Bulletin of the *Transilvania* University of Braşov • Vol 9(58), No. 2 - 2016
Series III: Mathematics, Informatics, Physics, 99-108

INTELLIGENT PREDICTION OF CONCRETE CARBORATION DEPTH USING NEURAL NETWORKS

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Abstract

Carbonation problem in concrete has the potential to cause severe degradations in structures and therefore, its accurate prediction is critical in the field of civil engineering. This study involves the results obtained from the preliminary investigations on the use of artificial neural networks (ANN) as a non-destructive method for the prediction of carbonation depth in concrete. A total of 225 experimental cases obtained from the related literature have been used as the training and testing data set, with 18 different input parameters identified to be influencing the output, which is the carbonation depth measured in concrete. Two learning schemes were suggested with varying training: testing data distributions and three different values for hidden neurons were tested in combination. Results show that the use of ANN for the prediction of carbonation depth has a potential to provide predictions with satisfactory accuracy. Variations in the coefficient of determination (R), the mean squared error (MSE) and in the number of iterations required for learning, within the proposed changing combinations of training:testing data distribution and the number of hidden neurons has been discussed. The combination of highest coefficient of determination (R), and the lowest mean squared error (MSE) that were determined as 0.975 and 0.0018 respectively, was observed when CGP method is used with 50%:50% training:testing data distribution) and with 10 hidden neurons.

2010 *Mathematics Subject Classification:* Primary 92B20, 68T10; Secondary 82C32, 93C85.
Key words: concrete carbonation, carbonation depth prediction, artificial neural networks, conjugate-gradient method.

1 Introduction

Carbonation is a deleterious concrete durability problem that occurs as carbon dioxide (CO2) gas in the atmosphere. It progresses through the pores of concrete,

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reacting with cement hydration products. This reaction is known to yield alteration in the concrete characteristics; a relatively denser reaction product, calcium carbonate (CaCO3) is formed and the naturally alkaline pH level of concrete pore solution is converted to acidic [1-4]. The alkaline nature of pore solution is known to provide protection for steel bars in the reinforced concrete structures against corrosion. Therefore, a continuous progress of carbonation process in concrete may yield severe deteriorations in the structures as a result of initiated steel corrosion, which is also known to cause expansion and cracks in concrete.

Therefore, understanding the progress of carbonation process ongoing in concrete structures using prediction methods has the potential to enable us to take precautions for the expected future damages and therefore, provides significant advancements in increasing safety as well as decreasing economical losses.

Traditional experimental methods for detecting carbonation depth in concrete are largely destructive [5-7] and usually not cost effective. Moreover, these traditional experimental methods only provide information on the specific case tested, without providing insight on the effect of each parameter influencing the progress of carbonation and therefore the extent of related future damage in the structures.

Artificial Neural Networks (ANN) have been widely used in various disciplines [8-15] and have been proven to be a reliable tool for performing predictions, enabling the users to have understanding on the effect of influencing input parameters on the determined output of concern.

Previous studies carried out by [16-17] have shown that Artificial Neural networks (ANN) have the potential to yield promising results in developing models cable of predicting carbonation depth based on factors influencing the progress of carbonation process in concrete. However, additional studies are required to provide further understanding on the influence of parameters and learning schemes selected in the ANN model for acquiring improved accuracy in prediction.

The objective of this study is to evaluate the feasibility of ANN as a non-destructive method in the prediction of carbonation depth in concrete by two selected learning schemes by considering a detailed list of factors; in the form of [18] input parameters that are known to affect the progress of carbonation depth in concrete. Information on the learning schemes, including testing:training data distribution and selected hidden neuron values, as well as the ANN algorithm used are explained in detail in sections below.

2 Methodology

In this study, the four conjugate gradient algorithms used are; Scaled conjugate gradient backpropagation (SCG), Conjugate gradient backpropagation with Powell-Beale restarts (CGB), Conjugate gradient backpropagation with Fletcher-Reeves updates (CGF) and Conjugate gradient backpropagation with Polak-Ribire updates (CGP). All the methods except SCG employ line search which is calculations for global error function or its derivative. SCG in order to scale the step size, uses the Levenberg-Marquadt method.

