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Concrete Structures Life Span Based on Carbonation Rate Using Artificial Neural Network

MF Nuruddin[1], ABM Diah[2], TR Biyanto[3], M Sigit Darmawan[4], Ridho Bayuaji[4],

[1] Civil Engineering Department , Universiti Teknologi PETRONAS, Malaysia
[2]Universiti Teknikal Malaysia
[3]Jurusan Teknik Fisika FTI ITS
[4] Program Diploma Teknik Sipil FTSP ITS

Abstract

The study on the influence of carbonation on concrete is critical as it affects the life span of the concrete structure when corrosion of reinforcement takes place. This research elucidates the carbonation effect on concrete from different environments and concrete samples of grades 15, 20, 25, 30, 35, 40, and 50 MPa. Two set of samples were considered namely controlled sample in the laboratory and on sites samples. In conclusion, it was found that across the board on average, carbonation improved the concrete integrity by 11%. The development of the model using neural networks for the prediction of a carbonation penetration, which consists of two input variables and one output variable were presented.

Keywords: accelerated carbonation chamber, phenolphthalein spray method, artificial neural network

Abstrak

Penelitian pengaruh karbonasi pada beton sangat penting karena mempengaruhi umur struktur beton ketika besi tulangan mengalami korosi. Penelitian ini memaparkan efek karbonasi pada beton dari lingkungan yang berbeda dan mutu beton 15, 20, 25, 30, 35, 40, dan 50 MPa. Dua kondisi perawatan benda uji dilakukan yakni di laboratorium dan di lapangan. Kesimpulan menyatakan bahwa ditemukan di seluruh penampang rata-rata benda uji, karbonasi meningkatkan integritas beton 11%. Pengembangan model menggunakan jaringan saraf disajikan untuk prediksi penetrasi karbonasi, yang terdiri dari dua variabel input dan satu variabel output.

Kata kunci: karbonasi dipercepat, metode percikan phenolphthalein, jaringan saraf tiruan

1. Introduction

Discussion on the CO_2 in the presence of moisture reacts with $Ca(OH)_2$ that can reduce the alkalinity level concrete. The penetration of CO_2 is faster when concrete is porous.

Calcium carbonate, as a product of carbonation, may occur in concrete in three forms namely calcite, vaterite, and aragonite. Thus, the carbonation process causes significant changes in the phase composition and pore structure of concrete. The amount of carbonation is significantly increased in the concrete that has a high water to cementing materials ratio, low cement content, short curing period, low strength, and highly permeable (porous) paste.

The depth of carbonation in good-quality, well-cured concrete is generally of little practical significance as long as embedded steel has adequate concrete cover.

A concrete has a pH value of approximately 12.5, mainly due to the presence of calcium hydroxide formed in the process of cement hydration. Reinforcing steel is fully protected against it in the concrete with a pH value of over 11. During the carbonation process, the pH of a concrete is gradually reduced, and when it reaches below 9.5, the protective oxide film on a steel surface is completely destroyed.

This carbonation penetration corresponds to the rate of diffusion of carbon dioxide. To determine carbonation diffusivity (D), carbonation depth (X_c) is measured at various ages (t) according to FICK's law, which gives:

$$X_c = k(Dt)^{\frac{1}{2}} \quad (1)$$

2. Artificial Neural Network

Neural networks, also referred to as Connectionist Models, or Parallel Distributed Processing (PDP), computational models inspired by the understanding on the biological structure of neurons and the internal operation of the human brain. Research in neural network was started in the 1940's when an endeavour in the search for means of constructing a brain-like computing machine was undertaken, and the mathematical foundation for this learning paradigm was essentially laid during that period. Since then, the advancement of this field has been dramatized by the landmark conceptualization of computational models of neurons, the maturation of concepts of associative memory and connectionism, and the breakthrough in the development of learning algorithms.

Neural networks are information-processing systems that can be thought of as a black box device that accept input and produce output. Each neural network has at least two physical components: connections and processing element (neuron). The combination of these two components creates neural networks. In a broad sense, neural networks consist of three principal elements:

- Topology, how a neural network is organized into layers and how those layers are connected.
- Learning, how information is stored in the network.
- Recall, how the stored information is retrieved from the network.

