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Study of the effect of chloride diffusion coefficient in concrete using neural network models

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Abstract

Chloride diffusion is one of the main causes of deterioration of concrete structures. Much research has been done to study the diffusion of chlorides in concrete, experimentally and theoretically. Since chloride diffusion experiments are time consuming, it is desired to develop a model to predict chloride profiles in concrete. This paper investigates the feasibility of using a neural network as an adaptive synthesizer as well as a predictor to meet such a requirement.

Neural network models were therefore created to predict the chloride diffusion coefficient. The models were formed from the results of the chloride profile experiments. The input parameters were the water/binder ratios, the amount of silica fume and the environmental conditions of the samples. The output parameter was the chloride diffusion coefficient.

Neural network models are multi-layer Perceptron models and differ in the number of layers and hidden neurons. To verify the accuracy of the model, an ANN model was created and the output of the model was compared with the test samples. The result shows that both neural network models have the ability to predict the chloride diffusion coefficient with good accuracy.

Keywords: neural network model, chloride diffusion coefficient

1. Introduction

We Reinforced concrete is one of the most durable and cost-effective building materials. The durability of reinforced concrete depends on the environment and exposure conditions, including factors such as carbonation, corrosion, alkaline reaction and freezing/thawing [1,2]. Corrosion of reinforcing steel resulting from the entry of chloride ions is one of the most important problems related to the durability of concrete structures. Prevention of reinforcement corrosion is mainly done in the design phase by using high quality concrete and a suitable coating. It is well known that steel is protected from corrosion by a microscopic oxide layer (passive film: γ-Fe2O3-H2O) that forms in the highly alkaline state of the concrete pore solution. This protective film suppresses the dissolution of iron to negligible values and, in addition, this oxide is insoluble and very stable [3]. Corrosion occurs due to the loss of the alkalinity of the concrete in the form of carbonates, thus providing a direct route for the chlorides to approach the reinforcing steel and prevent the repassivation reaction that leads to pitting corrosion [4]. Carbonates, chlorides and sulfates can be present in the concrete during the use of polluting aggregates or the addition of CaCl2 during the mixing stage or they are under the influence of sea water or ground water in concrete and can also result from environmental attack on concrete. around coastal regions. Carbonization destroys the protective oxide layer present on the surface of the steel embedded in the concrete, leading to corrosion. As the corrosion of the embedded steel continues, the formed products place great stress on the surrounding concrete, leading to cracking and later deformation of the concrete. These stresses can reach 450 MPa [5]. Corrosion control methods include cathodic protection, surface treatments of reinforcing bars, and the use of additives in concrete [6]. The use of

Mixed that include additional cementing materials, such as silica fume, blast furnace slag, fly ash or natural pozzolan, is a solution that leads to mixes with more chloride resistance [7].

There are a number of computational analysis techniques dealing with concrete [8-12]. One of the most popular techniques is artificial neural network (ANN) [13, 16]. Topcu and Sndemire [17] used ANN and fuzzy logic to predict the mechanical properties of recycled aggregate concretes containing silica fume. They obtained successful simulation results by ANN and fuzzy logic. Altun etc. [18] used ANN to predict the compressive strength of lightweight concrete with the addition of steel fibers.

and compare the results of the ANN with the results of the multilevel regression technique. They concluded that ANN predicts the compressive strength of lightweight concrete with added steel fibers more accurately than multi-layer regression. Sakla and Ashour [19] predicted the pull-out capacity of simple adhesive anchors using

