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Dam Deformation Prediction Based on Wavelet Neural Network Considering Multiple Influencing Factors

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Abstract: In order to predict the deformation displacement of the dam and maintain the safety of the dam operation, this paper takes the Xiaolangdi Dam in Luoyang City, Henan Province as the research object, and uses the 52-period monitoring data of a monitoring point on the dam as the data source. The Spearman rank correlation coefficient analysis method was used to analyze the correlation of 15 influencing factors affecting the dam deformation, and the main influencing factors were determined. The wavelet neural network is constructed, the optimal wavelet function and the number of hidden layer nodes are determined, and the dam displacement prediction is realized. By comparing with BP neural network, the superiority of wavelet neural network is verified. The results show that the main factors affecting dam deformation are T0, sinT, cosT and H, respectively. The RMSE and MAE of the prediction results of the wavelet neural network are 0.1932 dm and 0.1398 dm, respectively, which are reduced by 0.6092 dm and 0.444 dm compared with the BP neural network. The research results can provide some reference value for the safe operation and maintenance of the dam.

Keywords: Impact Factor; Spearman; Wavelet Function; Wavelet Neural Network.

1. Introduction

Since the founding of new China, in order to improve the development of the national economy, China has begun to build a large number of dams. According to the data of the National Bureau of Statistics, up to now, the number of large, medium and small dams that have been successfully built in China has reached nearly 100,000, ranking first in the world[1]. Although the establishment of the dam provides a very favorable guarantee for the development of the national economy and science and technology, due to the early establishment of many dams, the design technology of the dam was not perfect, and the geological conditions and hydrological knowledge were not enough. Understand, resulting in a relatively low standard of design engineering, thus leaving many hidden dangers for the safety of the dam. With the passage of time, the aging of the dam, these security risks have been gradually revealed, which poses a serious threat to people 's property and life. Therefore, it is of great significance to maintain dam safety by establishing a dam deformation prediction model to predict dam deformation.

At present, domestic and foreign researchers have achieved rich research results on dam deformation prediction. In 2016, Spain 's Salazar Fernando et al.used the augmented regression tree to model eight radial displacements and four leakage flows of the Labels dam, discussed the possibility of model interpretation, calculated the relative influence of each predictor, and obtained some correlation diagrams[2]. In 2018, Xing Yin et al.proposed a prediction model (IAGA-BP) combining improved genetic algorithm and BP neural network to solve the problem of unsatisfactory prediction accuracy of dam deformation. The results show that the IAGA-BP model can improve the prediction accuracy of dam deformation and has good stability[3]. In 2019, Liu Zhongbao proposed an adaptive particle swarm neural network algorithm and added an adaptive mutation operator to improve the ability of particles to jump out of local search and achieve accurate prediction of dam displacement[4]. In the same year, Erkan Kose et al.tested the effectiveness of the multivariate grey prediction model in dam deformation prediction. The results show that the predicted value of the grey model is in good agreement with the actual value[5]. In 2022, Yang et al.conducted an experimental study on the application of LSTM model to dam deformation prediction, and used AAFSA to optimize parameters, which provided a new method for dam prediction analysis[6]. Although the above methods have realized the deformation prediction of the dam, most of them do not consider the influence factors of the dam deformation in the prediction process, resulting in low prediction accuracy. Therefore, in order to explore the influence of different influencing factors on dam deformation and realize the high-precision prediction of dam deformation, this paper combines wavelet analysis with traditional artificial neural network to establish a wavelet neural network that takes into account multiple influencing factors, so that it has good approximation ability and fault tolerance ability to realize the prediction of dam deformation.

Based on the 52-period horizontal displacement deformation data of a monitoring point of Xiaolangdi Dam, the Spearman rank correlation coefficient analysis method is used to calculate the correlation between dam deformation and undetermined influencing factors, and the principal component factors affecting dam deformation are determined. The wavelet neural network prediction model is constructed to determine the optimal wavelet function and the number of hidden layer nodes. Combined with the principal component factors affecting the dam deformation, the dam deformation prediction is realized, which provides a certain reference value for the safe operation and maintenance of the dam.

