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Application of neural network merging model in dam deformation analysis

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Abstract: In order to improve the prediction accuracy and test the generalization ability of the dam deformation analysis model, the back-propagation (BP) neural network model for dam deformation analysis is studied, and the merging model is built based on the neural network BP algorithm and the traditional statistical model. The three models mentioned above are calculated and analyzed according to the long-term deformation observation data in Chencun Dam. The analytical results show that the average prediction accuracies of the statistical model and the BP neural network model are ±0.477 and ±0.390 mm, respectively, while the prediction accuracy of the merging model is ±0.318 mm, which is improved by 33% and 18% compared to the other two models, respectively. And the merging model has a better generalization ability and broad applicability.

Key words: dam deformation analysis; neural network; statistical model; merging model

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As it is known to all, building dams is one of the most important engineering measures for the comprehensive utilization of water resources, and all the countries in the world are now attaching great importance to it. The water conservancy and hydropower engineering have brought huge economic benefits to human beings, such as flood controlling, power generation, water supply, shipping, irrigation, tourism, cultivation and so on. However, there is a certain degree of risk in constructing dams since the dam-break phenomenon will cause huge economic losses and even serious casualties. Therefore, dam safety becomes more prominent and important, and the establishment of a good dam deformation analysis model is exactly an important means to ensure the safe operation of the dam.

Since the 1950s, methods of dam deformation analysis have been put forward in succession by many scholars in Italy[1], Austria[2] and Korea[3]. Compared with other countries, the analysis of dam monitoring data started later in China, but some effective progress has also been made by domestic scholars[4-6]. At present, the conventional models of dam deformation analysis are divided into three classes: the statistical model, the deterministic model and the mixed model. There is no doubt that these classical deformation analysis models have played very important roles for dam deformation prediction in the past several decades. But it is undeniable that because of the complexity of the actual engineering, the under fitting problem which commonly exists in regression models results in a low prediction accuracy in such kind of models.

In recent years, with the continuous development of new disciplines, the wavelet analysis[7], the grey theory[8], fuzzy mathematics[9] and the artificial neural network[10-11] have been applied to the analysis of dam monitoring data, which enrich the dam deformation analysis models. Because of its self-organization, self-adaptability, association ability, self-learning ability and very strong nonlinear mapping ability, the neural network has now been used in a wide range of applications. Based on the vertical displacement observation data of the dam, the statistical model, the conventional BP neural network model and the merging model are built up in this paper, and the prediction effects of the three models are compared and analyzed.

1 Overview of Three Dam Deformation Analysis Models

1.1 Statistical model

The statistical model is the most mature and widely used model in dam safety monitoring. By qualitative analysis we know that the vertical displacement of a gravity arch dam at any point can be divided into three main parts: hydraulic pressure component, thermal component and aging component[5]. Combined with the specific circumstance of the dam, the statistical model for the vertical displacement is

$$\delta = \delta_H + \delta_T + \delta_A \tag{1}$$

where δ is the vertical displacement; δ_H is the hydraulic pressure component; δ_T is the thermal component; and δ_A is the aging component.

The expression of the hydraulic pressure component of the vertical displacement is

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$$\delta_H = \sum_{i=1}^{3} a_i H^i \tag{2}$$

where H is the water depth in front of the dam, namely the reservoir water level; and a_i is the hydraulic factor regression coefficient.

The thermal component is mainly due to the temperature variations of the dam body and the bedrock. The Chencun Dam has been in operation for more than thirty years, and the dam body is in the state of the quasi-stationary temperature field. Therefore, the thermal component can be represented by a periodic function

$$\delta_T = \sum_{j=1}^{2} \left(b_{1j} \sin \frac{2\pi j t}{365} + b_{2j} \cos \frac{2\pi j t}{365} \right) \tag{3}$$

where t is the cumulative number of days between the observation day and the first observation day of the modeling time; and b_{1j}, b_{2j} are the thermal factor regression coefficients.

The aging component is a comprehensive reflection of many effects such as concrete creep and so on, and its causes are very complex. In this paper, we use the model as follows:

$$\delta_A = c_1 \theta + c_2 \ln \theta \tag{4}$$

where θ is the cumulative number of days between the observation day and the first measuring day divided by 100, and c_1, c_2 are the aging factor regression coefficients.

