Research on Hydraulic Concrete Strength Prediction Model Based on ANN-RBF Neural Network

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Abstract. In recent years, with the continuous development of construction engineering level, the number of hydraulic buildings and dam projects has gradually increased, and the prediction of hydraulic concrete strength, as the main component of buildings, is particularly important. Based on the radial basis function (RBF) provided in the neural network (ANN), the SPSS27 platform is called, considering that the method has the characteristics of automatic adaptation to determine the network and the absence of the need to give initial weights artificially. The method is applied to the prediction of hydraulic concrete strength model, and experimental data are processed using the ANN-RBF method to obtain the results of the factors and their joint effects on the concrete strength, which is a more intuitive way to understand the interrelationship of the factors and their influence mechanism. The results show that the method is able to predict the results well and the research is of great importance for accurate prediction of the strength of hydraulic concrete.

Keywords: Strength prediction; ANN-RBF; concrete.

1. Introduction

In recent years, with the development of society and the advancement of technology, the development of Chinese industry has reached an unprecedented height. But one has to look at this matter with dialectical thinking. Such a "boom" will bring many problems to the environment. In order to cope with the current important strategy of environmental protection, the excellent characteristics of concrete use has become an irreplaceable mainstay of today's industrial use.

Today, the calculation methods based on concrete strength prediction have undergone a major innovation to present the concrete strength prediction results more accurately and intuitively. Concrete strength is affected by a variety of factors, and these factors acting individually and together do not have a purely linear relationship with the mathematical relationship of concrete strength, so a neural network method (ANN) needs to be established to deal with the infinite approximation to the ideal environment under non-linear relationships. The radial basis function (RBF) method has the characteristics of automatic adaptation to determine the network and no need to give initial weights artificially. It is also able to maximize the approximation with few neurons. If it is applied to the prediction of hydraulic concrete strength model, the experimental data processing to obtain the results of the factors and their joint effect on the concrete strength, the prediction results will be more intuitive and accurate. The current research on concrete strength prediction is still conducted by many YANG [1] The optimal possible values of the matching parameters such as ash-water ratio and silica fume substitution were determined by the error back propagation learning algorithm (BP algorithm) in the neural network method, and finally the best formulation solution with ash-water ratio of 2.0 and silica fume substitution of 6.3% was obtained. XI [2] By combining various intelligent algorithms such as BP neural network and simulated annealing algorithm, multiple neural network prediction models were established to predict the strength of concrete in large sample sizes. DING [3] By using a combination of multiple neural network models, a dual parallel neural network model was trained to build a prediction model with concrete strength prediction for its prediction. ZHANG [4] A chaotic particle swarm algorithm is used to optimize the concrete strength prediction model with least squares support vector machine (LSSVM). The prediction results are empirically tested by using several concrete strength data with small errors. CUI [5] A support vector machine prediction model for strength prediction of high-strength concrete is developed using support vector machine theory. The accuracy of this model is verified by comparison. YU[6] The strength prediction of high-strength concrete with the proportion of fly ash in the cementitious material, the amount of cementitious material, and the cement-to-water ratio of concrete permeability as the influencing factors by prediction techniques based on artificial intelligence methods (including fuzzy logic, expert systems, neural networks, and genetic algorithms).GAO[7] A concrete strength prediction model based on SVR algorithm and coded in MATLAB was used to predict the strength of concrete at an early stage of construction. The feasibility of the algorithm was finally proved by testing the experimental data.

The traditional statistical mathematical methods cannot deal with multi-factor modeling problems, which are time-consuming and laborious; support vector machine (SVM) has low modeling efficiency; and BP network has local minima and slow convergence speed. The radial basis function (RBF) neural network is superior to these computational methods in many aspects. The network can infinitely approximate the theory when many factors are involved, and when the set of centroids is selected appropriately, few neurons can obtain a good approximation effect, it also has the advantage of the only best approximation point, and uses a linear optimization algorithm that guarantees global convergence, which greatly improves the training speed of the network. Therefore, this paper uses RBF warp network to predict concrete strength. This study provides an effective methodology for providing a strength prediction model with generalization.

