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Chloride-Induced Corrosion of Reinforcement in Concrete Structures Predicted Using Artificial Neural Network

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ABSTRACT

Using the trained successful neural network, a sensitivity analysis to determine the influence of variables such as changes in maximum width of cracks, peels off concrete, exposed reinforcement fittings, etc., shall be determined on the injured level.The mechanical properties of concrete are determined, and steel corrosion in concrete embedded function is analyzed using the effective voltage. Artificial neural networks have been shown to have a structure similar to the function of biological neurons and enjoy the unique ability to self-learning, mapping, and functional approximation. The output can be used to predict the extent of the damage phase of the lifetime maintenance plan.All the stress level of concrete, water-cement ratio, cement, fine aggregate, coarse aggregate, cement ratio and age was tested as an input parameter and is made of all training and testing was done in MATLAB.

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INTRODUCTION

Continental environments often are threatened only after 20 to 30 years and heavy repairs are necessary. After 15 years in the marine environment from exposure to destructions, heavy repairs are required. It is expected that concrete structures to be permanent and then, regardless of the initial and maintenance are made. In order to develop an efficient repair and maintenance program, it is important to assess the durability of existing structures. Hence, a lot of researches have been done on vulnerability assessment, design and durability of concrete repair. However, there is a lack of data and the complex mechanism limits the quantitative assessment of structural deterioration in the demolition of structures. One the most important results of the durability of concrete structures is corrosion of reinforcing steel as a result of chloride ion penetration. Prevention of corrosion of armature is primarily used in the design of high quality of concrete and affordable coverage.

2 - The cover concrete bridges exposed to chlorides:

1-2 - Mechanism of chloride-induced corrosion of reinforcement in concrete structures:

The main cause of deterioration of the concrete slab covering in North America is resulted from chloride on corrosion of steel bars. Chloride is obtained by ice salt that penetrates the concrete slab, and reaches the top layer of armature and accumulates until reaching a critical concentration in the literature as "chloride threshold level “where in the steel reinforcement begins to corrode. Reinforcement steel referred to is protected by Pass the iron oxide film on its surface in a highly alkaline solution in the pores of the concrete. Released chloride in the dissolution of iron oxide layer, followed by dissolution of the steel.Hence, the corrosion of armature starts after passing through the film, then will be broken by chloride ions arriving at concentrations above the threshold on the steel surface (assuming that both oxygen and moisture for corrosion exist), and the activity of electrochemical reactions begins that produce corrosion or rust to create. Corrosion products, water uptake make a considerable increase in size, and induce stress in the surrounding concrete, causing cracking in concrete or delaminate to lose cohesion between reinforcement and concrete surface and may eventually leading to failure of concrete structures due to reduce in coherence, strength and flexibility [1].

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3 - Time to corrosion prediction models using artificial intelligence:

3-1 - integrated neural network model for Monte Carlo simulation:

Artificial Neural Networks (ANN) are for data processing system comprising a number of interconnected simple computational elements as "neurons" inspired by the architecture of the shell of the brain (Fausett 1994), which is addressed.ANN method uses simple arithmetic operations to solve complex problems that are ill-defined and have a high degree of nonlinearity. Using ANN to predict the deterioration of the bridge for the first time is presented by So banjo (1997). More advanced ANN model was developed by Tokdemir *et al*. (2000), which additional dominant factors, such as class highways, design, materials, and traffic volume is incorporated. Time series based on ANN model was developed by Lu *et al*. (2001) to predict the future state of the industry for the conditional rule [1].

In this study, a back propagation neural network (BPNN) was used approximately for the relationship between the onset of the upper layer of reinforcing steel corrosion in concrete bridge deck and its governing parameters. Although other neural network architectures, such as generalized regression neural network (GRNN) and genetic adaptive network (s) can provide faster training, BPNN is selected by Moselhi *et al*. (1991) due to its mapping capability and wide application in civil engineering (1991).

ANN model is designed to detect network architecture (i.e. the number of input neurons, output neurons, hidden layers and neurons in each hidden layer) and network configuration (activation function and learning rate). Network architecture consists of four neurons in the input layer and one neuron in the output layer, which represents the onset of corrosion (TI). Optimal numbers of hidden layer according to the experiences between the generalization and mapping capabilities of neural networks have been identified.In fact, due to the ability of these networks to approximate any nonlinear mapping and designation function of unknown relationship, Hornik *et al*. (1989) input and output variables is limited to one or two hidden layers.ANN three-tier faster computing and have better generalization ability and Tamura (Tateishi 1997) also reported that will be 95% of applications based on three-layer network with only a few exceptions (Simpson, 1996).Neural Network Simulator "BrainMaker"(California Scientific Software 1996) developed a three-layer BPNN model was used for this program. These models need to be trained and validated before using it to illustrate input-output relationship between input parameters and the onset of corrosion. Using Monte Carlo simulation (MCS) for the generation of the training and test sets according to statistical distributions governing parameters obtained from the data was passed. Input values of the ANN model is randomly generated and fed into the mechanistic model to obtain the output values of the neural network training and credit to apply. A total of 200 cases were created and divided into three categories: (1) Training set (60%), (II) test set (20%) and (III) the validation set (20% of cases). Training set was used to refine the network weights. Test set was to measure network performance while training the network was used to optimize the design. Validation set was used to evaluate the overall performance of the trained network.

