Neural Network Method Based on Concrete Carbonation Depth Prediction

Duo Wu*, Yuanrong Liu, Yuxue Yin, Zhiyong Deng and Zhifu Liu

1Department of Civil Engineering, Nanchang Institute of Technology, Nanchang Jiangxi 330029, China
*Corresponding author’s e-mail: 2018994667@nit.edu.cn

Abstract. Carbonation is a typical disease that affects the long-term durability of concrete. In this paper, neural network toolbox in MATLAB software was employed to analyze sample parameters such as CO2 concentration, compressive strength, age and water-cement ratio in concrete carbonation research, and to predict the depth of carbonation. The results show that under the premise of setting reasonable parameters, the sample training results are satisfactory, the average error is about 7%~14%, which basically meets the precision requirements of the preliminary identification of concrete carbonation depth.

1. Introduction
The durability of concrete structures is one of the main problems perplexing the engineering field at present [1]. With the improvement of material technology and process, the service life of engineering structures has also increased, but at the same time, the problems brought by it have also increased. Concrete cracking and steel corrosion [2] are often caused by external environmental erosion and internal fatigue damage of structures in service period. There are usually many reasons for such diseases, but the damage caused by freeze-thaw, salt erosion and carbonization accounts for a high proportion.[3].

Carbonization is a typical durability failure of concrete. Under long-term erosion, carbonization [4] on the one hand will reduce the alkalinity of concrete; on the other hand, it will also increase the amount of hydrogen ions in the concrete hole solution, thus weakening the protection of the internal reinforcement layer, leading to the occurrence of damage. Therefore, it has good application value and research significance to study the carbonation depth of concrete.

The carbonization of concrete is a complex physical and chemical process. Based on Fick's first law, many scholars have carried out related researches on theoretical carbonization models and deep prediction models. The current models of concrete carbonation depth are mostly based on the three elements of time, CO2 concentration and compressive strength. With reference to the existing concrete carbonization research [5], it can be found that: qualitatively, time and CO2 density are directly proportional to the carbonation depth, while the compressive strength is inversely proportional to the carbonation depth; quantitatively, the magnitude of the square root should be taken into consideration. In summary, the carbonation depth model as shown in Equation (1) is basically formed:

\[ D = \lambda \sqrt{\frac{C}{f_{cu}T}} \]  

(1)
Where $D$ is the carbonation depth of concrete; $\lambda$ is the concrete influence coefficient; $C$ is CO$_2$ concentration in the test environment; $f_{cu}$ is the compressive strength of the standard cube before carbonization.

2. BP Neural Network Algorithm for Predicting Concrete Carbonation Depth

2.1. BP neural network system

BP neural network algorithm [6] is a typical non-feedback multilayer forward network model. Through this algorithm, the carbonation depth of concrete can be predicted. A number of neurons of input layer, hidden layer and output layer can be set. Through the training and learning of relevant parameters, the corresponding neural network nonlinear model was built, as shown in Figure 1.

As can be seen from Figure 1, BP neural network is a typical multi-layer forward network model with no feedback. $M$ represents the number of input neurons, $N$ represents the number of hidden layer neurons, and $K$ represents the number of output neurons. $M = \{m_1, \cdots, m_m\}$ is the training parameter sample combination of the input layer; $N = \{n_1, \cdots, n_n\}$ is the hidden layer neuron output and the neural network input layer, $K = \{k_1, \cdots, k_k\}$ is the expected output.

2.2. Prediction step

2.2.1. Determination of neural network function

BP neural network usually uses the newff function to determine

$$\text{net} = \text{newff}[P,T,[S1 S2...S(N-1)],\{TF1 TF2...TFNI\}, \text{BTF}, \text{BLF}, \text{PF}, \text{OPF}, \text{DF}, \text{DDF}]$$

Where $P$ refers to input vector, $T$ output vector, $S_i$ the number of hidden layer neurons, $T_{Fi}$ transfer function, $\text{BLF}$ network threshold Learning function, $\text{IPF}$ input processing function, $\text{OPF}$ output processing function, $\text{DDF}$ data division function.

