ISSN: 2414-1895 DOI: 10.6919/ICJE.202110_7(10).0038

Prediction of Concrete Slump Model based on BP Neural Network

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Abstract

A method of using WEKA data mining tools to accurately establish a slump prediction model was studied, and 103 sets of concrete mix tests were carried out. Based on the BP neural network algorithm to predict the slump model, analyze the influence of different neural network test methods on the evaluation index, and determine the optimal model solution through repeated iteration and optimization. The results show that the BP neural network model has the advantages of high algorithm accuracy, good network performance and high efficiency. Conclusions: The 10-fold cross-validation test method of the neural network is more suitable for the prediction of the slump model; the global prediction correlation level and algorithm accuracy of the three-layer neural network model are higher than that of the two-layer neural network, but the network performance of the two-layer neural network is more stable. The network parameters for predicting model accuracy are ranked as learning rate, momentum factor, number of training iterations, and number of hidden nodes in order of influence.

Keywords

BP Neural Networks; Optimal Parameters; Slump; Prediction Model; Concrete; WEKA.

1. Introduction

The comprehensive national strength of our country is increasing and the construction industry maintains sustained and rapid development. At the same time, people's requirements for construction projects are increasing. Whether the quality and safety of construction projects can be fully guaranteed has become a hot spot of widespread concern from all walks of life. In terms of the global use of building materials, concrete is one of the materials with the greatest demand and the strongest applicability [1]. Slump is an important indicator to measure the homogeneity of concrete quality. It is embodied in that excessive slump will slow down the hardening speed of concrete and low strength after hardening, which greatly affects the quality of the project. In addition, precise control of slump is a prerequisite to ensure excellent performance of concrete. In actual engineering, slump measurement tests often require a lot of time, manpower and materials, and it is difficult to obtain test results quickly and accurately. Therefore, studying the concrete slump prediction model is of extraordinary significance to the theory and application of construction engineering.

In recent years, the application of neural networks in various industries has become increasingly mature. In the construction industry, I-Yeh described methods for predicting slump and compressive strength of high-performance concrete [2,3]; Venkata et al. evaluated the strength characteristics of self-compacting concrete based on the feasibility of artificial neural networks [4]; Duan et al. predicted the compressive strength of RAC [5]; Ji et al. used neural networks to conduct in-depth algorithm research on concrete mix ratio [6]; Demir predicted the elastic modulus of ordinary and high-strength concrete [7]; Vinay predicted the slump of ready-mixed concrete based on genetic algorithm [8]; Li Dihong and others predicted the comprehensive performance of concrete through BP neural network [9].

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Judging from the research status at home and abroad, the application of neural network in the field of slump prediction is still very few. In this paper, the concrete slump prediction is based on the BP neural network model, and the optimal model solution is finally obtained by studying the optimized parameters of the prediction model used. After demonstration, the optimized BP neural network prediction model is feasible, which provides a new practical idea for practical engineering applications.

2. Establishment of Concrete Slump Model Based on BP Neural Network

2.1 Introduction to BP Neural Network

Neural Networks(NNs) are composed of widely interconnected processing units, which can not only accurately classify large amounts of unrelated data, but also have good predictive functions [10,11]. The structure of NNs essentially imitates the structure and function of the human brain nervous system to build a neural network model. The network architecture is shown in Fig. 1 (take two layers as an example), including an input layer, a hidden layer, and an output layer. Most neural networks are based on back propagation, and neural network back propagation training algorithm is to adjust the weight of neurons through the gradient descent method, the purpose is to minimize the multi-layer feedforward neural The error between the actual output of the network and the expected output [12], in other words, until the mean square error of all training data is minimized to the specified error range.

