

A neural network method for analysing concrete durability

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This paper describes the use of an artificial neural network (ANN) method for the analysis of relationships between a number of input parameters and observed damage owing to reinforcement corrosion. Data on the effects of the environmental conditions, structure and properties of concrete on the degree of damage caused by steel corrosion have been gathered on 11 concrete bridge structures in a Croatian moderate continental climate. The main causes of deterioration were chloride ions, from de-icing salts, and accelerated carbonation owing to the higher carbon dioxide concentration on highways and in towns. The methodology of data gathering from surveys, diagnosis and remedial works to concrete structures is described. The damage was classified into six categories based on the type of remedial work necessary. As the parameters are time dependent and show high scatter, a probabilistic-like approach was adopted using an ANN for fuzzy feature categorisation as a tool for classification of the degree of damage. The ANN was successfully trained and validated for the range of data from the investigated bridges. The outputs of the work could be used for fuzzy prediction of the extent of damage in the structure service life and for planning the maintenance. The outputs can also be used to assist in the design and restoration of the reinforced concrete structures.

Notation

c	concrete cover depth
cc	cement content
C_r	water-soluble chloride content at the rebar level by mass of concrete
C_s	water-soluble chloride content in the surface layer by mass of concrete
d	carbonation depth
E	measurements of a half-cell potential according to ASTM C 876-91
Edge	categorical parameter for considering an impact of reinforcement in an edge of a structural part
f_c	compressive strength of concrete
l	categorical parameter for considering an impact of water leakage

p	porosity
t	bridge age
w	moisture content of the concrete by volume

Introduction

The safety of engineering concrete structures, the expected service life of which is 120 years,¹ is often threatened and substantial repairs are necessary after only 20 to 30 years of exposure. In addition to the flaws in building standards, design and unsatisfactory construction, the direct causes are

- accelerated carbonation owing to the higher carbon dioxide concentration on highways and in towns
- chloride ions from de-icing salts, the fastest of which activate corrosion of steel
- freezing and thawing cycles, which 'find' the flaws in composition and curing of concrete.

The products of corrosion (rust) occupy up to six times greater volume than steel and exert substantial stresses on the surrounding concrete, resulting in deterioration of concrete. The outward manifestations of the rusting process 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

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loss of bond between the steel and concrete owing to cracking and spalling or as a result of the reduced steel cross-sectional area.²

The principal factors influencing the rate of deterioration caused by reinforcement corrosion are known.²⁻⁸ Corrosion of reinforcing steel in concrete is a very complex phenomenon that involves many factors; these are not currently well understood and both parameters for concrete durability and environmental exposure show a high scatter and are time dependent. There are models describing certain phases of the complex process of steel corrosion and destruction of concrete cover caused by chloride ions, for example the process of chloride penetration, carbonation, propagation of corrosion process and destruction of reinforcement and concrete. Overall, however, analytical correlation among the influential parameters and the various kinds of damage has not been established. Surveys, diagnosis and remedial works to 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.

There are several ways to predict the service life of reinforced concrete (RC) structures with the help of various deterministic empirical models⁹⁻¹⁸ or experimental methods.⁸

To include uncertainty of the various parameters to generate reliable service life predictions, probabilistic modelling has been utilised as opposed to a deterministic method. Probabilistic modelling of the deterioration mechanisms has gained strong momentum during the past few years.¹⁹⁻²⁷ For the probability approach, a number of sophisticated statistical methods exist which may be adopted for the durability analysis. Owing to a lack of relevant input data for an analysis and as a number of assumptions have to be made, a very simple model based on a Monte Carlo simulation has been developed.^{19,27} A probabilistic-based durability analysis has been applied for obtaining a more controlled durability and the long-term performance durability design of new concrete structures, as well as an improved basis for condition assessment of existing concrete structures in a marine environment.^{19,25} There are still many areas in which further research is needed to improve the current knowledge of the parameters of the models.

Recently, there has been a growing interest in using artificial neural networks (ANNs), in engineering applications.²⁸⁻³⁶ Neural network analysis is an analytical technique that can be applied to complex problems described by a large amount of data. It does not require a knowledge of physical processes involved (black box modelling), but, rather, it identifies the relationships present in a set of data. Thus it may be applied to problems where more conventional mathematical solutions are not feasible. Of course an expert on the investigated process is needed to direct the development of the ANN model. Neural networks are generally

used to predict individual results. Their use in evaluating the relationships of the results and influencing variables represents a relatively novel approach. This is, however, particularly useful when the values of the variables are difficult to control, as is the case for many of the variables affecting concrete degradation.

In this paper data on input parameters and observed damage resulting from reinforcement corrosion in 11 concrete bridge structures located in a Croatian moderate continental climate have been gathered. A probabilistic-like approach has been applied to account for the randomness and time dependency of the parameters. The ANN modelling^{37,38} with fuzzy prediction of the extent of damage has been employed. Influence of the various parameters on the degree of damage, ranges of values for parameters associated to certain categories and interactions among parameters has been investigated. The outputs of the work could be used for planning the maintenance; they can also assist in the design and restoration of the RC concerned.