The optimum number of neurons in the hidden layer, which leads to reliable results through trial and error method, determines as the use of a network of nerve cells that is not able to "learn" the problem, while makes the use of multiple neuron network "memory" and not "learn”. Optimal number of hidden neurons is sufficient to achieve a trade-off between these requirements and ensure that satisfactory results cannot be determined in advance, however, rule of thumb known as Baum - Haussler and Baum (Haussler1988) was used to provide estimates roasted, and it was the first number that follows:

N hidden in which the number of hidden neurons; N train: number of training examples; N tolerance: error tolerance; N pts.: number of data points in each training example and N output: Number of output neurons. Higher and lower numbers of hidden neurons were used in the trial and error method, and network performance of each number was evaluated by the root mean square error (RMSE) and mean absolute error (MAE) by the test set. The optimal number of hidden neurons, both in size to 10 minimizes the error was found.

For network settings, functions are handled with connecting to the input and output layers of the network in a specific area that will enable efficient network. This range is usually scaled between 0 and 1 or 1-1. Simulator activation functions are used, such as sigmoid, threshold, step, linear, and Gaussian functions that are presented. Selection is the most appropriate function of a matter of trial and error. Scaling range flake between 0 and 1 using the logistic sigmoid activation function to the best settings for the current program was provided. Learning rate that is the detection rate of the connection weights during training is adjusted based on a specified network performance. Learning rate to change from 1.0 to 0.1 according to the percentage of correct predictions was determined in every instruction cycle (from 100% to 0%) [1].

4 - Neural networks and their application to damage assessment of reinforced concrete structures:

4-1 - Neural Networks:

A network of artificial neurons, usually called neural network. The data processing system consisting of a number of simple, widely interconnected processing elements in the brain is thought to induce the architectural theme of structure. Thus, neural networks are often unable to do the things that people are doing well, but the poor often do ordinary computer. Characteristics and capabilities of neural networks are not provided by any other technology. Approximate functions of neural networks are the raw sample data [2].

F generated unknown function gives pair example from a set of input vectors X = (x1, x2, x3... xn) in the n-dimensional space and a set of output vectors Y = (y1, y2... yn) the space M - next.It can be as Y = f (x) can be expressed that modified parameters of the example in expressed sample data such as neural connection weights between artificial neurons respond to input, output, and approximate to input-output responses of the nervous system and the unknown estimable example.

In this study, the sigmoid transfer function is expressed as the equation (L) may be used where 6 is the slope of the sigmoid [2].

4-2 - Functional damage assessment of reinforced concrete structures:

Quantitative damage assessment of reinforced concrete structures due to lack of sufficient data, the diversity and complexity of the mechanism of injury patterns of damage does not have been done. The degree of injury is usually shown by four or five levels, the judgment of experienced engineers inspection is identified based on visual observations. The number of declining structure increases year over year, and it cannot be expressed to increase the experts to assess the damage. The adjusted data and the development of expert system for assessing damage checkpoint are to reduce the demands. In this study, the use of such an important features of neural networks is done that have the ability to model the relationship between input – output of the complex system and training it is done by efficiently use of the large shrimp of a set of given inputs of the actual data and a sensitivity analysis to determine the impact of each variable changes in the level of damage is conducted [2].

5 - Damage Assessment System Using Neural Networks:

TEPCO inspected the thermal power plants along the shore of Tokyo Bay in the damage modes. Inspections are conducted every half year since 1983.In order to efficiently use of the data obtained, a research project started in which the various transformations are considered by computer assisted systems, including data base systems, statistical analysis systems, damage assessment systems, and damage forecasting systems. Damage assessment system is proposed in this paper is an obtained result of the project [2].

5-1 - selected variables for neural network:

According to the environmental conditions where the construction of thermal power plants is placed, attention is centralized on the chloride, which causes localized damage to the RC structure. In order to find the important variables that may severely damage due to the chloride of reinforced concrete structures injury, 13 variables were selected as inputs of neural networks and four variables were chosen as the desired output. However, the real judgment is often different from what it has been determined by the level of injury. Judging has been carried out by the experience and sense of Engineers inspections [2].