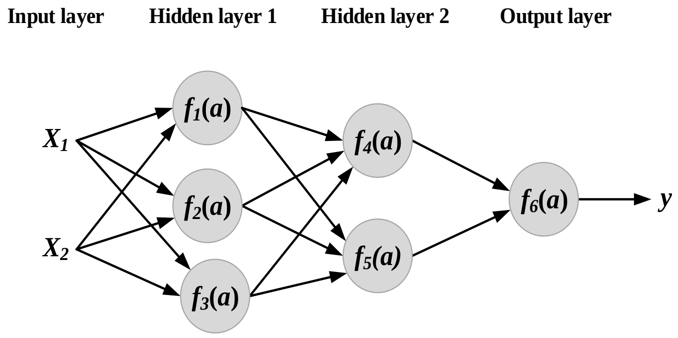

Fig. 1 Two-Layer NNs architecture

In the establishment of the neural network model, once the data is trained, the input parameter values of the project will be presented to the network, and the network will use the existing weights and thresholds developed during the training process to calculate the node output value. Such a trained neural network can not only reproduce the original test results trained by it, but also approximate other similar test results through its generalization ability [13]. Among them, a continuously differentiable nonlinear function is required, and the S-type logarithmic nonlinear function is usually used as the transfer function [14].

$$y_j = f(\alpha_j) = \frac{1}{1+e^{-\alpha_j}} \tag{1}$$

Where α_j is the net value of the sum of the weight and the input product. y_j is the output of the node.

$$\alpha_j = \sum_i \omega_{ij} \cdot x_i - \theta_j \tag{2}$$

Where y_j is the output of the node, x_i is the input of the node, ω_{ij} is the weight (connection strength) between the nodes, and θ_j is the internal offset in the output node.

2.2 Data Set and Input and Output Samples

This test is a data set composed of 103 sets of experimental data, and the concrete mix is shown in Table 1. Among them, cement, blast furnace slag, fly ash, water, superplasticizer, coarse aggregate, fine aggregate and fluidity are the inputs of neural network variables, and the slump is the output of variables.

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Table 1. Concrete mix ratio

Mix ratio	Cement (kg/m^3)	Slag (kg/m^3)	fly ash (kg/m^3)	Water (kg/m^3)	Superplasticizer (kg/m^3)	coarse aggre - gate (kg/m^3)	fine aggregate (kg/m^3)	Flow (mm)	Slump (cm)
C-1	273	82	105	210	9	904	680	62	23
C-2	162	148	190	179	19	838	741	20	1
C-3	147	89	115	202	9	860	829	55	23
C-4	145	0	227	240	6	750	853	58.5	14.5
C-5	148	109	139	193	7	768	902	58	23.75
C-6	374	0	0	190	7	1013	730	42.5	14.5
C-7	310	0	143	218	10	787	804	46	13
C-8	148	180	0	183	11	972	757	20	0
C-9	146	178	0	192	11	961	749	46	18
⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮
C-100	165.3	143.2	238.3	200.4	7.1	883.2	652.6	27	17
C-101	194.3	0.3	240	234.2	8.9	780.6	811.3	78	26.5
C-102	150.3	111.4	238.8	167.3	6.5	999.5	670.5	36.5	14.5
C-103	303.8	0.2	239.8	236.4	8.3	780.1	715.3	78	25

2.3 Test Method and Model Prediction Evaluation

In order to make the established prediction model more accurate, the data set was trained, tested, and ten-fold cross-validation. The response error curve of the test results is shown in Fig. 2. The fitting curve of the actual measured value of the neural network and the prediction result is shown in Fig. 2. Shown in Fig. 3.

