Use of neural network to evaluate rebar corrosion in continental environment

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Abstract

Data on the effects of the structure and properties of concrete onto the degree of damage caused by steel corrosion have been gathered on seven concrete bridge structures in Croatian moderate continental climate. 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. It was demonstrated that the developed model could predict degree of damage confidently within the observed period. The model is able to recognize and evaluate the effect of individual parameters on the damages. Interactions and sensitivities among parameters were investigated. The developed model could be useful for planning the maintenance of investigated structures and design of remedial works.

Keywords: rebar corrosion, continental climate, damages categorization, simulation, classification artificial neural network.

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1.0 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. 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].
There are several ways to predict the service life of reinforced concrete structures [2-10]. The principal factors influencing the rate of deterioration caused by reinforcement corrosion are known [1, 3-7]. There are models describing certain phases of the complex process of steel corrosion and destruction of concrete cover caused by rebar corrosion, e.g. 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. There is currently no rational and reliable method that can predict the damages caused by reinforcement corrosion in concrete structures. 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 explores the feasibility of using artificial neural networks (ANN) to create an intelligent model for determination of reinforcement corrosion in concrete structures. 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. The influence of parameters on the degree of damage, the ranges of values for parameters associated to certain categories, and interactions among parameters were investigated.

2.0 ANN-based model

The architecture of ANNs mimics that of biological neurons and their operation essentially simulates the internal operation of the human brain [8-10]. 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 parameters in the system without any prior knowledge about the nature of these interactions [8]. 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 [8]. 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.

2.1 Classification networks for feature categorization

For a prediction of the most likely categorical group for a given input pattern, classification network for characterization of distinct features (i.e., feature categorization) was used. Pattern classifiers map distinct input patterns onto their respective output classes. The classification networks produce Boolean output responses [8], i.e., zero indicates that the input pattern is not within the specific class, and one indicates that it is. The *actual* output from the neural network is a numerical value between 0 and 1, and can represent the "probability" that the input pattern corresponds to a specific class. Classification networks used for feature categorization activate only one output response for any input pattern, and select that category based on which output response has the highest value (score). A classification problem has three major regions [8]: (1) *a decision region*, which corresponds to a unique output class within the input space; (2) *a decision boundary*, which is the intersection of two different decision regions; and (3) *a transition* region, which is the buffer between two different decision regions where *fuzzy inferences* about the classifications are made. The primary method for measuring the effectiveness of a neural network is misclassification rate, that is, the percentage of testing (recall) and validation (generalization) examples misclassified from a given data set [8].

3.0 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 Croatian moderate continental climate [11-21]. The mean temperature in January ranges mostly from 0 °C to -2 °C. The mean temperature in July is 22 °C. An annual rainfall is between 700 mm and 1000 mm. 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. Data used in this paper were gathered in three steps. Firstly, visual survey of the bridge was conducted with categorization of damages on the basis of outward appearance. Secondly, *in situ* and laboratory tests of specimens taken from representative spots were examined in details. Finally, in the case where detail examination did not confirm the damage category determined by visual survey, visual estimates were corrected.

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, 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

Damage categories were chosen so that they corresponded to the types of repair works that would be required to repair the damage [22,23]. On the basis of visual survey, a number of representative spots of categories 0 through 3 were selected for detailed testing and verification of visually estimated categories. These spots were tested by exact measurement of parameters defining their structure and properties. The categories 4 and 5 represent obvious damages; therefore further verifications of the damage categories were not necessary.

Parameters that affect the steel corrosion in concrete (micro location conditions, structure, and properties of concrete) listed in Table 2 and Figure 1 were used in this study for training the ANN model to predict the degree of damage. 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 [24] 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. This means that the variability of the porosity with the cover depth is not considered. Moisture content in concrete, *w* was estimated as equilibrium value for average relative humidity of air measured throughout the year. For spots where water leakage was observed 100% relative humidity was assumed. The values for cement content (*cc*) and water-cement ratio (*w/c*) were taken from design documentation.

Table 2: Range or categories, mean values and standard deviations of input parameters (continuous and categorical).

