ISSN 0543-5846
METABK 52(3) 379-381 (2013)
UDC – UDK 669.14.018:620.17:004.032:608.4=111

PREDICTION OF METAL CORROSION BY NEURAL NETWORKS

Received – Prispjelo: 2012-09-12
Accepted – Prihvaćeno: 2012-12-17
PreliminaryNote – Prethodnopriopćenje

The contribution deals with the use of artificial neural networks for prediction of steel atmospheric corrosion. 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 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 strongly non-linear system depending on various meteorological-chemical factors and interaction between them and on material parameters. Nowadays there is certain chance to predict a corrosion loss of materials by artificial neural networks. Neural networks are used primarily in real systems, which are characterized by high nonlinearity, considerable complexity and great difficulty of their formal mathematical description.

Key words: artificial neural networks, atmosphericcorrosion, prediction, model

INTRODUCTION

Atmospheric corrosion is the most common way of damage of steel materials. Such damage is caused by the factors as a temperature change, humidity, solar radiation, and chemicals. At atmospheric the corrosion process leads to anodic and cathode electrochemical reaction. The electrochemical reactions take place in a thin layer of electrolyte. Basic condition for the origin and progress of atmospheric corrosion is thus creation of an electrolyte layer on the metal surface and condensation of atmospheric moisture. Atmospheric corrosion as an electrochemical process is very complex, non-linear system depending on various climatic and pollution parameters and variables related to material. It is not simple to determine effect of affecting parameters on the process of degradation of materials exposed under "outdoor" conditions [1].

Evaluation and quantification of corrosion processes is time consuming and classical mathematical function are inadequate for prediction of these non-linear processes [2]. Nowadays there is certain chance to predict a corrosion loss of materials by artificial intelligence methods.The prediction of time-dependent and strong non-linear events belongs to perspective applications of artificial 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].

Figure 1 Effect of atmospheric corrosion

ARTIFICIAL NEURAL NETWORKS

Artificial neural networks (ANN) 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

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a simplified way a function of a biological neuron by means of mathematic relations (Figure 2).

A neuron consists of a body, called a soma, which the input transmission channel in the form of dendrites leads to; the output is provided by axon [4]. The formal neuron has n of generally real inputs $x_1,...,x_n$ corresponding to dendrites. All inputs are assessed by appropriate synaptic weights $w_1,...,w_n$ which are generally also real. Weights determine the transmission rate of the input signal. The weighed sum of input values presents the inner potential of the neuron z [4]:

$$z = \sum_{i=1}^{n} w_i x_i - h \tag{1}$$

Output (state) of the neuron $y$modelling the electric impulse of the axon is generally given by a non-linear transfer function σ, the argument of which is the inner potential of z.

$$y = \sigma(z) \tag{2}$$

Learning is a basic and essential feature of neural networks. This fact expresses the basic difference between so far common usage of computers and usage of means based on neural networks. To create a user programme we had to aim all our effort at creation of algorithms which transform the input data base into the output data base. But neural networks do not need that difficult stage. The way in which the input data will be transformed into the output data is determined by the learning stage based on the above mentioned exposure of samples (examples) describing a given problem - *training set.* So there is no need to create an algorithm. That need is substituted by submitting a training set to the neural network and by its learning. Knowledge is recorded especially through the strength of linkages between particular neurons. Linkages between neurons leading to "correct answer" are being strengthened and linkages leading to "wrong answer" are being weakened by means of repeated exposure of examples describing the problem area [3].

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 [3].

PREDICTION OF CORROSION LOSS OF STRUCTURAL CARBON STEEL

Before design and creation of neural network it was necessary to execute data conditioning for network

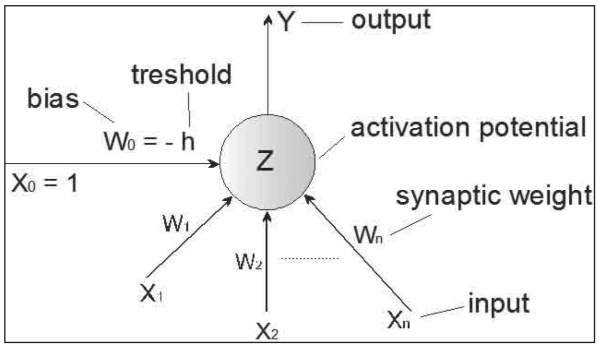

Figure 2 Mathematical model ofneuron

training. Data from the institute SVÚOM Ltd. 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 (Figure3).

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.

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 feedforward neural network whose topology 6-7-1 (Figure 4).