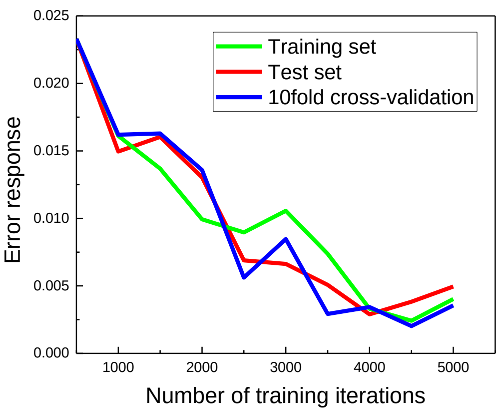

Fig. 2 Prediction response error of NNs model

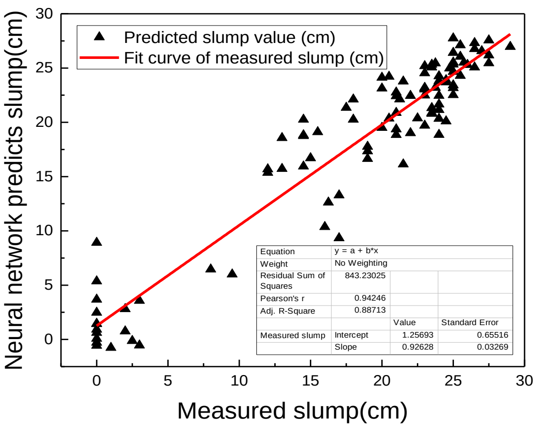

Fig. 3 Fitting curve of measured and predicted results of NNs

It can be seen from Fig. 2 and Fig. 3 that the response errors of the entire data used in the training set or the test set are 2.42‰ and 3.83‰, respectively, and the response error under the ten-fold cross-validation method is 2.02‰; from the discrete points of the data on the fitted straight line The degree of dispersion indicates that the prediction has reached an extremely significant level with the actual measurement. The ten-fold cross-validation method of the neural network has the advantages of high prediction accuracy, good effect, and high reliability. Therefore, the 10-fold cross-validation method used in this experiment is more suitable for the prediction of the slump model.

3. Parameter Optimization and Result Analysis of BP Neural Networks

Based on the superiority of the BP neural network 10-fold cross-validation algorithm, the coefficient of determination (R^2) and root mean square error (*RMSE*) are used to evaluate the prediction model. Among them, *RMSE* represents the degree of difference between the actual measurement and the prediction. To better monitor and evaluate the network performance, the smaller the value of 1, the

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better the network performance; R^2 is a measure of the degree to which the independent variable considers the measured dependent variable. Between 0 and 1, the value is closer to 1. It shows that the correlation level of the prediction model is more significant [15,16].

Now randomly adjust the selected network optimization parameters in the table to output the evaluation index of the prediction result, and then call the Jar package of the BP neural network model to model it, verify the consistency of the output result, and realize the batch modeling.

Table 2. Optimization Parameters of BPNNs Model

Parameter Type	Parameter selection range									
Learning rate	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9	1.0
Momentum factor	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9	1.0	-
First-level nodes	3	4	5	6	7	8	9	10	11	12
Two-level nodes	3	4	5	6	7	8	9	10	11	12
Number of iterations	500	1000	1500	2000	2500	3000	3500	4000	4500	5000

3.1 Research on Two-layer BP Neural Networks

In order to explore the influence of the learning rate on the network performance under the number of hidden nodes in the neural network. Fig. 4 shows the curves of training results based on different hidden node numbers and learning rates (LR). the result shows:

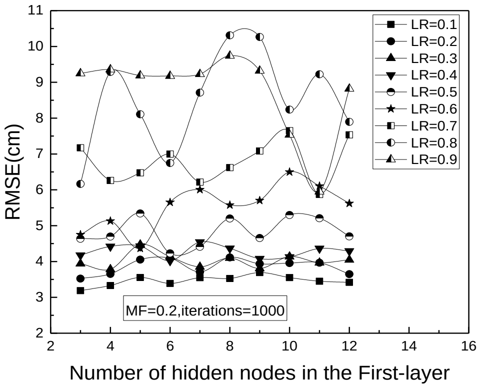

Fig. 4 Effects of learning rate on network performance

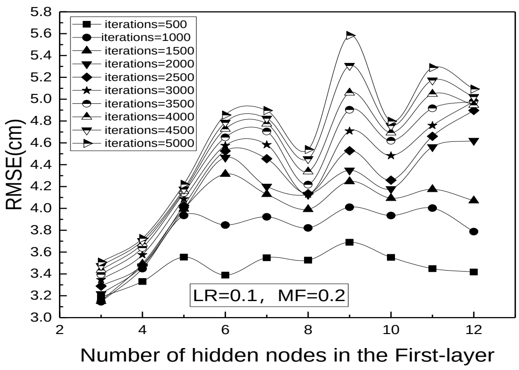

Fig. 5 Effect of the number of training iterations on network performance

Fig.5 shows the curve of the training results based on the number of hidden nodes and the number of training iterations. The result shows:

(1) When the number of training iterations = 500, 1000, the accuracy of the algorithm is stable, and the RMSE is between (3, 4).