Input parameters		Range or categories	Mean value or typical category	Standard deviation
Continuous input	Age, *t*, years	1 to 91	26.2	21.4
	Cover depth, c, cm	0.2 to 6.5	3.2	1.5
	Surface Cl^-, C_s, %*	0.00 to 0.35	0.071	0.12
	Rebar level Cl^-, C_r, %*	0.00 to 0.30	0.038	0.08
	Carbonation depth, *d*, cm	0.0 to 3.5	1.8	0.9
	Moisture content, *w,* vol.%	1.7 to 3.5	2.5	0.5
	Cement content, *cc*, kg/m^3	220 to 480	370	69.8
	Water-cement ration, *w/c*	0.42 to 0.65	0.5	0.05
	Compress. strength, f_c, MPa	10.0 to 75.0	44.7	18.3
	Porosity, *p*, vol. %	10.0 to 19.1	13.8	2.0
Categorical input	Rebar in edge, *Edge*	Yes or no	No	-
	Leakage, *l*	Yes or no	No	-

*wt.% of concrete, water-soluble chloride content

Average temperatures and relative environment humidity at the relatively close locations of the investigated structures are similar (continental climate), 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 attributes (influential parameters), and an output vector of 6 attributes (damage categories). The range, mean value and standard deviation of continuous input parameters and categories for categorical parameters used in training of ANN model are presented in Table 2

4.0 Training of ANN

For building and training the neural network several software packages were used [25-28]. To provide an ANN model with good generalization capability the data were divided into sets of 183 training and 30 validation records, Table 3 and 4. The actual outputs were presented to the network as binary vectors, i.e. zero indicates that the input pattern is not within the specific class, and one indicates that it is. 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.

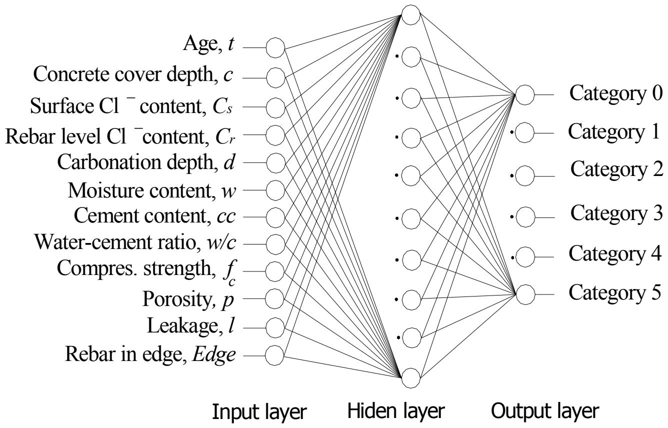


Figure 1: Architecture of selected network: one hidden layer with ten neurons (for clarity, not all neuron connections are shown).

4.1 Neural network architecture

For the modeling purpose a feed-forward neural network using back-propagation algorithm was employed. It should be noted that it is possible to achieve satisfactory results with different network architectures. 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. This involved the development and testing of more than 100 networks. Network input layer consisted of 12 neurons representing influential parameters. The output layer consisted of 6 neurons, for each of the damage category. There was one hidden layer, which was made up of 10 neurons. A sigmoid transfer function, *logsig*, was employed as an activation function for all processing units (neurons) with full connection adopted among units in different layers within the network, as shown in Figure 2. Elements, i.e. attributes in input and six output vectors were normalized between 0 and 1 to be compatible with the limits of the sigmoid transfer function, *logsig*. 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.

5.0 Discussion

5.1 Testing of ANN model using training data

A successfully trained network is characterized by its ability to predict damage category for the data it was trained on. Therefore, the trained network was used to predict the damage category for input parameters already used in the training process. The training process was completed with misclassification rate = 9.29%. Clearly the network has learned the relationship between input parameters and respective damage category effectively, and the model performance on the training data is satisfactory.

5.2 Validation of ANN model

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 from within the range of the input parameters used in the training. Therefore, the ability of the ANN model thus developed to predict the damage category of new input parameters excluded from the training data must be validated. The model was presented with a total of 30 records and was required to predict the damage category associated with each set of values for influential parameters. Validation of ANN model resulted with misclassification rate = 16.67%. Misclassification rate is not high for this highly heterogeneous material. All misclassifications were wrong for only one order of category, Table 5, and all categories 4 and 5 were correctly classified. This can be attributed to the uncertainty of the corrosion occurrence evaluation for "undamaged" surfaces.

Table 3: The number of correctly and falsely predicted categories by developed ANN model for training and validation data records (the matrix diagonal represents correctly predicted categories).

Training							Validation						
	Predicted							Predicted					
True	0	1	2	3	4	5	True	0	1	2	3	4	5
0	69	1	0	0	0	0	0	5	1	0	0	0	0
1	4	14	1	0	0	0	1	0	3	1	0	0	0
2	0	2	10	2	0	0	2	0	1	4	2	0	0
3	0	0	3	22	2	0	3	0	0	0	4	0	0
4	0	0	0	1	21	0	4	0	0	0	0	6	0
5	0	0	0	0	0	31	5	0	0	0	0	0	4

5.3 Contribution Factor

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. 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[33]. The higher the absolute sum of those weights is, the more the parameter is contributing to the classification. 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.
The contribution factor for individual input parameters in predicting the damage category was evaluated. The idea of the contribution factor analysis was found in the Neuroshell [25], where a specific module calculates contribution factors. Based on the final set of weights, given by the software [24,25], a contribution factor was calculated. Importance of parameters in ascending order, Figure 2, is as follows: Cover depth, *c*; Age, *t*; Carbonation depth, *d*; Chloride content at rebar level, C_r; Compressive strength, f_c; Water-cement ratio, *w/c*; Water content, *w*; Rebar in an edge of structural part, *Edge*; Water leakage, *l*; Porosity, *p*; Surface chloride content, C_s.