2. Research Area and Data Source

2.1. Overview of the study area

The Yellow River Xiaolangdi Water Conservancy Project is located in Xiaolangdi, Mengjin County, Luoyang City, Henan Province, China. It is a large-scale water conservancy project with flood control, irrigation, power generation and other functions. It is mainly composed of dam engineering, flood discharge engineering and power generation engineering. The dam is built on a overburden layer with a depth of more than 70 meters, with a maximum height of 154 meters. The total length of the dam crest reaches 1667 meters, and the total volume reaches 50 million cubic meters. The dam type is a loam inclined core wall rockfill dam, and a concrete cut-off wall with a depth of more than 80 meters is applied. The Sanmenxia dam is 130 kilometers above the dam project, and the Huang-Huai-Hai plain is downwards. The total capacity of the reservoir is as high as 12.65 billion cubic meters, controlling nearly 100 % of the Yellow River sediment above the Huayuankou of the Yellow River, and its power station is installed 6 units, with a total capacity of 1.8 million kilowatts, and annual power generation is close to 5.1 billion kilowatts per hour. In addition, due to its unique hydrological conditions and complex terrain and geological conditions, the project is considered by experts at home and abroad to be one of the most challenging dam projects in the history of dam engineering in the world.

Figure 1. Picture of the study area

2.2. Data source

According to the stress and deformation law of the dam, the deformation of the dam is relatively small in the direction along the dam axis, and the main deformation direction is perpendicular to the dam axis. Therefore, this paper only analyzes the horizontal displacement data of Xiaolangdi Dam perpendicular to the axis direction. We selected the horizontal displacement deformation data of a monitoring point of Xiaolangdi Dam for a total of 52 experiments. The experimental data are shown in Table 1.

3. Establishment of WNN Prediction Model

Wavelet neural network is a kind of neural network based on the topological structure of BP neural network. The wavelet basis function is used as the transfer function of the hidden layer node. The signal propagates forward and the error propagates backward[8].

Let $X_1,X_2,X_3,\ldots\ldots,X_k$ be the input value of the wavelet neural network, $Y_1,Y_2,Y_3,\ldots\ldots,Y_m$ be the output value of the wavelet neural network, ω_{ij} be the weight between the input layer node and the hidden layer node, ω_{jk} be the weight between the hidden layer node and the output layer node.

When the input signal sequence is $x_i(i=1,2,3,\ldots\ldots,k)$, the hidden layer output calculation formula is:

$$h(j) = h_j\left(\frac{\sum_{i=1}^{k}\omega_{ij}x_i - b_j}{a_j}\right) \qquad j = 1,2,3,\cdots,l \tag{1}$$

Where $h(j)$ is the output value of the j node of the hidden layer; ω_{ij} is the weight between the input layer and the hidden layer of the wavelet neural network; b_j is the translation factor of the wavelet basis function h_j ; a_j is the scaling factor ; h_j is the wavelet basis function.

The network output layer formula of wavelet neural network is as follows:

$$y(k) = \sum_{i=1}^{l}\omega_{ik}h(i) \qquad k = 1,2,3,\cdots,m \tag{2}$$

In the formula, ω_{ik} represents the weight between the hidden layer and the output layer ; $h(i)$ denotes the output corresponding to the cth hidden layer node ; l represents the number of nodes corresponding to the hidden layer ; m represents the number of nodes corresponding to the output layer ;

The basic principle of wavelet neural network is very close to that of BP neural network. They both use gradient correction algorithm to correct the network weights. This correction method can make the predicted value of wavelet neural network continuously approach the expected value. Its correction algorithm is as follows :

(1) Firstly, the error of network prediction is calculated.

$$E = \sum_{k=1}^{m} yn(k) - y(k) \tag{3}$$

where $yn(k)$ represents the expected output ; $y(k)$ denotes the output of network prediction.

(2) According to the error E, the weights of wavelet neural network and the coefficients of wavelet basis function are corrected.

