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COMPARISON OF NEURAL NETWORK DURABILITY MODELS FOR REINFORCED CONCRETE STRUCTURES

Neven Ukrainczyk, Tomislav Matusinović
University of Zagreb, Faculty of Chemical Engineering and Technology,
Marulićev trg 20, HR-10000 Zagreb, Croatia, e-mail: nukrainc@marie.fkit.hr

Velimir Ukrainczyk
Most projekt, Sveti Duh 36, HR-10000 Zagreb, Croatia, e-mail: mostprojekt@zg.htnet.hr

Abstract:
Data on relevant structural parameters gathered on eleven reinforced concrete structures in continental and three in Adriatic marine environment at various ages have been used for training artificial neural networks. Two separate models, for continental and marine environments have been developed. Data for modeling in continental environment were gathered at ten different ages of bridges and consists of 213 records. Data on marine environment were gathered at seven different ages of structures and consists of 124 records. The effects of the structure, properties of concrete and environmental conditions onto the degree of damage caused by steel corrosion have been investigated. The damages were classified into five categories based on the type of necessary remedial works. The artificial neural network for feature categorization was used as a tool for classification of damage and prediction of damage degree.
This paper demonstrates the use of artificial neural networks in modeling the durability of reinforced concrete structures in marine and continental environment. A comparison of the two models regarding the different environments is given. The models are able to recognize and evaluate the effect of individual parameters on the damages. The developed models could be useful for planning the maintenance of investigated structures and design of remedial works.

Keywords: reinforced concrete structure, durability, corrosion, damage categorization, artificial neural network, modeling, marine and continental environment.

1 Introduction

The safety of engineering concrete structures, whose expected service life is 120 years according to BS ISO15686-1, is often threatened in continental environment after only 20 to 30 years of exposure, and heavy repairs are necessary. In marine environment after only 15 years of exposure heavy repairs are needed. Besides the flaws in building standards, design and unsatisfactory construction, the direct causes are: a) accelerated carbonation, due to the higher carbon dioxide concentration on highways and in towns; b) de-icing chloride ions, which the fastest activate corrosion of steel; c) freezing and thawing cycles, which "find" the flaws in composition and curing of concrete. The products of corrosion occupy up to six times greater volume than the steel, and exert substantial stresses on the surrounding concrete, resulting in deterioration of concrete. The outward manifestations of the rusting include staining, cracking, and spalling of the concrete. Concurrently, the cross section of the steel is reduced. In time, structural distress may occur either by loss of bond between the steel and concrete due to cracking and spalling or as a result of the reduced steel cross-section area [1]. The principal factors influencing the rate of deterioration caused by reinforcement corrosion are known [1-6]. There are models [1,2,6] describing certain phases of the complex process of steel corrosion and destruction of concrete cover caused by rebar corrosion, namely: process of chloride penetration, carbonation, propagation of corrosion process, and destruction of reinforcement and concrete. However, overall analytical correlation between influential parameters and certain kinds of damages has not been established. Survey, diagnosis, and remedial works of the concrete structures have generated extensive experimental data over the years, but the analysis of such data using traditional tools has not produced reliable predictive models. Recently, there has been a growing interest in using artificial neural networks in engineering applications.

This research demonstrates the use of artificial neural networks (ANN) in modeling the durability of reinforced concrete structures in marine and continental environment. A comparison of the two models regarding the different environments is given. The model can be used for prediction of the extent of degree in the structure service life, for planning the maintenance, and can assist in designing and restoration of the investigated reinforced concrete structures.

2 ANN-based models

The architecture of ANNs mimics that of biological neurons and their operation essentially simulates the internal operation of the human brain[6]. In recent years, ANNs have shown exceptional performance as a regression tool, especially when used for pattern recognition and function estimation. They are highly nonlinear, and can capture complex interactions among input/output variables in the system without any prior knowledge about the nature of these interactions. A neural network is an empirical modeling tool, and it does operate by "curve-fitting". However, some notable differences exist between neural networks and typical, traditional empirical models[6]. In comparison to traditional methods, ANNs tolerate relatively *imprecise*, *noisy* or *incomplete* data, *approximate* results, are less vulnerable to outliers, have better *filtering capacity*, and are more *adaptive*. Moreover, ANNs are also *massively parallel*, that is, their numerous independent operations can be executed simultaneously. Some of the limitations of the neural networks are possible long training times, the need for large amount of reliable training data, and no guarantee of optimal results.

For the prediction of the most likely damage degree, for a given input pattern, classification network for characterization of distinct features was used. The classification networks[6] produce Boolean output responses, i.e., zero indicates that the input pattern is not within the specific class, and one indicates that it is. Actually, *fuzzy inferences* about the classifications are made.