ANN-based model

The architecture of ANNs mimics that of biological neurons and their operation essentially simulates the internal operation of the human brain.³⁷ In recent years, ANNs have shown exceptional performance as a regression tool, especially when used for pattern recognition and function estimation.³⁸ They are highly non-linear and can capture complex interactions among input/output parameters in the system without any prior knowledge about the nature of these interactions.³⁹ A neural network is an empirical modelling tool, and it operates by 'curve-fitting'. Some notable differences exist, however, between neural networks and typical, traditional empirical models. 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 (determination of the optimal ANN architecture by educated trial-and-error process), the need for a large amount of reliable training data and no guarantee of optimal results. The principles of ANNs have been comprehensively discussed in available literature²⁸⁻⁴¹ and are therefore not addressed in the present paper.

Classification networks for feature categorisation

One of the most interesting issues of neural network models is their categorisation ability—that is, the capacity of the system for grouping a given set of correlated patterns (the examples) into distinct classes, in such a way that each concept represents the common features

of a set of examples. Statistical methods provide another alternative to this problem. Neural computing, however, outperforms the conventional statistical approach in many applications. Neural networks are very effective in fault diagnosis for a number of reasons. One of them, through training, is that the neural network can store knowledge about the process and learn directly from quantitative, historical fault information. It is possible to train networks based on historically ‘normal’ operation, and then compare that information with current data to determine faults. Furthermore, neural networks can identify causes and classify faults.⁴¹

For a prediction of the most likely categorical group for a given input pattern, usually classification networks are used for characterisation of distinct features (i.e. feature categorisation), (Fig. 1). This similarity classifier uses the training examples to develop a model for each class, and compares future test cases to this model in order to assign a score to define similarity. The classification networks produce Boolean output responses—that is, zero indicates that the input pattern is not within a specific class and one indicates that it is within a specific class.³⁸ For example, if a categorical output has three possible categories (three attribute output vectors), actual categories for a given input vector observed are presented by three attribute output vectors (see ‘Actual ANN output’ in Table 1): for a given set

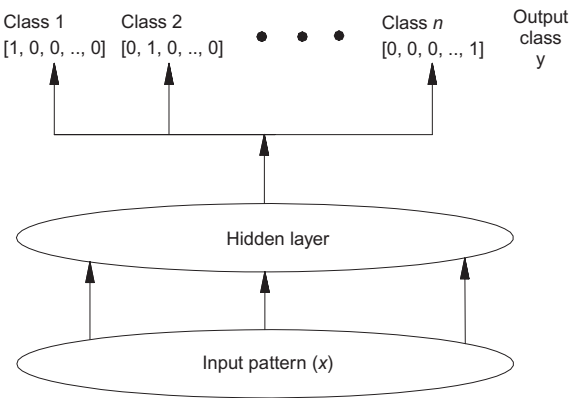


Fig. 1. A standard neural network architecture for pattern-classification networks

$x1$ presented is category 1; for a given set $x2$ category 2; category 3 for a given set $x3$). The predicted output from the neural network is a numerical value between 0 and 1 (see ‘Predicted ANN output’ in Table 1), and can represent the ‘probability’ that the input pattern corresponds to a specific class. Classification networks used for feature categorisation activate only one output response for any input pattern, and they select that category based on which output response has the highest value (score). For instance, in Table 1 category 2 is predicted for a given input vector $x2$.

Generally the best way to implement a multiple-class model is to use a separate output neuron for each class. Training is done by requiring the neuron corresponding to the class being presented to be highly activated, while all other neurons are required to be nearly off. A classification problem has three major regions in predicting output.

- (a) A decision region corresponds to a unique output class within the input space (case for set $x1$ in Table 1).
- (b) A decision boundary is the intersection of two different decision regions (set $x2$).
- (c) A transition region is the buffer between two different decision regions where fuzzy inferences^{37,38} about the classifications are made (set $x3$).

The primary method for measuring the effectiveness of a neural network is misclassification rate—that is, the percentage of testing (recall) and validation (generalisation) examples misclassified from a given data set.³⁸

Methodology

Data on the effects of the environmental conditions, the structure and the properties of concrete on the degree of damage caused by steel corrosion have been gathered on 11 bridges located in a Croatian moderate continental climate.⁴² The mean temperature in January ranges mostly from 0°C to -2°C. The mean temperature in July is 22°C. The annual rainfall is between 700 mm and 1000 mm. The data were gathered at ten different bridge ages: 1, 14, 22, 24, 28, 29, 31, 33, 55 and 91 years of exposure. The data consist of 213 records.

Table 1. An example for explaining a classification network for feature categorisation

Data set	Actual ANN output			Predicted ANN output		
	Category 1	Category 2	Category 3	Category 1	Category 2	Category 3
Input vector $x1$	1	0	0	1.00	0.00	0.00
Input vector $x2$	0	1	0	0.00	0.50	0.499
Input vector $x3$	0	0	1	0.05	0.2	0.9

The following describes:

- (a) Gathering data on
 - (i) damage and deterioration processes caused by steel corrosion at a certain bridge age
 - (ii) environmental conditions
 - (iii) properties of building materials at the time the damage was observed.
- (b) Sorting the data into a table suitable for training of neural network.
- (c) Building training, testing and validation of a neural network.
- (d) Simulation research using
 - (i) contribution analysis
 - (ii) profile plot (in the diagram $x = \text{age}$ plotted against $y = \text{score}$ for each category) for selected constant parameters.