Table 1. Data of a monitoring point of Xiaolangdi Dam[7]

Number of sample periods (period)	Water level (m)	Temperature (°C)	Time limit (day)	Time interval (day)	Displacement (dm)
1	240.9	18.8	0	0	1.56
2	237.45	19	15	15	0.869
3	243.26	19.4	33	18	1.683
4	234.24	19.6	48	15	2.536
5	238.5	20	62	14	0.412
6	237.2	21.8	97	35	-0.859
7	243.2	23	119	22	-0.185
8	240.96	24.4	147	28	-0.842
9	239.3	25.3	187	40	-0.932
10	240.45	25.5	204	17	-1.132
11	240.2	25.6	219	15	-1.339
12	240.1	25	236	17	-1.478
13	240.06	24.5	250	14	-1.216
14	239.85	24	266	16	-1.138
15	241.1	23.2	280	14	0.245
16	242.03	22.3	299	19	1.187
17	239.7	21.6	320	21	0.83
18	239.36	20.2	345	25	1.388
19	238.16	19.3	358	13	1.666
20	239.16	19	369	11	1.873
21	239.3	19.6	393	24	1.644
22	239.2	20.3	407	14	1.36
23	238.2	20.8	420	13	0.903
24	240.5	21.4	433	13	1.315
25	241.1	22	455	22	0.975
26	242.4	22.4	469	14	1.326
27	241.42	23	483	14	0.785
28	242.1	23.5	502	19	0.54
29	240.56	24.1	518	16	0.044
30	240.6	24.6	531	13	-0.915
31	238.5	25.2	546	15	-1.439
32	238.8	25.7	566	20	-1.924
33	239.6	25.8	583	17	-1.461
34	240.2	25.4	597	14	-1.333
35	240.7	25	610	13	-0.948
36	239.8	24.4	625	15	-0.859
37	240.5	23.6	638	13	0.261
38	239.95	21.9	665	27	1.07
39	240.3	20.3	694	29	0.839
40	240.8	19.6	727	33	1.99
41	239.7	20	759	32	1.873
42	239.3	21.2	790	31	1.382
43	239.5	22.7	821	31	0.468
44	243.15	24.2	853	32	0.785
45	238.5	25.1	884	31	-1.11
46	239.1	25.8	923	39	-1.656
47	241	25.6	950	27	-1.032
48	240.35	25	972	22	-0.748
49	239.56	23.8	1000	28	-0.67
50	242.2	21.4	1036	36	1.705
51	241.25	20.3	1062	26	1.984
52	240.69	19.5	1099	37	2.123

$$\omega_{n,k}^{(i+1)} = \omega_{n,k}^{i} + \Delta\omega_{n,k}^{(i+1)} \tag{4}$$

$$a_k^{(i+1)} = a_k^{i} + \Delta a_k^{(i+1)} \tag{5}$$

$$b_k^{(i+1)} = b_k^{i} + \Delta b_k^{(i+1)} \tag{6}$$

In the formula, $\Delta\omega_{n,k}^{(i+1)}$, $\Delta a_k^{(i+1)}$, $\Delta b_k^{(i+1)}$ are calculated by using the error of wavelet neural network prediction:

$$\Delta\omega_{n,k}^{(i+1)} = -\eta \frac{\partial E}{\partial \omega_{n,k}^{(i)}} \quad (7)$$

$$\Delta a_k^{(i+1)} = -\eta \frac{\partial E}{\partial a_k^{(i)}} \quad (8)$$

$$\Delta b_k^{(i+1)} = -\eta \frac{\partial E}{\partial b_k^{(i)}} \quad (9)$$

In the formula, η represents the learning rate.

4. Correlation Analysis of Dam Deformation Influencing Factors

4.1. Dam deformation influence factors

Through the analysis of a large number of dam deformation monitoring data, it can be known that no matter what type of dam, the main factors affecting its deformation can be divided into : water pressure factor, temperature factor and aging factor. These three factors work together on the dam, so that the dam is displaced in a certain direction. Therefore, in this paper, the dam displacement is divided into water pressure displacement component $f(h)$, time-dependent displacement component $f(\theta)$ and temperature displacement component $f(c)$, so the dam displacement calculation formula is :

$$f = f(h) + f(c) + f(\theta) \quad (10)$$

(1) Water pressure displacement component: It mainly represents some elastic and inelastic deformation caused by water pressure load on the dam. According to the knowledge of engineering mechanics, the deformation of the dam is related to the power of the water level. The relationship is as follows:

$$f(h) = \sum m_i (H^i - H_0^i) \quad (11)$$

In the formula, m_i represents the influence coefficient, H_0^i represents the water level of the initial day, and H^i represents the water level of the observation day.

