Prediction of compressive strength of mortar near sodium chloride by artificial neural network

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Abstract. The compressive strength value of cement mortar is usually affected by the amount of sodium chloride, chemical admixture and cement grade. Therefore, the artificial neural network model is used to predict the mortar strength values of different cement grades and sodium chloride (NaCl) content. In order to predict the compressive strength of the mortar, an artificial neural network model of cement grade, different water-cement ratio, sodium chloride solution content, an output neuron and four input neurons was established. After immersion in 0%, 5%, and 10% sodium trichloride solution for 60 days, the compressive strength was measured using 12 different ratios. Artificial neural network (ANN) analysis shows that ANN as a nonlinear statistical data modeling tool can establish a strong correlation between sodium chloride content and compressive strength of cement mortar. In addition, modeling tools have a greater impact on different cement grades (42.5, 32.5 MPa).

1. Introduction
Chloride ion corrosion is one of the factors affecting the durability of the structure. There have been many studies on the effects of structural corrosion such as chloride ions on the strength reduction of reinforced concrete. Cement mortar is often used in anticorrosive pipes as one of the most effective resources. A large number of studies have shown that the compressive strength of concrete is usually affected by parameters such as water-cement ratio, aggregate particle size, and aggregate content. However, the compressive strength of cement is the biggest factor that affects the compressive strength of mortar according to different standards. Usually cement grades are 32.5, 42.5 and 52.5 MPa. In other words, cement has different compressive strength at a constant water-cement ratio (W/C), especially the reaction rate of high-strength cement is higher than that of low-strength cement. Cement adds a large amount of low-active mineral admixture. In recent years, many models have been used to predict the compressive strength of cement-based materials, such as regression analysis, artificial neural networks, genetic algorithms, and fuzzy logic. Artificial neural networks (ANNs) were used to predict the compressive strength of mortar and concrete. Based on the predicted strength parameters of the mortar, the ANN model is used for prediction. Since strength is an important feature of concrete, the number of samples of concrete compressive strength in the laboratory is reduced, which is very useful for predicting the accuracy of the model.

For example, a total of 45 concrete samples are produced at 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 rates (20%, 40%, 60%, 80%), using ANN model for compressive strength of wet cured specimens (22±2°C) were measured at 3, 7, 28, 90 days. Using ANN model to predict the compressive strength of concrete samples with different specifications of cement, water cement ratio and curing...
time has high accuracy, which can be used as an effective method. As mentioned earlier, the compressive strength of mortar and concrete is affected by many parameters such as curing conditions, curing days, and water-cement ratio. Therefore, under the condition of constant water-cement ratio, the curing of different cement grades and different cement impregnation rates has a significant impact on the compressive strength of cement. This parameter will change any model currently available. In this study, artificial neural networks were used to predict the compressive strength of cement mortars produced from two cement grades 32.5 and 42.5 MPa. Water-cement ratio, 0%, 5%, 10% sodium chloride solution and compressive strength with different mix ratios. Using this data, an artificial neural network model was established and verified, indicating that the use of cement strength grades has an impact on the prediction of mortar compressive strength.

2. Material and hybrid design

The experimental research uses 12 kinds of W/C and super plasticizer (SP) mix design, the cement strength grade is 32.5 and 42.5 MPa, respectively. An experimental study was performed in the laboratory, and the 60-day compressive strength of the mortar near sodium chloride was compared by ANN prediction. 6 cement 32.5 MPa and 6 cement 42.5 MPa are shown in Table 1.

In addition, the cement grade II and other standard materials with a strength grade of 32.5, 42.5 MPa, and a specific gravity of 3.14 are used. The fine aggregate passing specific gravity is 2.62 and the fineness modulus is 2.48.

Table 1: Mix proportions of mortar

| mixture no. | Grade of cement | W/C | C (kg/m^3) | Fa/C | C Fa+W | Compressive strength(MPa) |
|-------------|-----------------|-----|------------|------|--------|---------------------------|
| 1           | 325             | 0.3 | 700        | 3    | 0.303  | 46                        |
| 2           | 325             | 0.3 | 700        | 2.5  | 0.357  | 45                        |
| 3           | 325             | 0.4 | 700        | 3    | 0.294  | 42                        |
| 4           | 325             | 0.4 | 700        | 2.5  | 0.344  | 40                        |
| 5           | 325             | 0.6 | 700        | 3    | 0.278  | 35                        |
| 6           | 325             | 0.6 | 700        | 2.5  | 0.322  | 24                        |
| 7           | 425             | 0.3 | 700        | 3    | 0.303  | 73                        |
| 8           | 425             | 0.3 | 700        | 2.5  | 0.357  | 72                        |
| 9           | 425             | 0.4 | 700        | 3    | 0.294  | 62                        |
| 10          | 425             | 0.4 | 700        | 2.5  | 0.344  | 60                        |
| 11          | 425             | 0.6 | 700        | 3    | 0.278  | 49                        |
| 12          | 425             | 0.6 | 700        | 2.5  | 0.322  | 45                        |

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

3. Artificial neural networks

A neural network is a non-linear statistical data modeling tool for the relationship between input and output data. It can be an adaptive system that changes the structure based on the information transmitted through the network during the learning phase. In the structure of neural networks, one is very familiar: the neurons of the feedforward network are arranged hierarchically. These layers are connected to each other. Elman ANN has a loop from the output of the hidden layer to the input layer. In this model, the compressive strength of several mortars is determined by ANNs. The ANN architecture shown in Figure 1 is called a feed-forward network, and the calculation is performed only in the feed-forward direction.