Data gathering and damage categorisation

Data used in this paper were gathered in two steps.⁴² First, a visual survey of the bridge was conducted with categorisation of flaws on the basis of outward appearance. Second, in situ and laboratory tests of specimens taken from representative spots were examined in detail.

Observed flaws were categorised as

- (a) defects formed during construction of a bridge
- (b) mechanical damage during use of structures
- (c) damage caused by steel corrosion.

For the purpose of modelling, data under (a) and (b) were interpreted as input parameters, while data under (c) were interpreted as output. In addition, data on environmental conditions, concrete properties and concrete compositions were considered as input parameters. Damage caused by steel corrosion has been classified into six categories according to the criteria described in Table 2. The measurements of a half-cell potential, E , according to ASTM C 876-91⁴³ on the 'undamaged' surfaces, indicate risks of corrosion occurrence. Damage categories were chosen so that they corresponded to the types of repair works that would be required to repair the damage.^{44,45}

Based on the visual survey, a number of representative spots of categories 0 to 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. Categories 4 and 5 represent obvious damage; therefore further verifications of the damage categories were not necessary.

Parameters that affect the steel corrosion in concrete (the microclimate conditions, the structure and the properties of concrete) are listed in Fig. 2 and Table 3; an example is given in Table 4. These parameters were used in this study for training the ANN model to predict the degree of damage.

Carbonation depth d ($\text{pH} < 9$) was estimated on drilled cores using the phenolphthalein test. Chloride ion concentrations at surface and rebar level, C_s and C_r represent the water-soluble chloride content and are expressed in terms of the mass of concrete. They were determined from concrete powder obtained by drilling three holes in four layers, each 2 cm thick. The test methods for chloride extraction and titration recommended by the AFREM group⁴⁶ were used. Chloride content values for C_s and C_r are averages of three samples tested. Water-soluble⁴⁷ chloride content is used as an appropriate parameter related to corrosion risk. The actual concrete strength, f_c , was determined from one drilled core for each macro location. A representative location for drilling the core was chosen on the basis of testing the concrete homogeneity by the Schmidt hammer. The porosity of concrete, p , was measured on the 3 cm thick outer layer of the drilled cores, as the general parameter of concrete quality. The variability of the porosity with the cover depth has not been considered. The moisture content in the concrete, w , was estimated as the equilibrium value for average relative humidity of air measured throughout the year. The values for cement content (cc) and water/cement (w/c) ratio were taken from design documentations. In practice cement content (cc , kg m^{-3}) is mixed with reasonable (1–2%) accuracy, while realisation of designed w/c ratio is considerably harder (deviation at quality construction ± 0.02). Since water content in mix design is a significant parameter regarding a structural durability, it was considered in the modelling by relying on design documentation.

The average temperatures and relative environment humidity at the locations of the investigated structures are similar (continental climate) due to their relative

Table 2. The categorisation criteria for damage 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, reinforcement corroded on the surface
5	Spalling of concrete cover Significant loss of rebar cross-section

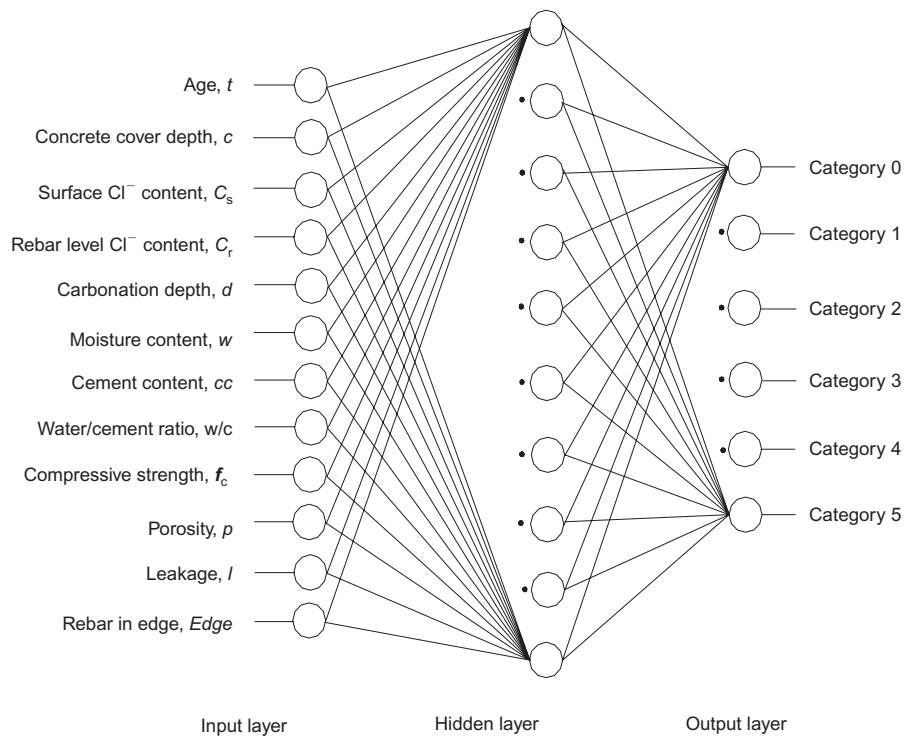


Fig. 2. Architecture of selected network: one hidden layer with ten neurons (for clarity, not all neuron connections are shown)

