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Exploitation of Artificial Intelligence Methods for Prediction of Atmospheric Corrosion

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Abstract. The contribution deals with the use of artificial neural networks for prediction of corrosion loss of structural carbon steel. Nowadays there is certain chance to predict a corrosion loss of materials by artificial intelligence methods, especially by neural networks. A model of neural network for prediction of corrosion loss of structural carbon steel based on the input environmental parameters affecting the corrosion of metals in the atmospheric environment (temperature, relative humidity, air pollution by sulphur dioxide and the exposition time) was created. The model enables to predict corrosion loss of steel with a sufficiently small error.

Introduction

Atmospheric corrosion of metal materials exposed under atmospheric conditions depends on various factors such as local temperature, relative humidity, amount of precipitation, pH of rainfall, concentration of main pollutants (e.g. sulphur dioxide) and exposition time. As these factors are very complex, exact relation for mathematical description of atmospheric corrosion of various metals are not known so far. Classical analytical and mathematical functions are of limited use to describe this type of non-linear system depending on various meteorological-chemical parameters and interaction between them and material factors (in some cases errors in corrosion prediction are more than 50%) [1,2].

The contribution deals with the use of artificial neural networks for prediction of corrosion loss of structural carbon steel. Nowadays there is certain chance to predict a corrosion loss of materials by artificial intelligence methods, especially by neural networks. Neural networks are suitable for approximation of relations among sensor-based data, especially among non-structured data, with a high degree of nonlinearity, inaccurate and incomplete data. This type of data often occurs in process of atmospheric corrosion. Neural networks are able to simulate dependences which can be hardly solved by classic methods of statistic data evaluation (e.g. regression analysis) and they are able to express more complex relations than these methods. Neural networks are suitable for modelling of complex systems especially from the reason that their typical property is capability of learning on measured data and capability of generalization [3].

Prediction of Atmospheric Corrosion by Neural Networks

Artificial neural networks use the distributed parallel processing of information during the execution of calculations, which means that information recording, processing and transferring are carried out by means of the whole neural network, and then by means of particular memory places. The basis of mathematical model of the neural network is a formal neuron which describes by a simplified way a function of a biological neuron by means of mathematic relations.

Learning is a basic and essential feature of neural networks. Knowledge is recorded especially through the strength of linkages between particular neurons. Linkages between neurons leading to a "correct answer" are strengthened and linkages leading to a "wrong answer" are weakened by means of the repeated exposure of examples describing the problem area. These examples create a so-called training set.

For all types of predictions neural networks are suitable to be used for their learning Back propagation algorithms. This algorithm is convenient for multilayer feed forward network learning which is created minimally by three layers of neurons: input, output and at least one inner (hidden) layer. Between the two adjoining layers there is always a so-called total connection of neurons, thus each neuron of the lower layer is connected to all neurons of the higher layer. Learning in the neural network is realized by setting the values of synaptic weights between neurons, biases or inclines of activation functions of neurons. The adaptation at Back propagation types of networks is also called „supervised learning“, when the neural network learns by comparing the actual and the required output and by setting the values of the synaptic weights so that the difference between the actual and the required output decreases. Fundamentals of ANN theory it is possible to find in [3].

The rate of inaccuracy between predicted and actual output represent a prediction error. In technical applications the error is mainly represented by following relations [4]:

- relation for *RMS* error (Root Mean Squared) – it does not compensate used units

$$RMS = \sqrt{\frac{\sum_{i=0}^{i=n-1}(y_i - o_i)^2}{n-1}} \tag{1}$$

- relation for *REL_RMS* error – it compensates used units

$$REL\_RMS = \sqrt{\frac{\sum_{i=0}^{i=n-1}(y_i - o_i)^2}{\sum_{i=0}^{i=n-1}(y_i)^2}} \tag{2}$$

where: n - number of patterns of a training or test set, y_i - predicted outputs and o_i - measured outputs.

Before design and creation of neural network it was necessary to execute data conditioning for network training. Data from the institute SVÚOM s.r.o. were used for neural networks learning. It concerns data from long-term exposure of samples that were measured at different parts of Czech Republic. The whole database was divided to data for network training and data for testing network capability of generalization. Data about local temperature, relative humidity, amount of precipitation, pH of rainfall, air pollution by sulphur dioxide and exposition time were used as an input vector. Corrosion weight loss of structural carbon steel represented an output vector (see Figure 1).