2.1 Data selection and use

The data used in this study has been extracted from related literature. Numerous experimental studies in the related literature have been reviewed and data sets that include sufficient and comparable experimental information have been selected. In this way, a total of 225 sample cases obtained from 9 different experimental works [20-28] was obtained to be used in this study.

Data set for each sample case is analyzed and as a result 18 input parameters that are known to influence progress of carbonation process are defined. Table-1 demonstrates these 18 input parameters that can be classified under 6 main groups. In all cases, cements blended with fly ash were used as the binder in concrete. In order to differentiate between the different types of cements and to identify their influence on concrete characteristics, contents for each cement compound have been considered as distinct input parameters. Similarly, as each study used different types of fly ashes, the individual contents of each fly ash compounds were considered as inputs. Note that even though the basic compounds of cement and fly ash seem the same, they should be considered separately due to being in different form and having different reaction rates when in cement and in fly ash forms. Besides cement and fly ash compositions, concrete mix design parameters, curing conditions applied to prepared concrete samples, conditions of the environment that the samples were exposed to and the age of each sample experiencing carbonation were considered as input neurons.

This study has focused only on one output parameter, which is the carbonation depth in concrete samples observed in each case. Data were normalized within the range of 0 and 1 and normalization was applied to each parameter within its set in order to minimize scaling variable towards zero thereby reducing their significance due variation in units.

	Influencing Factors	**Relevant Input Parameters**
Group-1	Cement Composition	4 parameters= CaO, SiO_2, Fe_2O_3, Al_2O_3 contents
Group-2	Fly Ash Composition	4 parameters= CaO, SiO_2, Fe_2O_3, Al_2O_3 contents
Group-3	Mix Design Parameters	4 parameters= Cement content, Fly Ash content, Water content, Water/binder ratio
Group-4	Concrete Curing Conditions	2 parameters= Relative Humidity, Duration of curing
Group-5	Environmental Conditions	3 parameters= CO_2 content, Relative Humidity, Temperature
Group-6	Time	1 parameter: Sample age

Table 1. Groups of factors influencing concrete carbonation and relevant input parameters belonging to these groups that are used in this study.

2.2 Network training

A three-layer feedforward backpropagation algorithm with one input layer, one hidden layer and one output layer was used on MATLAB 2015a platform for training of the network.

Two different learning schemes were established taking into consideration the reliability of results from previous studies on NNs [29] consisting of 40:60 and 50:50 training-testing ratio. Under each learning scheme, 4 different conjugate-gradient methods were used. The best combination of parameters that will minimize the mean squared error (MSE) between measured and predicted depth and at the same time establish a good generality of the network was identified.

There is no established rule in the selection of hidden neuron size [30]. Different researchers [31-32] have made proposed models for estimating number hidden neurons, however these models cannot be generalized to be valid for all cases involving neural networks [30]. A parametric analysis was carried out with varying numbers of hidden neurons, and therefore a decision tree was formed. Initial training of the network started with 5 hidden neurons in the hidden layer. Further analysis was performed with 10 and 15 hidden neurons to measure the sensitivity of the network towards the learning scheme. A logistic sigmoid transfer function was used in the hidden layer. The scale factor and initial step size were determined and the model was trained accordingly. Network goal was set to 0.001 over 20000 iterations.

For learning parameters, alpha (Scale factor that determines sufficient reduction in performance) was set to 0.1, 0.0001, and 0.3 for CGB, CGF, and CGP respectively. Beta (Scale factor that determines sufficiently large step size) was set to 0.001, 0.01, 0.001 for CGB, CGF, and CGP respectively. SCG algorithm sigma was 5.00E-05 for the two proposed learning schemes.

3 Results and discussions

The results obtained for the values of correlation coefficient (R) and mean squared error (MSE) as well as iterations required for learning with the aimed accuracy in each case are presented in Table 2.

