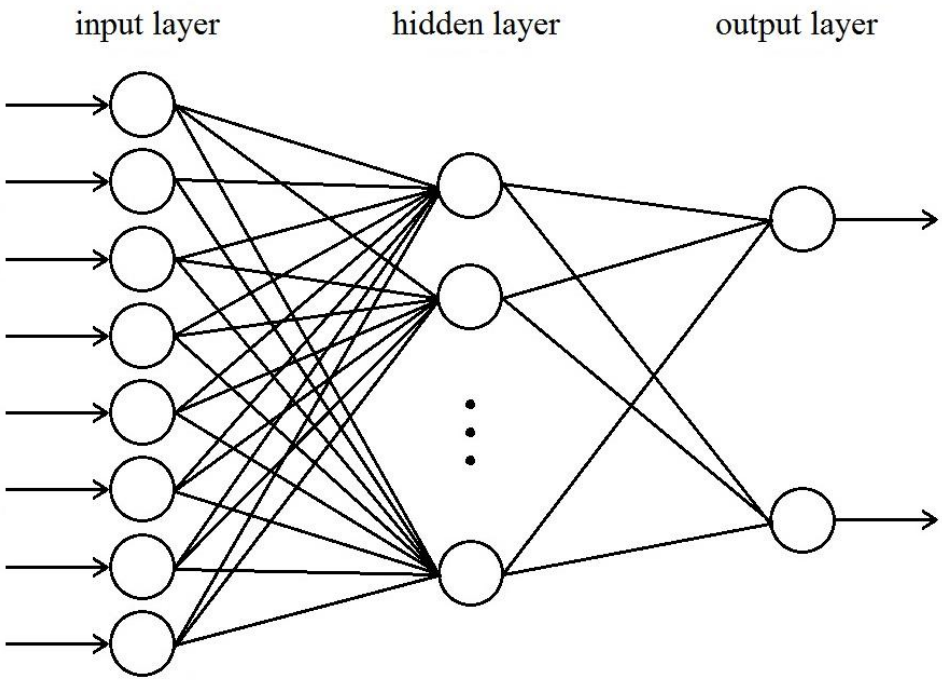

Fig. 1. Architecture of multifactor neural network.

Numerical experiments were performed using the following types of neural networks: generalized regression neural network (GR NN), linear neural network, radial basis neural network with a minimal number of neurons (RB NN MMN), radial basis neural network with zero error (RB NN ZE).

For training the neural network are used the results of the laboratory tests carried out in the model solution of sea water of different salinity for steels St3, 09G2, 10CrSND, 20Cr13 and 12Cr18N10T [10].

RESULTS OF THE NUMERICAL EXPERIMENT

The results of numerical experiments show that more correctly work:

– generalized regression neural network with a deviation of 10,7 out of 10 results are valid;

– linear neural network (7 of 10);

– radial basis neural network with the minimum number of neurons at G = newrb (A, Z, 0.00) (6 of 10);

– radial basis neural network with zero error when G = newrbe (A, Z, 100) (6 of 10).

Visual representation of linear estimation of objectivity work neural network is shown in Fig. 2. Figure red line is divided into two areas. The lower region is characterized by the permissible relative error of the numerical experiment, which satisfies 70% of the results.

The numeric value of the x-axis (Fig. 2-4) corresponds to: 1 - the potential to become 12Cr18N10T oxide film mV; 2 - capacity steel 12Cr18N10T without oxide film, mV; 3 - potential St3 steel with oxide film, mV; 4 - without the potential of steel St3 oxide film mV; 5 - potential 09G2 steel with oxide film, mV; 6 - 09G2 steel potential without the oxide film mV; 7 - capacity steel 20Cr13 with oxide film, mV; 8 - 20H13 without potential steel oxide film mV; 9 - the potential to become 10CrSND oxide film mV; 10 - steel 10CrSND potential without the oxide film mV.

