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THE ANALYSIS OF CHLORIDE DIFFUSION COEFFICIENT IN CONCRETE BASED ON NEURAL NETWORK MODELS

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ABSTRACT

Chloride diffusion is one of the major causes of deterioration of concrete structures. A large amount of research has been conducted to study the chloride diffusion of concrete, both experimentally and theoretically. Because chloride diffusion experiments are time consuming, it is desirable to develop a model to predict the chloride profiles in concrete. This paper studies the feasibility of using a neural network as an adaptive synthesizer as well as a predictor to meet such a requirement.

So some neural network models to predict chloride diffusion coefficient were made. The models were trained by results of chloride profile experiments. Input parameters were water to binder ratios, the amount of silica-fume and environmental condition of samples. The output parameter was chloride diffusion coefficient.

Neural network models are multi layer Perspetron models and they differ in the number of hidden layers and neurons. To control the accuracy of the model, an ANNs model was made and the result of the model was compared with test specimens. The result demonstrates that both neural network models have the ability of predicting the chloride diffusion coefficient with good accuracy.

Keywords: neural network model, chloride diffusion coefficient

1. INTRODUCTION

Steel reinforced concrete is one of the most durable and cost effective construction materials. The durability of reinforced concrete depends on the surrounding environment and exposure conditions, including the factors such as carbonation, corrosion, alkali-slices reaction and freezing/thawing [1,2]. Corrosion of reinforced steel resulting from the ingress of chloride ion is one of the most important issues concerning the durability of concrete structures. The prevention of reinforcement corrosion is primarily in the design stage with the use of high quality concrete and adequate cover. It is well known that steel is protected from corrosion by a microscopically thin oxide layer (Passive film: γ-Fe_2O_3-H_2O) that is formed in the highly alkaline condition of concrete pore solution. This protective film suppresses the iron dissolution to negligibly low values and furthermore, this oxide is insoluble and highly stable [3]. Corrosion occurs by loss of the alkalinity of concrete in the form of carbonates, thereby providing a direct route for chlorides to approach the reinforcing steel and prevent re-passivation reaction that leads to pitting corrosion [4].Carbonates, chlorides and sulphates media can be found in concrete when using contaminant aggregate, or adding $CaCl_2$ during the mixing step or they are found under the effect of sea-water or ground water on concrete and they can also result from an attack on concrete by the surrounding environment in coastal regions. Carbonation destroys the protective oxide layer presented on the surface of embedded steel in concrete leading to corrosion. As the corrosion of embedded steel continues, the products formed exert enormous stress on the surrounding concrete leading to cracking and later sapling of the concrete. These stresses have been reported to be as high as 450 Mpa [5]. Methods of corrosion control include cathodic protection, surface treatments of the rebar and the use of admixtures in concrete [6]. Use of blended cements incorporating supplementary cementing materials such as silica-fume, blast furnace slag, fly ash or natural pozzolan, is a solution that leads to mixtures with greater resistance against chloride [7].

There are a number of computational analysis techniques that deal with concrete [8-12]. One of the most known techniques is artificial neural network (ANNs) [13, 16]. Topcu and Sndemire [17] that used ANNs and Fuzzy logic for prediction of mechanical properties of recycled aggregate concretes containing silica fume. They obtained successful simulation result from both ANNs and fuzzy logic. Altun et al. [18] used ANNs for predicting the compressive strength of steel fiber added lightweight concrete and they compared ANN result with multi layer regression technique results. They concluded that ANNs predicts the compressive strength of steel fiber added lightweight concrete more accurately than multi layer regression. Sakla and Ashour [19] predicted tensile capacity of single adhesive anchors using ANNs. They concluded that ANN is a useful technique for predicting of tensile capacity of adhesive anchors. Since ANNs has taken into account nonlinear transfer functions, they can automatically consider the nonlinear relations between the data. Hence better prediction results than other statistical tools can be obtained in general. Topcu et al. [3] used ANNs to model corrosion currents of reinforced concrete. They used two types of cement and 3 different ratios of fly ash for their modeling. Their Ann model produced close prediction current values to currents measured in experiment. They concluded that ANN is an appropriate tool for modeling the corrosion currents. Parichatprecha, and Nimityongskul.[20] used ANNs to durability analysis of high performance concretes. Their results indicated that the ANN models can be used to efficiently predict the chloride ions permeability across a wide range of ingredients of HPC. Based on the simulated total charge passed model, built using trained neural networks, they also concluded that the optimum cement content for the design of HPC in terms of total charge passed ranges from 450 to 500 kg/m3.

The aim of this study is to construct an ANNs model to investigate the influence of mix proportion parameters on the resistance of chloride ion penetrability on concretes containing silica-fume. For this purpose, data for developing the neural network model are collected from the experiments. The design of the experimental program is based on the relevant parameters, namely W/B, cement content, silica fume content and some experimental data.