An ANN model consisting of 4 input nodes, 5 hidden layer nodes, and 1 output node is called ANN 4-5-1 model. Use the hyperbolic tangent function transfer function. The tangent function is non-linear, so it is important to normalize the original data before training the network. The output of the tangent
function is between 1 and -1. Therefore, for the input and output vectors, consider a linear transformation of the form Eq. (1):

\[
X_i = \frac{1.6(X_i - x_{\text{min}})}{(x_{\text{max}} - x_{\text{min}})} - 0.8 \quad \text{And} \quad Y_i = \frac{1.6(Y_i - y_{\text{min}})}{(y_{\text{max}} - y_{\text{min}})} - 0.8
\]

(1)

Fig1. The artificial neuron model

4. Analysis and discussion of neural network models

The artificial neural network consists of a prediction model of the strength of mortar near sodium chloride. Using the experimental data designed from 60 different mortar mix ratios in the existing literature, a neural network model with 5 hidden layers was established, and training and experiments were performed. Comparison of ANN strength model with existing empirical models: The network architecture used in this study is called 4-n-1. The first number is the number of input nodes including the water-cement ratio and the ratio of fine cement. For the percentage of cement and sodium chloride, n is the number of hidden nodes in this paper. Select n=5 as the optimal number of hidden nodes. The third bit is the number of output nodes based on resistance as the output, so the number of output nodes=1. The most commonly used back-propagation training algorithm is Levenberg-Marquardt, which was used in this study and the performance is the mean square error. The efficiency of a neural network depends on the randomness of the data set. To this end, a random number generator is used in MATLAB programming to assign random data points. In order to provide sufficient information for the training, verification and testing of neural networks, the comprehensive test results of compressive strength of different cement grade mortars near sodium chloride were first collected.

The neural network algorithm for predicting the compressive strength of different cement grade mortars near sodium chloride is shown in Figure 2. In the initial stage, cement grades 32.5 and 42.5 MPa are used together for training and test data, as shown in Figure 2. This shows that no matter the cement grade is 32.5, 42.5 MPa, the predictive ability of the ANN model is poor, indicating that the data entered in the ANN model may not be accepted in the ANN architecture, resulting in the lack of cement grade.

The ANN model predicts the experimental intensity measurements, and the correlation coefficients (R2) of the training and test data are 0.541 and 0.616, respectively, and the predictions are poor.
Based on this, a new cement neural network model based on architecture is proposed to predict the compressive strength of mortar near sodium chloride. The mortar compressive strength performance of the cement grade 32.5 MPa design, measurement and training test is shown in Figure 3. The results of the training phase show that the neural network successfully learns the relationship between different input parameters and output parameters of the mortar through the compressive strength of the mortar. Training and testing data for compressive strength predictions gave R² of 0.959 and 0.995. All cement types are 32.5 MPa and R² is 0.962. All statistical results show that the proposed neural network model is applicable, and its prediction of compressive strength is very close to the experimental value.
Fig. 3. Evaluation of target predicted compressive strength cement type 32.5(MPa) by ANN

However, considering cement type as an input parameter plays an important role in the performance network. The ANN prediction of cement grade 42.5 MPa is shown in Figure 4. This is similar to the 32.5 MPa cement grade. The artificial neural network analysis shows that the feed-forward algorithm can make the test data match the compressive strength of cement mortar better. The correlation coefficient $R^2=0.963$ between the measured compressive strength value and the predicted compressive strength value indicates that there is a strong relationship between the research parameters. The A2 model’s $R^2$ predictions for training, testing, and validation data are 0.932, 0.999, and 0.997, respectively. On the other hand, cement grades 32.5 and 42.5 can be used as input to artificial neural networks to improve the performance of artificial neural networks. All experimental values prove that, considering the type of cement (Figure 4 and Figure 5), the proposed ANN model is suitable for predicting compressive strength mortar near the sodium chloride value, which is very close to the experimental results. Experimental data verified the accuracy of the method and achieved good results. The results show that the artificial neural network system is a feasible method for predicting the compressive strength of mortar.

Fig. 4. Evaluation of target and predicted compressive cement type 42.5(MPa) by ANN

5. Conclusion
This study demonstrates the possibility of using neural networks to predict the compressive strength of mortars. The model was used to make an acceptable prediction of the compressive strength of mortar.
near sodium chloride, suggesting that neural networks can be a useful tool for understanding such systems. Therefore, the model can be used by engineers and technicians to determine the strength of the cement in a sodium chloride environment, and the strength is preferred. The addition of a high-water range water reducing agent in the mortar improved the compressive strength of the mortar at 60 d. Among them, sodium chloride reached 5% during the curing process will cause the compressive strength of cement to increase, the compressive strength of cement is 32.5 MPa, and the compressive strength of cement is 42.5 MPa. As the sodium chloride ion increased from 5% to 10%, the compressive strength of the cement decreased by 32.5 and 42.5 MPa. Increasing the sodium chloride ion makes the water-cement ratio 0.4, and the compressive strength decreases, while for more water-cement, the compressive strength increases. The Levenberg-Marquardt algorithm is considered the best learning algorithm. This model predicts the compressive strength of the mortar near sodium chloride. The consideration of cement parameter types is an important factor affecting network performance, and the data set has a great impact on network performance.

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