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Prediction of Mortar Compressive Strengths for Different Cement Grades in the Vicinity of Sodium Chloride Using ANN

Hamid Eskandari[a,*], Morteza Gharouni Nik[b], Mohammad Mahdi Eidi[a]

[a] *Department of Civil Engineering, Hakim Sabzevari University, Iran.*
[b] *School of Railway Engineering, Iran University of Science and Technology, University, Tehran, Iran.*

Abstract

The compressive strength values of cement mortar usually affect by sodium chloride quantities, chemical admixtures and cement grades so that an artificial neural network model was performed to predict the compressive strength of mortar value for different cement grades and sodium chloride (NaCl) percent. A three layer feed forward artificial neural network (ANN) model having four input neurons such as cement grades, various water to cement ratio, sodium chloride solution content, one output neuron and five hidden neurons was developed to predict of mortar each compressive strength.

To this aim, twelve different mixes under three sodium chloride solution of 0%, 5% and 10% submerged after 60 days has been adopted to measure compressive strength.

Artificial neural network (ANN) analysis indicated that by using ANN as non-linear statistical data modeling tool, a strong correlation between the sodium chloride percent of cement mortar and compressive strength can be established. Moreover modeling tools has great influence on the different cement grade such as 42.5 and 32.5 MPa.

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Keywords: Compressive Strength, NaCl, Cement Grade , 42.5, 32.5 , ANN;

* Corresponding author. Tel.: 0098 51 4401 3386; fax: 0098 51 4401 3386.
E-mail address: Hamidiisc@yahoo.com

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1.Introduction

There corrosion by chloride is one of the factors that reduce the durability of structures [1]. Many studies has been done on the effects of corrosion on structures such as chlorine ions reduces the strength of steel used in reinforced concrete samples [2-4]. Usually to prevent corrosion in lining pipes use of cement mortar is one of the most effective resources [5]. There are many works which were shown that the compressive strength of concrete usually affect by many parameters such as water/cement ratio, size of aggregate, aggregate and cement content. But it seems the factor of compressive strength of cement as per different standards that is a most affect the compressive strength of mortar [6-8]. The usually grades of cement are 32.5, 42.5 and 52.5 MPa in other words cement with constant water cement ratio (W/C) have various compressive strength, especially the higher strength cement has a higher reaction rate than that of the lower strength cement normally due to lower strength cement with lots of low active mineral admixtures added when it was manufactured in a factory [9]. As there are many type of modeling which has been applied by research's in recent years to predicted the compressive strength of cementations materials such as extrapolation method, regression analysis methods and artificial neural network, genetic algorithm and fuzzy logic [10-14]. And many researcher has been applied the artificial neural networks (ANNs) to predict compressive strength of mortar as well as concrete. based on prediction mortar strength parameters is done using ANN model and this predictive models for laboratory work can be very useful due to reduces laboratory samples that mostly for the compressive strength of concrete because strength is an important feature [15-22].

For example a total of 45 concretes sample were produced, in three different water–cement ratios (0.3, 0.4, and 0.5), three different cement dosages (350, 400, and 450 kg/m3) and four partial slag replacement ratios (20%, 40%, 60%, and 80%) to adopted model of ANN to predicte compressive strengths of moist cured specimens (22 ± 2 °C) were measured at 3, 7, 28, 90, and 360 days. The model are arranged in a format of six input parameters that cover the cement, ground granulated blast furnace slag, water, hyperplasticizer, aggregate and age of samples and, an output parameter which is compressive strength of concrete which the results showed that ANN can be an alternative approach for the predicting the compressive strength of ground granulated blast furnace slag concrete using concrete ingredients as input parameters [23]. There is a similar work adopted ANN model for compressive strength of concrete samples for 3, 7, 28 and 90 days on various types of cement, different water-cement ratio that showed the predicted compressive strength of concrete using the ANN model has high accuracy and very similar to laboratory samples that can be used as an effective method [24]. As mention above the compressive strength of mortar and concrete will affect by many parameter such as cured condition, days of curing, water/cement ratio, cement/fine aggregate and some others but the most sensitive parameter for compressive strength of cementations materials is cement grades which have been mention in initial introduction form one side and from another side that there is not enough research to ANN prediction model for the cement mortar strength in the vicinity of sodium chloride and it should be noted that the sodium chloride usually as destructive factor for concrete or cementations materials will be expected to change in the vicinity of sodium chloride [25, 26]. So that with water/cement ratio constant by different grades of cement and different curing percent immersed of sodium chloride grade of cement will affect the compressive strength obviously this parameter will changed the any model which has been developed till now. In this research used ANN to prediction of compressive strength of cement mortar that produced by two type of cement grade 32.5 and 42.5 MPa. Totally 72 different mix which are varies from water to cement ratio, sodium chloride solution of 0%, 5% and 10% as well as compressive strength. This data is used to constructed ANN model and verifying by some them to show that the use of cement strength grade has effect on prediction of compressive strength of mortar.