In the system identification view point, the advantages of neural networks to develop the model are nonlinear system, learning and adaptation, multivariable systems.

Multilayer perceptron (MLP) is the most used and studied neural network architecture today. It constructs a global approximation of a multi-input multi-output function in a similar manner as fitting of a low order polynomial through a set of data points. Figure 1 illustrates the example of MLP networks, which consist of input, hidden and output layers.

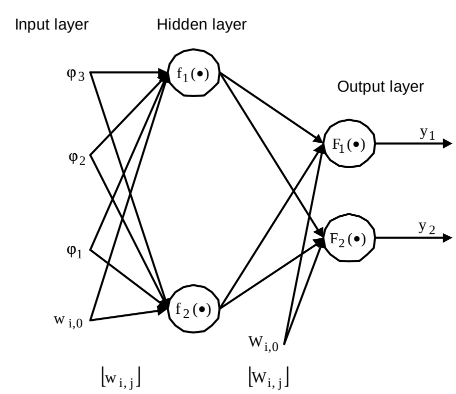

Fig.1. Structure of multilayer perceptron

An important and useful feature of MLP networks is that the gradient and other Jacobians of the model can be computed efficiently in a hierarchical and parallel manner using the chain rule differentiation. This gradient computation method is called the generalized delta rule or error back propagation (Rumelhart, Hinton et al. 1986). This is commonly considered as a minimization method, i.e. it also includes the steepest descent parameter update. The terms forward pass and backward pass are used in this study to denote the computation of the predictions (forward) and the gradients (backward) only. Common nonlinear least squares methods are Levenberg-Marquardt (LM) and Gauss-Newton (GN). The MLP network is selected for the basic building block to be used in this study although localized representations have some useful properties over the MLP network.

The mathematical formula expressing the MLP networks takes the form:

$$y_i = F_i\left[\sum_{j=1}^{n_h} W_{i,j} \cdot f_j\left(\sum_{l=1}^{n_\varphi} w_{j,l}\,\varphi_l + w_{j,0}\right) + W_{i,0}\right] \quad (2)$$

All continuous function can be approximated to any desired accuracy with neural networks of one hidden layer of hyperbolic tangent hidden neuron and a layer of linear output neuron (Cybenko 1989).

3. Methodology

This research elucidates the carbonation effect on concrete from different environments where concrete samples of grades 15, 20, 25, 30, 35, 40 and 50 were monitored. The measurements of carbonation depths of structures exposed to various environments were taken using phenolphthalein spray method (McCarthy 1991; John Newman 2003; M. Thiery 2007). Two sets of samples were considered namely controlled sample in the laboratory and on sites samples.

In the laboratory, the effect of carbonation was accelerated by using accelerated carbonation chamber (4% CO_2) and monitorings were done from the first week until the 40th week (Nuruddin 2001). This was done because the carbonation process is a slow process and takes many years (depending on the durability and concrete grade) to carbonate for just a few millimeters.

At the site, samples of similar grades as the ones in the laboratory were taken from existing structures which had undergone six different exposures. The six exposures were rural – not exposed to rain, rural- exposed to rain, inside building, urban-not exposed to rain, urban-exposed to rain and marine.

The ages of concretes monitored for carbonation tests were from 1 year up to 40 years. Since 1 week in accelerated carbonation chamber is equivalent to 1 year on site, a correlation between the two sets of data was done. As a result, Fadhil-Abu Bakar Chart (F-AB) was produced to analyze the data obtained so that the laboratory data could explain carbonation characteristic via correlation equations acquired. It was found that good correlation prevailed between laboratory data and the on site data. From the correlation, the life span and the covercrete could be estimated or proposed for design purposes. On top of that three periodic stages (in terms of age), carbonation depths were introduced to facilitate planned maintenance works. These estimates were introduced via simple and user friendly computer programs. The programs can be used as guidelines by practicing concrete technologists as standards in design and maintenance, The F-AB chart can also be utilized to improve the Malaysian Standards MS 1195 Part 1 1991 on covercrete requirements exposed to different exposures. Also in this research, a study on the concrete integrity was carried out. The effect of carbonation on the concrete integrity was monitored through ultrasonic pulse velocity test, rebound hammer test, and crushing strength test.