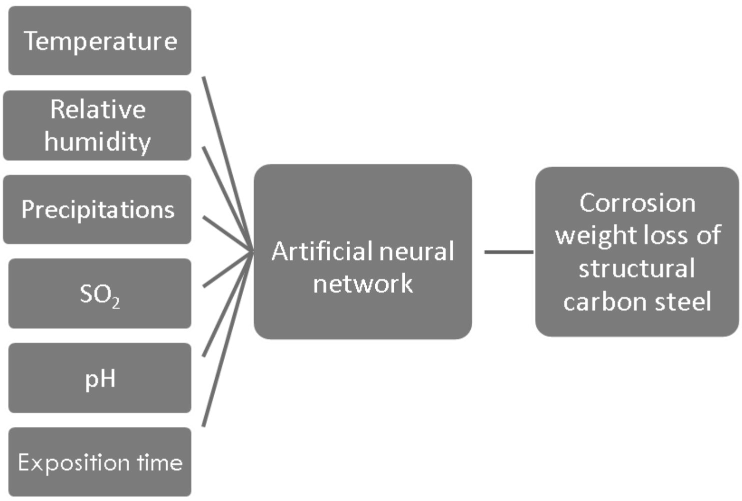

Figure 1 - Structure of input and output data.

Neural networks were created in software STATISTICA – Neural Networks. This system enables among others a choice of most suitable with the best performance, it contains efficient investigative and analytic techniques and enables to achieve summary descriptive statistics, to execute sensitive analysis and to create response graphs.

A model of neural network for prediction of corrosion loss of structural carbon steel based on the input environmental parameters affecting the corrosion of metals in the atmospheric environment was designed.

For particular neural network models a quality of network adaptation to the submitted patterns and generalization scale were observed. The best results of predicting corrosion weight loss proved multilayer feed-forward neural network whose topology 6-4-1 is shown on Fig. 2.

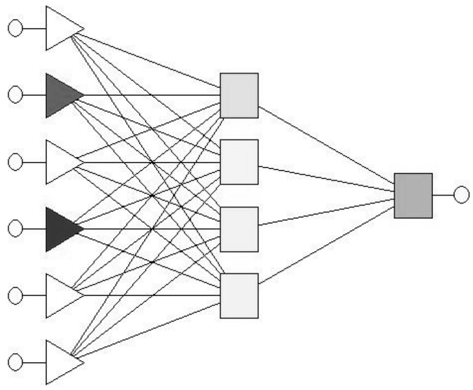

Figure 2 - Structure of artificial neural network with topology 6-4-1.

Prediction errors calculated according to relations (1) a (2) are RMS = 40 [g.m-2] and REL_RMS = 6 %. Comparison of measured and predicted data is represented on Fig. 3. The model enables to predict corrosion loss of steel with an adequately small error.