2. Hydraulic concrete influence factor index system construction

2.1. Maintenance age

The effect of curing age on concrete properties in engineering is mainly due to the fact that curing age causes more significant changes in the microstructure of the material and thus has an important effect on the strength and mechanical properties of concrete. Therefore, in this experiment, we used the curing age as an indicator of strength influencing factor. In this experimental design, we chose 7d, 28d and 60d curing ages for the strength experiments. Finally, by testing the compressive strength and tensile strength of concrete, we can conclude that (1) the overall trend is that the longer the age, the stronger the concrete is. (2) Relative to the percentage of concrete strength at age 7d to concrete strength at age 60d and the percentage of concrete strength at 28d to concrete strength at 60d, it can be seen that the growth of late strength is significantly smaller than that of the early stage, so it is significant to strengthen the development of concrete strength by early curing.

2.2. Aggregate species

China's vast territory, unique climate and advantageous geographical location make our country very rich in ore resources. Consequently, local stone and other materials are used to mix concrete. This situation prompted us to think about the effect of different aggregate varieties on the strength of concrete. In this experiment, we used concrete with sand and gravel aggregate varieties of river sand and sea sand, respectively. The results can be obtained from the experimental testing of the compressive and tensile strength of concrete by controlling the variables and the statistics of various mathematical and physical methods: the overall trend is that the strength of concrete with sand and gravel aggregate as river sand is stronger than that of concrete with sea sand. A careful analysis of the data shows that the concrete strength of river sand has a steeper curve due to the influence of other factors, while the concrete of sea sand has a smoother curve.

2.3. Water to glue ratio.

The water-cement ratio, as the name implies, is the mass ratio of the amount of water used in concrete to the amount of cementitious materials. The size of the water-cement ratio directly affects all aspects of concrete, such as its durability, strength and compatibility. In particular, it has a significant impact on the strength. In this experiment, we selected three water-cement ratio data, respectively, 0.33, 0.41, 0.5. By observing the compressive and tensile strength of concrete under the same conditions of other influencing factors, we can conclude that the size of the water-cement ratio and the growth of the compressive and tensile strength of concrete is negatively correlated, that is, the larger the water-cement ratio, the smaller the strength of concrete.

2.4. Aggregate shape

The differences in the chemical composition of the coarse aggregate particles involved in the concrete will have an impact on the properties of the concrete, especially the shape of the coarse aggregate particles. Different particle shapes have different particle diameters, so the difference in particle shape affects the strength of the concrete by influencing the arrangement of internal results. Therefore, a comparative analysis based on available data should be conducted to explore the effect of different shapes of coarse aggregate particles on the strength of concrete. Three different aggregate shapes were used in this experiment, namely block, flake and mixed aggregates. Finally, it can be concluded that the influence of aggregate shape on the strength effect of concrete is in the following order: mixed aggregate > block > flake. That is, the larger the diameter of the aggregate, the stronger the concrete.

In summary, the experimental index system of concrete that affects the water-cement ratio constructed in this paper is shown in Table 1;

Table 1 Concrete strength influence index system

Indicator Name	Indicator code	Unit	Reference
Maintenance age	X1	Day	[8]
Aggregate species	X2	--	[9]
Water to glue ratio	X3	--	[10]
Aggregate shape	X4	--	[11]

3. ANN-RBF Method

In 1985 Powell proposed a multivariate interpolation RBF method. 1988 Broomhead and Lowe first applied RBF to neural network design, constructing the first RBF neural network.[12] . The principle of the network is that any function can be expressed as a weighted sum of a set of basis functions, i.e., the transfer function of each hidden layer neuron is chosen so that it constitutes a set of basis functions to approximate the unknown function. It consists of an input layer, a hidden layer, and an output layer.

The hidden layer basis functions of RBF neural networks have various forms, and the commonly used function is the Gaussian function, i.e., the input layer input $X = [x_1\ ,\ x_2\ ,...,\ x_n\ ]$,the actual output is $Y=[y_1\ ,\ y_2\ ,...,\ y_p\ ]$. The input layer implements $X \rightarrow R_i(X)$ and the output layer implements the nonlinear mapping from $R_i(X) \rightarrow y_k$ the linear mapping, and the output layer output is shown in equation (1).

$$\hat{y}_k = \sum_{i=1}^{m} \omega_{ik} R_i(x)\,, k = 1,2,\dots,m \tag{1}$$

Where: *n is the number of nodes in the input layer*; *m is the* number of nodes in the hidden layer; *p is the* number of nodes in the output layer.ω_{ik} is the connection weight of the *i-th neuron in* the hidden layer to the k-th neuron in the output layer.$R_i(x)$ is the action function of the *ith neuron in the hidden layer is* shown in equation (2).

$$R_i(X) = exp(-\|x - C_i\|^2 \,/\, 2\sigma_i^2)\,, i = 1,2,\dots,m \tag{2}$$

Where X is an n-dimensional input vector.C_i is the center of the ith basis function, a vector with the same number of dimensions as Xσ_i is the width of the *ith basis function; and* m is the number of perceptual units. a schematic diagram of ANN is shown in Figure 1.