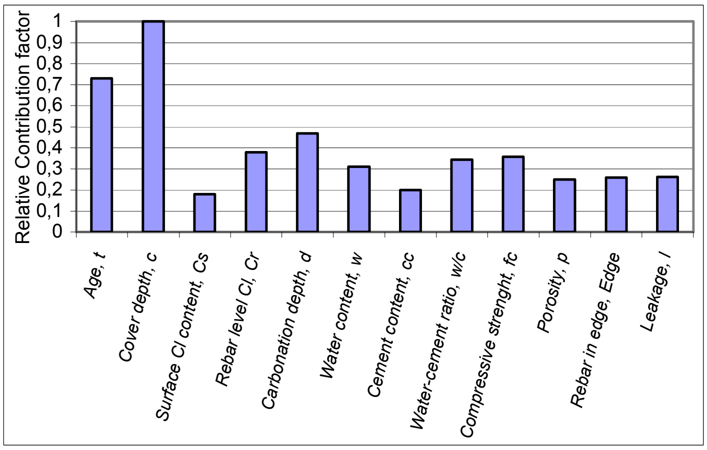
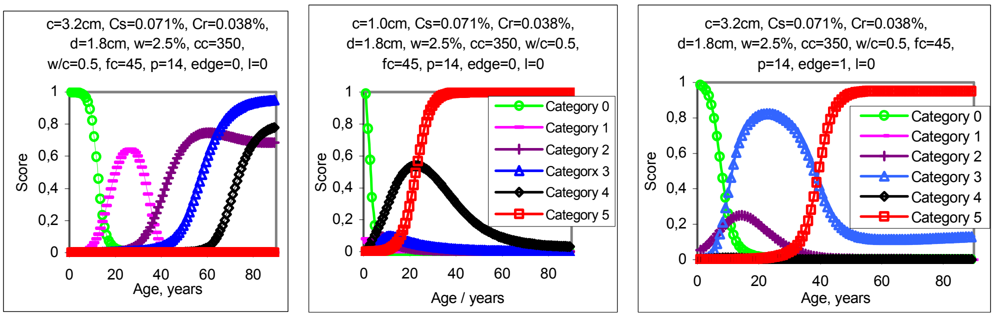


Figure 2: Relative contribution factor for individual input parameters in predicting the damage category.

To investigate the interactions and sensitivities among parameters, the parameters listed above were chosen for further simulation research using profile plots, Figure 3 to 5.

5.4 Profile Plot

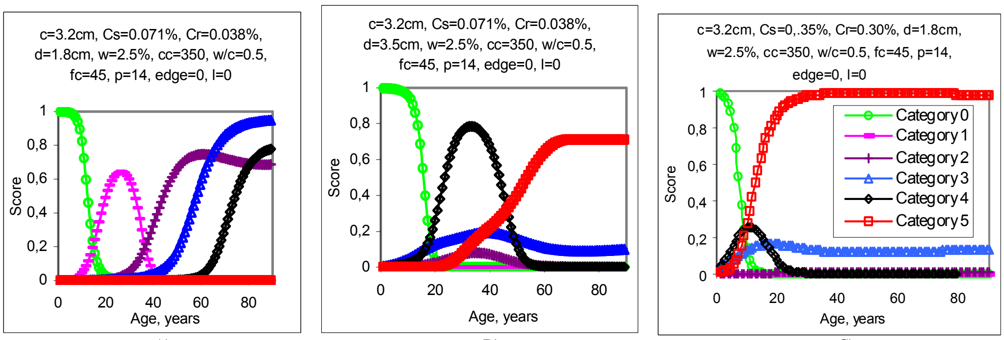
Categorical output has six categories (six attributes output vectors) drawn upon kinds of damages. The model predicts scores (values between 0 and 1) for each of these six categories (outputs). The final category predicted by the model is the one with highest score. Profile plot is the best way to visualize the fitted model. For the purpose of simulating the impact of parameters and interactions among parameters, the respective parameter was assigned the mean, minimum and maximum values in its range. All other parameters were held at their typical (mean) values shown in Table 2. Examples of the simulation results are illustrated in profile plots with *fuzzy inferences* about the classifications, Figure 3 to 5.
Figure 3A), 4A), and 5A) shows a profile plot for mean values of continuous input parameters and the following categorical input parameters: rebar not in an edge of structural part (*edge* = 0), and no water leakage (*l* = 0). In that case, the score of the category 2 prevail after 38 years of exposure when category 3 starts to emerge, therefore requiring repair works. After 60 years score of category 4 rises, meaning that the structural safety could be endangered.
Figure 3 B) shows simulation performed with fixed cover depth, *c*, at 1.0 cm with all the other parameters from the previous case remained unchanged. The score of the category 4 now prevails