(2) Temperature displacement component: It mainly refers to the partial deformation of the dam caused by the influence of temperature change. This deformation is generally elastic and recoverable. The main reason for this is that the dam is not all exposed to the outside, and the temperature of the dam body is not exactly the same on and under the water, which will lead to the tilt of the dam. When the temperature above the water is higher than the temperature under the water in summer, the dam will tilt upwards, and the opposite is true in winter. Therefore, temperature is a very important part of dam deformation. The expression of temperature displacement component is as follows:

$$f(c) = \sum_{i=1}^{n} k_i T_i \quad (12)$$

In the formula, k_i represents the coefficient; T_i represents the average temperature of the day before the observation.

(3) Time-dependent displacement component: Time-dependent displacement component is one of the most complex factors affecting dam displacement. It mainly represents the deformation of the dam over time. This deformation is generally more severe when the dam is just built, but with the increase of operating years, it will slowly become stable. The expression of aging component is as follows:

$$f(\theta) = C_1\theta + C_2 \ln\theta \quad (13)$$

In the formula, C_1 and C_2 represent the coefficients, θ= 0.01t, t represents the cumulative number of days from the observation day to the beginning of the observation day.

In summary, the main influencing factors affecting dam displacement can be listed as follows : H、H^2、H^3、H^4、H^5、T_0、θ、θ^2、θ^3、θ^4、θ^5、lnθ。In addition, due to the periodicity of temperature, it is necessary to introduce temperature factors *sinT*, *cosT*, *sinT*^{2}(T=2*pi*t/365, t represents the number of days between the observation day and the initial observation day, θ= 0.01t) , a total of 15 influencing factors.

4.2. Correlation analysis of impact factors based on Spearman

Spearman rank correlation coefficient is a test method without parameters, which is mainly used for the strength of the relationship between variables and variables. In the absence of the same data, if a variable is a strictly monotone function of another variable, the Spearman rank correlation coefficient is +1 or -1, which is called the variable complete Spearman rank correlation. Its expression is as follows:

$$r_s = 1 - \frac{6\sum_{k=1}^{n} d_i^2}{n^3 - n} \quad (14)$$

In the formula, n represents the number of samples, and the original data x_i and y_i are sorted from large to small. Let $x_i^{'}$ and $y_i^{'}$ be the position of the original data after sorting from large to small. $x_i^{'}$ and $y_i^{'}$ are called the rank of x_i and y_i, and the rank difference is $d_i = x_i^{'} - y_i^{'}$.

According to the 15 influencing factors of dam deformation determined above, combined with the relevant monitoring data of Xiaolangdi dam, Spearman rank correlation coefficient is used to calculate the correlation between these influencing factors and displacement, and the calculated correlation coefficient is tested for significance, so as to determine the main factor affecting dam deformation. The calculation results are shown in Table 2.

Table 2. Spearman rank correlation coefficient and statistic t of influence factors and dam displacement

Impact factors	Correlation coefficient	Statistic t
H	0.1396	0.996
H^2	0.1396	0.996
H^3	0.1396	0.996
H^4	0.1396	0.996
H^5	0.1396	0.996
T_0	-0.9013	-14.716
$\sin T$	0.3113	2.317
$\cos T$	0.8629	12.074
$\sin^2 T$	-0.1186	-0.845
θ	0.0296	0.209
θ^2	0.0296	0.209
θ^3	0.0296	0.209
θ^4	0.0296	0.209
θ^5	0.0296	0.209
$\ln\theta$	0.033	0.233

The verification process of Spearman rank correlation coefficient using significance test is as follows:

(1) First, establish the null hypothesis and the reserve hypothesis.

H_0 represents Spearman 's rank correlation coefficient $r = 0$, not significant.

H_1 represents Spearman 's rank correlation coefficient $r \neq 0$, significant.

(2) Construction and calculation of statistics

The statistic t is used to verify whether r is significant. The calculation formula is as follows. The calculation results are shown in Table 2.

$$t = r\sqrt{\frac{n-2}{1-r^2}} \tag{15}$$

(3) Determine the significance level and the negative domain.