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

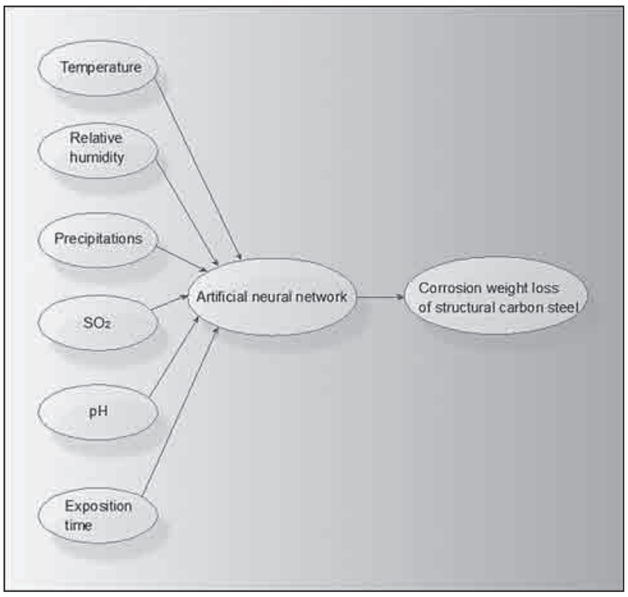

Figure 3 Structure of input and output data

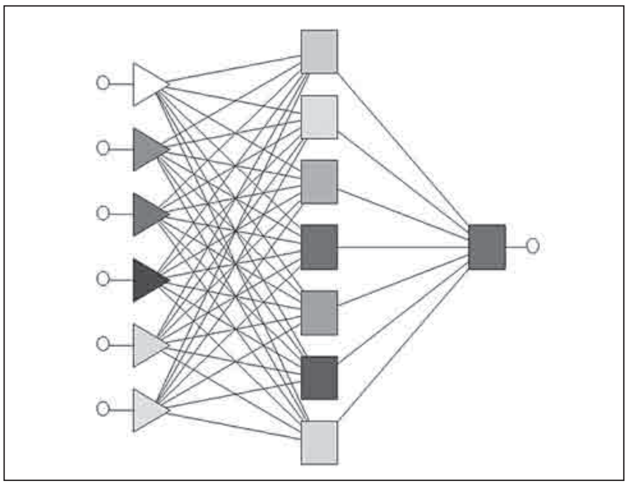

Figure 4 Structure of artificial neural network with topology 6-7-1

basis of input data setting to predict the corrosion weight loss of structural carbon steel in dependence on various climatic and pollution parameters.

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

The relation for RMS error calculation (Root Mean Squared) – it does not compensate for unitsused

$$\mathrm{RMS} = \sqrt{\frac{\sum_{i=0}^{i=n-1} (y_i - o_i)^2}{n-1}} \tag{3}$$

The relation for REL_RMS error calculation – it compensates for unitsused

$$\mathrm{REL\_RMS} = \sqrt{\frac{\sum_{i=0}^{i=n-1} (y_i - o_i)^2}{\sum_{i=0}^{i=n-1} (y_i)^2}} \tag{4}$$

where: n - number of patterns of a training or test set, y_i - predicted outputs, o_i - measured outputs[3].

Prediction errors of the chosen neural network model calculated according to relations (3) a (4) are RMS = 40 [g.m^{-2}] and REL_RMS = 6 %. Comparison of measured and predicted data is represented on Figure5. The model enables to predict corrosion loss of steel with an adequately small error.

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 sensitive analysis are shown on Table 1.It was found that air pollution by sulphur dioxide and exposition time have the most influence on corrosion weight loss of structural carbon steel.

CONCLUSION

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 data. 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.An extended model of the metalcorrosion loss can be created using results of this prediction system and visualization methods [5]. This way it will be possible to visualize, present and study results of modelling processes.

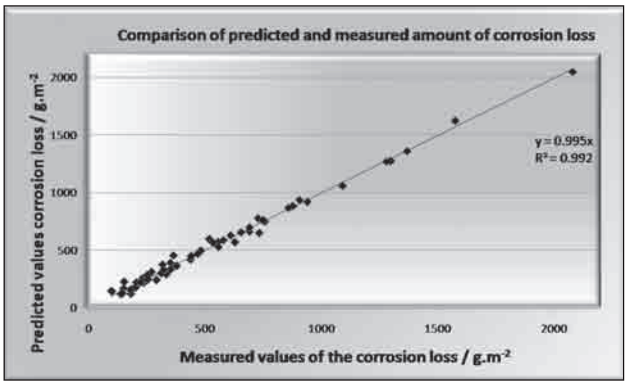

Figure 5 Comparison of measured and predicted data

Table 1 **Sensitive analysis**

Variable	Relative importance of the variables	Sequence
SO_2	48,25	1
Exposition time	42,58	2
pH	13,45	3
Relative humidity	2,85	4
Precipitations	2,51	5
Temperature	1,29	6

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Note: The responsible person for English language is the lecturer from TU Ostrava, Czech Republic