Real-time Strength Prediction of Different Types of Concrete Based on BP Neural Network

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ABSTRACT

In terms of information processing, artificial neural network is similar to the synaptic connection structure in the human brain. As a mathematical model for information processing, it is widely used in various fields like biology, medicine and construction engineering. This paper adopts the back propagation neural network and predicts the strength of concrete considering a variety of impact factors. Firstly, it introduces the basic principle of the neural network algorithm based on brain neural mechanism, and summarizes the safety problems in concrete projects and concrete strength prediction methods. With the real-time strength prediction BP model for different types of concrete proposed in this paper, a nonlinear mapping relationship between concrete strength and impact factors can be established, which effectively reduces the number of concrete trials and improve the quality of concrete. The measured results show that the accuracy of concrete strength prediction is higher than 96%. Therefore, this model can provide theoretical guidance for better application of concrete in construction projects.

Key Words: BP neural network, concrete, impact factor, strength prediction

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Introduction

With the large-scale infrastructure construction and rapid economic development in China, the safety of civil engineering has received more and more attention. Concrete is a widely used basic material in civil construction. Therefore, its safety and quality has become a hotspot of engineering research (Lataste *et al.*, 2003). Concrete strength is the core of concrete quality control, an important basis for structural design and construction and one of the most important properties of concrete (Beeby, 1995). So accurately determining the real-time strength of concrete materials is very important to determining the safety status of the structures, ensuring the safe use of structures and reduce maintenance costs.

Concrete strength not only can be measured through actual field sampling and calculation, but also can be predicted with the help of a mathematical model (Stoppel *et al.*, 2012). Currently, the strength prediction methods include Bowromi formula, curve fitting, grey theory prediction and neural network methods (Abbasloo *et al.*, 2018). The neural network method, as a mathematical model based on the brain neural information processing mode, is widely used in concrete strength prediction. Some scholars have compared the neural-network-based prediction model with the traditional regression method and found that the accuracy of the neural network prediction model is much higher than that of the traditional regression method (Xu *et al.*, 2015); and some scholars have established a neural network model considering 7 factors related to mix proportion like the maximum size of broken stones, degree of collapse, water, sand and cement, and trained the

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learning samples with the model (Ilunga and Stephenson, 2005). Although a number of results have been achieved in the research on the combination of neural network and concrete, there are still deficiencies in the comprehensiveness of the factors and the speed of sample training.

The artificial neural network prediction model proposed in this paper can quickly establish nonlinear mapping relationships between the concrete strength and its impact factors and conduct real-time strength prediction for different types of concrete, which not only effectively reduces the number of concrete trials, but also greatly improves the concrete quality and work efficiency and saves costs. Specifically, this paper uses the back propagation (BP) neural network to simulate the basic characteristics of the brain and its information processing mechanism, and then establishes a neural network model (Cheng *et al.*, 2016). Firstly, it introduces the basic principle of the neural network algorithm, and summarizes the safety problems in concrete projects and the current concrete strength prediction methods. Based on the theoretical basis, this paper establishes a BP network model for real-time strength prediction of different types of concrete, and improves the training accuracy and convergence of the model by optimizing different input layers and hidden layers and making training corrections.

Theoretical basis for concrete and neural network research

Principle of neural network

Artificial neural network (ANN), proposed based on neuroscience research, is a neural network model that simulates the basic characteristics of the brain. This model is most applied in BP neural network, i.e. BP training algorithm (Wang and Xiang, 2008). In essence, it is a system that physically simulates the human brain's information processing mechanism, but it not only has the general computing power to process data, but also has the learning and memory capabilities. Therefore, BP neural network has been successfully used in many fields, especially in such fields as pattern recognition, image processing, control optimization, forecasting and artificial intelligence.

The BP neural network is similar to the information processing mode of the brain neurons. Figure 1 shows the topology of the BP neural network.