2. Material and Mix design plan

A total 12 mix design by several of W/C and super plasticizer (SP) and also two cements strength grade (32.5 and 42.5 MPa) were employed for experimental investigations. The experimental investigations were made in the laboratory to compare the 60-day compressive strength of mortar in the vicinity of sodium chloride by ANN prediction. The six mixes made by cement 32.5 MPa and six mixes made by cement 42.5 MPa are shown in Table.

In addition specification materials which used such as cement type II with the strength grades that used were, with a strength of 32.5 and 42.5 MPa, and specific gravity of 3.14, fine aggregate was passing 4.75 mm sieve with specific gravity 2.62 and the fineness modulus 2.48.

Table 1. Mix proportions of mortar.

Mixture no.	grade of cement	$\frac{W}{C}$	$C\left(\frac{kg}{m^3}\right)$	$\frac{Fa}{C}$	$\frac{C}{Fa+W}$	Compressive strength (MPa)		
						0 % NACL	5%	10% NACL
1	325	0.3	700	3	0.303	46	58.75	51.56
2	325	0.3	700	2.5	0.357	45	53.43	49.68
3	325	0.4	700	3	0.294	42	54.37	47.81
4	325	0.4	700	2.5	0.344	40	53.75	47.18
5	325	0.6	700	3	0.278	35	79.67	45.12
6	325	0.6	700	2.5	0.322	24	66.56	42.62
7	425	0.3	700	3	0.303	73	57.4	55.13
8	425	0.3	700	2.5	0.357	72	56.1	54.36
9	425	0.4	700	3	0.294	62	55.4	52.9
10	425	0.4	700	2.5	0.344	60	53.95	52.4
11	425	0.6	700	3	0.278	49	53.3	51.9
12	425	0.6	700	2.5	0.322	45	52.51	50.7

Water = W, Cement=C, Fine Aggregate = FA , Compressive strength 60 -day = Fc

Compressive strength tests were carried out using 5 × 5 × 5 cm cubes that were moist cured in a salt water tank and loaded in a compression machine Fig. 1.

3. Artificial Neural Networks

ANNs are non-linear statistical data modeling tools for relationships between inputs and outputs dada which can be an adaptive system that changes its structure based on information that flows through the network during the learning phase. There is on ANN architectures which is very familiar: feed-forward networks have their neurons arranged in layers. These layers have connections to each other and the Elman ANN has a loop from the output of the hidden layer to the input layer [13]. In this model several feature mortar with compressive strength by ANNs. ANN architecture shown in Fig.2, this is called feed-forward type of network where computations proceed along the forward direction only.

