Research on Concrete Carbonation Depth Prediction Algorithm Based on BP-AR

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Abstract. The influence factors of concrete carbonation depth are numerous and complex, and carbonation reaction has strong dependence on time. The accuracy of existing concrete carbonation depth prediction methods is not accurate enough, because all factors can not be taken into account. The BP-AR fusion algorithm is proposed. In this algorithm, the BP neural network is used to predict the carbonation depth, and then the prediction value is further corrected by time series method. It has been experimentally verified that by using the time series method, the regularity of carbonation reaction with time can be found through the carbonation depth value predicted by BP neural network. The BP-AR algorithm predicts the carbonation depth more accurately than BP neural network, and makes up for the large prediction errors caused by limited data volume.

1. Introduction
The key factor of affecting the durability of concrete structures is concrete carbonization. The security of people and property can be threatened by durability damage of concrete structures. Therefore, high-precision prediction of concrete carbonation depth is of great significance [1]. By the prediction of carbonation depth, the durability problem can be found in time, and the structure is strengthened and maintained to minimize the loss.

There are many studies about the concrete carbonation at home and abroad. Ditao NIU et al. combined theoretical analysis with experimental results, and established a calculation model for concrete carbonation depth prediction [2]. Haiyan ZHANG et al. took the strength grade of concrete, environmental temperature and humidity, the density of CO₂ and carbonization time as main influential factors on carbonization depth of concrete, and established concrete carbonation depth mathematical prediction model [3]. Woubishet Zewdu Taffe’s et al. established a concrete carbonation depth prediction model by using machine learning methods [4]. Benying WU et al. used Bayesian method to predict concrete carbonation depth [5]. There are many factors affecting the carbonization of concrete and the elements are coupled with each other. Some unpredictable biochemical reactions such as fungi, mildew, etc. may occur during the carbonization process, further affecting the carbonization reaction. All the affecting factors cannot be considered comprehensively through existing carbonation depth prediction methods, which bring about large errors or limitations of the model prediction results.
In actual engineering, the factors affecting the depth of carbonization include temperature, humidity, water-cement ratio, admixture content, sulfur dioxide concentration, carbon dioxide concentration, etc. When BP neural network is used to predict the depth of carbonation, the time dependence of concrete carbonization reaction is neglected, and the depth of carbonization cannot be accurately predicted. Only using the time series method, long-term measured data of carbonization depth is required. In practical engineering applications, the depth of carbonization is not easy to measure, and even the structural performance and appearance of concrete buildings are destroyed during the measurement process, which makes the model more difficult to establish. Since the concrete carbonation reaction is continuously carried out on the basis of existing concrete carbonization, and there is a strong time dependence in the carbonization reaction, in addition to some simple and easy to measure influence factors The change of carbonization reaction with time should also be taken into account in the process of concrete carbonation depth prediction. In this paper, BP-AR fusion algorithm is used to correct the prediction value based on BP neural network prediction of carbonation depth. Through experimental verification, the prediction accuracy is improved by using the fusion algorithm.

2. BP-AR Fusion Algorithm

Please follow these instructions as carefully as possible so all articles within a conference have the same style to the title page. This paragraph follows a section title so it should not be indented[2-3].BP(Back Propagation) Neural network is a multi-layer feedforward network trained by error inverse propagation algorithm and has strong nonlinear mapping ability. The AR(Auto Regressive) model is one of the commonly used models of time series and is a special form of the ARMA(Auto Regression Moving Average) model. Time series prediction is based on the past and present observation data of the predicted things. Through its inherent statistical characteristics and development laws, specific models are constructed to speculate on the future development trend of things. The ARMA model can be expressed as

\[ y_t - \varphi_1 y_{t-1} - \varphi_2 y_{t-2} - \cdots - \varphi_p y_{t-p} = \varepsilon_t - \theta_1 \varepsilon_{t-1} - \theta_2 \varepsilon_{t-2} - \cdots - \theta_q \varepsilon_{t-q} \]  

(1)

\( \varphi \) is an autoregressive coefficient; \( \theta \) is moving average coefficient; \( p \) is autoregressive order;\( q \) is moving average order.