Table 3. 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	1–91	26.2	21.4
Cover depth, c : cm	0.2–6.5	3.2	1.5
Surface Cl^- , C_s : %*	0.00–0.35	0.071	0.12
Rebar level Cl^- , C_r : %*	0.00–0.30	0.038	0.08
Carbonation depth, d : cm	0.0–3.5	1.8	0.9
Moisture content, w : vol.%	1.7–3.5	2.5	0.5
Cement content, cc : kg/m^3	220–480	370	69.8
Water/cement ratio, w/c	0.42–0.65	0.5	0.05
Compressive strength, f_c : MPa	10.0–75.0	44.7	18.3
Porosity, p : vol.%	10.0–19.1	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

closeness, so the influence of these parameters on the different impacts to the rebar corrosion was not considered. As no data were available for influences of admixtures, type of blended cement, and freezing and thawing cycles, these parameters were not considered.

There are three characteristic spots (three micro locations) within a certain macro location. Characteristic micro positions within the macro location were chosen as places of different characteristic damage categories.

Test results from 213 examined spots are summarised into 213 sets (records) of data. A subset of 12 samples of data for training and testing of the ANN model is given in Table 4. The data are arranged in a patterned format. Data used for network training, testing and validation contain sets of pairs: the records. Each pair consists of an input vector of 12 attributes (influential parameters) and an output vector of six attributes (damage categories). The range, mean value and standard

Table 4. Samples of data for training and testing of the ANN model

Spot No.	Continuous and categorical input parameters														Actual output		ANN output							
	1	2	3	4	5	6	8	9	10	11	12	14	Predicted	Score (3)	Score (0)	Score (5)	Score (4)	Score (2)	Score (1)					
	Cont.	Cont.	Cont.	Cont.	Cont.	Cont.	Cont.	Cont.	Cont.	Cont.	Cont.	Cat.	Cat.	<i>l</i>	<i>Edge</i>	<i>p</i> : %	<i>f_c</i> : MPa	<i>w/c</i>	<i>cc</i> : kg/m ³	<i>w</i> : %	<i>d</i> : m	<i>C_f</i> : %	<i>C_s</i> : %	<i>c</i> : cm
1	28	3-0	0-002	0-002	1-5	2-5	350	0-52	25-52	16-7	0	0	3	0-47	0-01	0-00	0-19	0-07	0-02					
2	28	6-0	0-002	0-002	1-5	2-3	350	0-52	25-52	16-7	0	0	0	0-00	0-94	0-00	0-00	0-05	0-07					
3	28	1-9	0-002	0-002	2-0	2-7	350	0-52	25-52	16-7	0	0	5	0-00	0-02	0-84	0-17	0-00	0-00					
8	28	2-5	0-001	0-000	2-0	2-2	350	0-52	23-81	14-6	0	0	3	0-09	0-00	0-01	0-11	0-00	0-00					
33	33	2-2	0-011	0-003	0-5	1-7	480	0-42	75-00	11-5	0	0	1	0-10	0-00	0-00	0-15	0-13	0-21					
36	33	2-3	0-011	0-011	0-7	3-0	480	0-42	75-00	11-5	0	1	4	0-22	0-00	0-10	0-31	0-17	0-14					
53	33	4-5	0-003	0-003	2-0	3-5	350	0-52	54-50	13-3	0	1	2	0-00	0-05	0-00	0-02	0-43	0-11					
80	14	5-5	0-032	0-000	2-0	3-5	300	0-58	32-70	16-7	0	1	2	0-00	0-10	0-00	0-01	0-23	0-11					
82	14	2-0	0-032	0-032	2-0	3-5	300	0-58	30-20	16-0	0	1	4	0-02	0-47	0-01	0-69	0-02	0-00					
98	91	1-7	0-006	0-002	3-5	2-6	300	0-55	11-00	13-8	0	0	5	0-00	0-00	1-00	0-07	0-00	0-00					
99	91	4-6	0-006	0-002	3-5	2-6	300	0-55	11-00	13-8	0	0	3	0-77	0-00	0-01	0-27	0-05	0-00					
153	24	5-5	0-013	0-004	1-0	2-5	480	0-48	54-40	11-1	0	0	0	0-00	0-82	0-00	0-00	0-25	0-26					

deviation of the continuous input parameters and categories for categorical parameters used in training of the ANN model are presented in Table 3.

Training of the ANN

For building and training the neural network, several software packages were used.⁴⁸⁻⁵¹ To provide an ANN model with good generalisation capability the data were divided into sets of 183 training and 30 validation records (randomly selected 17% of data as validation set). The actual output was presented to the network as a binary (Boolean) output vector³⁸ (Table 1 and Fig. 1). The training procedure comprised iterative calculations of the weight coefficients by minimising the criteria function. After each iteration, the network predicted outputs using training (recall) and validation (generalisation) records. To avoid over-fitting (over-training), and thus enabling a good generalisation capability, training was stopped when the misclassification rate of the validation records started to deviate from the misclassification rate of the training records (network weight coefficients saved for least validation error) (Fig. 3).