2. ARTIFICIAL NEURAL NETWORKS

Artificial neural networks are computing systems that simulate the biological neural systems of the human brain. They are based on a simplified modeling of the brain's biological functions exhibiting the ability to learn, think, remember, reason, and solve problems. Conceptually, a neural networks model consists of a set of computational units and a set of one-way data connection joining units or weights as shown in Figure 1.

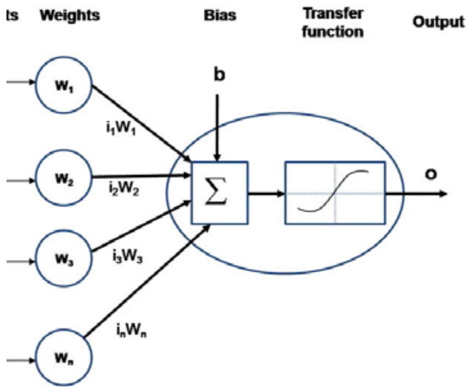

Figure 1. Single processing element of ANNs

Units that receive no input from others are called input nodes, while those with no outgoing links are called output nodes. All other intermediate units are called hidden nodes. The multi-layered model has several layers, and each layer consists of numerous neurons which are connected with each other. In this model, information is sent from input layer to output in one direction, and learning is preceded so as to minimize the difference between the output of the model and the target output. ANNs can solve challenging problems of interest to computer scientists and engineers such as pattern classification, categorization, function approximation, prediction and forecasting, optimization, content-addressable memory, and control robotics. Rumellhart et al. [21] developed a method called error back-propagation, or more simply back-propagation, for learning associations between input and output patterns using more than the two layers of Rosenblat's original perceptron. Back-propagation is a supervised learning technique that compares the responses of the output units to the desired response, and readjusts the weights in the network so that the next time when the same input is presented to the network, the network's response will be closer to the desired response. Errors that arise during the learning process can be expressed in terms of mean square error (MSE) and are calculated using Eq. (1).

$$MSE = \left(\frac{1}{p}\right) * \sum_{j} \left(t_j - \sigma_j\right)^2 \qquad (1)$$

In addition, the absolute fraction of variance (R^2) and mean absolute percentage error (MAPE) are calculated using Eqs. (2) and (3), respectively.

$$R_2 = 1 - \left(\frac{\sum_j (t_j - \sigma_j)^2}{\sum_j (\sigma_j)^2} \right) \quad (2)$$

$$MAPE = \frac{1}{p} \sum_j \left(\left| \frac{\sigma_j - t_j}{\sigma_j} \right| * 100 \right) \quad (3)$$

where t_j is the target value of j_{th} pattern, σ_j is the output value of j_{th} pattern, and p is the number of patterns.

3. EXPERIMENTAL STUDIES

3.1. Materials Used

3.1.1. Cement and silica-fume

In experimental studies, the CEM I 425 R Portland cement which is produced by Tehran cement factory were used.

3.1.2. Aggregates

Crushed sand and crushed stone aggregates were used. The maximum particle size of aggregates is 20 mm. As a result of the experiment, the specific gravities of sand and crushed stone are obtained as 2.62 and 2.71 kg/dm^3, respectively.

3.2. Mix Proportions

Cement type I.425 was used in concrete mixtures. Concretes are produced using 0, 7 and 10% replacement level of SF by weight of cement. These specimens were cured at 28, 90 and 270 days. The amounts of materials used in 1 m^3 concrete are given in Table 1.

Table 1: Mix design of specimens

Specimen code	W/B	csf/(c+csf)*	sand	gravel
M-35-0	0.35	0	800	1050
M-35-7	0.35	7	800	1050
M-35-10	0.35	10	800	1050
M-40-0	0.4	0	800	1050
M-40-7	0.4	7	800	1050
M-40-10	0.4	10	800	1050
M-50-0	0.5	0	800	1050
M-50-7	0.5	7	800	1050
M-50-10	0.5	10	800	1050

***csf : content of silica-fume in concrete**

4. EXPERIMENTAL PROGRAM AND DATA COLLECTION

The first step in developing the network is to obtain good and reliable training and testing examples. To obtain the data for developing the neural network models, different experiments were done on specimens. The aim of these experiments was to find a relationship between mix design and chloride diffusion coefficient in concrete. For this reason, the specimens were exposed to chloride in 3 different conditions for more than 270 days. The environmental conditions were submerge, tidal and atmospheric zone. Persian Gulf modeling room of Building and Housing Research Center (BHRC) was used to model the mentioned environment. In addition to this experiment, RCPT, concrete compressive strength and water permeability of concrete under pressure were done to find a relationship between concrete durability contents and chloride penetration coefficient. Results of experiments can be finding in ref. [22].