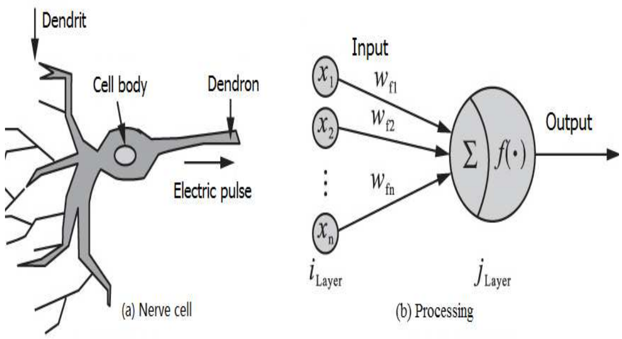


Figure 1. BP neural network topology

A BP network is a three-layer feed-forward hierarchical network consisting of input layers, hidden layers and output layers. The neurons of adjacent layers are fully connected, but those on each layer are not connected. The topology of a concrete BP network is shown in Figure 1. In this study, the prediction model adopts a BP network structure with multiple input layers, multiple hidden layers, and one output layer (Taşpınar, 2015).

Analysis of concrete strength prediction methods

Concrete strength prediction methods mainly include the Bowromi formula prediction, curve fitting, grey theory prediction and neural network method.

(1) Bowromi formula was proposed by Bowromi, a Swiss concrete expert, in 1930. The concrete strength formula is built on the relationship between ordinary concrete strength and cement strength and water-binder ratio. The concrete strength prediction using this formula is called the Bowromi formula prediction (Ismail M. P. *et al.*, 1996).

(2) Curve fitting method
The curve fitting method is to find the coefficients of the corresponding functions through mathematical statistics of the experimental data and then establish an empirical formula or a mathematical model. Curve fitting can be carried out using the software's own fitting functions, or it can be customized as needed. As the curve fitting method is based on experimental data, it is more consistent with the actual patterns and quite accurate. Because of this, it is currently the main method used to process concrete experimental data. However, there are many factors that affect concrete strength. If all these factors are considered as independent variables

of the concrete strength prediction curve, the prediction accuracy of concrete strength will be even higher, but in the meantime, the process of establishing the concrete strength curve will be very complex (Carino, 1994).

(3) Grey theory prediction method
Grey prediction uses the GM (1, 1) model to predict the evolution of system behaviour eigenvalues. In this method, the sequence prediction is to predict the size and time of the evolution of a certain thing. The age-based concrete strength prediction precisely satisfies the criteria for sequence prediction. It conducts an accumulated generating operation to the original data and builds a differential equation and solves it. Then it conducts an inverse accumulated generating operation to generate the prediction value, which will be of very high accuracy (Trtnik *et al.*, 2009).

(4) Neural network method
Artificial neural network has never faded from people's attention since its rise in the 1940s. Now its application scope is also becoming increasingly wider. It mainly includes BP neural network, radial basis function network, Hopfield network, adaptive resonance theory, and Kohnoen self-organizing feature map, ART network and wavelet neural network. By simulating the brain's information analysis processing method, the neural network stores the knowledge (causal laws) trained by the network in the form of multiple sets of weights and threshold values in each neuron (Słoński, 2010).

Featured with super-large-scale integrated execution capability, analysis and design consistency, biological neural simulation, and adaptability, the neural network can effectively overcome the problems of other concrete strength prediction methods, such as poor linearity, large dispersion, and difficult curve fitting. Therefore, this paper chooses the BP neural network to simulate brain neurons to predict the real-time strength of different types of concrete.

BP network model for real-time strength prediction of different types of concrete

Selection of training and testing samples

In this study, the P•O 42.5 grade cement was used. After being mixed with a concrete mixer and tapped with a vibrostand, it was placed in the standard curing room for curing. At the same time, in order to ensure that the concrete would experience sufficient changes in strength, the materials adopted a wide range of water to binder (W/B) ratio (0.3-0.55) and also contained other mineral admixtures (coal ash, silica fume and slag) and additives, basically covering the common range of concrete used in structures; and natural coarse and fine aggregates have different particle sizes and their own substitutions. In this study, a total of 495 data were collected. All data were randomly divided into 3 categories, including 330 learning data, 99 prediction data, and 66 validation data.

