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Chloride and Carbonation Analysis using Diffusion Coefficient from Artificial Neural Network

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1. Introduction

Chloride penetration into concrete does not significantly affect the performance of the material properties of concrete, however, it does cause reinforcing bar corrosion. This corrosion of the reinforcement reduces the durability of the reinforced concrete structure. In particular, nuclear power plants are built on the seaside for cooling water supply, and the high concentration of chloride in seawater makes it essential to predict chloride penetration. Therefore, chloride penetration experiments have been conducted on concrete in various environments and concrete mixture proportions.

Carbonation penetration does not directly cause a significant decrease in concrete strength or corrosion of reinforcement. However, carbonated concrete is susceptible to chloride erosion, which leads to rapid chloride diffusion. Therefore, an evaluation technique that considers the combined deterioration of chloride and carbonation penetration is required.

Artificial Neural Network (ANN) theory is one of the optimization techniques and is used in various disciplines. In this study, ANN is used to predict the chloride diffusion coefficient and carbonation depth, and to predict reinforcing bar corrosion based on simple chloride and carbonation composite degradation.

2. Artificial Neural Network (ANN)

The theory of ANN was first attempted by McCulloch and Pitts et al. ANN is a generalization of the model of neurons as the unit of information processing of stimuli and responses. Unlike traditional regression analysis, ANN uses connection strengths weighted by multiple data to learn. The error of the expected value through this learning process decreases as the number of training times increases, and learning is stopped when the final error range is converged.

In order to derive output values through neural network theory, it is common to go through a normalization process through data processing of input values. The number with each property must be normalized to one value in the learning recognition process, which has a range depending on the preprocessing or postprocessing transfer function characteristics of the data.

3. Prediction of Aging Effect of Concrete using ANN

To train an ANN, the results of experiments conducted by previous researchers were used. 535 experiments were used to determine the chloride diffusion coefficient and 300 experimental results were used to predict the carbonation depth. Lee and Kwon (2012), Choi and Choi (2009) and other 20 papers were used for chloride diffusion experimental database and Van et al (2019), Atis (2003) and other 17 papers were used to make database of carbonation test results.

3.1 Chloride

The input variables for training the ANN model for chloride were cement type, water-cement ratio, water, blast furnace slag, fly ash, silica fume, and maximum aggregate size. Table I shows the range of variables used.

Table I: Data base

	Chloride	Carbonation
Cement type	I, II, III, IV, V	I, II, III, IV, V
W/C	0.25-0.6	0.28-0.69
Water	35-270	100-269
GGBS	0-0.7	0-0.85
FA	0-0.7	0-0.7
SF	0-0.15	0-0.125
Max. Agg. size	9.5-32	-
SP	-	0-12

Figure 1 (a) shows the comparison of chloride diffusion coefficient predicted by ANN and test. The variation in chloride diffusion coefficient characteristics as mixture design is roughly as follows: 1) The greater the water-cement ratio, the greater the diffusion coefficient. 2) The higher the amount of cement, the higher the diffusion coefficient value. and 3) Blast furnace slag and silica fume reduce the chloride diffusion coefficient. Chloride diffusion is expected to be affected by the degree of compactness of the concrete, as it penetrates between cement particles. However, the chloride diffusion coefficient is difficult to explain in a simplified way because it is a result of the accelerated test, micropore structure, chloride phase equilibrium, thermodynamic ductility analysis, etc.