A new fusion algorithm BP-AR is proposed based on BP neural network and time series method. The flow chart can be expressed as shown in Figure 1 below. The BP-AR algorithm steps can be expressed as follows:

\[
\begin{bmatrix}
  x_{11} & x_{12} & \cdots & x_{1n} \\
  x_{21} & x_{22} & \cdots & x_{2n} \\
  \vdots & \vdots & \ddots & \vdots \\
  x_{m1} & x_{m2} & \cdots & x_{mn}
\end{bmatrix}
\rightarrow
\begin{bmatrix}
  y_1 \\
  y_2 \\
  \vdots \\
  y_m
\end{bmatrix}
\]

(2)

\( x_{i1}, x_{i2}, \cdots, x_{in} \) represents \( n \) influence factors of concrete carbonation, total \( m \) group. \( y_1, y_2, \cdots, y_m \) is the output value corresponding to each row in the input matrix, and is also the expected depth of carbonization.
Time series data

Whether it is a stationary time series

Differential processing

NO

YES

Autocorrelation and partial autocorrelation function graph

Determine model type

Parameter Estimation

Determining the model order

Time series correction value \( w \)

Weighted average

Final carbonation depth prediction \( y' \)

End

Figure 1. BP-AR algorithm flow chart

Step1: The influence factors are used as the input of the BP neural network, and the carbonization depth prediction value \( z_i \) is used as the output of the BP neural network, as shown in equation (3). The experimental set is divided into a training set and a test set. The training set samples are used to train the BP neural network, and the test set is used to verify the model.

\[
\begin{bmatrix}
  x_{11} & x_{12} & \cdots & x_{1n} \\
  x_{21} & x_{22} & \cdots & x_{2n} \\
  \vdots & \vdots & \ddots & \vdots \\
  x_{m1} & x_{m2} & \cdots & x_{mn}
\end{bmatrix}
\begin{bmatrix}
  F_{bp}
\end{bmatrix}
\begin{bmatrix}
  z_1 \\
  z_2 \\
  \vdots \\
  z_m
\end{bmatrix}
\]

A three-layer BP neural network model with temperature, humidity, carbon dioxide concentration, water-cement ratio, cement dosage and carbonization time as the input layer and carbonization depth as the output layer was established. Its network topology is shown in Figure 2.

Figure 2. BP neural network topology

The number of hidden layer neuron nodes can be determined by the following empirical formula:

\[
l = \sqrt{m + n + a}
\]

\[
l = \sqrt{0.43mn + 0.12n^2 + 2.54m + 0.77n + 0.35 + 0.51}
\]
m, n are the number of neuron nodes in the input layer and output layer respectively, a is a constant between 1 and 10.

Step 2: The laws of \( z_{t-1}, z_{t-2}, \cdots, z_{t-p} \) and \( z_t \) are analyzed by time series method (\( z_t \) is the BP neural network prediction value of carbonization depth at time i). The time series prediction value at time \( t \) \( w_t \) is obtained by further correcting the carbonization depth value at time \( t \).

\[
P_{\text{series}}(z_{t-1}, z_{t-2}, \cdots, z_{t-p}) \rightarrow w_t \tag{6}
\]

Among them, the basic principles of the autocorrelation function (ACF) graph and the partial autocorrelation function (PACF) graph are shown in Table 1.

| ACF | PACF | Model Ordering |
|-----|------|----------------|
| trailing | p-order truncation | AR(p) model |
| q-order truncation | trailing | MA(q) model |
| trailing | trailing | ARMA(p,q) model |

The AIC criterion method is used to accurately determine the model order. For the AIC criterion function, when

\[
AIC(n_0, m_0) = \min_{1 \leq n, m \leq M/N} AIC(n, m) \tag{7}
\]

then \( n_0 \) and \( m_0 \) are determined as the best model order. After the model is determined, the least square method (LS) is used to estimate the parameters of the model. The least squares estimation method is based on the minimum variance. When the expected value of the squared error between the actual value and the estimated value is the smallest, the corresponding parameter estimation value is the optimal parameter estimation value. Its model is assumed to be

\[
y_i = \alpha_0 + \alpha_1 x_{i1} + \alpha_2 x_{i2} + \cdots + \alpha_n x_{in} + e_i, \quad i = 1, 2, \ldots, N \tag{8}
\]

where \( y \) is the observed data, independent variable \( x \) is known, \( \alpha \) is the parameter to be estimated, and \( e \) is the zero mean error. When the sum of squared errors is the smallest, then \( \hat{\alpha} = (\hat{\alpha}_1, \hat{\alpha}_2, \cdots, \hat{\alpha}_n)^T \) is the least squares estimate of parameter \( \alpha \). As shown in Equation 9.