3 Data gathering and damage categorization

Data on the effects of the structure and properties of concrete onto the degree of damage caused by steel corrosion have been gathered on eleven bridges located in continental environment [3,9]. The data were gathered at ten different ages of bridges: 1, 14, 22, 24, 28, 29, 31, 33, 55 and 91 years of exposure. The data consists of 213 records. The data on three concrete structures located in Adriatic marine environment [4,5] were gathered at seven different ages of concrete structures: 1, 20, 23, 27, 29, 31 and 73 years of exposure. The data consists of 60 records from the Vir bridge, 53 records from Krk bridge, and 11 records from former Torpedo factory. For the purpose of modeling data on damages caused by steel corrosion were interpreted as output. In addition, data on concrete properties and concrete compositions were considered as input parameters. Damages caused by steel corrosion were classified into five categories according to the criterion described in Table 1. The measurements of a half-cell potential, *E* (reference electrode $Cu/CuSO_4$), according to ASTM C 876-91 on the "undamaged" surfaces, indicate risks of corrosion occurrence.

Table 1: The categorization criteria for damages caused by steel corrosion.

DAMAGE CATEGORY	REINFORCED CONCRETE STRUCTURE STATE
0	No corrosion $E > -200$ mV (reference electrode $Cu/CuSO_4$)
1	Possible corrosion $E < -200$ mV
2	Cracks < 0.2 mm
3	Cracks > 0.2 mm, staining on the concrete surface
4	Large cracks, spalling, loss of bond between steel and concrete, reinforcement corroded on the surface
5	Spalling of concrete cover Significant loss of rebar cross section

Parameters that affect the steel corrosion in concrete (micro location conditions, structure, and properties of concrete) listed in Fig. 1 were used in this study for training the ANN models. Concrete cover depth, *c* was measured by profometer. Chloride ions concentrations at surface and rebar level, C_s and C_r represent water-soluble chloride content and are expressed in terms of the mass of concrete. They were determined on concrete powders obtained by drilling three holes in four layers, each two centimeters thick. The test methods for chloride extraction and titration recommended by the AFREM group were used. Chloride content values for C_s and C_r are averages of three samples tasted. Water-soluble chloride content is used as an appropriate parameter related to corrosion risk. The actual concrete strength, f_c was determined on one drilled core for each macro location. Representative location for drilling the core was chosen on the basis of broad testing of concrete homogeneity by Schmidt hammer. Carbonation depth, *d* (pH<9) was estimated on core by phenolphthalein test The porosity of concrete, *p* was measured on the 3 centimeters thick outer layer of the drilled core, as the general parameter of concrete quality. Moisture content in concrete, *w* was estimated as equilibrium value for average relative humidity of air measured throughout the year. The values for cement content (*cc*) and water-cement ratio (*w/c*) were taken from design documentation. The influence of the microclimate was considered through and with the parameters of: the orientation and exposure, *OE* (unexposed structural element is sheltered from the environment); the splashing zone, *sz*; the height above the sea level, *h*; and the horizontal distance from the sea, *d*. Average temperatures and relative environment humidity at the relatively close locations of the investigated structures are similar