Learning scheme	Optimization method	Hidden neuron distribution								
		5H			10H			15H		
		R	MSE	iter	R	MSE	iter	R	MSE	iter
LS1-40:60	CGB	***0.966***	***0.0025***	1120	0.953	0.0032	419	***0.965***	***0.0024***	***390***
	CGF	0.939	0.0041	1077	0.95	0.0035	***392***	0.942	0.0040	607
	CGP	0.963	0.0025	1828	***0.966***	***0.0023***	464	0.946	0.0037	487
	SCG	0.947	0.0036	***688***	0.96	0.0027	489	0.941	0.0043	523
LS2-50:50	CGB	0.967	0.0023	683	0.97	0.0021	643	***0.964***	***0.0025***	841
	CGF	0.939	0.0043	1141	0.966	0.0024	661	0.96	0.0028	697
	CGP	***0.97***	***0.0020***	994	***0.975***	***0.0018***	***547***	0.956	0.0031	***395***
	SCG	0.967	0.0023	***550***	0.969	0.0022	675	0.963	0.0029	600

Table 2: Results obtained for the two defined learning schemes (LS-1 & LS-2) with varying training:testing data distribution for selected hidden neuron values.

LS1 and LS2 comparison for constant 5 Hidden Neurons: the selected distributions of training:testing data is observed to yield a significant difference mainly on the number of iterations. Increase in the training data from 40% to 50% is observed to yield a significantly lower number of iterations. This tendency is even more evident for CGB and CGP methods within this case. The coefficient of determination R and mean squared error MSE are observed to be improved only slightly as a result of this increase in the training data set while hidden neuron value was kept constant at 5.

LS1 and LS2 comparison for constant 10 Hidden Neurons: for this case of relatively increased number of hidden neurons, the coefficient of determination R is observed to be improved more significantly for each method with the increase in the percentage of training data from 40 to 50%. Similarly, the improvement in the MSE is more detectable with the increase in training data percentage for this hidden neuron value. However, the number of iterations required with each method is observed to increase with the increase of training data percentage from 40 to 50%, unlike what is observed in the case of 5 hidden neurons.

LS1 and LS2 comparison for constant15 Hidden Neurons: Similar to the case of 10 hidden neurons, the increase in the percentage of data dedicated to training from 40 to 50%, is observed to improve R and MSE parameters while the number of iterations required seems to be affected negatively with this increase.

Therefore, within these selected combinations of parameters, increased percentage of training data, from the case of LS1 to LS2, improves R and MSE values more significantly for 10 and 15 hidden neurons, but the number of iterations required for learning is only improved (i.e. decreased) only in the case of 5 hidden neurons.

For constant 40:60 % distribution of data for training:testing, presented in learning scheme-1 (LS1); the increase in the number of hidden neurons from 5 to 10 and then to 15 is observed to mainly affect the performance in the aspect of number iterations required. This increase in the number of hidden neurons had caused a significant decrease in the number of iterations required, while R and MSE values were observed not to be affected significantly in the positive manner. For LS-1, the best R and MSE values combination is observed with 10 hidden neurons.

For constant 50:50 % distribution of data for training:testing, presented in learning scheme-2 (LS2); the increase in the number of hidden neurons from 5 to 10 seems to improve R (since it increases) and MSE (since it decreases). However, the performance observed with these parameters seems to be negatively affected with the increase of hidden neurons from 10 to 15. In this latter case it is observed that for each method R is observed to be decreased and MSE is observed to have an increased value. In parallel with this observation, the number of iterations is observed to be positively affected for CGB and CGF methods with the increase in the number of hidden neurons from 5 to 10 and it is negatively affected with the change from 10 to 15 hidden neurons. On the other hand, CGP method yields a decreasing number of iterations even with the change from 10 to 15 hidden neurons. SGC method is observed to yield the lowest number of iterations with 5 hidden neurons for LS2. For LS2, the best R and MSE values combination is also observed with 10 hidden neurons, like in the case of LS1. When all network training parameter combinations presented in Table-2 are considered, the best combination for coefficient of determination R and mean squared error MSE are observed to be obtained when CGP method is used in learning scheme-2 (50:50 distribution) with 10 hidden neurons. Figures 1 and 2 show, the training performance graph and the regression plot for this selected cased that is observed to yield the best R and MSE combination.