\[
E(\alpha) = E(\alpha_1, \alpha_2, \cdots, \alpha_n) = \sum_{i=1}^{N} (y_i - \alpha_0 - \alpha_1 x_{i1} - \cdots - \alpha_n x_{in})^2 = \sum_{i=1}^{N} e_i^2 \tag{9}
\]

Step 3: The final carbonation depth prediction value \( \hat{y}_i' \) is obtained by weighted average of BP neural network prediction values \( z_i \) and time series prediction values \( w_i \).

\[
\hat{y}_i' = \frac{1}{2} z_i + \frac{1}{2} w_i \tag{10}
\]

Step 4: The final predicted values are compared with the BP neural network predictions and expected values, respectively. Comparing the final predicted value \( \hat{y}_i' \) with the BP neural network prediction value \( z_i \) and expected value \( y_i' \).

3. Experiment and Analysis

In order to verify the validity of the concrete carbonation depth prediction model proposed in this paper, more than 300 sets of data were collected in literature 9, literature 10, and literature 11. The collected 300 sets of test data are divided into two parts as the training set and test set of BP neural network. After many adjustment experiments, the number of neurons in the hidden layer \( l \) was finally determined to be 13. The training error curve and fitting curve of BP neural network are shown in Fig. 3. It can be seen from Fig. 3 that the BP neural network target error 0.001 is reached in step 1319, and the predicted value and the true value fit R=0.997.
In this paper, accelerated carbonation experiments were used to design two sets of concrete specimens with different mixing ratios. The relevant parameters of each group are shown in Table 2. The carbonation depth is measured every 5 days from the 10th day.

Table 2. Concrete test piece related parameters

|                | Cement consumption/ kg·m⁻³ | Water cement ratio | temperature/ °C | humidity/% | Carbon dioxide concentration/% |
|----------------|---------------------------|-------------------|-----------------|-----------|-------------------------------|
| Group A        | 276                       | 0.4               | 20              | 75        | 20                            |
| Group B        | 390                       | 0.55              | 20              | 70        | 20                            |

First, the trained BP neural network is used to predict the carbonation depth of the A and B groups. Then, the top 15 (ie 10-80 days) BP neural network prediction data in each group is selected as the input of the A and B groups, and the time series model is established to predict the carbonization depth in the future. Then, by performing zero-meanization and stationarity processing on the two sets of data, the smooth time series data is obtained. The autocorrelation function and the partial autocorrelation function of the data of the two groups A and B are obtained by using MATLAB, as shown in Fig. 4 and Fig. 5. It can be seen from the Fig. 4 that the autocorrelation function (ACF) of Group A is tailed, and the partial autocorrelation function (PACF) is truncated. From this, it is judged that the data of Group A is suitable for the model type as the AR model. The calculation of the AIC criterion function for the model order of the Group A data is 1, 2, and 3, as shown in Table 3.
Table 3. AIC criterion function calculation table for group A data

| Model order | 1     | 2     | 3     |
|-------------|-------|-------|-------|
| AIC(n)      | 1.19  | 2.42  | 0.73  |

When n=3, the AIC value is the smallest, so the model of group A is AR(3), which can be expressed as

\[ y_t = \theta_1 y_{t-1} + \theta_2 y_{t-2} + \theta_3 y_{t-3}, \quad t = 4,5,\ldots,15 \]  

(11)

Parameter estimation using least squares method to obtain \( \hat{\theta} = (1.86, -1.34, 0.51)^\top \). Therefore, the AR(3) model of group A can be expressed as

\[ y_t = 1.86 y_{t-1} - 1.34 y_{t-2} + 0.51 y_{t-3} \]  

(12)

Autocorrelation plot and partial autocorrelation of group B are shown in Figure 5. It can be seen from the Fig. 5 that the autocorrelation function (ACF) of Group B is tailed, and the partial autocorrelation function (PACF) is truncated, so the AR model is selected. The calculation of the AIC criterion function for the model order of the group B data is 1, 2, and 3, as shown in Table 4.