The ANN model for the prediction of carbonation depth was developed using MATLAB 7.1

The proposed model based on neural network is shown in Figure 2. It consists of the characteristic strengths and the number of weeks as the input and the carbonation depths as the output. Regarding to the previous research (Jin-Keun Kim 2009), the penetration of carbonation was exaggerated by the level of strength and the age of a concrete.

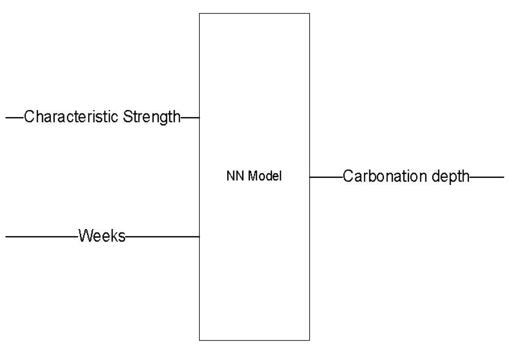

Fig. 2. Proposed model based on NN for Carbonation depth

4. Result and Discussion

Neural network model was done in FIR (Finite Impulse Response) structure with input variables of the model consisting of the present input only. The equation of the model output can be expressed as follows:

$$\hat{Y} = f(U_1, U_2) \qquad (3)$$

Carbonation depth neural network model with Multi Layer Perceptron (MLP), trained by Levenberg Marquard learning algorithm for 200 times computer iteration is the best neural network structure to produce good Root Mean Square Error (RMSE).

The neural model should be trained with training data to determine fixed values of the weights. Then, the fixed weights will be used to validate the neural model using the other input output data. The benefit of system identification is measured using (RMSE), which can be written as follows:

$$\text{RMSE}=\sqrt{\frac{\sum_{i=1}^{N}(y_i-\hat{y}_i)^2}{N}} \qquad (4)$$

Figure 3 shows that the best RMSE equals to 0.211 for training and 0.455 for validation produced by NN with hidden node 27. So, NN with hidden node 27 is recommended to be used as the carbonation penetration in rural-not exposed to rain model.

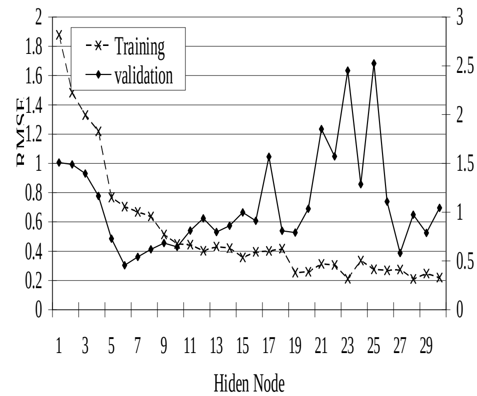

Fig. 3. RMSE training & validation for different hidden nodes

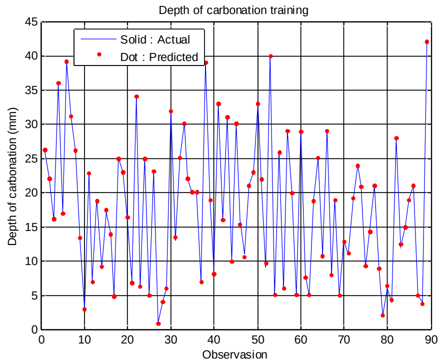

Fig. 4. Trainings for carbonation penetration in rural-not exposed to rain

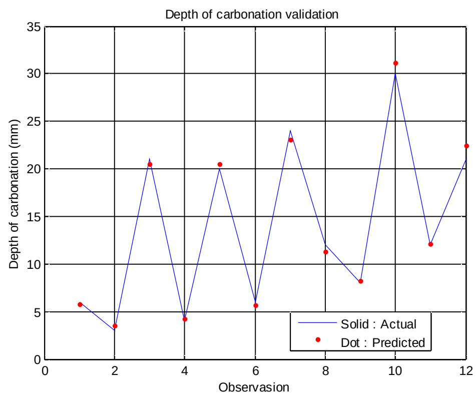

Fig. 5. Validation for carbonation penetration in rural-not exposed to rain

It is always desirable that the trained neural networks model is also validated on a set of data that was not used for training the networks (Figure 4). Using fixed values of the weights that are obtained in the training phase, the neural networks should produce the predicted output from the new input data in the validation phase as in Figure 5.