BP network model design

(1) Strength impact factor analysis
Impact factors to the real-time strength of different types of concrete are summarized as follows: cement type, W/B ratio, mineral admixture to cementitious material consumption ratio, aggregate type and gradation, age, curing conditions, and construction technology. The gradients differ greatly in the quantities of original sample data. To facilitate subsequent processing, the data are normalized to values between 0 and 1. The specific normalization formula is:

$$y = \frac{x+(x_{max}-9x_{min})/8}{(x_{max}-x_{min})/0.8} \quad (1)$$

where, x_{max} and x_{min} are the maximum and minimum values in the sample data, x represents the original sample data and y represents the normalized value. The formula used keeps the pre-processed data from extreme values 0 and 1, which not only reduces the difficulty of neural network training but also reduces the number of trainings (İlker Bekir Topçu and Sarıdemir, 2008).

(2) Layer node number design
According to the analysis of impact factors, 18 parameters such as the amount of cement and various mineral admixtures, replacement rates of sand and stone, recycled aggregates, water consumption, age, and additives are taken as input variables; and strength is the only output variable. The number of intermediate hidden layer nodes is the most critical step in neural network design: if the number of hidden layer nodes is too small, the neural network will have less ability to obtain sample information, making it hard to discover and extract the internal patterns of the samples; if the number of hidden

layer nodes is too large, the neural network will probably have less generalization ability, resulting in an increase in training time of the neural network. Therefore, the number of hidden layers is set to 15, but the numbers of input layers and hidden layers still need to be optimized:

1) Optimization of input layer number. Through the comprehensive analysis of the above impact factors and correlation results, and according to the impacts of the factors on each grade of strength, the input layers are set to 5, 9, 15 and 18, respectively.

2) Optimization of hidden layer number. Based on the above structure, there is no accurate numerical calculation for the number of intermediate hidden layers, but generally formula 2 can be used in calculations:

$$\frac{n+m}{2} \leq l \leq n+m+10 \tag{2}$$

where, l represents the number of hidden layer neuron nodes, m the number of input layer neuron nodes, and n the number of output layer neuron nodes. According to the above analysis, m and n are substituted into the formula, and the optimal number of hidden layer nodes in different neural networks can be initially obtained. After comparison and analysis, the optimal numbers of hidden layer nodes are listed in Table 1.

Table 1. Different layers of nodes under different neural networks

Enter the number of layers	5	9	15	18
Hidden layer range	3~16	5~19	8~26	10~29
Hidden layer number	5,7,10, 13,15	5,7,10, 13,15,17,20	8,12,15, 19,22,26	10,15,18, 22,25,29
Output layer number	1	1	1	1

(3) Parameter setting

The transfer function between neurons in each layer is the sine s-type transfer function, and the connection strengths are 0.01/0.1, 0.01/0.3, 0.01/0.5, 0.01/0.7, 0.1/0.1, 0.1/0.3, 0.1/0.5, 0.1/0.7, 0.3/0.1, 0.3/0.3, 0.3/0.5, 0.3/0.7, 0.5/0.1, 0.5/0.3, 0.5/0.5 and 0.5/0.7. The network learning function adopts the BP learning rules with momentum terms. The initial learning efficiency is 0.1 and the momentum factor is 0.9. The training function uses a combination of the gradient descent method and the quasi-Newton method, i.e. the Levenberg-Marquardt BP algorithm; and the maximum number of training steps is 50 000 and the mean squared error is 0.0001. The initial values of BP neural network weights and thresholds are randomly generated by the system and constantly adjusted through back propagation to minimize the value of the network performance analysis function (Madandoust *et al.*, 2012).

