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APPLICATION OF NEURAL NETWORK IN PREDICTING DAMAGE OF CONCRETE STRUCTURES CAUSED BY CHLORIDES

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Abstract: *In recent years artificial neural networks (ANN) have shown exceptional performance as a regression tool, especially when used for pattern recognition and function estimation. Artificial neural networks mimic the structure and operation of biological neurons and have the unique ability of self-learning, mapping, and functional approximation. They are highly nonlinear, massively parallel, and can capture complex interactions among input/output variables in the system without any prior knowledge about the nature of these interactions. The ANN for feature categorization was used as a tool for classification of damage and prediction of expected future degree of damage. Data on the effects of the environmental conditions, structure, and properties of concrete onto the degree of damage caused by steel corrosion have been gathered on three concrete structures in Adriatic marine environment. The data were gathered at seven different ages of concrete structures. The damages were classified into five categories based on type of remedial works required to repair the damage. The model that was developed can be useful for*

planning the monitoring, design of remedial works as well as in improvement of their protection. The influence of variability (sensitivities) of the principal influencing parameters, the ranges of values for principal influential parameters associated to certain categories, and interactions among influential parameters were investigated.

1. INTRODUCTION

The corrosion of steel in concrete has received increasing attention for more than three decades because of great damages observed on the structures in marine environment and highways exposed to de-icing salts. Chloride ions are considered to be major cause of premature corrosion of steel reinforcement. The safety of engineering concrete structures is often threatened in such environment after only 15 to 20 years of exposure, and heavy repairs are necessary. Survey, diagnosis, and remedial works of the concrete structures have generated extensive experimental data over the years. In the previous research[1] the feasibility of using ANN to create an intelligent model for reinforcement corrosion of two bridges in marine environment has been demonstrated. Developed ANN model demonstrated the ability to recognize and evaluate the effect of individual parameters on the damages caused by steel corrosion. Using the ANN model it was possible to rate influencial parameters by the contribution factor analyses. Evaluated importance of individual parameters onto magnitude of damages, in ascending order, was as follows:

1. Concrete cover depth, *c*	10. Porosity
2. Chloride ions concentration at the rebar level, C_r	11. Specified strength
3. Splashing zone, *sz*	12. Compressive strength
4. Age, *t*	13. Water-cement ratio
5. Rebar in an edge of structural part, *Edge*	14. Cement content
6. Moisture content, *w*	15. Rebar diameter
7. Height above the sea level, *h*	16. Cement type
8. Exposure, *ex*	17. Horizontal distance from sea
9. Chloride ions concentration in the surface layer, C_s	18. Chloride diffusion coefficient

The parameters 1 to 9 listed above correspond to those with the most influence in the specific cases, consent with the previous reports on the parameters affecting concrete corrosion in marine environment[2-5]. Effect of the dominant influence parameters on the score of each damage category during 120 years has been investigated by their variation in extreme conditions. The developed ANN model indicated that the parameters usually considered to be of a high importance for concrete structure assessment: strength, water-cement ratio, and cement content, have no dominant influence on chlorides induced steel corrosion.

In this paper additional data sets, obtained by surveys and examinations of same reinforced concrete structures in marine environment, but for older ages, were used for an additional training of ANN and for a validation of the predictions. Moreover, another, much older, concrete structure has been introduced. Only the most influential parameters 1 to 9 were used as input parameters for the new building of ANN.

2. ANN-BASED MODEL

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. METHODOLOGY

Data on the effects of the environmental conditions, structure, and properties of concrete onto the degree of damage caused by steel corrosion have been gathered on three concrete structures located in the Adriatic marine environment[1,7-11]. The data were gathered at seven different ages: 1, 20, 23, 27, 29, 31 and 70 years of exposure.
The Prevlaka-Vir bridge was built in the year 1976. The bridge has ten spans and the length of the whole bridge is 378 m. The reinforced concrete lie in the range from zero to 14 meters above the sea level. The Krk bridge was built in the year 1980. At that time, that was the bridge with the largest span of the arch in the world. Transition from the mainland to the island of Krk was realized with two arches with the spans of 390 m and 244 m. The arches lie in the range from zero to 60 meters above the sea level.
Restoration of historical industrial architecture in Europe has been active for last 15 years. Conformably, launching spot for torpedoes in former Torpedo factory at Rijeka docks, Figure 1, which invented and produced world’s first torpedoes, will be preserved as an industrial and historic monument since it is under the UNESCO heritage protection. Hence, the restoration study was initiated[7]. The reinforced concrete structure of launching ramp has been exposed to severe marine environment for over 70 years.

Figure 1. Launching ramps for torpedoes in former Torpedo factory.

In this paper, the new data, three data sets from Prevlaka-Vir bridge and three data sets from Torpedo factory, where used for additional training of the ANN model with nine influential parameters. The new data were also used to verify the prognosis made by the ANN model developed in the previous research[1].