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ANN. They concluded that ANNs are a useful technique for predicting the tensile capacity of adhesive anchors. Since ANNs take nonlinear transfer functions into account, they can
automatically takes into account non-linear relationships between data. Therefore, in general, prediction results can be obtained than other statistical tools. Topcu etc. [3] used ANN to model corrosion currents in reinforced concrete. They used two types of cement and 3 different proportions of fly ash for their model. Their Ann model produced prediction current values close to experimentally measured currents. They concluded that ANN is a suitable tool for modeling corrosion currents. Parichatprecha and Nimityongskul.[20] ANNs used for stability analysis of high performance concretes. Their results showed that ANN models can be used to effectively predict chloride permeability in a wide range of HPC components. Based on the simulated total transmitted load model built with trained neural networks, they also concluded that the optimal cement content for the HPC design in terms of total transmitted load ranges from 450 to 500 kg/m3.
The objective of this study is to build an ANN model to study the influence of mix proportion parameters on the penetration resistance of chloride ions in concretes containing silica fume. For this purpose, the data to develop the model of the neural network are collected from the experiments. The design of the experimental program is based on the relevant parameters, namely W / L ratio, 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.

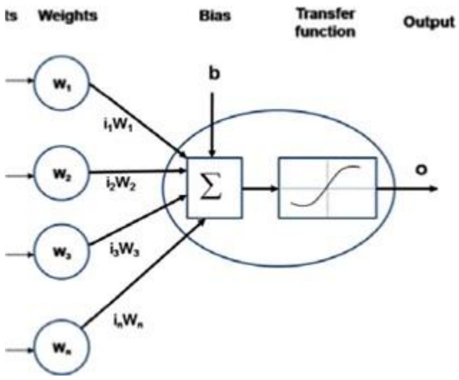

Fig 1. Single processing element of ANNs

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).

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

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

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

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

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. Artificial neural networks

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/dm3, 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 m3 concrete are given in Table 1.

Table 1
Summary 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. Materials Used