Neural network architecture

For modelling purposes a feed-forward neural network using a 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 Fig. 2. 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. The network input layer consisted of 12 neurons representing influential parameters. The output layer consisted of six neurons, for each of the damage categories. There was one

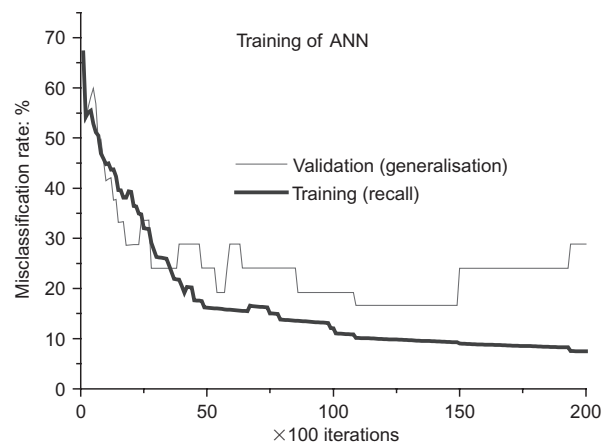


Fig. 3. Misclassification rate of the training and validation records

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 Fig. 2. Elements—that is, attributes in input—and six output vectors were normalised between 0 and 1 to render them compatible with the limits of the sigmoid transfer function, *logsig*. Weights and biases were initialised 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.

Discussion

Testing of ANN model using training data

A successfully trained network is characterised by its ability to predict the damage category for the data on which it was trained. Therefore, the trained network was used to predict the damage category for input parameters already used in the training process; see Table 4 (ANN output). The training process was completed with a misclassification rate of 9.29%, which indicates that 17 out of 183 testing (recall) examples were misclassified. The number of correctly and falsely predicted categories by the developed ANN model for the testing data records is shown in Table 5. The matrix diagonal in Table 5 represents correctly predicted categories. 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.

Validation of the ANN model

The validity of a successfully trained ANN model is determined by its ability to generalise 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 devel-

oped 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 unseen records and was required to predict the damage category associated with each set of values for influential parameters. The number of correctly and falsely predicted categories by the developed ANN model for the validation data records is shown in Table 5. The matrix diagonal in Table 5 represents correctly predicted categories. Validation of the ANN model resulted in a misclassification rate of 16.67 %, which indicates that 5 out of 30 validation (generalisation) examples were misclassified. The misclassification rate is not high for this highly heterogeneous material. Categories 4 and 5 were accurately (more correctly) classified (Table 5). This can be attributed to the uncertainty of the corrosion occurrence evaluation for 'undamaged' surfaces.

The appropriate training and validation sets presented here were obtained by a cross-validation method. The cross-validation method consisted of validating the ANN (with above architecture and parameters) 50 times using random (different) selection of the data, as a 17% generalisation set. Each time the training misclassification rate and the validation misclassification rate were calculated, and ranged from 8.2% to 10.4% and from 13% to 20% respectively. Based on the cross-validation method the ANN with the most frequent value of misclassification rate was taken as the model presented here. The standard deviation for training misclassification rates is 0.93 and for validation misclassification rates is 1.34. Low dispersion validates the selected model.

It should be emphasised that the developed model is valid only for the data range from the investigated bridges. The general application of the model to all structures exposed to rebar corrosion damage is questionable. Only structures in a similar climate, with values of input parameters within the range used in the training, shown in Table 3, can be analysed. The ANN model can do interpolation (demonstrated by validation

Table 5. The number of correctly and falsely predicted categories by developed ANN model for the training and the validation data records (the matrix diagonal represents correctly predicted categories)

	Training						Validation						
	Predicted						True	Predicted					
	0	1	2	3	4	5		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

of ANN), whereas extrapolation is doubtful. New data records obtained by additional surveys and examinations of RC structures should be used for an additional training of ANN and for a validation of the predictions. The more data are available, the more reliable a prediction of damage degree by ANN will be obtained.

Simulation research

Contribution factor. A contribution factor is a measure of the importance of the respective parameter in predicting the network's output, relative to the other input parameters in the network.³² A contribution factor for each input parameter is obtained by adding absolute (coefficient) values of weights that connect one input neuron (variable) to all the inner layer neurons. The higher the absolute sum of those weights, the more the parameter is contributing to the classification. Neural networks are, however, 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 Neuroshell,⁴⁸ where a specific module calculates contribution factors. Based on the final set of weights given by the software,⁴⁹ a contribution factor was calculated. The importance of parameters in descending order estimated by contribution factor analysis (Fig. 4), is as follows: cover depth, *c*; age, *t*; chloride content at rebar level, *C_r*; carbonation depth, *d*; compressive strength, *f_c*; water/cement ratio, *w/c*; water content, *w*; rebar in an edge of structural part, *Edge*;

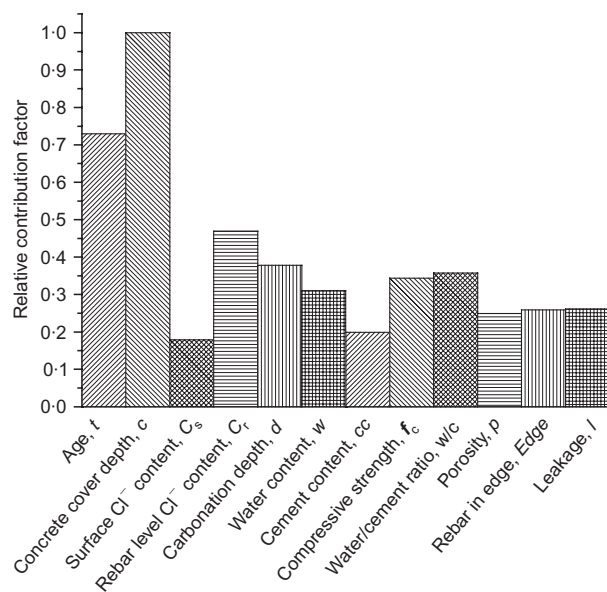


Fig. 4. Contribution factor for individual input parameters in predicting the damage category relative to the most influential input parameter (concrete cover depth)

water leakage, *l*; porosity, *p*; surface chloride content, *C_s*.