3.1. Data gathering and damage categorization

Damages caused by steel corrosion were classified into five categories according to the criterion described in Table 1. Damage categories were chosen so that they corresponded to the types of repair works that would be required to repair the damage[1,8-10]. There were three measuring spots (three micro locations) within certain macro location. Characteristic micro positions within the macro location were chosen on places of different damage categories[1]. 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.

DAMAGE CATEGORY	REINFORCED CONCRETE STRUCTURE STATE
0	No corrosion E > -200 mV
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, corrosion of prestressing steel

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

Average temperatures and relative environment humidity at the locations of the Prevlaka-Vir bridge, the Krk bridge, and the Torpedo factory are similar, so these experimental data were not considered as a possible parameter of a different influence to the rebar corrosion. The influence of the microclimate was considered with the parameters of the exposure (unexposed spot is sheltered from the environment; wind, rain…) and the height above the sea level.
The data used for network training, testing and validation contain sets of pairs. Each pair consists of an input vector of 9 elements (influential parameters), and an output vector of one element (damage category). The range and mean value of continuous input parameters and categories for categorical input parameters used in training of ANN model are presented in Table 2.

3.2. Training of ANN

For building and training the neural network several software packages were used[11-14]. To provide an ANN model with good generalization capability the data were divided into 100 training and 17 validation sets. 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) sets. To avoid over-fitting (over-training), and thus enable a good generalization capability, training was stopped when the misclassification rate of the validation sets started to deviate from the misclassification rate of the training sets.

Input parameter		Range or categories	Mean value
Continuous input	Age, years	1 to 70	22.2
	Cover depth, cm	0.10 to 7.00	2.77
	Rebar level Cl^-, C_r, %*	0.09 to 0.80	0.32
	Surface Cl^-, C_s, %*	0.01 to 0.45	0.165
	Moisture content, *w*, vol.%	1.90 to 3.90	2.38
	Height above sea, *h*, m	1.1 to 50	13.2
Categorical input	Rebar in edge, *Edge*	Yes or no	No
	Splashing zone	Yes or no	No
	Exposure	Exposed or unexposed	Exposed

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

Table 2. Range or categories and mean value of input parameters

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. Using trial and error method it was determined that the chosen architecture, Figure 1, produces better results than other network structures.

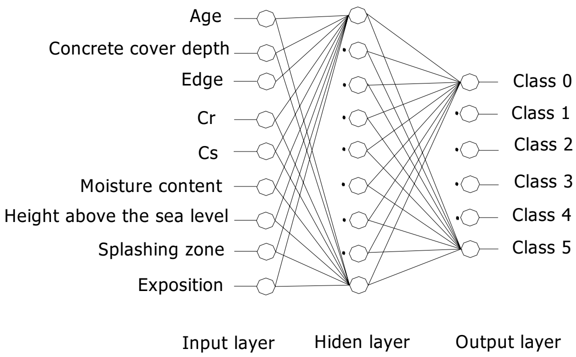


Figure 2. Architecture of selected network (for clarity, not all neuron connections are shown).

A sigmoid 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 in input and six output vectors were normalized between 0 and 1 to be compatible with the limits of the sigmoid 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.

4. DISCUSSION

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 = 9.00%. 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.

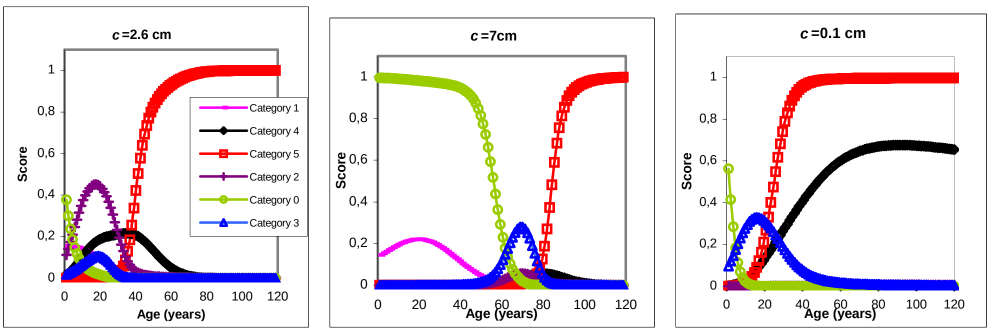
The validity of a successfully trained ANN model is determined by its ability to generalize its predictions beyond the training data and to perform well when it is presented with unfamiliar new data from within the range of the input parameters used in the training. Therefore, the ability of the ANN 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 17 sets 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 = 11.76%. The new data, three data sets from Prevlaka-Vir bridge and three data sets from Torpedo factory, were also used to verify the prognosis made by the ANN model developed in the previous research[1]. Validation resulted with misclassification rate = 0.00%, i.e. all categories 5 were rightly classified.