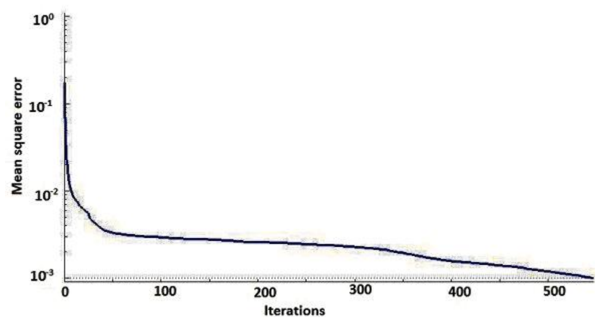

Fig. 1. Best MSE graph for combination determined in the case of CGP method, 50:50 distribution and 10 neurons

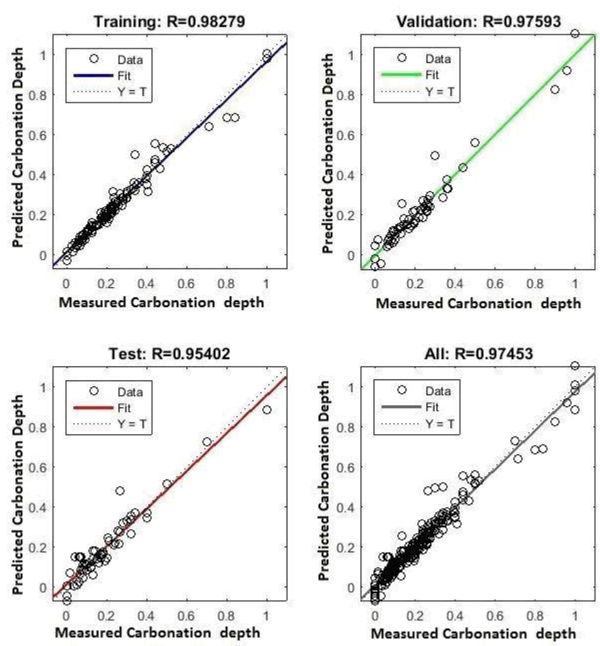

Fig. 2. Regression plot for predicted against measured carbonation depth

for training, testing and validation dataset for the highest R value obtained in the case of 50:50, CGP-10H.

When all network training parameter combinations presented in Table-2 are considered, the best combination for the coefficient of determination R and mean squared error MSE are observed to be obtained when CGP method is used in learning scheme-2 (50:50 distribution) with 10 hidden neurons. Figures 1 and 2 show, the training performance graph and the regression plot for this selected case that is observed to yield the best R and MSE combination.

4 Conclusions and recommendations

Preliminary investigations for ANN applications on the prediction of carbonation depth in concrete have been carried out in this study with a special focus on the effect of varying number of hidden neurons and training:testing data distributions. The results obtained from four Conjugate- gradient methods have been discussed.

The results obtained results indicate that the use of ANN for the prediction of carbonation depth has a potential to provide predictions with satisfactory accuracy. However, it is observed that the coefficient of determination (R), mean squared error (MSE) and the number of iterations required for learning are affected significantly by the changing combinations of training:testing data distribution and the number of hidden neurons. Within the range of parameter combinations tested in this study, the best result combination suggesting the highest coefficient of determination (R), and the lowest mean squared error (MSE) was yielded when CGP method is used in learning scheme-2 (50:50 distribution) with 10 hidden neurons.

Further studies are recommended to be carried out with a greater range of hidden neurons and training:testing data distributions in order to be able to explore the effect of these parameters on the accuracy of the proposed model, which eventually would contribute to carrying out improved prediction practices for the determination of carbonation depth in concrete.

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