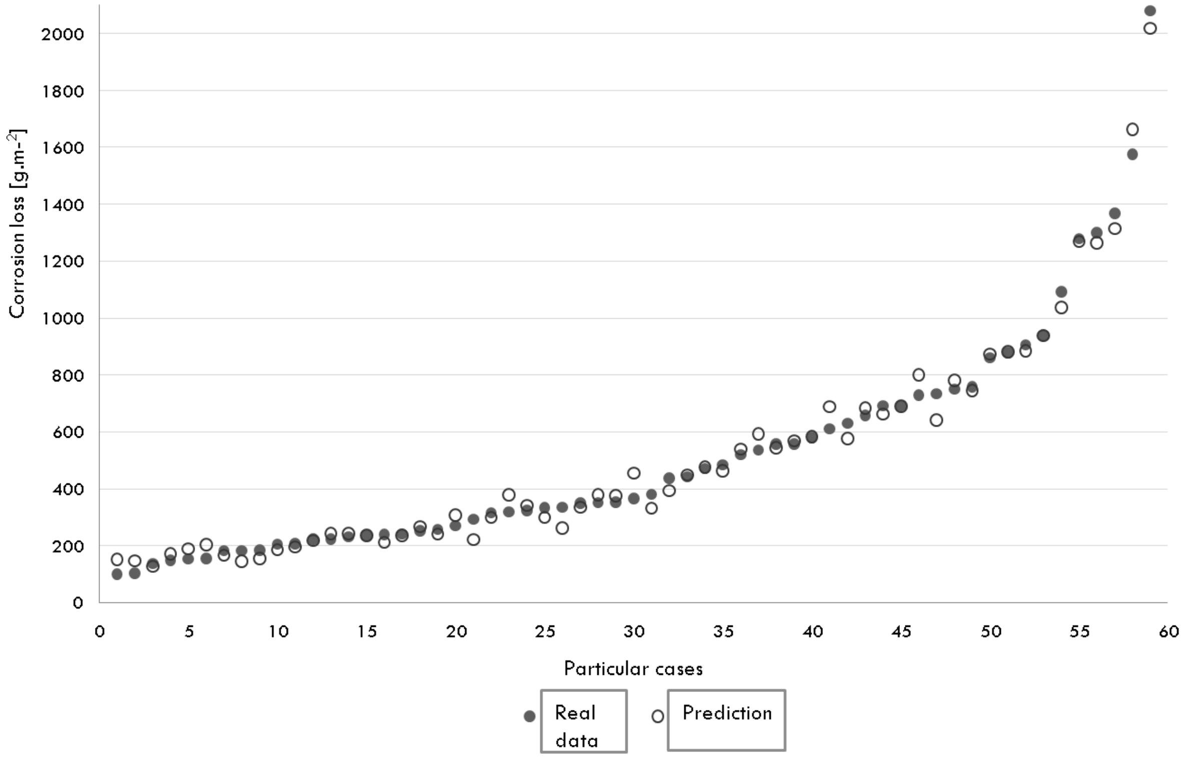

Figure 3 - Comparison of measured and predicted data.

A source code version of these neural networks was generated in C++ and the parameters of selected neural network were implemented to the program independent on STATISTICA software. This program enables on the basis of input data setting to predict the corrosion weight loss of structural carbon steel in dependence on various climatic and pollution parameters.

For this neural model a sensitivity analysis was executed. The sensitivity analysis shows how significantly each input value influences the output value. Results of the sensitivity analysis are shown on Fig. 4. It was found that air pollution by sulphur dioxide and exposition time has the most influence on corrosion weight loss of structural carbon steel.

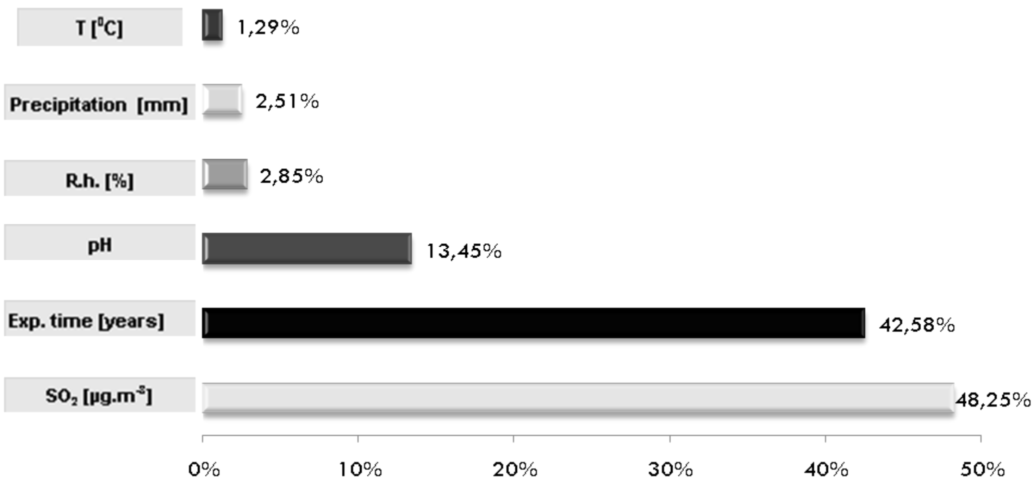

Figure 4 - Sensitivity analysis.

Conclusions

A model of neural network for prediction of corrosion loss of structural carbon steel based on the input environmental parameters affecting the corrosion of metals in the atmospheric environment was created. The model enables to predict corrosion loss of steel with an adequately small relative error (6 %). After evaluation of achieved results we can state that exploitation of neural networks is advantageous, if it is necessary to express complex mutual relations among sensor-based. It was verified that usage of artificial neural networks for prediction of corrosion loss of materials is very perspective. In the long term horizon a specification of metal corrosion loss prediction methods will have a great importance for a number of designers, construction and other companies.

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