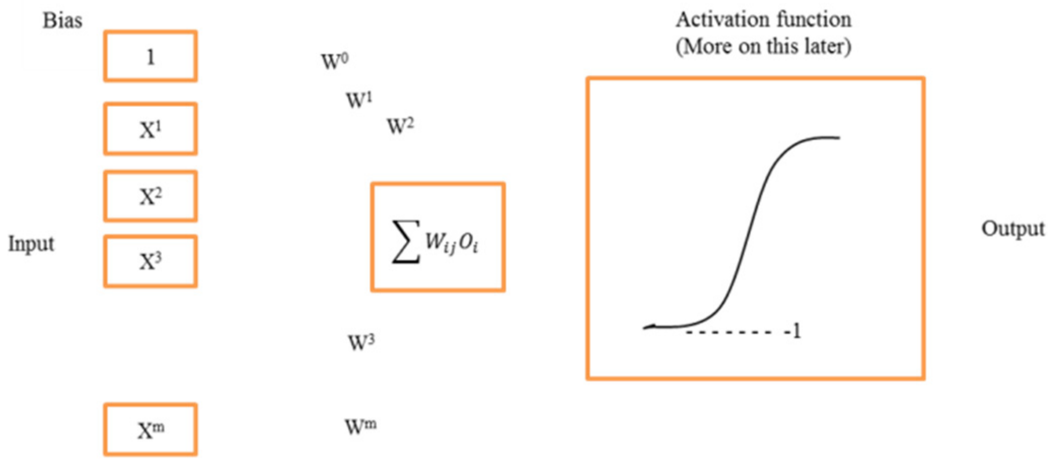

Fig. 1. The artificial neuron model

Fig. 2. Specimens sample of compressive strength test.

An ANN model consisting of 4 input nodes, 5 hidden layer nodes, and one output nodes, which will be referred to as ANN 4-5-1 model.

The hyperbolic tangent function transfer function is adopted. The tangent function is nonlinear and, so, it becomes essential to normalize the original data before training the network. Output from a tangent function range is between 1 and -1. Therefore the following form of the linear transformation viz. Eq. (1) is considered for the input and output vectors:

$$x_i = \frac{1.6(x_{i0} - x_{\min})}{(x_{\max} - x_{\min})} - 0.8 \qquad And \qquad Y_i = \frac{1.6(Y_{i0} - Y_{\min})}{(Y_{\max} - Y_{\min})} - 0.8 \tag{1}$$

where X_{io} and X_i are the ith components of the input vector before and after normalization respectively and Y_{io} and Y_i are the ith components of the output vector before and after being transformed, respectively. The X_{max}, X_{min}, Y_{max} and Y_{min} are the maximum and minimum values of all the components of the input vectors and output vectors before the normalization, respectively[22].

4. ANN model analysis and discussion

The proposed ANN consists of the strength prediction model for mortar in the vicinity of sodium chloride. Using, an ANN model with five hidden layers was constructed, trained and tested using the available test data of 60 different mix-designs of mortar gathered from the available literature.

Comparison of ANN strength model with existing empirical models:

The network architecture used in this study was called ANN 4-n-1, where the first digit is the number of input nodes Which contains water-cement ratio, the ratio of fine cement, relative to the total water and cement fines and the percentage of sodium chloride, n is the number of hidden nodes which In this paper, n = 5 is selected as the optimal number of hidden nodes and third digit is the number of output nodes that according to consider the resistance as output So the number of output nodes = 1. The most common back propagation training algorithm is Levenberg–Marquardt which was used in this investigation and performance that is used is mean squared error. The efficiency of neural network depends upon the randomness of data set, to achieve this a random number generator was used in MATLAB programing which distributes random data points[27]. As the first step for providing sufficient information for training, verifying and testing of neural networks, a comprehensive set of test results on the mortar compressive strength for different cement grades in the vicinity of sodium chloride was collected.

Prediction of mortar compressive strength for different cement grades in the vicinity of sodium chloride using neural network algorithm can be seen summarized in Figs 3-5.

In initial stages the both cement grades such as 32.5 and 42.5 MPa is used in training and testing data together which is plotted in Fig 3. This shown that regardless of the cement grades such as 32.5 and 42.5 MPa the ANN model can be poor predicted which indicates a lack of cement grades as input data in ANN model may not be acceptable in architecture of ANN.

ANN model predicted the experimental strength measurements with the correlation coefficient (R2) of 0.541 and 0.616 for training and testing data respectively, that shown poor prediction.