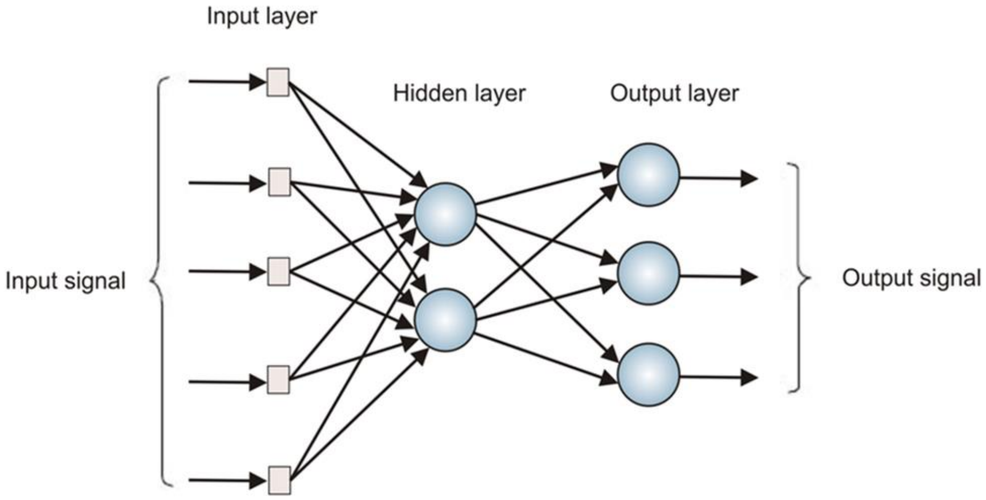

Figure 1 ANN topology

4. Test index setting

Since we have to adjust the number of cells in the hidden layer, there will be differences in the predicted results when the number of hidden layers is different, and the predicted results also deviate from the actual experimental data when the number of hidden layers is different, we need to check the predicted results and determine the number of hidden layers when the set number of hidden layers is the closest to the actual value, so as to achieve The purpose of more accurate prediction. The conventional algorithm test indexes areR^2 , MSE, SSE, DFE, etc. In this paper, we select MSE andR^2 The algorithm test is performed.

The MSE equation is shown in equation (3):

$$MSE=\frac{1}{m}\sum_{i=1}^{m}(y_i-\hat{y})^2 \tag{3}$$

R^2The formula is shown in equation (4).

$$R^2=\mathbf{1}-\frac{\sum_{i=1}^{n}(y_i-\hat{y})^2}{\sum_{j=j}^{n}(y_j-\bar{y})^2} \tag{4}$$

in the equationy_i *represents the actual value, the*$\hat{y}$ *represents the predicted mean value, and*$\bar{y}$ *represents the mean value of the actual value.*R^2 The range of MSE is [-1, 1], and the closer its value is to 1 or -1, the better the fit between predicted and actual values, and vice versa, the worse it is to 0. The range of MSE is [0,∞], and the closer its value is to 0, the better the reliability of the data prediction, and vice versa, the worse it is to 1. The trend is the same asR^2 The trend is the opposite.

5. Experiment and Analysis

5.1. Data Experiment

By designing the experiments and processing the data according to the experiments, a total of 72 sets of experimental data were obtained, and in view of the limitation of space, the experimental results of each concrete measured (in part) are shown in Table 2.

Table 2 Experimental results (TOP 10)

	Control variables				Strength data	
	Conservation age X_1	Water to glue ratio X_2	Maintenance age X_3	Gum ratio X_4	Tensile stress Y_1	Compressive stress Y_2
Concrete block 1	60	River sand	0.33	Block	57.8	5.1
Concrete block 2	60	River sand	0.33	Block	54.2	6.0
Concrete block 3	60	River sand	0.33	Block	56.0	5.6
Concrete block 4	60	River sand	0.41	Block	41.7	4.0
Concrete block 5	60	River sand	0.41	Block	41.2	4.2
Concrete block 6	60	River sand	0.41	Block	41.5	4.1
Concrete block 7	60	River sand	0.5	Block	31.0	3.3
Concrete block 8	60	River sand	0.5	Block	29.2	3.5
Concrete block 9	60	River sand	0.5	Block	30.1	3.4
Concrete block 10	60	River sand	0.33	Flakes	50.7	5.6

5.2. Strength prediction

In this paper, based on the above data, brought into SPSS software, RBF operation was performed, MSE and R2 were set as model testing parameters, in which, by adjusting the number of hidden layer neurons 10-30, covariates were rescaled normalized, 70% of cases were randomly assigned for training and 30% for testing according to the relative number of cases, totaling 100%. The results of compressive strength were obtained as shown in Table 3, and the results of tensile strength are shown in Table 4.