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

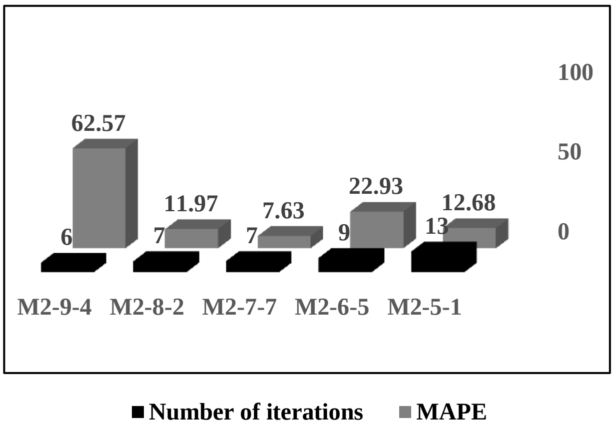

Fig 2. The summary of results of M2 ANNs model

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

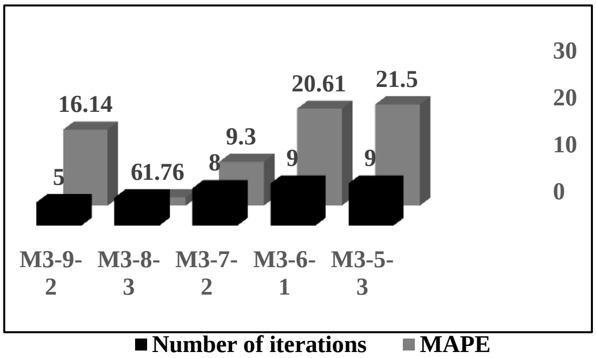

Fig 3. The summary of results of M3 ANNs model

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

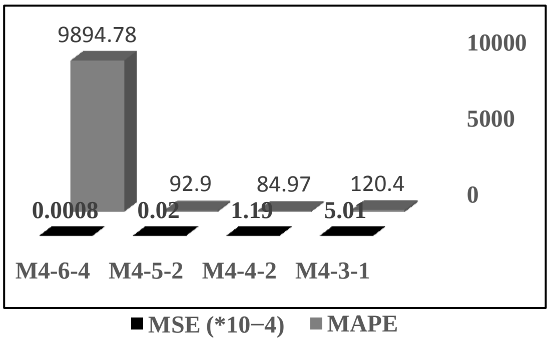

Fig 4. The summary of results of M4 ANNs model

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

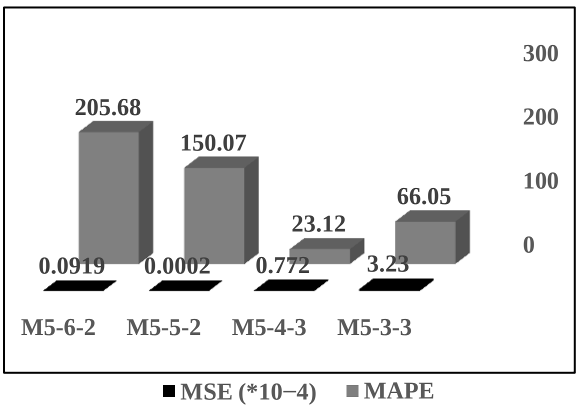

Fig 5. The summary of results of M5 ANNs model

Table 8
The summary of results of M6 ANNs model

Code	Number of iterations	ımber 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

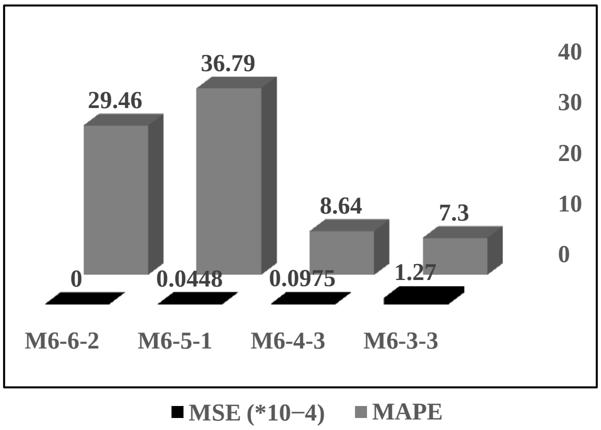

Fig 6. The summary of results of M6 ANNs model

Table 9
The summary of results of M7 ANNs model

Code	Number of iterations	lumber 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

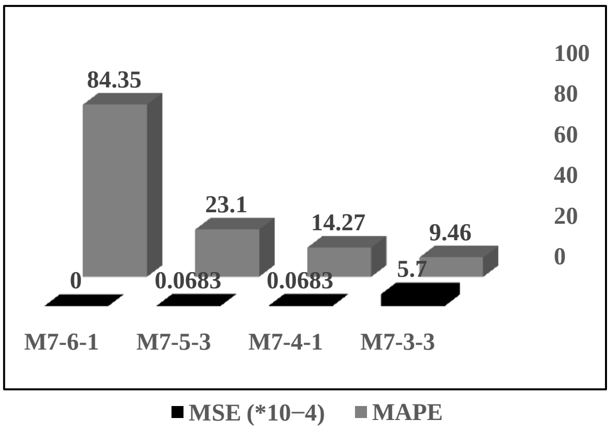

Fig 7. The summary of results of M7 ANNs model

As the results show, the selection of mix design parameters (E/B and F.S percentages) gives better results than RCPT. This is due to the uncertainties in the RCPT. In addition, the number of neurons in the hidden layer and the number of hidden layers relative to each other have a positive effect on the ANN results. This is due to the non-linear nature of chloride diffusion in concrete.

6. Conclusion

After testing, we observed that chloride diffusion in concrete varies depending on the SF ratio used instead of cement and the water/binder ratio. As a result of the analysis, ANN structures are presented that produce actual prediction values close to the measured ones, and the robustness of the ANN structure is tested. 7 ANN models were tested and in each model, the input and output parameters were varied to find the best input variable to predict the chloride diffusion coefficient in concrete.
The results show that the W/B ratio and the percentage of silica fume in the concrete are better inputs than the RCPT results. In addition, the results show that the number of neurons in the hidden layer and the number of hidden layers relative to each other have a positive effect on the output of ANN. In summary, it is concluded that ANN is a suitable tool for modeling the chloride diffusion coefficient in concrete.

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