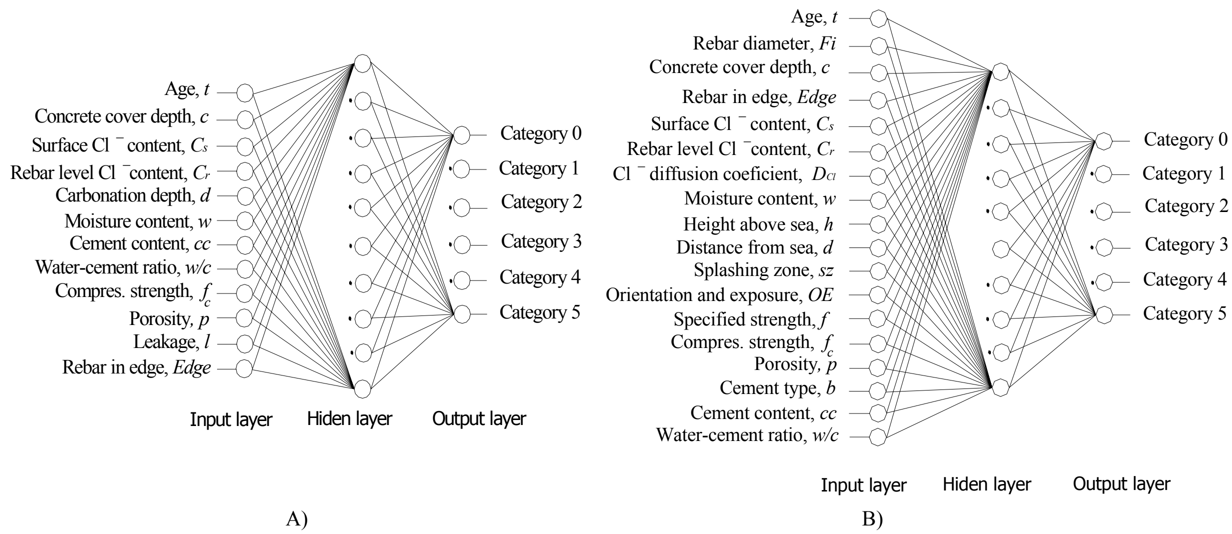


Figure 1: Architecture of selected networks for A) continental and B) marine environment: one hidden layer with ten neurons (for clarity, not all neuron connections are shown).

for a given climate (continental or marine), so these influences were not considered as a possible parameter of a different impact to the rebar corrosion. As no data were available for influences of admixtures, type of blended cement, and freezing and thawing cycles these parameters were not considered. The data are arranged in a patterned format. Data used for network training, testing and validation contain sets of pairs, records. Each pair consists of an input vector of 12 (18-marine) influential parameters and an output vector of 6 attributes (damage categories), Fig. 1.

4 Training and validation of ANN models

For building and training the neural network several software packages were used [10-13]. To provide an ANN model with good generalization capability the data were divided into sets of 183 (94) training and 30 validation records. A feed-forward neural network using back-propagation algorithm was employed. The training procedure comprised iterative calculations of the weight coefficients by minimization of criteria function. After each epoch, the network predicted outputs using training (recall) and validation (generalization) records. To avoid over-fitting (over-training), and thus enable a good generalization capability, training was stopped when the misclassification rate of the validation records started to deviate from the misclassification rate of the training records. The chosen architecture is shown in Figure 1. The determination of the optimal number of hidden layers, the number of processing elements and the network parameters used was largely achieved by an educated trial and error process testing more than 100 networks. A sigmoid transfer function, *logsig*, was employed as an activation function with full connection adopted among units in different layers. Weights and biases were initialized randomly with an initial weight range = –0.3 to +0.3. The following values of network parameters were used: learning parameter = 0.5 and momentum = 0.5. A successfully trained network is characterized by its ability to predict damage category for the data it was trained on. The training process was completed with misclassification rate = 9.3%(7.4%). The validity of a successfully trained ANN model is determined by its ability to generalize its predictions beyond the training data and to perform well when it is presented with unfamiliar new data. The model was presented with a total of 30 records excluded from training. Validation of ANN model resulted with misclassification rate = 16.6%(13.3%). Misclassification rate is not high for this highly heterogeneous material.

Table 2: The number of correctly and falsely predicted categories by developed ANN models (continental/marine environment). The matrix diagonal represents correctly predicted categories.

continental/marine environment													
Training							Validation						
	Predicted							Predicted					
True	0	1	2	3	4	5	True	0	1	2	3	4	5
0	69/3	1/1	0/0	0/2	0/0	0/0	0	5/3	1/0	0/0	0/0	0/2	0/0
1	4/0	14/8	1/1	0/0	0/0	0/0	1	0/0	3/2	1/0	0/0	0/0	0/0
2	0/0	2/1	10/35	2/0	0/0	0/1	2	0/0	1/0	4/11	2/0	0/0	0/0
3	0/0	0/0	3/0	22/5	2/0	0/0	3	0/0	0/0	0/0	4/2	0/0	1/0
4	0/0	0/0	0/0	1/0	21/29	0/1	4	0/1	0/0	0/0	0/0	6/9	0/1
5	0/0	0/0	0/0	0/0	0/0	31/7	5	0/0	0/0	0/0	0/0	0/0	4/1

5 Comparison of ANN models for continental and marine environment

By adding absolute coefficient values of weights that connect one input signal to all the inner layer neurons, one gets a number for each input parameter named a contribution factor [3-5]. The contribution factor is a measure of the importance of respective parameter in predicting the network's output, relative to the other input parameters in the network [11]. However, neural networks are also capable of finding patterns among several parameters, none of which is highly correlated with the output but which together form a pattern that uniquely determines the output. Based on the final set of weights, given by the software [10-13], a contribution factor was calculated, fig. 2. In both environmental climates the Cover depth is the principal parameter. For the marine environment the top six influencing parameters in ascending order are the Rebar level chloride content, Splashing zone, Age, Rebar in an edge of the structural part, Orientation and exposure and Height above a sea. For the continental climate the top six are the Age, Carbonation depth, Rebar level chloride content, Compressive strength, Water-cement ratio and Water content.