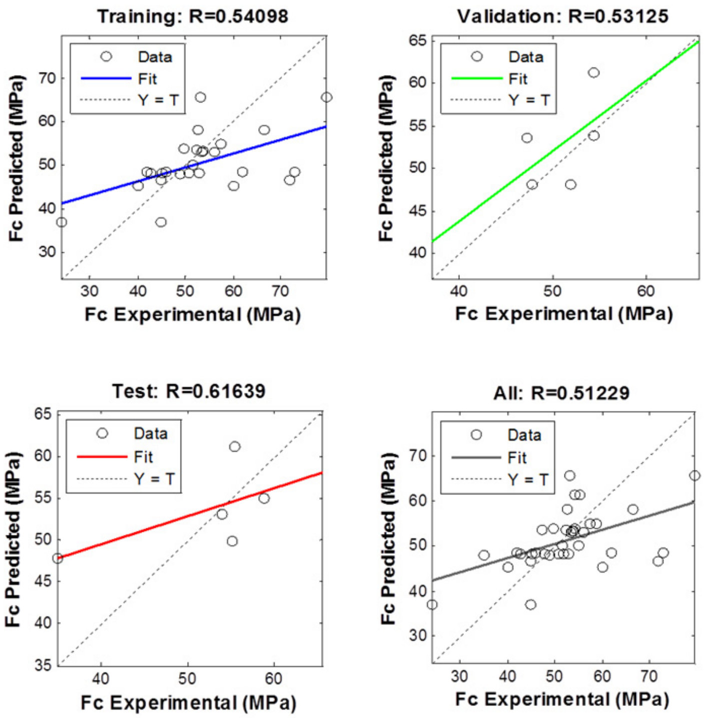

Fig. 3. ANN response in predicting the compressive strength

Due to clarifying this idea the new architecture ANN model is defined based on cement grades to prediction of compressive strength of mortar in vicinity of sodium chloride. The performance of compressive strength of mortar for design, actual and training test sets for cement grades of 32.5 MPa can be seen in Fig 4. The results of training phase indicated that the proposed neural network was successful in learning the relationship between the different input parameters and the output parameter via compressive strength of mortar. s. The R2 of 0.959 and 0.995 were obtained for the training and testing data of compressive strength prediction. Also data for all cement type 32.5 MPa with a R2 of 0.962. All of the statistical values demonstrate that the proposed ANN model is suitable and it predicts the compressive strength values very closely to the experimental value.

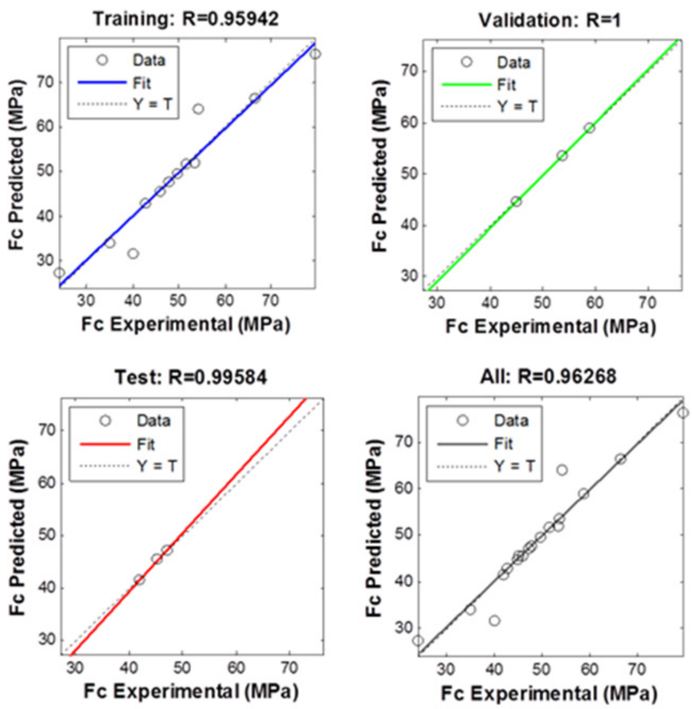

Fig.4. Evaluation of target and predicted compressive strength cement type 32.5 (MPa) by ANN