(4) Error evaluation indices

In order to compare learning, prediction, and validation effects in a neural network, according to the evaluation principles and practices, error evaluation indicators such as MAE (mean absolute error), MAPE (mean absolute percent error), and MSE (mean square error) are usually used to conduct comprehensive measurement and evaluation. This study selects RMSE (root mean square error) to evaluate network performance, as shown in formula 3:

$$RMSE = \sqrt{\frac{e_1^2+e_2^2+e_3^2+\cdots+e_n^2}{n-1}} \tag{3}$$

where, e_n represents the deviation between the predicted value and the actual value of the n-th figure; and n represents the number of samples. RMSE is used to measure the deviation between the observed value and the true value, which can reflect the measurement accuracy. Performance assessment is critical. If the simulated performance is not good, then the network parameters need to be changed to improve the network performance and achieve the desired effect. For this study, the smaller the RMSE, the higher the prediction data accuracy, i.e., the better the network performance.

Analysis of different concrete strength prediction results based on BP neural network

Content analysis of the BP neural network model

There are many factors that affect the real-time strength of concrete, and the different factors have different impacts. Therefore, in the same artificial neural network model, we can establish different BP network prediction models by selecting different input layers and hidden layers, and finally choose the optimal model. The establishment of the optimal BP network model requires many training corrections to make it have higher accuracy and convergence, and then it can well predict the real-time strength of concrete, laying a theoretical foundation for further application in engineering. The model structure is shown in Figure 2.

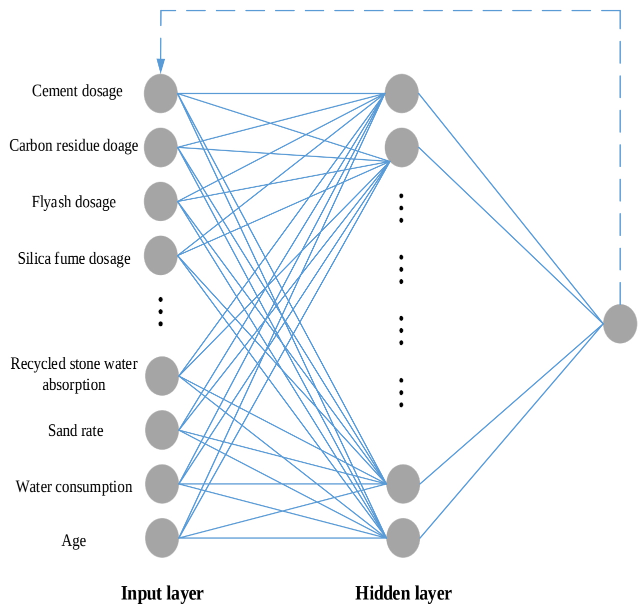


Figure 2. Model structure diagram

Optimization analysis of the BP neural network model

(1) After the self-learning and prediction of training samples and test samples in the neural network, with different numbers of input layers, the simulation error rates are shown in Table 2.

Table 2. The Simulation error rate

Enter the number of layers	Hidden layernumber	Output layer number	RMSE	
			Learning	Forecast
5	15	1	1.58	3.98
9			1.29	3.72
15			1.22	2.61

From the data in the table, it can be seen that, when the number of hidden layers is constant, adjusting the number of input layers will affect the prediction result – the error rate decreases with the increase of the number of layers. Most of the sample data and simulation data are well fitted, indicating that the BP network model has high accuracy and small errors and can well predict the real-time strength of concrete.

Figure 3 shows the distribution of RMSE with different numbers of hidden layers when the number of input layers is 5, 9, and 15.

The optimal number of hidden layers and their corresponding connection strength under the different numbers of input layers are as follows:

(1) When the number of input layers is 5, the optimal number of hidden layers is 15, the connection strength is 0.1/0.7 and RSME is 1.58/3.7;

(2) When the number of input layers is 9, the optimal number of hidden layers is 15, the connection strength is 0.5/0.7, and RSME is 1.29/3.72;

(3) When the number of input layers is 15, the optimal number of hidden layers is 15, the connection strength is 0.3/0.3, and RSME is 0.93/2.61;

Generally, for an optimal structure, the number of hidden layers ≥ the number of input layers. When the number of input layers is small, the number of hidden layers tends to multiply. However, as the number of hidden layers increases, the time cost also increases significantly.