(2) It takes about 2500 iterations of the backpropagation neural network to reach the same level of error. At this time, the neural network almost converges, but the training error of the model is relatively large at this time.

Fig. 6 shows the influence surface based on different learning rates and momentum factors on the correlation of the prediction model. The results show that:

(1) When the learning rate and momentum factor are both less than 0.4, the accuracy of the algorithm is stable, and the prediction correlation has reached a high level.

(2) When the learning rate∈[0.1, 0.7] and the momentum factor∈[0.4, 0.7] increase simultaneously and sequentially, the correlation of the prediction model decreases in a waterfall. When the momentum factor ∈(0.7,1], the correlation of the model prediction reaches a very low level, but the change of the learning rate has almost no effect on the prediction correlation. There is a possibility

that as the momentum factor increases, the neuron's weight change is unstable (oscillation), resulting in unstable changes beyond the prediction range of model performance.

In order to test the degree of influence on the network performance when the learning rate = 0.1 and the number of training iterations = 2500, the influence curve of the momentum factor is drawn, as shown in Fig. 7. According to the comparative analysis of the results of Fig. 4 and Fig. 7: while keeping other parameters unchanged, the influence of learning rate on network performance is greater than the momentum factor, but the influence of the two on the correlation level of the prediction model is roughly the same.

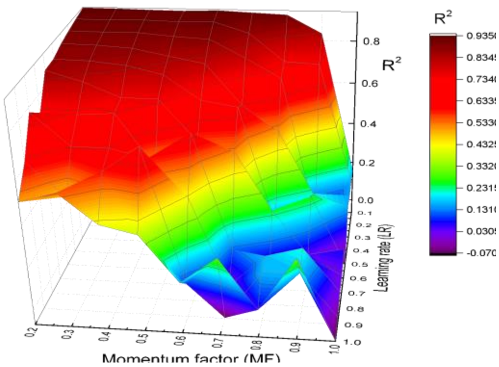

Fig. 6 Effects of learning rate and momentum factor on model correlation levels

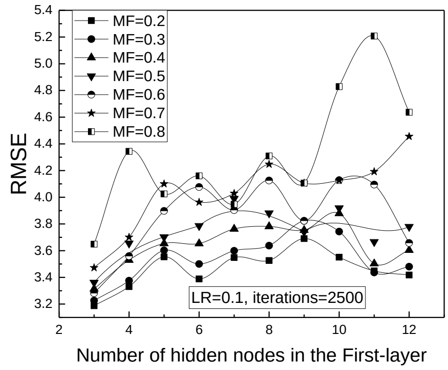

Fig. 7 Effect of momentum factor on network performance

Table 3. Optimal Parameter Solution of the Model of Double BP-NNs

Number of Hidden Layers	Number of Hidden Nodes	Learning Rate	Momentum Factor	Number of Training Iterations
1	3	0.1	0.25	2500

In order to determine the optimal parameter solution of the two-layer neural network model, the relationship surface between network parameters and R^2 is drawn. From Fig 8 and Fig 9, the following three types of situations reflect the high level of correlation of neural network prediction: ① Learning rate $\in[0.1,0.15]$, the number of hidden nodes$\in[3,5]$; ②the learning rate $\in[0.25,0.35]$, the number of hidden nodes=7; ③the learning rate$\in[0.1,0.15]$, the number of hidden nodes=11. It shows that the slump prediction model established by the neural network in the training iteration is generated under an extremely limited and complex parameter area. Now the model parameters are optimized for the interval with high correlation level, and the following optimal network parameter solutions are obtained. Show in Table 3.