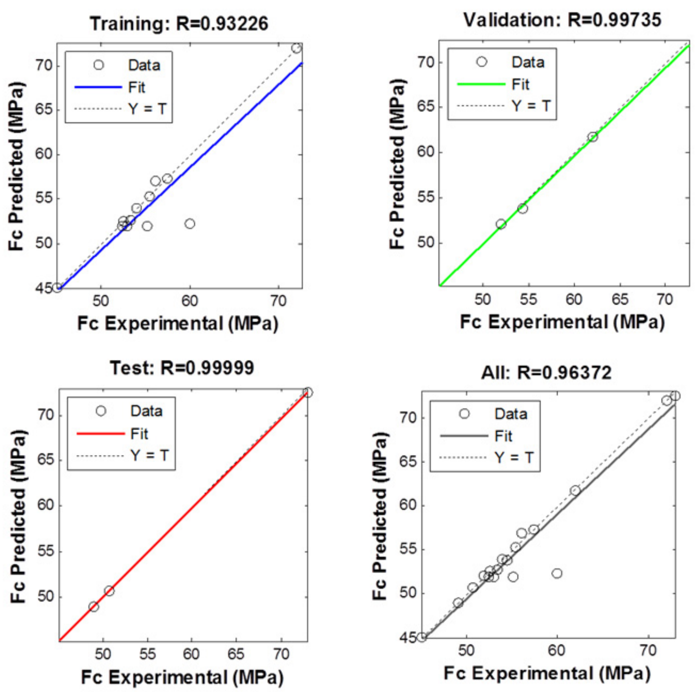

Fig.5. Evaluation of target and predicted compressive cement type 42.5 (MPa) by ANN.

However, considering the type of cement as input parameters important role in performance network [28]. Moreover the ANN prediction for cement grades of 42.5 MPa is plotted in Fig. 5. This shows similar to plotted for cement grades of 32.5 MPa. ANN analysis indicates that a good agreement between experimental data and compressive strengths of cement mortars can be establish by using feed forward algorithm. The coefficient of correlation between the measured and predicted compressive strength values is calculated as $R^2 = 0.963$ representing a strong relationship for the investigated parameters. ANN model predicted R^2 of 0.932, 0.999 and 0.997 for training, testing and validation data respectively. In the other hand the cement grades of 32.5 and 42.5 as input of ANN can increase the performance of ANN. All experimental values prove that considering the type of cement (Fig. 4 and 5) the proposed the ANN model is suitable to predict the compressive strength mortar in the vicinity of sodium chloride values very close to the experimental results. The precision of the proposed Figures was verified by available experimental data and showed good performance. The results have demonstrated that artificial neural networks system is practicable methods for predicting compressive strength of mortar.

5. Conclusion

This study was demonstrating possibilities of adopting neural networks to predict the compressive strength of mortar. The acceptable predictions of the mortar compressive strength in vicinity of sodium chloride by this model which indicate that ANNs could be a useful tool for understanding such systems. Consequently, the model could be utilized by engineer to optimally choose strength as a function of measured cement properties in environment of sodium chloride. Increase high water range reducer in mortar causes good increase in compressive strength at 60 day. There sodium chloride in the process of curing up to 5% causes increase the compressive strength and then will decline for cement 32.5 MPa but for cement 42.5 MPa. With increases Sodium chloride ions from 5 to 10 % reduced compressive strength for cement 32.5 and 42.5 MPa. Increase of sodium chloride ions, to the water/cement ratio of 0.4, reduced compressive strength and for more water/cement ratio, increases the compressive strength. The Levenberg– Marquardt algorithm is found to be the best learning algorithm. The ANN model predicts the compressive strength of mortar in the vicinity of sodium chloride. The considering the parameter type of cement is an important factor indicates that data sets could strongly affect the performance of a trained network.

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