Traditionally important factors influencing the rate of deterioration caused by reinforcement corrosion—porosity (*p*), strength (*f*) and w/c ratio—are in the middle of the list of parameters stated above, because they influence the rate and amount of chloride, moisture and carbonation penetration.

To investigate the interactions and sensitivities of the parameters, the parameters listed above were chosen for further simulation research using profile plots (Figs 5–7). The use of the ANN in evaluating the influence (sensitivities) of parameters on the degree of damage, the ranges of values for parameters associated to certain categories and an interaction among parameters has been demonstrated (Figs 5–7).

Profile plot. The output has six categories (six attributes output vectors) dependent on the kind of damage, shown in Table 4 as ‘ANN output’. The model predicts scores (values between 0 and 1) for each of these six categories (outputs) (Table 4). The final category predicted by the model (in Table 4 as ‘ANN output, predicted’) is the one with the highest score. The profile plot is the best way to visualise the fitted ANN model, as it depicts a one-dimensional cross-section of the higher-dimensional fitted surfaces. To generate one profile plot, 100 predictions are performed by varying bridge age between 1 and 91 years (Table 6) and keeping all the others fixed at a pre-specified (mean) value. After the scores for each of the six categories were taken, as predicted by the model, they were plotted against a bridge age. A profile plot enabled studying the ranges of values for given parameters associated to certain categories as well as the interactions among parameters.

For the purpose of simulating the impact of parameters and interactions among parameters, the respective parameter was assigned to mean, minimum and maximum values in its range (Table 6). All other parameters were held at their typical (mean) values shown in Table 3. The results of those simulations are illustrated in profile plots (Figs 5–7).

Figures 5(a), 6(a) and 7(a) show 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 this case, the score of the category 2 prevails after 38 years of exposure when category 3 starts to emerge, therefore requiring repair works. After 60 years the score of category 4 rises, meaning that the structural safety could be endangered.

Figure 5(b) shows simulation performed with fixed cover depth, *c*, at 1.0 cm with all the other parameters from the previous case unchanged. The score of the category 4 now prevails after only six years and reaches a maximum at 24 years when category 5 prevails, showing the importance of concrete cover depth. Fig.

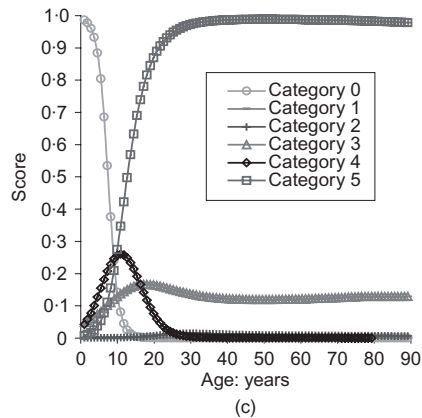
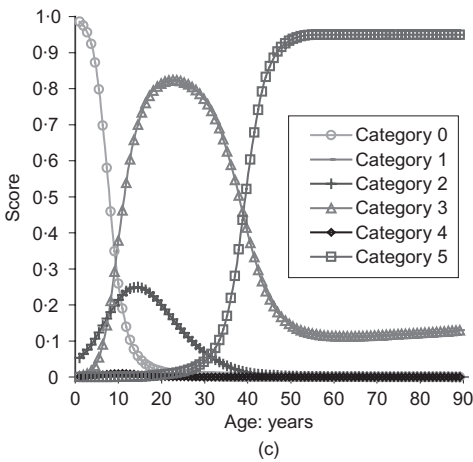
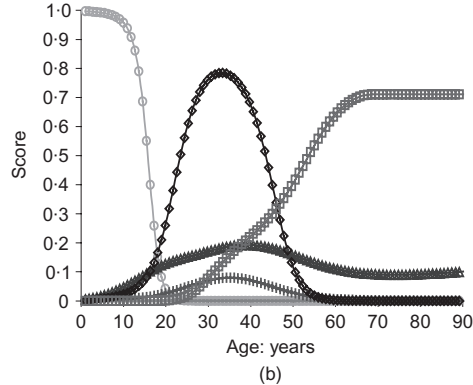
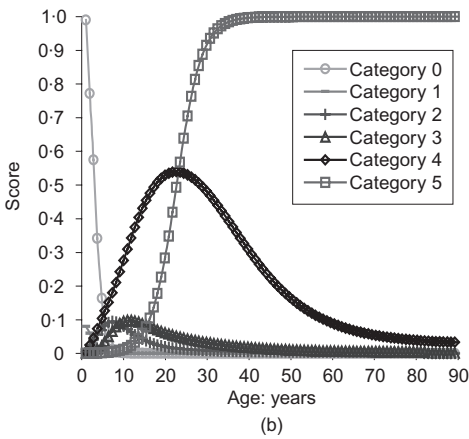
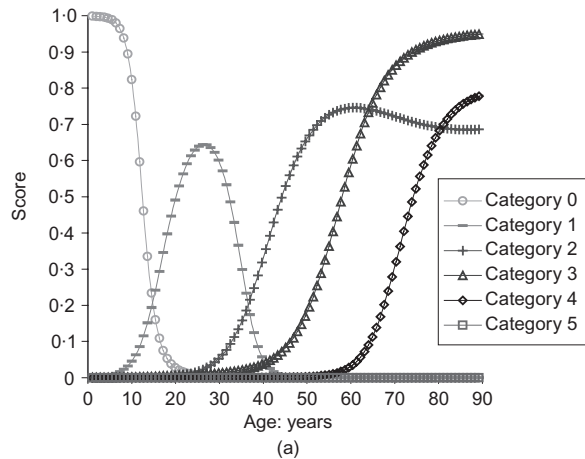
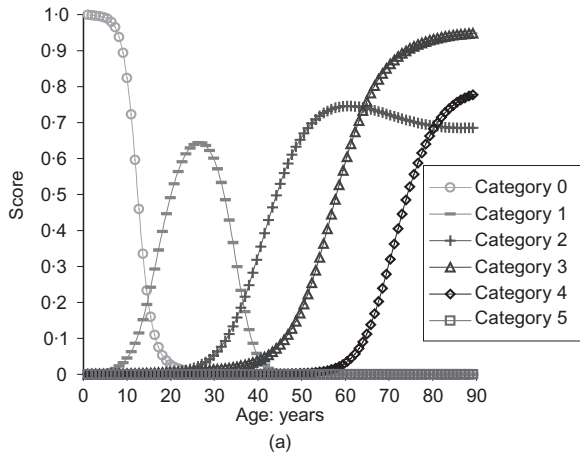