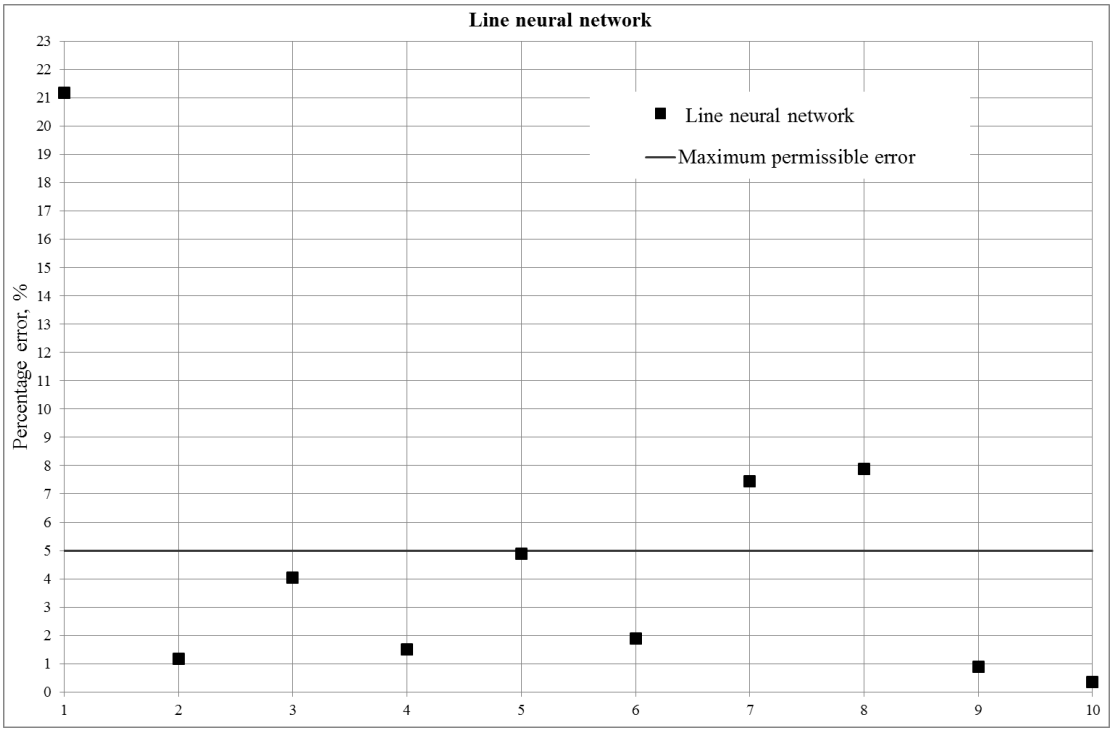

Fig. 2.The visual presentation of evaluation objectivity linear neural network operation.

The relative error is beyond the maximum permissible errors in forecasting potential rust-resisting steels.

In order to improve the quality of forecasting potential rust-resisting steels, it is decided to conduct further research, by splitting the training sample based on the corrosion resistance of steel:

1. Carbon and alloy no rust-resisting steel - St3, 09G2, 10CrSND;
2. Rust-resisting steel - 20Cr13 and 12Cr18N10T.

The results predicting the potential for carbon and alloyed not rust-resisting steels are shown in Fig. 3 demonstrate the following:
– generalized regression neural network with a deviation of 10, 5 of 6 results are valid, the unsatisfactory result is outside the margin slightly;
– linear neural network (6, 6);
– radial basis neural network with the minimum number of neurons at G = newrb (A, Z, 0.00) (5 of 6);
– radial basis neural network with zero error when G = newrbe (A, Z, 100) (5 of 6).

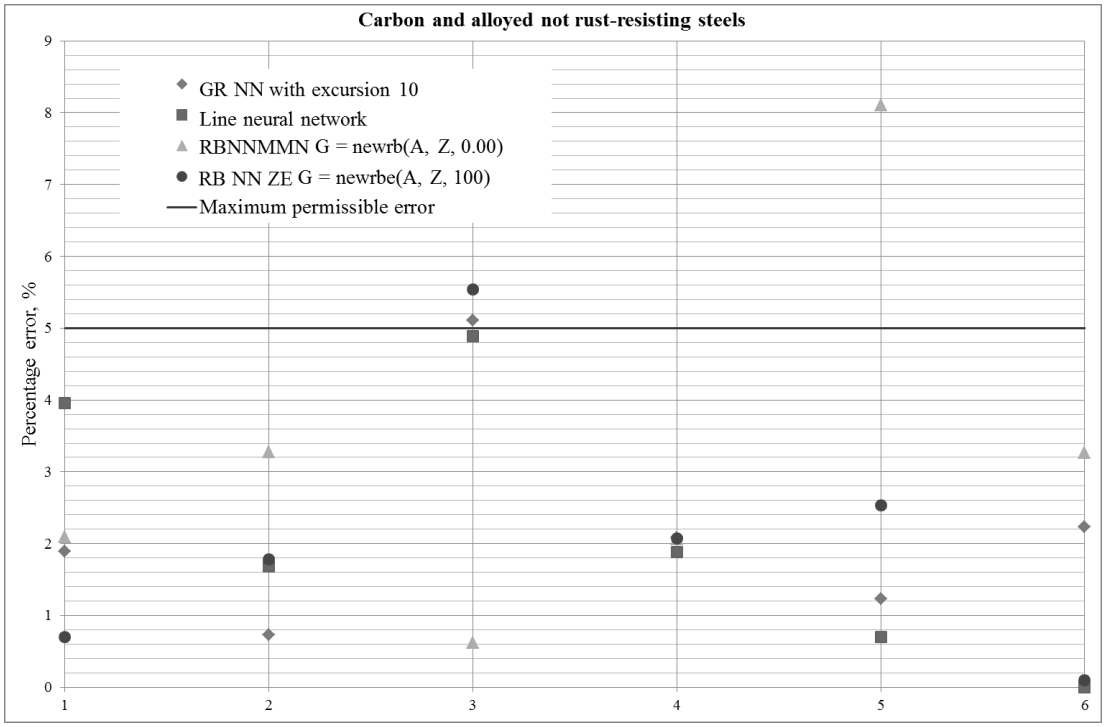

Fig. 3.The visual presentation of evaluation objectivity works of different kinds of neural networks for carbon and alloyed not rust-resisting steels.