Table 3 Compressive strength prediction table

Number of hidden layer neurons	MSE	R2
10	32.428	0.727
11	8.620	0.928
12	7.237	0.941
13	5.834	0.953
14	4.441	0.965
15	4.095	0.968
16	3.920	0.970
17	3.974	0.970
18	2.901	0.978
19	4.205	0.965
20	2.928	0.976
21	21.531	0.819
22	3.002	0.975
23	2.603	0.979
24	2.181	0.982
25	1.099	0.991
26	1.062	0.992
27	1.013	0.992
28	0.957	0.993
29	0.714	0.995
30	1.946	0.984

Table 4 Tensile Strength Prediction Table

Number of hidden layer neurons	MSE	R2
10	0.183	0.826
11	0.066	0.938
12	0.062	0.943
13	0.061	0.944
14	0.059	0.947
15	0.049	0.957
16	0.044	0.961
17	0.040	0.965
18	0.035	0.970
19	0.051	0.951
20	0.032	0.970
21	0.025	0.977
22	0.026	0.977
23	0.024	0.978
24	0.025	0.978
25	0.025	0.978
26	0.025	0.979
27	0.024	0.980
28	0.045	0.957
29	0.038	0.965
30	0.024	0.978

5.3. Analysis and Discussion

From the two parameters of TABLE3 and 4, it can be seen that the predicted value of compressive strength is closest to the actual value when the number of neurons in the hidden layer is 29. When the number of neurons in the hidden layer is 27, the predicted value of compressive strength is closer to the actual value. The relationship between the predicted and actual values at this time is shown in Figure 2 and Figure 3.