2.2.2. Determination of the number of neurons in the hidden layer

BP neural network is a multi-layer neuron structure including input layer, several hidden layers and output layer. The number of neurons in the input layer and output layer can be determined according to actual measurement conditions, but the number of neurons in the hidden layer is difficult to determine. At present, there is no corresponding selection standard for the number of neurons in the hidden layer, and most of them are determined by experiential value or multiple trial calculations. As an important "black box theory" affecting BP neural network algorithm, the number of hidden layer
neurons will have a great impact on sample training. If fewer hidden layer neurons were selected, the combination of training samples would be insufficient; if there are more neurons in the hidden layer, the training speed will be reduced, and the generalization ability of the network will become worse. Many scholars at home and abroad have conducted a large number of studies based on the determination of the number of neurons in the hidden layer. According to the previous studies, the following formula was used in this paper to determine the number of neurons in the hidden layer.

\[ n \leq \sqrt{u + v + w} \]  \hspace{1cm} (2)

\( u \) represents the number of neurons in the input layer, \( v \) the number of neurons in the output layer, and \( w \) the constant between 1~10.

2.2.3. Sample training and learning
The training of samples includes parameter input and expected output. In this paper, the input sample of BP network is the sample combination composed of \( \text{CO}_2 \) concentration, time, compressive strength, water-cement ratio and other attribute parameters of concrete. The output sample corresponds to the carbonation depth of concrete after training.

After the training sample and network structure are determined, the appropriate training function can be selected. Common neural network training functions include trainbfg, trainrp, traingd and trainlm. The trainlm function based on Levenberg-Marquardt optimization has the characteristics of fast training speed, high accuracy of results and good adaptability. This paper intends to select this training method.

After the corresponding training parameters are determined, the training samples can be started until the network reaches convergence. If the network cannot completely converge, the parameters need to be adjusted to re-train the samples.

2.2.4. Carbonation depth prediction
After the training of the neural network, the prediction of the carbonization depth of concrete can be started. Several groups of sample parameters were selected for training as the corresponding initial sample data, and the predicted carbonation depth corresponding to the target sample could be output after the training of BP neural network.

3. Numerical example

3.1. Basic conditions
Data algorithms based on neural network pattern often rely on sufficient sample data. Therefore, this paper intends to collect the carbonation depth test data of several groups of attribute sample parameters of concrete for analysis, in order to obtain a network model suitable for the carbonation depth of concrete.

According to the above analysis, the influencing factors of concrete carbonation mainly include time, \( \text{CO}_2 \) concentration, compressive strength and water-cement ratio. The carbonation depth of unknown groups of concrete was identified by referring to the test data in Reference [7-10]. The processed data are shown in Table 1.

| No. | Carbonization time/d | \( \text{CO}_2 \) density/% | Humidity/% | Temperature/({\degree}C) | Water-cement ratio | 28d compressive strength of concrete/MPa | Carbonization depth test value |
|-----|-----------------------|-----------------------------|------------|--------------------------|-------------------|-----------------------------------------|-------------------------------|
| 1   | 30                    | 20                          | 75         | 18                       | 0.35              | 39.9                                    | 2.6                           |
| 2   | 30                    | 20                          | 75         | 18                       | 0.4               | 35.4                                    | 8.8                           |
| 3   | 30                    | 20                          | 75         | 18                       | 0.5               | 21.7                                    | 12.4                          |
| 4   | 30                    | 20                          | 75         | 18                       | 0.65              | 15.3                                    | 16.6                          |
Table 1 shows the carbonation depth obtained by the test parameters of concrete carbonization time, CO₂ concentration, temperature and humidity, water-cement ratio, 28d compressive strength. Among the 28 groups of concrete test data mentioned above, 1-11, 13-19, 21-23 and 25-27 are training samples, and 12, 20, 24 and 28 are unknown carbonation depth test sample data for neural network prediction analysis.

3.2. Selection of training parameters
The above 24 sets of training sample data were normalized and used as the input parameters of the neural network. According to the characteristics of this experiment, the activation functions of the hidden layer and the output layer were selected as tansig and logsig functions, respectively, the number of iterations was 5000, and the expected error was 0.00001. The number of neurons in the hidden layer can be calculated from equation (2), and the range is 4~13. Based on experience, the number of neurons in the hidden layer was selected as 3, 5, and 8 to be compared.