A) B) C)

Figure 3: Profile plots for simulating the impact of the concrete cover depth and rebar position: A) c=3.2cm $edge$=0; B) c=1.0cm; C) rebar in an edge of structural part ($edge$=1).

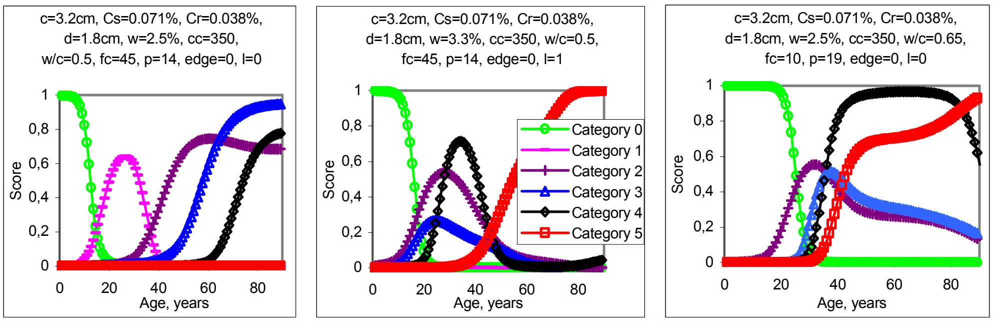
after only 6 years and reaches maximum at 24 years when category 5 prevails, showing the importance of concrete cover depth. Figure 3 C) shows the profile plot for the case where the reinforcement was in an edge of a structural part so the carbonation and chloride ions penetrate from both sides. Figure 4 B) shows the influence of maximum carbonation depth, d = 3.5 cm (instead of mean value C_s = 1.8 cm). All the other parameters remained unchanged as those for Figure 4 A). Due to the higher carbonation depth than the concrete cover depth, category 4 prevails after only 20 years. Figure 4 C) shows the influence of higher chloride ion concentration, C_s = 0.35 % (instead of mean value C_s=0.071%) and C_r=0.30% (instead of mean value C_r=0.038%). All the other parameters remained unchanged as those for Figure 4 A). After only 10 years the structural safety could be endangered.



A) B) C)

Figure 4: Profile plots for simulating the impact of carbonation depth and chloride ion concentration: A) d=1.8cm C_s=0.07% C_r=0.038%; B) d=3.5 C) C_s=0.35% C_r=0.30%.

Figure 5 B) shows the impact of water leakage. For water content value, w = 3.3 % was assigned. All other parameters remained unchanged as those for Figure 5 A). Category 0 stops to prevail after 17 years, when category 2 and 3 starts to emerge. Category 4 prevails after 28 years, and category 5 after 47 years. Figure 5 C) simulates the importance of concrete cover quality. The lowest quality was presented to the model: w/c=0.65; f_c=10; p=19. All others parameters were maintained at their mean values, Figure 5 A). Category 4 prevails after 36 years.
Likewise, the impact of other individual parameters values on the damage degree and interactions among input parameters were investigated.



A) B) C)

Figure 5. Profile plots for simulating the impact of water leakage and concrete cover quality: A) w/c=0.5 p=14 f_c=45; B) *leakage* = 1, w = 3.3 %; C) w/c=0.65 f_c=10 p=19.

6.0 Conclusions

The damages of reinforced concrete structures caused by steel corrosion as a function of bridge age, concrete structure and properties are difficult to predict analytically. It was demonstrated that the developed ANN model could predict degree of damage confidently within the observed period. The model is able to recognize and evaluate the effect of individual parameters on the damages caused by steel corrosion.

Using the developed ANN model it was possible to rate influential parameters by the contribution factor analyses in ascending order: Cover depth, c; Age, t; Carbonation depth, d; Chloride content at rebar level, C_r; Compressive strength, f_c; Water-cement ratio, w/c; Water content, w; Rebar in an edge of structural part, *Edge*; Water leakage, l; Porosity, p; Surface chloride content, C_s.

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 investigated reinforced concrete structures.

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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