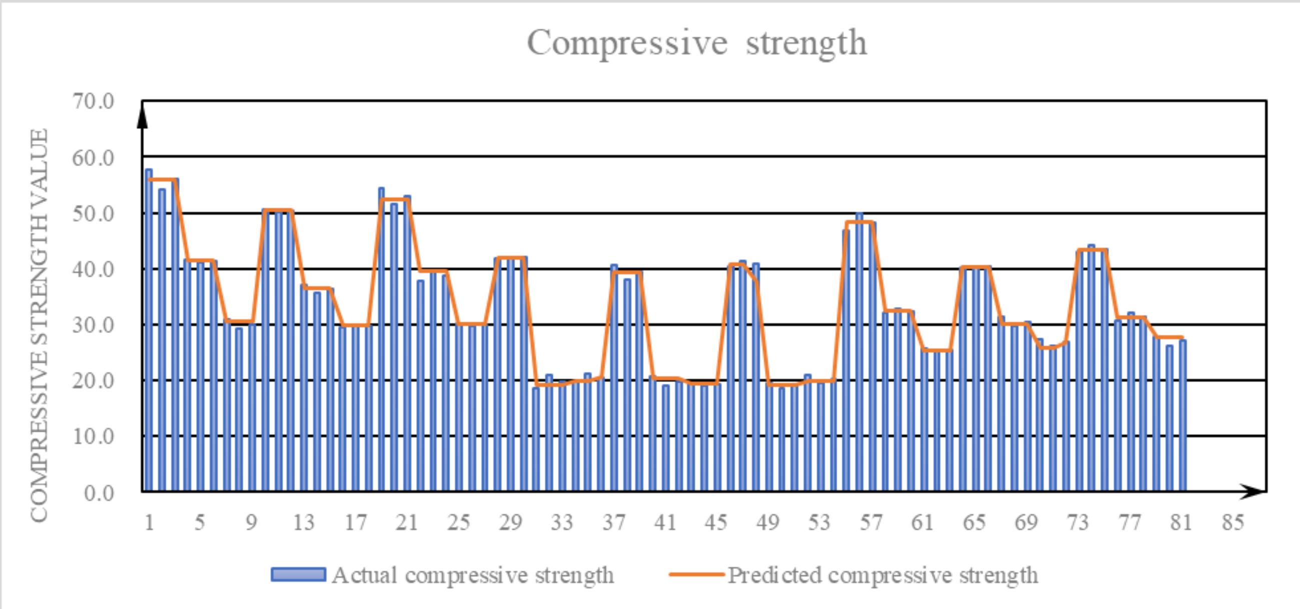

Figure 2 Comparison of predicted compressive strength

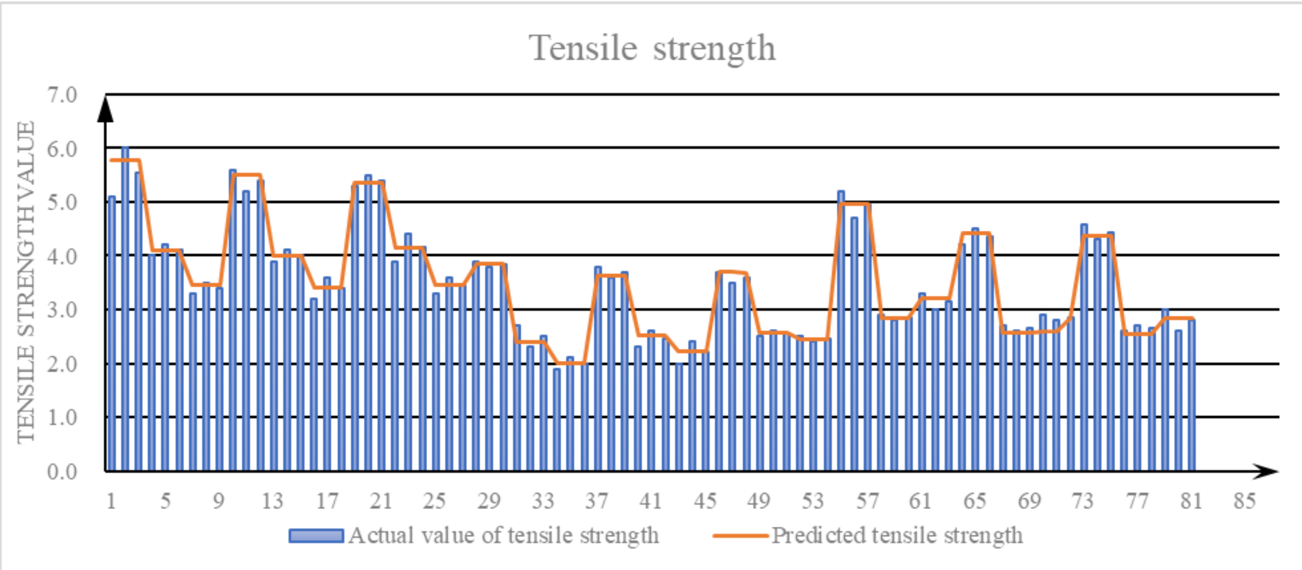

Figure 3 Comparison of tensile strength predictions

From TABLE 3, the predicted and actual values of compressive strength when the number of hidden layers is 29 are shown in Figure 1, where the MSE is closest to 0, indicating that the deviation between the predicted and actual values is small, and the value of R^2 is close to 1, indicating that the accuracy of the predicted values is high. Similarly, the relationship between the predicted and actual values of tensile strength when the number of hidden layers is 27 can be derived from TABLE 4 as Figure 2, where the MSE value is closer to 0 and the R^2 value is closer to 1. From the data, the accuracy of tensile strength prediction is better than the accuracy of compressive strength prediction, but the accuracy of compressive strength prediction is sufficient to meet the engineering requirements, so the above predicted data can achieve the The above predicted data can achieve the expected effect.

6. Conclusion

In this paper, three important indicators for concrete strength prediction are firstly constructed, which are curing age, water-cement ratio, aggregate shape, and aggregate species. The concrete was measured by the control variables method, and the results can be derived from the effect of these four indicators on the strength of concrete. Then the obtained data were brought into SPSS software, RBF operation was performed, and MSE and R2 were set as model testing parameters, in which, by adjusting the number of hidden layer neurons 10-30, the experiments showed that the predicted values given in this paper were closer to the actual values.

(1) The shorter the age of maintenance, the higher the compressive strength and tensile strength of concrete

(2) For concrete materials, sea sand can improve the compressive and tensile strength of concrete better than river sand.

(3) The shorter the age of maintenance, the higher the compressive and tensile strength of concrete

(4) The predicted value of compressive strength is closest to the actual value when the number of hidden layer neurons is 29.

(5) The predicted value of compressive strength is closer to the actual value when the number of hidden layer neurons is 27

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