4.1 Profile Plot

Categorical output has six categories (six output vectors) drawn upon six kinds of damages, as shown in Figure 2. The model predicts scores for each of these six categories. The final category predicted by the model is the one with highest score. Profile plot is the best way to visualize the fitted model. By varying only one predictor (parameter) between two values and keeping all the others fixed at some pre-specified values we get the profile plot – which is a one dimensional cross section of the high dimensional fitted surfaces. After the scores for each category were taken, as predicted by the model, they were plotted against variable predictor. Profile plots enable one to study the ranges of values for given predictor associated to certain categories as well as the interactions among predictors. The extrapolation of the observations up to 120 years was applied to plan the maintenance activities. To simulate the impact of input parameter values, certain constant values, the high, the mean and the low were altered. Examples of the simulation results are illustrated in profile plots with *fuzzy inferences* about the classifications, Figure 3 and 4.

Figure 3 A) shows a profile plot for mean values of continuous input parameters and the following categorical input parameters:

(1) the spot is exposed (unexposed spot is sheltered from the environment; wind, rain…);
(2) the spot is not in the edge of a structural part; and
(3) the spot is not in the splashing zone.

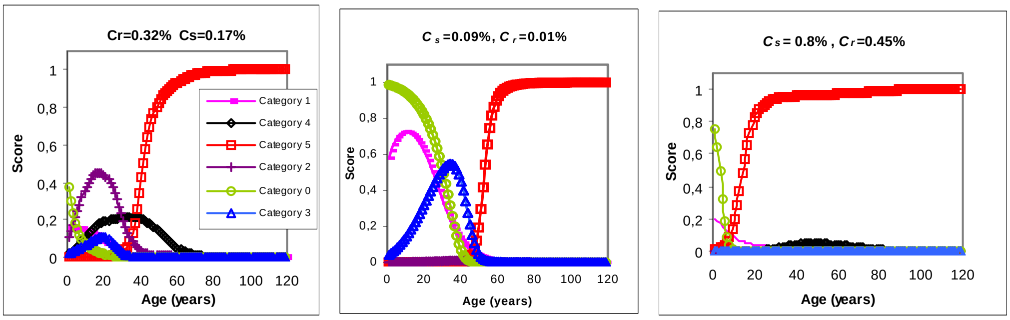


A) B) C)

Figure 3. Profile plots for simulating the impact of the concrete cover depth: A) c=2.6cm; B) c=7cm; C) c=0.1cm.

In that case, the score of the category 2 reached its maximum after 18 years of exposure, therefore requiring repair works. After 45 years category 4, and after 38 years category 5 prevail, meaning that the structural safety could be endangered. Figure 3 B) shows simulation performed with fixed maximum cover depth, *c*, at 7cm with all the other parameters from the previous case unchanged. The greatest score of the category 0 was prolonged from 25 years to 62 years. The score of the category 3 reaches maximum after 70 years, while category 5 is the most frequent after 78 years. Figure 3 C) shows the outcome for thinner concrete cover, down to 0,1 cm, maintaining all other parameters unchanged. The category 0 was prevailing only up to 5 years, when the score of the category 3 started emerging, reaching its maximum in the 15th year. After 15 years the score of categories 4 and 5 suddenly started to rise, prevailing after only 22 years.

Figure 4 B) shows the influence of lower chloride ion concentration, C_s=0.09% (instead of mean value C_s=0.32%) and C_r=0.01% (instead of mean value C_r=0.17%). All the other parameters remained unchanged as those for Figure 4 A).



A) B) C)

Figure 4. Profile plots for simulating the impact of chloride ion concentration: A) C_s=0.32% C_r=0.17%; B) C_s=0.09% C_r=0.01%; C) C_s=0.8% C_r=0.45%.

The category 0 is now dominant up to the 30th year, when the third category started to prevail. Category 5 prevails after 50th year.

Figure 4 C) shows the influence of higher chloride ion concentration by setting those parameters values to the maximum, C_s=0.8% and C_r=0.45%, maintaining all other parameters unchanged. After 7 years the score of the category 0 stops to prevail, while the category 5 became most frequent after 10 years, due to the intensive steel corrosion.

Likewise, the impact of other individual parameters on the damage degree and interactions among input parameters were investigated.

5. CONCLUSIONS

Predicting the damages of reinforced concret structures caused by chloride-induced steel corrosion as a function of bridge age, structure, and environmental conditions is difficult to achieve analytically. In this paper, it has been demonstrated, that the developed ANN model, with only the most influential parameters as input parameters, can predict damage degree accurately and instantly. The model demonstrated the ability to recognize and evaluate the effect of individual parameters on the damages caused by steel corrosion. Interactions among input parameters were investigated as well.

Effect of the dominant influence parameters on the score of each damage category during 120 years has been investigated by their variation in extreme conditions. The method could be a useful tool for planning the maintenance of the structures. Obviously the tool can be used only as a forecast, and needs to be assessed by structure survey.
The new data, three data sets from Prevlaka-Vir bridge and three data sets from Torpedo factory, have verified the prognosis made by the ANN model developed in the previous paper.
New data sets obtained by additional surveys and examinations of reinforced concrete structures in marine environment could be used for an additional training of ANN and for a validation of the predictions. The more the data are available, especially for older reinforced concrete structures, the more reliable prediction of expected future damage degree by ANN could be performed.

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