When the significant level $\alpha = 0.05$, the negative domain $\Theta = \{t \,||\, t| > t_{0.025}(50)\}$.

After verification, we can find that the three factors of T_0, *sinT* and *cosT* are significantly correlated with the dam displacement, the five factors of H, H_2, H_3, H_4 and H_5 are nearly significantly correlated with the dam displacement, and the other influencing factors are basically not significantly correlated with the dam displacement. Finally, the four influencing factors of T_0, *sinT*, *cosT* and H are determined as the main factor of dam deformation.

5. Dam Deformation Prediction Based on Wavelet Neural Network Model

5.1. Selection of wavelet function

The establishment of the wavelet neural network model is to use the wavelet function as the excitation function to construct the network. Therefore, selecting a wavelet function suitable for the wavelet neural network plays a very important role in the training of the network and the quality of the predicted results. Morlet function and Mexican Hat function are commonly used in wavelet neural network prediction. Both of them belong to non-orthogonal wavelet basis functions. Morlet wavelet function is generally used for classification, image recognition and feature extraction. Mexican Hat function is often used for system recognition[9]. The wavelet neural network is established by using these two wavelets respectively, and the root mean square error of the prediction results is compared. The results are shown in table 3.

(1) Morlet wavelet function expression:

$$y = \cos(1.75)e^{-x^2/2} \tag{16}$$

(2) Mexican Hat wavelet function expression:

$$y = (1-x^2)e^{-x^2/2} \tag{17}$$

The function image is shown in Fig.2:

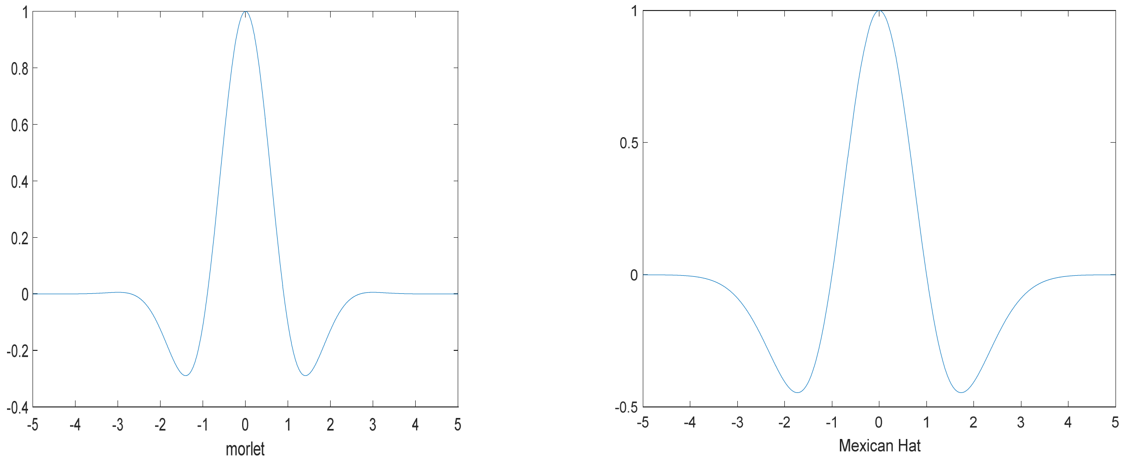

Figure 2. Image of Morlet wavelet function and Mexican Hat wavelet function

Table 3. Root mean square error of different wavelet function training and test results

Wavelet function	RMSE of training results(dm)	RMSE of test results(dm)
Morlet	0.3595	0.2155
Mexican Hat	0.3990	0.2669

It can be seen from Table 3 that the root mean square error of the training and test results of the wavelet neural network constructed by two different wavelet functions is in the same order of magnitude, but the accuracy of the training and test results of the wavelet neural network constructed by the Morlet function is slightly higher than that of the wavelet neural network constructed by the Mexican Hat function. It is found that the stability of the Morlet function prediction is higher. Therefore, this paper uses the Morlet function as the excitation function between the input layer and the hidden layer.