Similar results for rural-exposed to rain, inside building, urban-not exposed to rain, urban-exposed to rain and marine training and their validation phases are shown in Table 1.

Table 1 Hidden Nodes, RMSE Trainings and Validations in five treatments

Types of Treatments	Hidden Nodes	RMSE Trainings	RMSE Validations
Rural-exposed to rain	5	1.00405E-05	1.19399E-05
Inside building	11	0.455665113	0.896553064
Urban-not exposed to rain	12	0.388084912	1.218888201
Urban-exposed to rain	11	0.523809475	1.217708338
Marine	29	0.199081312	1.341934236

Thus, the neural networks model can handle nonlinearities and complexities of characteristic strengths and the different numbers of week with good RMSE trainings. Based on the above results, it is also easy and simple to develop the nonlinear model using neural networks, and it requires less computational time.

The correlation coefficient R that shows what proportion of the variation of the predicted values can be attributed to the linear relationship with the actual values is given by the formula:

$$R = \frac{S_{xy}}{\sqrt{S_{xx} \times S_{yy}}} \qquad (5)$$

Where:

R = correlation coefficient
S_{xy} = covariance of x with y
S_{xx} = variance of x
S_{yy} = variance of y

The graph of the predicted depth of carbonation penetration in rural-not exposed to rain against. The experimental depth of carbonation penetration in rural-not exposed to rain values is illustrated in Figure 6. The correlation coefficient is 0.9995 for rural-not exposed to rain which was distributed evenly on both sides of the line, which indicates an extremely good performance of the model.

The correlation coefficients for the union exposures are shown in Table 2.

Table 2 Correlation coefficients for different exposures

Types of Exposures	R^2
Rural- exposed to rain	0.9984
Inside building	0.9967
Urban-not exposed to rain	0.9980
Urban-exposed to rain	0.9990
Marine	0.9996

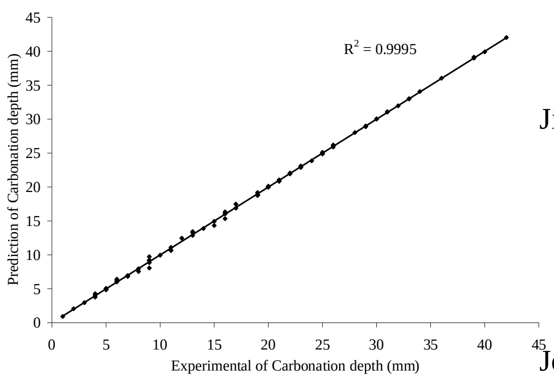

Fig. 6. Predicting the accuracy of neural-network system for carbonation penetration in rural-not exposed to rain

5. Conclusions

The development of the model using neural networks for the prediction of a carbonation penetration, which consists of two input variables and one output variable were presented. The structure of the model is a multilayer perception. In general, the designed neural networks can anticipate the nonlinearities and complexities of a carbonation penetration. The neural networks model can produce good results in modeling with RMSE = 0.211, 1.004x10-5, 0.456, 0.389, 0.523, 0.199 for rural–not exposed to rain, rural-exposed to rain, inside building, urban-not exposed to rain, urban-exposed to rain and marine respectively in the training phase. In the validation phase, RMSE = 0.455, 1.193x10-5, 0.896, 1.219, 1.218, 1.342 for rural–not exposed to rain, rural-exposed to rain, inside building, urban-not exposed to rain, urban-exposed to rain and marine respectively. Therefore, the neural networks model could be used as an alternative tool to predict the depth of a carbonation penetration.

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