Fig. 5. Profile plots for simulating the impact of the concrete cover depth and rebar position: (a) $c = 3.2$ cm, $C_s = 0.071\%$, $C_r = 0.038\%$, $d = 1.8$ cm, $w = 2.5\%$, $cc = 350$, $w/c = 0.5$, $f_c = 45$, $p = 14$, $edge = 0$, $l = 0$; (b) $c = 1.0$ cm, $C_s = 0.071\%$, $C_r = 0.038\%$, $d = 1.8$ cm, $w = 2.5\%$, $cc = 350$, $w/c = 0.5$, $f_c = 45$, $p = 14$, $edge = 0$, $l = 0$; (c) $c = 3.2$ cm, $C_s = 0.071\%$, $C_r = 0.038\%$, $d = 1.8$ cm, $w = 2.5\%$, $cc = 350$, $w/c = 0.5$, $f_c = 45$, $p = 14$, rebar in an edge of structural part $edge = 1$, $l = 0$; mean values for other parameters and categories as shown in Table 3

5(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. Fig. 6(b) shows the influence of maximum carbonation

Fig. 6. Profile plots for simulating the impact of carbonation depth and chloride ion concentration: (a) $c = 3.2$ cm, $C_s = 0.071\%$, $C_r = 0.038\%$, $d = 1.8$ cm, $w = 2.5\%$, $cc = 350$, $w/c = 0.5$, $f_c = 45$, $p = 14$, $edge = 0$, $l = 0$ (b) $c = 3.2$ cm, $C_s = 0.071\%$, $C_r = 0.038\%$, $d = 3.5$ cm, $w = 2.5\%$, $cc = 350$, $w/c = 0.5$, $f_c = 45$, $p = 14$, $edge = 0$, $l = 0$; (c) $c = 3.2$ cm, $C_s = 0.35\%$, $C_r = 0.30\%$, $d = 1.8$ cm, $w = 2.5\%$, $cc = 350$, $w/c = 0.5$, $f_c = 45$, $p = 14$, $edge = 0$, $l = 0$; and with mean values for other parameters and categories as shown in Table 3

depth, $d = 3.5$ cm (instead of mean value $C_s = 1.8$ cm). All the other parameters remained unchanged as those for Fig. 6(a). Owing to the higher carbonation depth than the concrete cover depth, category 4 prevails after only 20 years. Fig. 6(c) shows the influence of higher chloride ion concentration, $C_s = 0.35\%$ (instead