5.2. Determination of the number of hidden layer nodes

In the wavelet neural network, the choice of the number of hidden layer nodes is very important for the success of network establishment. The number of hidden layer nodes mainly affects the generalization ability and network training speed of wavelet neural network. When the number of hidden layer nodes is too small, the performance ability of the network may be insufficient, the learning process may not converge, the generalization ability of the network is weak, and the prediction accuracy is not high. When the number of hidden layer nodes is too much, the network learning time is long, the network is easy to oscillate, and the network is easy to train too much, which makes the fault tolerance performance of the network decrease. Therefore, in order to build a good prediction model, we must choose a suitable number of hidden layer nodes. However, there is no standard expression for the selection of the number of hidden layer nodes. We can only rely on the empirical formula summarized by the predecessors through continuous research to determine the approximate range, and then determine the most suitable number of hidden layer nodes through training experiments. The empirical formulas used in this paper are as follows :

$$l = \sqrt{m+n} + i \tag{18}$$

In the formula, m represents the number of input neurons, n represents the output neurons, and i represents a number between 1 and 10.

Combined with the correlation analysis of the influence factors of Xiaolangdi dam deformation in Chapter 4.1, it can be seen that the number of input neurons of the wavelet neural network is 4, and the number of output neurons is 1.Therefore, combined with the empirical formula of the number of hidden layer nodes, it can be determined that the range of the number of hidden layer nodes of the wavelet neural network is 3 to 13. According to this range, the training experiment method is used to train the network with different hidden layer nodes, and the dam displacement is predicted. The root mean square error of the prediction results is calculated, and the optimal number of hidden layer nodes is determined by comparison. The root mean square error of the training and test results obtained from the experiment is shown in Table 4 and Fig.3.

Table 4. Root mean square error of training and test results of different hidden layer nodes

Number of hidden layer nodes	RMSE of training results(dm)	RMSE of test results(dm)
3	0.4518	0.3481
4	0.3906	0.3149
5	0.3665	0.2662
6	0.3488	0.2874
7	0.3162	0.1932
8	0.3257	0.2169
9	0.3583	0.3494
10	0.3969	0.3377
11	0.3274	0.3524
12	0.3683	0.3611
13	0.3674	0.3997

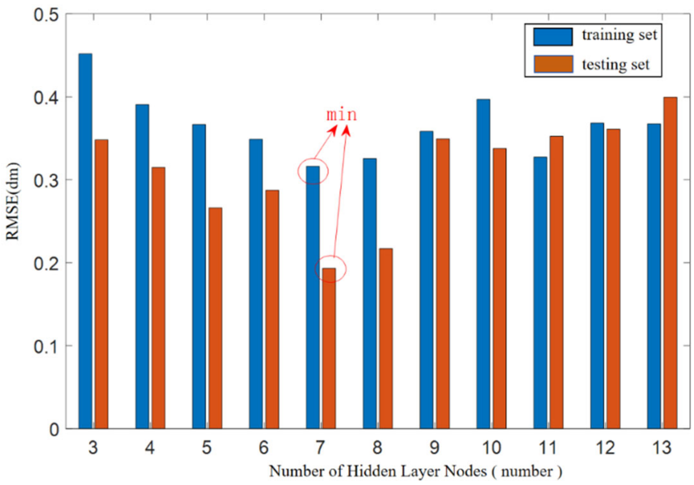

Figure 3. Root mean square error of training and test results of different hidden neuron nodes

From the experimental results, it can be known that when the number of hidden layer nodes is 7, the root mean square error of the training results is 0.3162 dm, and the root mean square error of the test results is 0.1932 dm, which is the smallest relative to the number of other hidden layer nodes. It shows that the training effect of the network with 7 hidden layer nodes is relatively good and the prediction accuracy is high. Therefore, in this paper, the number of hidden layer nodes of wavelet neural network is determined to be 7, and the network neuron structure is established as 4-7-1.

5.3. Analysis of prediction results

The training and test results of the established wavelet neural network prediction model and the BP neural network training and test results are compared with the measured values. So as to explore the feasibility of wavelet neural network in dam deformation prediction. The comparison results are shown in Fig.4, Fig.5 and Table 5.