5-2 – Training for Neural Networks:

In this study, four-layer back propagation neural network is used that is done from databases sorted by TEPC0 [8], 18 periodic inspection data of RC beams as patterns. Back propagation network consists of 13 neurons in the input layer, 15 in two hidden layers and 4 in output layer. Network was trained successfully with small error.

To evaluate the usefulness of the neural network system is expanded, 14 data from the database TEPCO] were selected, and their injuries were estimated using a neural network system [2].

5-3 - Sensitivity analysis of neural modeling:

Sensitivity analysis is used to determine important variables that can severely affect damage levels of RC structures. The sensitivity analysis of the trained neural network was used as a mapping function to model the input-output relationship such as y = f (x) where x is a set of input vectors with 13 elements and Y output vector series, the output of which has 4 elements.

Determining the optimal number of hidden layers, number of processing elements and network parameters are obtained largely by trial and error process can be achieved. The development and testing affects more than 100 networks. The input layer of the network consists of 12 neurons representing the influential parameters. The output layer consists of six neurons for each category is affected.

There is a hidden layer consisting of 10 neurons. Sigmoid transfer function was logosid; it is used as the activation function for all processing units (neurons) with full communication connections between units in different layers within the network, the elements of the feature vector of the input and six outputs between 0 and 1were normalized with sigmoid transfer function constraints, Logosyd. Below the lattice parameter values used are: learning parameter = 0.5 and momentum = 0.5. Surface is I11 is given by considering the maximum width of the crack [2].

6 - Training and validation of the ANN model:

Feedback of neural network was produced using the back propagation algorithm. Teaching methods include iterative weighting coefficient calculated by minimizing the criteria function. After each period, the output network is predicted with the use of Learning (CALL) and validation (generalization) criteria. To avoid over-fitting (overtraining), thus enabling a good generalization, the training was stopped when the floor rate of credit records, educational records will start to deviate from the class rate. Determining the optimal number of hidden layers, number of processing elements and network parameters is largely educated and a process of trial and error testing, training is achieved in networking over 100 times. Sigmoid transfer function, logosig was done as activation function and all the units connected to work done in different layers. The weights and the bases are randomly initialized in initial weight range = -0.3 to -0.3. The following values of the parameters used in the learning network and the Acceleration parameter = 0.5 = 0.5 successfully trained network is characterized by its ability to predict damage for a given category in which it was trained. Learning process was completed by classification rate = 9.3% (7.4%). Verification models are trained by ANN successfully predicted their ability to generalize beyond the training data set, and it has to be provided when the new offering is unfamiliar.A total of 30 criteria were excluded from the offered training. ANN model validation is done by classification rate = 16.6% (13.3%).the floor rate is not very high for this heterogeneous material [3].

7 - Previous studies by ANN:

Yeh, Casper Kyuik and Ley and Sery and Lee enforced different ways of prediction based on NNs to predict the properties of ordinary concrete and high performance concrete. Diaz and Poulyadou using the neural networks to predict the strength and depression of ready mixed concrete and concrete with high resistance, in which chemical additives or mineral additives were used. According to the authors, the neural network models are the better performance than those with multiple regressions, especially in reducing the spread of forecasts. Aztas *et al*. (2006) NN can be used to develop a method for predicting the compressive strength of HSC with reasonable efficiency. They are arranged for the data used for the NN model in the form of seven input parameters that cover the water-binder ratio and water content ratio, fine aggregate, fly ash content, the air being drawn content, regular replacement of steam silica. The proposed NN model predicts the compressive strength of HSCs recession. Bykasgaloo *et al*. state using soft computing techniques coding genes and neural networks to predict 28-day compressive strength of Portland cement composite. Besides they use the stepwise regression analysis forecasts an idea about the power of soft computing techniques in comparison with classical statistical methods [4].

8 – Training:

98 test beams were grouped randomly into two sets: a training set containing Persian date 79 beams 79, and set credit with 19 beams. To avoid reducing the learning rate, the output and input data were scaled near the endpoints.After conducting a number of trials, the network parameters that were considered in this study are as follows: Number of input parameters: 11, number of output parameters: 1, number of hidden layers: 1, number of hidden neurons: 11, hyperbolic tangent activation function in the first layer and the hidden layer, the last layer the identity function in the last layer, speeding up training of the back propagation algorithm, the acceleration factor: 0.9; learning Rate: 0.1; cycle of education: 5000, a network is trained, carefully the output of a network using the mean square error that is controlled is as follows:

Where TI experimental values and the Xi values predicted by the network are placed. The value of this error is 0.0111 and 0.0039 for the validation of the whole experimental set (training + validation.) In addition, the ratio between the experimental and predicted shear strength for the validation set, resulting in calculation of an average value of 0.9605 with a coefficient changes of 16%.All previous results show that the error is reduced to an acceptable level, and network learning can be correct if the possibility of obtaining better results with other configurations cannot be discarded [5].