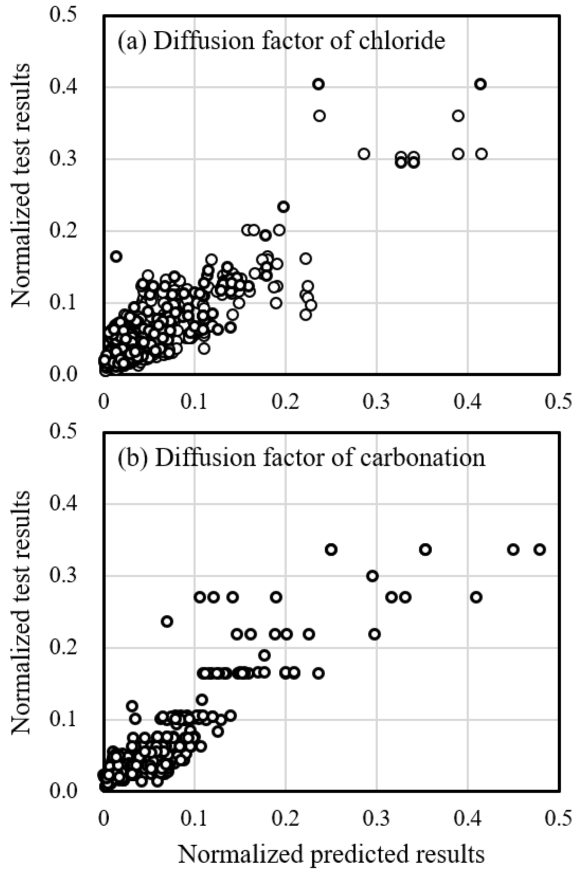

Fig. 1. Comparison of test and predicted results.

Based on the chloride diffusion coefficient, the concentration of chloride according to depth can calculated using below equation.

$$\frac{C}{C_0} = \mathrm{erfc}\frac{1-\gamma}{2\sqrt{\gamma}} = \mathrm{erfc}\left(\frac{x}{2\sqrt{Dt}}\right)$$

where, C and C_0 are the chloride concentration of outside and target depth, x is the depth, D is the chloride diffusion coefficient, and t is time.

2.2 Carbonation

Similar to the chloride diffusion coefficient prediction, a database was built for the carbonation depth. The input variables for training the ANN prediction model for carbonation were cement type, water-cement ratio, water, blast furnace slag, fly ash, silica fume, super-plasticize. Table 1 shows the range of variables.

Figure 1(b) shows the prediction results. The depth of carbonation was predicted appropriately in all ranges. The carbonation depth can obtain using below equation

$$Dpeth = A\sqrt{t}$$

The depth of carbonation penetration is proportional to the square root of time.

4. Composite Aging of Concrete

There are few experimental results applying composite degradation of concrete. Therefore, the following assumptions were used to simulate the composite degradation. 1) Carbonation depth is not affected by chloride. 2) The chloride concentration in the carbonated concrete is the same as the chloride concentration of outside. 3) The decrease in chloride concentration starts at the depth where carbonation ends. and 4) The chloride diffusion coefficient is then calculated independently of carbonation. As a result of this research, a prediction program was created and extended to calculate the fragility of reinforced concrete wall.

5. Conclusions

Using ANN, the conclusions from the chloride diffusion coefficient and carbonation depth predictions are as follows:

1) Based on domestic and foreign experimental data, the database applied artificial neural network and trained using eight input variables to derive the prediction results.
2) Comparing the predicted results with the actual experimental results, the predictions were relatively accurate.

However, the assumptions made in this research about composite aging degradation may be different in some cases, and further research is required.

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REFERENCES

[1] Lee S. H. and Kwon, S. J. (2012). "Experimental study on the relationship between time-dependent chloride diffusion coefficient and compressive strength. *Journal of the Korea Concrete Institute*, 24(6), 715-726.

[2] Choi, D. S. and Choi. J. J. (2009). *Relationship between Chloride Diffusivity and the Fundamental Properties of Concrete*. Journal of the Korean Society of Hazard Mitigation, 9(1), 15-20.

[3] Van den Heede, P., De Schepper, M., and De Belie, N (2019), Accelerated and natural carbonation of concrete with high volumes of fly ash: chemical, mineralogical and microstructural effects. *Royal Society open science*, 6(1), 181665.

[4] Atis, C. D. (2003). Accelerated carbonation and testing of concrete made with fly ash. *Construction and Building Materials*, 17(3), 147-152.