4.1. Variables Selected for Neural Networks

Considering the environmental conditions at the construction sites and in order to find the important variables that might strongly affect the chloride diffusion coefficient, 7 different ANNs were selected with different input variables and hidden layers. 1 variable was chosen as the desired output. Table 2 gives the list of the ANNs inputs and outputs. In this study, the neural networks were developed and performed under MATLAB programming. The learning algorithm used in the study was gradient descent with adaptive learning rate back-propagation, a network training function that updates weight and bias values according to gradient descent with adaptive learning rate [21]. The error incurred during the learning process was expressed in terms of mean-squared-error (MSE).

Table 2: Input and output parameters of ANNs

Code	Input				Output		Number of Data
	W/B	SF (%)	RCPT index	Time of exposing	RCPT index	Diffusion coefficient D	
M1	*	*			*		24
M2	*	*		*		*	16
M3	*	*		*		*	16
M4			*	*		*	24
M5			*	*		*	24
M6			*	*		*	24
M7			*	*		*	24

All model structures were based on the following cases:

1. The minimum and maximum neurons in the hidden layer were changing between 1.5 and 3 times the input number of parameters. For example, in the model with 2 input parameters, the number of hidden layer neurons was 3 to 6.
2. The number of iterations and MSE between output parameter of model and test data was the criteria used for selecting the best model.

5. RESULTS AND DISCUSSION

For 7 models, the summary of models has been collected in tables 3-9. According to the criteria mentioned for choosing the best model in each ANNs, the selected model has been shown in different colors in the rows.

Table 3: The summary of results of M1 ANNs model

Code	Number of iterations	Number of neurons in hidden layer	MSE ($*10^{-4}$)	MAPE
M1-3-1	6	3	6.52	7.93
M1-4-4	5	4	6.52	7.93
M1-5-6	5	5	6.52	7.93
M1-6-4	4	6	6.52	7.93

Table 4: The summary of results of M2 ANNs model

Code	Number of iterations	Number of neurons in hidden layer	MSE ($*10^{-4}$)	MAPE
M2-5-1	13	5	1	12.68
M2-6-5	9	6	1	22.93
M2-7-7	7	7	1	7.63
M2-8-2	7	8	1	11.97
M2-9-4	6	9	1	62.57

Table 5: The summary of results of M3 ANNs model

Code	Number of iterations	Number of neurons in hidden layer	MSE ($*10^{-4}$)	MAPE
M3-5-3	9	5	1	21.50
M3-6-1	9	6	1	20.61
M3-7-2	8	7	1	9.30
M3-8-3	6	8	1	1.76
M3-9-2	5	9	1	16.14

Table 6: The summary of results of M4 ANNs model

Code	Number of iterations	Number of neurons in hidden layer	MSE ($*10^{-4}$)	MAPE
M4-3-1	1000	3	5.01	120.4
M4-4-2	1000	4	1.19	84.97
M4-5-2	1000	5	0.02	92.90
M4-6-4	1000	6	0.0008	9894.78

Table 7: The summary of results of M5 ANNs model

Code	Number of iterations	Number of neurons in hidden layer	MSE ($*10^{-4}$)	MAPE
M5-3-3	1000	3	3.23	66.05
M5-4-3	1000	4	0.772	23.12
M5-5-2	1000	5	0.0002	150.07
M5-6-2	1000	6	0.0919	205.68

Table 8: The summary of results of M6 ANNs model

Code	Number of iterations	Number of neurons in hidden layer	MSE ($*10^{-4}$)	MAPE
M6-3-3	1000	3	1.27	7.30
M6-4-3	1000	4	0.0975	8.64
M6-5-1	1000	5	0.0448	36.79
M6-6-2	1000	6	$8.04*10^{-9}$	29.46

Table 9: The summary of results of M7 ANNs model

Code	Number of iterations	Number of neurons in hidden layer	MSE ($*10^{-4}$)	MAPE
M7-3-3	1000	3	5.7	9.46
M7-4-1	1000	4	0.0683	14.27
M7-5-3	1000	5	0.0683	23.10
M7-6-1	1000	6	$3.33*10^{-8}$	84.35

As it can be seen from the results, the selection of mix design parameter (W/B and S.F percentage) makes better output than RCPT. It is because of the uncertainties of RCPT. Furthermore, both the number of neurons in hidden layer and number of hidden layers in relation with each other has a positive effect in ANNs output. It's because of the nonlinear nature of chloride diffusion in concrete.

6. CONCLUSION

After the tests, it is observed that the diffusion of chloride in concrete changes by SF ratio used instead of cement and water to binder ration. As a result of the analysis, ANN structures that produce close prediction current values to measured ones are presented and the robustness of ANN structure is tested. 7 ANN model was tested and in each model, the input and output parameters was changed to find the best input variable for prediction of chloride diffusion coefficient in concrete. The results show that W/B ration and percentage of silica-fume in concrete are better inputs than RCPT results. Furthermore, the results show that both the number of neurons in hidden layer and number of hidden layers in relation with each other has positive effect in ANNs output. To sum up, it is concluded that ANN is an appropriate tool for modeling the diffusion coefficient of chloride in concrete.

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