9 - ANN model verification:

Correctness of ANN model was successfully trained to generalize its ability to predict beyond the training data set and for good conduct was determined and it was provided when was unfamiliar with the new data within the range of the input parameters used in the training. Thus, the ability of ANN models should be confirmed to predict the result of a new category of damage parameters excluded from the training data. The model was presented with a total of 30 hidden rules and the prediction of the damage groups associated with each set of values of presented parameters.ANN model verification is leading to the classification rate of 16.67%, which indicates that 5 of the 30 validations (generalization) were incorrectly classified. The wrong class rate is not high for this highly heterogeneous [6].

Categories 4 and 5 were carefully (more correctly) classified. It can be attributed to corrosive uncertainty for repeated assessment of 'normal' levels. Proper training and validation sets are presented here to provide a cross-validation method. Cross-validation method is included the credit of ANN with architecture and the above parameters is 50 times using (different) set of random data as a whole 17 percent. Each time the amount of training and validation classification rate is calculated, and from 8.2% to 10.4% and ranged from 13% to 20% of a determined time. Based on interaction with the regular ANN accuracy rate of classification error as the model, it is presented here. Standard deviation is 0.93 for the training class rate, so there is a 1.34 credit class. Low dispersion of the selected model is confirmed [6].

It should be emphasized that the developed model is for the range of the bridge data validity. General application of the model for all structures exposed rebar corrosion damage is questionable.

Only in a climate similar to the values of the input parameters used in the area of education can be analyzed. ANN model can be interpolated as shown by the accuracy of the ANN, while extrapolation is dubious. New data and review additional documents obtained by the examination of reinforced concrete structures should be used for additional training ANN and predictive validity. More data are available, a more reliable prediction ANN than damage the balance degree will be obtained [6].

10 - Experimental Methods:

10-1 - Set the input nodes:

Primary causes of damage in reinforced concrete using longevity and injury based on practical engineering problem analysis and theoretical studies have found that is as follows.

(1) Environmental factors: The main causes affecting the engineering of concrete containing S0 ~ 4 -, Mg and ~, CI, Ca 2 + hydronium concentration, reaction zones, and the dissolution of the freezing cycle and alternately dry and wet conditions and had eight aspects.

(2) Cement: Cement penetration in concrete engineering of cement, cement ratio, combined ratio, water and ash and cement dosage was five of eight.

(3) the defense level

(4) plurality of configuration

Cycles of freezing and dissolving by 0 or 1 is used.

Alternation between wet and dry Cement Type: Split Portland Cement Joint, Joint Anti Portland cement, Portland cement, Portland cement, bauxite, and advanced anti-Portland type V, from 0 -4 is characterized.

RC: without blending into the water loss, dehydration, advanced composition on average, three levels combination lower water levels.

10-2 - Set the output nodes:

Due to practical engineering demands for lifetime corrosion resistant concrete sulfate diagnosis and evaluation, the output of the network are defined by two aspects:

One area is the lifetime, the other being damaging levels.

Both are confirmed by the following facts: The actual range is lifelong.

Damage level is divided into seven levels:

First level: is a good, solid, few or no cracks, hard to increase or decrease the intensity due to its design.

Second: Show spots, a few nests, leaving the non-hole aggregate level, a reduction of about 10% compression.

Level III: The aggregate started showing up, the steel began to erode, cracks and holes are filled with water.

Level IV: The Show strength, show some rocks, erosion of corroded steel.

Fifth level: bursting out at the edges, corners are rounded, medium steel corrosion.

Level VI: serious damage, tangles become partially into the batter, seriously exposed rusted steel corrosion.

Level Seven: fully damaged cannot be used [7].

Conclusion:

• ANN and CBR models provided a good mapping between the governing parameters (depth of concrete cover, chloride concentration, apparent diffusion coefficient, and threshold chloride concentration) and showed the onset of corrosion.

• ANN and CBR models have the potential for uncertainty analysis of computationally efficient mechanical model used to predict the occurrence of corrosion.

• The results showed that the integration of ANN and CBR techniques and Monte Carlo simulation provides a good prediction when compared with the field data.

• The model can be extended to investigate the structure and design of planned maintenance works Reconstructive is useful. Unfortunately, data on additives, type of cement mixing and freezing and thawing cycles available. Probably by including in the model, the ANN model is better than that of output.

• In summary, we can conclude that ANN is a useful tool for modeling the corrosion current. Unfortunately, data on additives, blended cements, and freezing and thawing cycles available. Probably, if integrated, ANN model is a better model for determining the output is obtained.

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