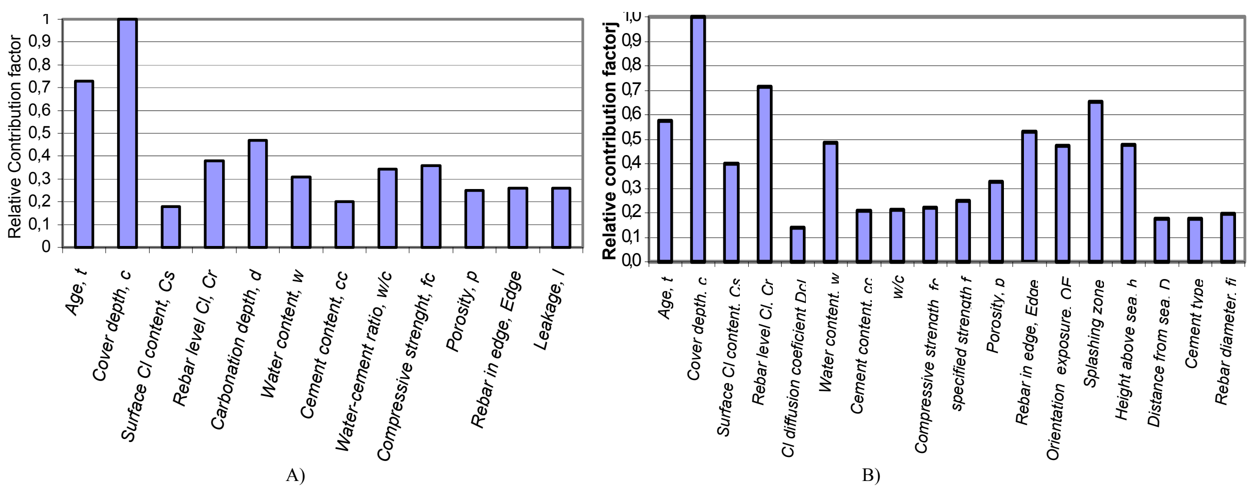
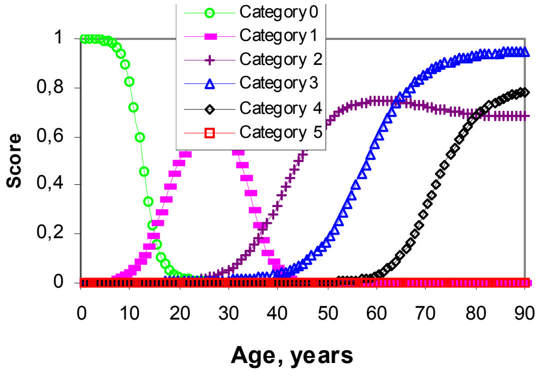


Figure 2: Relative contribution factor for individual input parameters in predicting the damage category for the two models: A) continental and B) marine environment.

An example of the simulation results is illustrated in Figure 3 where *fuzzy inferences* about the classifications are made. A comparison shows how much the rate of the deterioration of structures in marine environment is faster than in the continental climate.



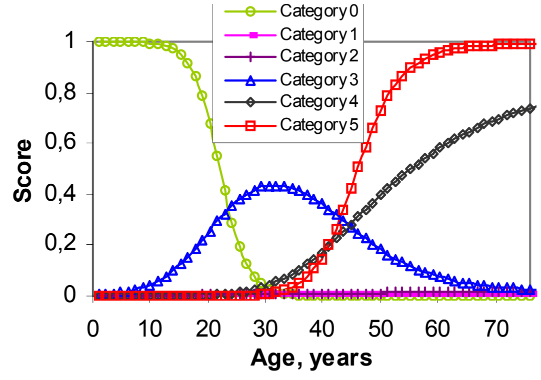


Figure 3: Simulations with mean value parameters for A) continental and B) marine climate.

6 Conclusions

The models are able to recognize and evaluate the effect of individual parameters on the damages caused by steel corrosion. In both environmental climates the Cover depth is the principal parameter that determine the structural service life. The developed models could be useful for planning the maintenance of investigated structures and design of remedial works. Unfortunately, data on admixtures, type of blended cement, and freezing and thawing cycles were not available. Possibly, if included, ANN model would form a pattern that better determines its output.

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