For each input layer structure, the impact factors should be sorted and analyzed for importance. The specific data processing is as follows:

Then the weight analysis is performed. Using the formula $C_{A1} = W_{A1} \times W_{OA}$, $\gamma_{A1} = (|C_{A1}| + |C_{A2}| + |C_{A3}|)$ and $S_1 = \gamma_{A1} + \gamma_{B1}$, we obtain Table 3.

Table 3. Distribution of **γ**

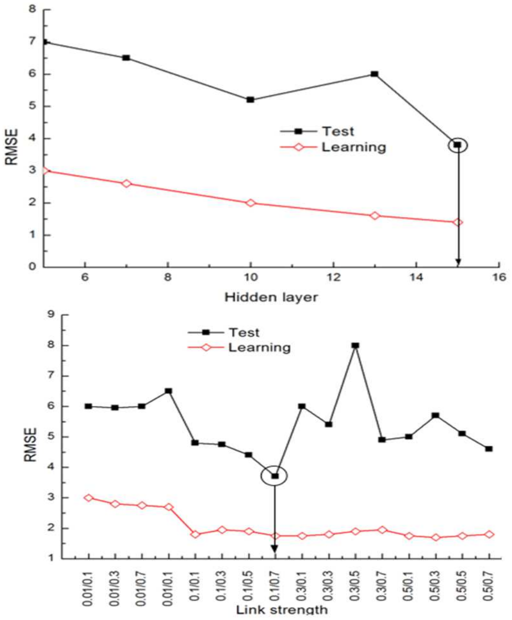
	Hidden A	Hidden B	Total number
Input 1	γ_{A1}	γ_{B1}	S_1
Input 2	γ_{A2}	γ_{B2}	S_2
Input 3	γ_{A3}	γ_{B3}	S_3

At last, using the formula $RI_1 = S_1/(S_1 + S_2 + S_3) \times 100$, we obtain the importance analysis diagram as shown in Figure 5.

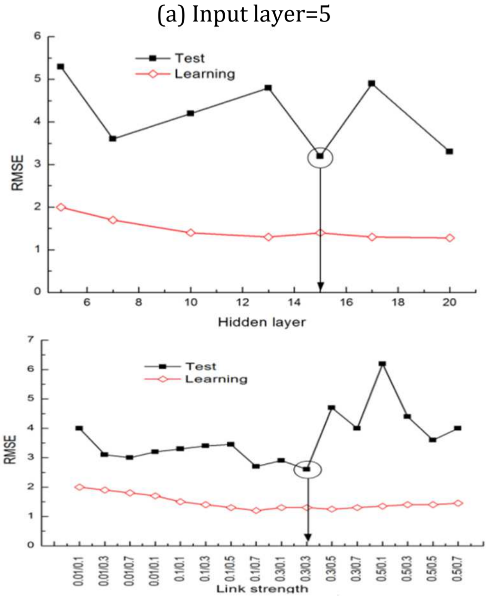
From the RSME and the importance analysis diagram, it can be found that the optimal structure of the BP neural network model based on the human brain neuron mechanism has 15 input layers, 15 hidden layers and a connection strength of 0.3/0/3. Through 50,000 BP neural network trainings, the convergence accuracy reaches 0.001, and the regression coefficient is 0.98, indicating that the measured values well fit the predicted values. The correlation coefficient R^2 is 0.96, indicating that the measured values are highly correlated with the predicted values.

Conclusions

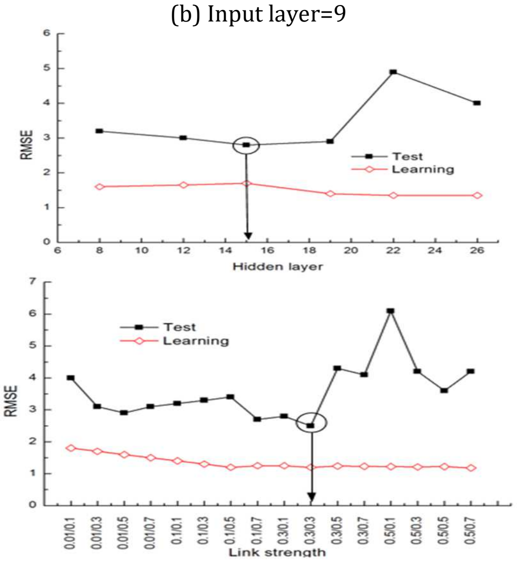
In order to better realize real-time prediction of concrete strength and ensure project safety, this paper uses the back propagation artificial neural network that simulates the neural signal processing mechanism to perform concrete strength prediction.