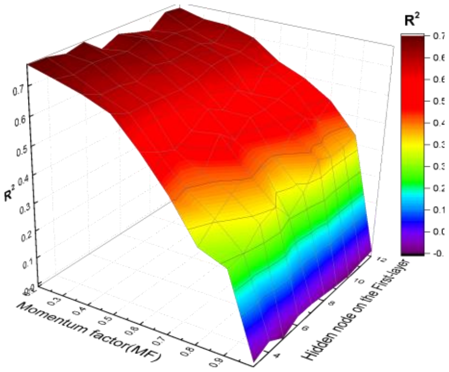

Fig. 8 Influence of momentum factor and hidden nodes on the correlation of prediction model

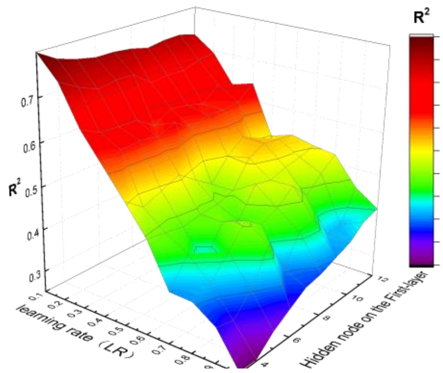

Fig. 9 Effect of learning rate and hidden nodes on the correlation of prediction model

ISSN: 2414-1895 DOI: 10.6919/ICJE.202110_7(10).0038

3.2 Research on Three-layer BP Neural Network

From the analysis results of the two-layer neural network prediction model, it can be seen that if the momentum factor or the learning rate is too large, the weights of the network will be updated too much, resulting in excessive system prediction deviation. In order to ensure the reliability of the prediction model training results, all parameter values whose momentum factor and learning rate are both greater than 0.4 are screened out. Therefore, the considered two-layer hidden layer neural network parameters are as follows: learning rate∈[0.1, 0.4], momentum factor∈[0.1, 0.4], number of training iterations∈[500, 3000], number of first layer nodes∈[3, 12], the number of second-level nodes∈[3, 12], show in Table 2 for specific values.

Under the condition that the learning rate=0.1, momentum factor=0.2 and the number of first-level nodes=10 remain unchanged, the relationship curves of *RMSE* and R^2 with the number of iterations and the number of second-level nodes are drawn, as shown in Fig. 10 and Fig. 11. The result shows:

(1) The *RMSE* is in the (3,4) interval, and the training network performance is good and stable;

(2) Compared with Fig. 8, the three-layer neural network has better network performance and prediction level than the two-layer neural network while keeping other parameters unchanged. For example: from the fluctuation range of the curve, when the number of iterations=3000, the maximum *RMSE* of the second layer is about 4.8cm, and the maximum *RMSE* of the third layer is about 3.78cm, which indicates that the network performance of the three-layer algorithm is more stable than that of the two-layer;

(3) Under the same hidden nodes, the predicted correlation level decreases slightly with the increase of the number of iterations. At this time, the number of hidden nodes is not the main factor affecting network performance. When the number of training iterations=1000~3000, the trend of each curve is the same, and the range of the root mean square error will gradually approach 0 due to the increase of the number of iterations, indicating that the performance of the training network in this iteration interval is good.

After many iterations and optimization learning, the best network parameters selected are as follows:

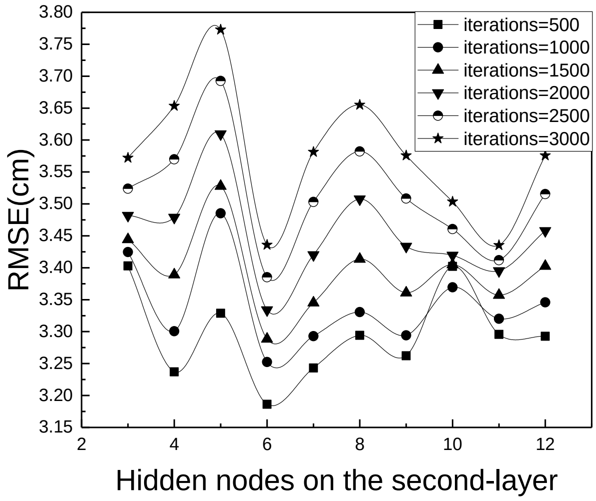

Fig. 10 Effect of the number of training iterations on network performance

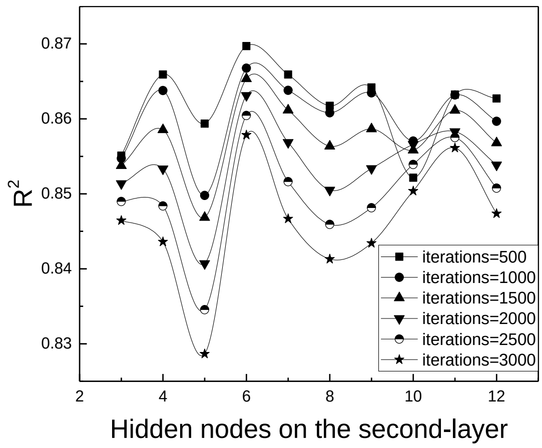

Fig. 11 Effect of the number of training iterations on the correlation of prediction model

Table 4. Optimal Parameter Solution of Three-tier BP-NNs Model

Number of Hidden Layers	Hidden node on the first layer	Two-Layer hidden nodes	Learning Rate	Momentum Factor	Number of Training Iterations
2	10	5	0.1	0.2	500

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3.3 Comparative analysis of results

Compared with the two-layer neural network, the 3-layer has a better prediction effect, and the correlation level and algorithm accuracy of its prediction model is the better than that of the two-layer neural network; However, the network performance of the two-layer neural network will be more stable. The most important factors are affecting the accuracy of the slump model are the learning rate and the momentum factor. Their values should be controlled within 0.4, otherwise the loss function value will be very large, even beyond the range of performance prediction. The concrete slump prediction model using 2-layer or three-layer neural network has its own advantages. Finally, the optimal slump prediction model was selected, as shown in Fig.12.

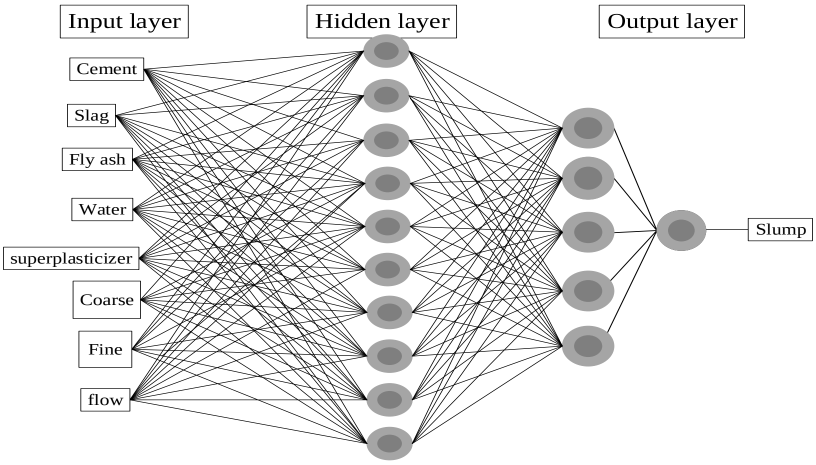

Fig. 12 Neural network model under optimal parameter solution

4. Conclusion

(1) The ten-fold cross-validation method based on neural network is applied to the model prediction of concrete slump, and it has high prediction accuracy. The response error is only 2.02‰, and the RMSE and R2 are 2.933cm and 0.887, respectively.

(2) The accuracy of the slump prediction model that affects the neural network is sorted by influencing factors as learning rate > momentum factor > number of training iterations > number of hidden nodes; too large a learning rate and momentum factor make the adjustment of the network weight value unstable and unstable It will exceed the prediction range of the model performance, resulting in an excessively large value of the loss function.

(3) Compared with the two-layer neural network, the three-layer has better predictive ability, and its prediction model has a higher correlation with the actual measurement, but the network performance of the two-layer neural network is more stable, and each has its own prediction advantages. Therefore, the BP neural network model under the optimal parameter solution meets the actual engineering needs.

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