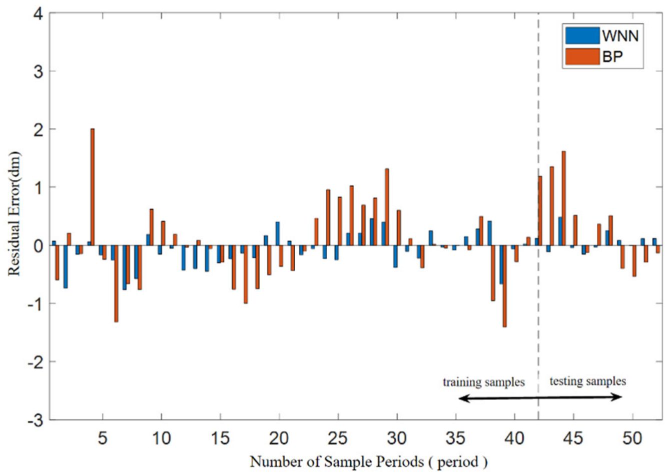

Figure 4. Residual comparison diagram

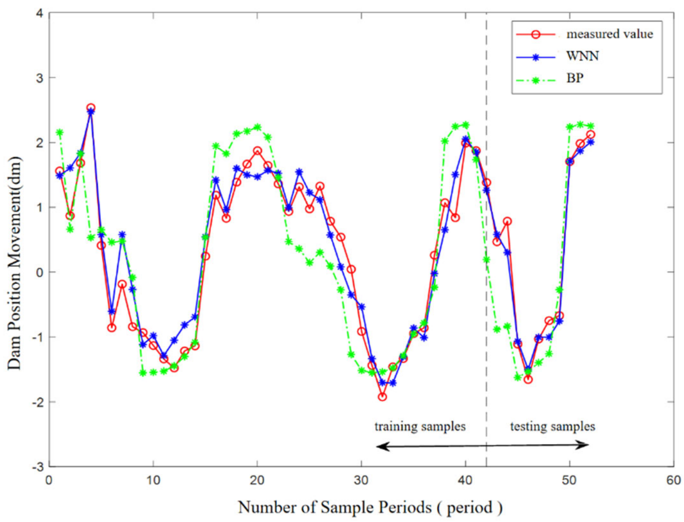

Figure 5. Comparison of prediction results

Table 5. Comparison of evaluation indexes

Evaluating indicator	WNN training error	WNN test error	BP training error	BP test error
RMSE (dm)	0.3162	0.1932	0.7162	0.8024
MAE (dm)	0.2554	0.1398	0.5552	0.5838
MAPE	0.5795%	0.16%	1.321%	0.764%

First of all, it can be seen from Fig.4 that the residual values of wavelet neural network training and test results are generally smaller than those of BP neural network. Then, it can be seen from Fig.5 that the wavelet neural network prediction results have a higher degree of fitting with the measured values. Finally, according to the evaluation index of Table 5, the RMSE, MAE and MAPE of wavelet neural network training results are reduced by 0.4 dm,0.2998 dm and 0.7415 % respectively compared with BP neural network. The RMSE, MAE and MAPE of the test results are reduced by 0.6092 dm,0.444 dm and 0.604 % respectively compared with BP neural network. Therefore, combined with the above, the wavelet neural network has better learning ability, stronger approximation ability and higher prediction accuracy than the BP neural network, which shows that the wavelet neural network has a better effect in dam deformation prediction.

6. Conclusion

This paper takes Xiaolangdi Dam in Henan Province as the research object, and determines the main influencing factors of dam deformation through Spearman correlation analysis. The wavelet neural network is constructed, and the dam deformation prediction is realized by combining the main influencing factors. The main conclusions are as follows:

(1) By calculating the Spearman correlation coefficient between the 15 influence factors and the dam displacement, the principal component factors affecting the dam deformation are determined to be T_0, *sinT, cosT*, *H*, respectively.

(2) A wavelet neural network model considering multiple influencing factors is constructed. The optimal wavelet function and the optimal number of neuron nodes of the model are determined. Combined with the main influencing factors of dam deformation, the dam deformation prediction is realized. By comparing the prediction results of BP neural network, the prediction accuracy of this model is higher, which proves the superiority of the model. ,2015,1-10

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