Sample 12 was selected as the object for specific parameter comparison. Due to the differences in neural network thresholds, there would be some differences in the structure layer after each training, and the output layer was the average value of the three training sessions. The training results are shown in Table 2.

| Number of hidden layer neurons | Learning rate | Identification value | Average | Average error |
|---------------------------------|--------------|----------------------|---------|---------------|
| 3                               | 0.01         | 16.73 17.78 15.57    | 16.69   | 4.99%         |
|                                 | 0.02         | 16.12 17.09 15.17    | 16.13   | 1.42%         |

Table 2: Training results of different parameters
According to the results in Table 2, it can be determined that when the number of neurons in the hidden layer was 8 and the learning rate was 0.01, the recognition effect was better. Therefore, the remaining samples were trained according to this parameter.

3.3. Prediction and identification of unknown carbonization depth

The remaining three groups of data, 20, 24 and 28, were taken as the output layer samples to verify the corresponding carbonization model. The above-mentioned setting parameters were employed to verify, and the results are shown in Table 3.

| Measured value of carbonation depth | Identification value | average error |
|------------------------------------|----------------------|---------------|
|                                    | First time | Second time | Third time | average value | average error |
| 7.7                                | 7.8813     | 7.8646      | 8.9093     | 8.22          | 6.73%         |
| 36.45                              | 30.6921    | 31.0645     | 31.2982    | 31.02         | -14.90%       |
| 20.1                               | 21.9079    | 23.2651     | 23.9097    | 23.03         | 14.57%        |

It can be seen from Table 3 that the use of BP neural network algorithm to predict the carbonation depth of concrete has a certain recognition accuracy, and the error accuracy is about 7% to 14%, which basically meets the requirements of the preliminary identification of concrete carbonation depth.

4. Results

In this paper, BP neural network algorithm was adopted to identify the carbonation depth based on various properties and test parameters of concrete, and the following conclusions are drawn:

(1) From a qualitative point of view, the depth of concrete carbonization is basically proportional to time, CO₂ concentration and other factors, and inversely proportional to the compressive strength; from a quantitative point of view, these factors should consider the square root value.

(2) It is feasible to use BP neural network algorithm to predict the carbonation depth of concrete, and the prediction accuracy error is about 7%~14%, which basically meets the requirements of the preliminary identification of concrete carbonation depth.

(3) In order to further improve the prediction accuracy, relevant models should be optimized or other types of neural network models should be introduced.

Acknowledgments

This work was partially supported by the Research Project of Jiangxi Provincial Department of Education (GJJ190980).

References

[1] Zhan Q P., Yin Y X., Wu Duo., et al.(2020) Design of testing device for durability erosion of concrete beam. Shanxi Architecture, 2020,46(09): 90-92.
[2] Wu D., Teng Y. X. (2019) Research status and prospect of durability of steel-polypropylene fiber reinforced concrete. Journal of Nanchang Institute of Technology, 38(4): 23-28.

[3] Zhang G. T., Tian H. X., Li B. Y., et al. (2018) Deicer-Frost Scaling of Steel polypropylene Hybrid Fiber Reinforced Concrete. Materials Review, 32(14): 2396-2399, 2406.

[4] Wu D., Liu Y. L., Yin Y. X., et al. (2021) Research on Prediction Model of Carbonization Depth of Steel Fiber Concrete Based on Second-order Fitting Method. Journal of Nanchang Institute of Technology, 40(01): 34-39.

[5] Smolczyk H. G. (1968) Proceedings of 5th International symposium on chemistry of cement. Tokyo, Vol.3, 343-368.

[6] Wu Duo., Liu L. J., Miao R. S. (2017) Neural network method in bridge condition assessment by using B-TBU model. Journal of Jiangsu University (Natural Science Edition), 38(04): 466-471.

[7] Zhang Y., Jiang L. X. (1998) A practical mathematical model of concrete carbonation depth based on the mechanism of carbonation. Industrial Construction, 28(1): 16-19.

[8] Chen L. T. (2007) Study on concrete carbonation model and parameters. Xi’an: Xi’an University of Architecture and Technology.

[9] Tu Y. M., Lü Z. T. (2006) Research on the experimental of prestressed concrete structures in carbonation environment and the predition model of carbonation depth. Industrial Construction, 36(1): 47-50.

[10] Fang J., Mei X. G. (1996) The study on main factors influencing concrete carbonation and reinforcement corrosion. Water Resources and Hydro-power Engineering, (2): 35-43.