The results predicting the potential for rust-resisting steels are shown in Fig. 4 demonstrate the following:
– generalized regression neural network with a deviation of 10, 4 of the 6 results are valid;
– linear neural network (3 of 6);
– radial basis neural network with the minimum number of neurons at G =

newrb (A, Z, 0.00) (4, 6);
– radial basis neural network with zero error when G = newrbe (A, Z, 100) (3 of 6).

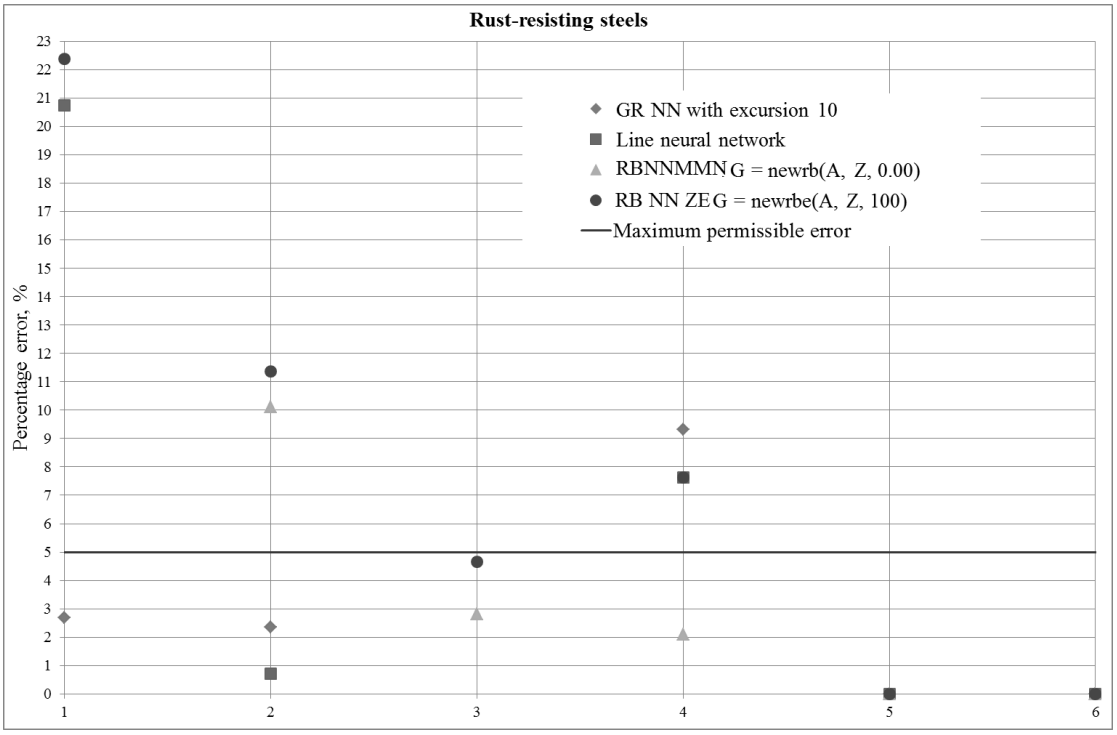

Fig. 4.A visual representation of evaluation objectivity works of different kinds of neural networks for rust-resisting steels.

CONCLUSION

Using several types of neural networks we performed the numerical experiment of the potential prediction of steel with an oxide film and the potential of steel without the oxide film for various kinds of steel and salinity of sea water. The most effective for tasks neural network on the basis of permissible relative error of the numerical experiment was identified, which satisfies 70% of the results.

The next step in improving the quality of the prediction performed potentials by dividing the learning sample based on the corrosion resistance of steel.

The linear neural network provides the highest accuracy of forecasting the potential for carbon and alloy steel - 100% of the results do not exceed the maximum allowable relative error. However, other types of neural networks provide sufficient accuracy - 83% results.

For stainless steels the highest prediction of accuracy potential provides a generalized regression neural network and radial basis neural network with a minimal number of neurons.

Thus high performance neural network for predicting the potential with oxide film and the potential without the oxide film was determined for various steel.

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