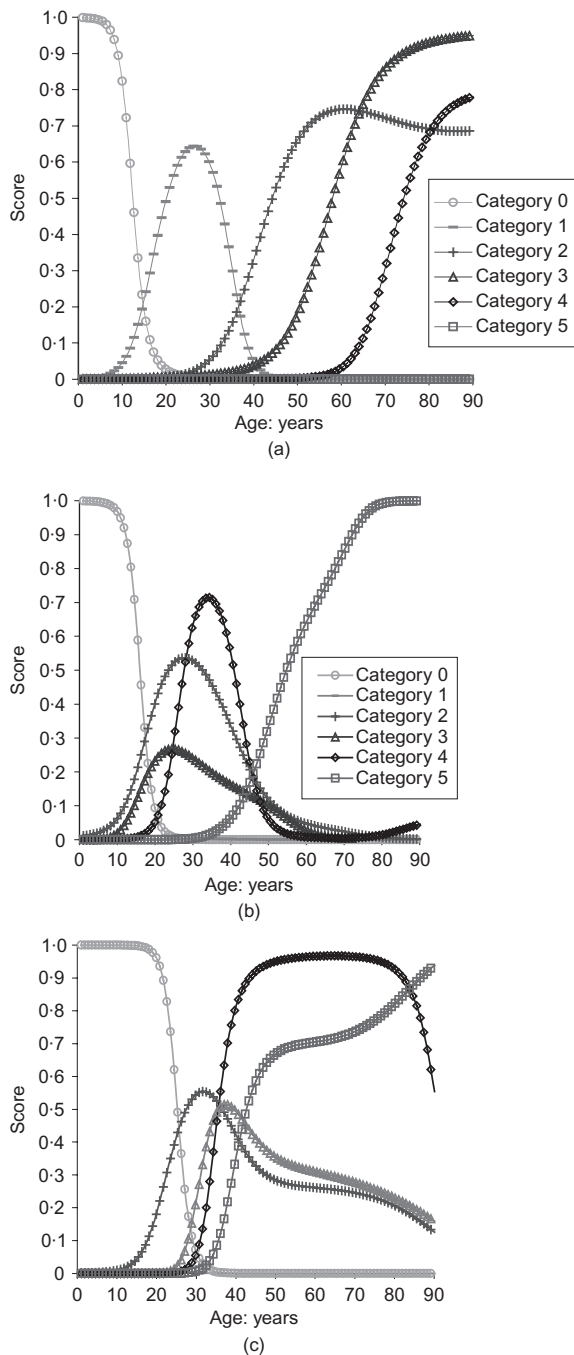


Fig. 7. Profile plots for simulating the impact of water leakage and concrete cover quality: (a) $c = 3.2$ cm, $C_s = 0.071\%$, $C_r = 0.038\%$, $d = 1.8$ cm, $w = 2.5\%$, $cc = 350$, $w/c = 0.5$, $f_c = 45$, $p = 14$, $edge = 0$, $l = 0$; (b) $c = 3.2$ cm, $C_s = 0.071\%$, $C_r = 0.038\%$, $d = 1.8$ cm, $w = 3.3\%$, $cc = 350$, $w/c = 0.5$, $f_c = 45$, $p = 14$, $edge = 0$, $l = 1$; (c) $c = 3.2$ cm, $C_s = 0.071\%$, $C_r = 0.038\%$, $d = 1.8$ cm, $w = 2.5\%$, $cc = 350$, $w/c = 0.65$, $f_c = 10$, $p = 19$, $edge = 0$, $l = 0$; and with mean values for other parameters and categories as shown in Table 3

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 Fig. 6(a). After only ten years the structural safety could be endangered.

Fig. 7(b) shows the impact of water leakage. For water content value, $w = 3.3\%$ was assigned. All other parameters remained unchanged as those for Fig. 7(a). Category 0 ceases to prevail after 17 years, when category 2 and 3 start to emerge. Category 4 prevails after 28 years, and category 5 after 47 years. Fig. 7(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 (Fig. 7(a)). Category 4 prevails after 36 years.

Likewise, the impact of other individual parameter values on the damage degree and interactions among input parameters were investigated. The significance of the various influence factors as a function of age is difficult to deduce quantitatively from profile plots (in a form of a one factor number) owing to the different evolution of a number of damage categories during ageing as well as the interdependence of interactive parameters, but a comparison of respective profile plots shows qualitatively the impact of the parameter and enables the range of ages associated with each category to be studied quantitatively.

Conclusions

Damage to RC structures caused by steel corrosion as a function of bridge age, concrete structure and environmental conditions is difficult to predict analytically. As the parameters are time dependent and show high scatter, a probabilistic-like approach was adopted using an ANN modelling with fuzzy inferences for damage prediction. It was demonstrated that the developed ANN model was successfully trained and validated for the range of data from the investigated bridges. An ANN method for evaluating the relationships of the results and influencing variables was described. The model was able to recognise and evaluate the effect of individual parameters on the damage caused by steel corrosion. Simulations of parameter interactions and impact were performed. Using the developed ANN model it was possible to rate the more influential parameters by contribution factor analysis. The results could be used to predict the extent and severity of degradation in a structure during its service life, to plan the maintenance and to assist in the design and restoration of RC structures.

Unfortunately, data on admixtures, type of blended cement, and freezing and thawing cycles were not available. Possibly, if included, the ANN model would form a pattern that better determines its output. New data records obtained by additional surveys and examinations of RC structures should be used for an additional training of ANN and for a validation of the predictions. The more data that are made available, the more reliable prediction of damage degree by ANN can be performed.

Table 6. Explaining a profile plot generation

Reference									
Simulation No.	Input parameters				Predicted output				
	<i>t</i> : years	Impact	Continuous	Categorical	1	2	3	4	5
1 : : : : 100	1 : : : : 91	Mean values held (Table 3)		Typical, as in Table 3	Score (5 × 100 values)				
Impact simulation									
	Input parameters				Predicted output				
	<i>t</i> : years	Impact	Continuous	Categorical	1	2	3	4	5
	1...91 1...91	Min. Max.	Mean Mean	Typical, as in Table 3	Score				

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