(a) Input layer=5



(b) Input layer=9



(C) Input layer=15

Figure 3. Optimized structure and simulated renderings

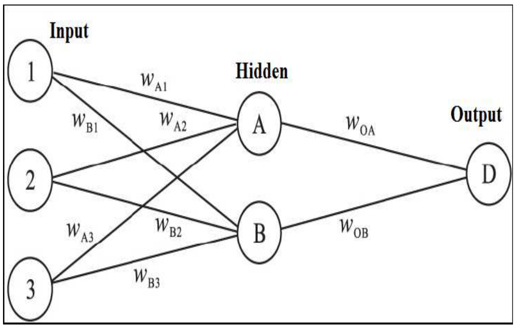


Figure 4. Model structure diagram

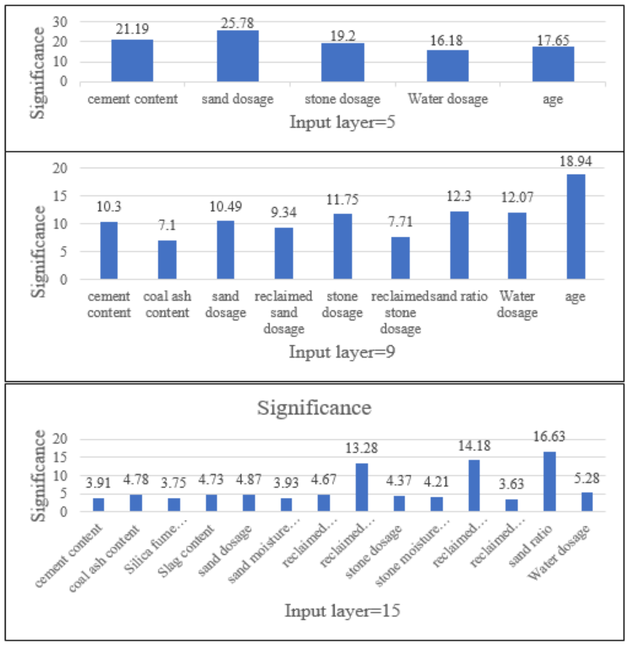


Figure 5. Analysis of importance

After selecting appropriate training samples and considering different impact factors, it establishes a BP neural network model for concrete strength prediction and optimizes the input, hidden and output layers. Through neural network self-learning and prediction, this paper carries out optimization analysis and obtains corresponding research results. The main conclusions and significance of this paper are as follows:

(1) 18 parameters such as the amount of cement and mineral admixtures, and replacement rates of sand, stone and recycled aggregates, water consumption, age, and additives are taken as input variables, and strength as output variable, which can improve the accuracy of real-time concrete strength, and at the same time reduce the computation amount of the neural network.

(2) By changing the numbers of input layers and hidden layers, this paper finds the optimal combination and establishes the optimal BP network prediction model. The optimal model structure has 15 input layers, 15 hidden layers and 1 output layer, with a connection strength of 0.3 /0.3; then data are applied to calculate the importance of impact factors and analyze the convergence curve. Finally, the data fitting degree of the model reaches 96%.

(3) Based on the actual concrete testing data, this paper combines the computer technology with the neural network technology for application in the actual projects. Through continuous improvement, this model has much higher speed and accuracy of data calculation and more fully express the changing pattern of concrete strength. This study has laid a certain theoretical foundation for better application of concrete in actual projects.

Authors acknowledge

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