Table 4. AIC criterion function calculation table for group B data

| Model order | 1     | 2     | 3     |
|-------------|-------|-------|-------|
| AIC(n)      | -2.0429 | -2.1429 | -1.9390 |

When n=2, the AIC value is the smallest, so the model of Group B is AR(2), which can be expressed as

\[ y_t = \theta_1 y_{t-1} + \theta_2 y_{t-2}, \quad t = 3,4,\ldots,15 \]  

(13)

Parameter estimation using least squares method to obtain \( \hat{\theta} = (1.81, 0.817)^\top \). The AR(3) model of group B can be expressed as

\[ y_t = 1.81 y_{t-1} - 0.817 y_{t-2} \]  

(14)

From Equations 12 and 14, the predicted depths of six time series carbonization depths from day 85 to day 110 of group A and group B are obtained. The final predicted \( y' \) value is obtained by weighted averaging as shown in Equation 10. The comparison of carbonization depth prediction is shown in Table 5 and Table 6.
Table 5. Comparison of carbonation depth prediction values of group A

| Experiment number | Experimental value/mm | BP Predictive value/mm | Relative error/% | BP-AR Predictive value/mm | Relative error/% |
|-------------------|-----------------------|------------------------|-----------------|---------------------------|-----------------|
| A1                | 22.7                  | 22.58                  | -0.5            | 22.66                     | -0.2            |
| A2                | 23.2                  | 23.00                  | -0.9            | 23.14                     | -0.2            |
| A3                | 23.6                  | 23.32                  | -1.2            | 23.51                     | -0.4            |
| A4                | 24.0                  | 23.77                  | -1.0            | 23.92                     | -0.3            |
| A5                | 24.7                  | 24.45                  | -0.8            | 24.57                     | -0.5            |
| A6                | 25.5                  | 25.9                   | 1.6             | 25.71                     | 0.8             |

Table 6. Comparison of carbonation depth prediction values of group B

| Experiment number | Experimental value/mm | BP Predictive value/mm | Relative error/% | BP-AR Predictive value/mm | Relative error/% |
|-------------------|-----------------------|------------------------|-----------------|---------------------------|-----------------|
| B1                | 23.8                  | 24.05                  | 1.1             | 23.78                     | -0.1            |
| B2                | 24.6                  | 25.08                  | 2.0             | 24.85                     | 1.0             |
| B3                | 25.2                  | 25.49                  | 1.2             | 25.62                     | 1.6             |
| B4                | 26.0                  | 26.36                  | 1.4             | 26.00                     | 0               |
| B5                | 26.9                  | 27.18                  | 1.1             | 27.03                     | 0.5             |
| B6                | 27.6                  | 28.15                  | 2.0             | 27.90                     | 1.1             |

The comparison between predicted and measured values is shown in Figures 6 and 7.

Figure 6. Comparison of predicted and expected values of carbonation depth in group A

Figure 7. Comparison of predicted and expected values of carbonation depth in group B

As can be seen from Table 5, Table 6, and Figure 6, Figure 7, the carbonation depth prediction value using the BP-AR fusion method is closer to the expected value than the BP neural network prediction value, and the relative error is also smaller. Since the carbonization reaction at the next moment is affected by the carbonization reaction at the previous moment, when the BP prediction value error at a certain time is large, the time series correction value at the next moment will be greatly affected. For example, when the relative error of the BP prediction value of the B2 group reaches 2%, the influence of the BP-AR prediction value of the B3 group at the next moment fluctuates greatly. However, through time series prediction, the intrinsic development law is found according to the past
carbonization depth value to speculate the future development trend, the relative error is reduced to 1.6%, and the accuracy of carbonization depth prediction is improved.

which not only compensates for the problem that the BP neural network model fails to fully consider the factors affecting the carbonization reaction, improves the prediction accuracy, and also predicts the model in the time series. On the basis of improvement, the difficulty of model establishment is reduced.

BP neural network and time series prediction method are combined by BP-AR algorithm to predict carbonation depth, which not only compensates for the problem that the factors affecting the carbonization reaction cannot be fully considered when using the BP neural network model, improves the prediction accuracy, and also further improves on the basis of the time series prediction model, and the model is less difficult.

4. Conclusions

Through the fusion algorithm BP-AR, the future development law is estimated based on the past concrete carbonation depth value by using the time series method, and the BP neural network prediction value is corrected. Under the condition that the influencing factors of concrete carbonation depth are complex and variable, and the data of cross-coupling and known influence parameters are limited, the prediction accuracy of carbonization depth is improved. In practical engineering, the advantage of using this fusion method is that long-term measured data of carbonization depth is not required, and model establishment is less difficult. The data used in this paper is that the accelerated carbonation test data cannot be completely equivalent to natural carbonization. Further research on the prediction of natural carbonization conditions remains to be done.

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