In summary, the statistical model of the vertical displacement is

$$\delta = \delta_H + \delta_T + \delta_A = a_0 + \sum_{i=1}^{3} a_i H^i + \sum_{j=1}^{2} \left(b_{1j} \sin \frac{2\pi j t}{365} + b_{2j} \cos \frac{2\pi j t}{365} \right) + c_1 \theta + c_2 \ln \theta \tag{5}$$

where a_0 is the constant term.

1.2 Conventional BP neural network model

The error back-propagation network is the most widely used and effective one in the existing dozens of artificial neural network models. Usually, the BP neural network consists of the input layer, the hidden layer and the output layer. The main idea of the BP algorithm is to divide the learning process into two stages[12].

1) The forward propagation process: The input information is given, and the actual output value of each unit is calculated layer-by-layer.

2) The back propagation process: If the expected output value is not obtained in the output layer, then we calculate the difference between the actual output and the expected output layer-by-layer recursively in order to adjust the weights.

Use these two processes repeatedly and obtain the minimum error signal, and when the error achieves the expected requirements, the learning procedure of the network ends. The structure of the BP neural network model is shown in Fig. 1.

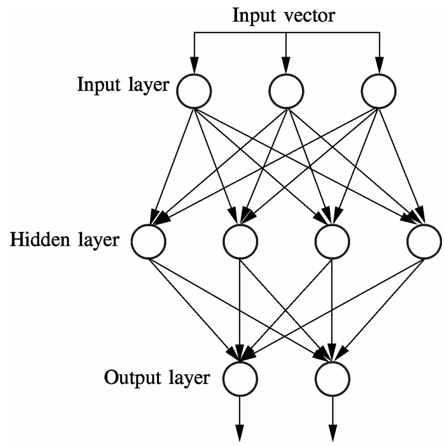

Fig. 1 Structure of the BP neural network model

The specific structure of the BP neural network model in this paper is as follows:

1) The input layers are all the factors that affect the dam deformation. There are nine factors in hydraulic pressure component, thermal component and aging component in this paper, namely, H, H^2, H^3, $\sin \frac{2\pi t}{365}$, $\cos \frac{2\pi t}{365}$, $\sin \frac{4\pi t}{365}$, $\cos \frac{4\pi t}{365}$, θ, $\ln \theta$. The selection of the parameters and the meaning of the symbols are the same as the statistical model.

2) The number of hidden layer nodes is P, which is always determined by tentative calculation or experience. In this paper, $P = 16$.

3) The output layer is the measured vertical displacement value y_0. So the structure of the BP neural network model is $9 \times 16 \times 1$ in this paper.

1.3 Neural network merging model

The merging model is a method to compensate for the error of the hypothetical model based on the BP neural network model[13]. The specific structure of the neural network merging model in this paper is as follows:

1) The input layers are all the factors that affect the dam deformation and the fitted value of the statistical model y_s, namely, H, H^2, H^3, $\sin \frac{2\pi t}{365}$, $\cos \frac{2\pi t}{365}$, $\sin \frac{4\pi t}{365}$, $\cos \frac{4\pi t}{365}$, θ, $\ln \theta$ and y_s.

2) The number of hidden layer nodes is P, which is always determined by tentative calculation or experience. In this paper, $P = 16$.

3) The output layer is the difference between the measured vertical displacement value y_0 and the fitted value of the statistical model y_s. Note that the final result of the merging model is the sum of the simulated value of the neural network and the fitted value of the statistical model y_s. So the structure of the neural network merging model

is $(9+1)\times 16\times 1$ in this paper.

2 Case Study

2.1 Project overview and modeling data selection

Located in the upper reaches of the Qingyi River, the Chencun Dam is a comprehensive medium-sized water conservancy and hydropower project. The concrete gravity arch dam has 28 sections from left to right, and the total reservoir capacity of the dam is 2.825×10^6 m^3.

The observation data of the vertical displacement of a certain observation point in Chencun Dam between January 1999 and December 2006 are used for deformation analysis. The gross error is eliminated by data preprocessing and finally 96 samples are selected, 12 samples for each year. Now the 96 samples are divided by the following three conditions:

1) Sample classification 1: The 60 samples from 1999 to 2003 are selected as the learning samples, and the rest 36 samples from 2004 to 2006 are selected as the testing samples.

2) Sample classification 2: The 72 samples from 1999 to 2004 are selected as the learning samples, and the rest 24 samples from 2005 to 2006 are selected as the testing samples.

3) Sample classification 3: The 84 samples from 1999 to 2005 are selected as the learning samples, and the rest 12 samples in 2006 are selected as the testing samples.

2.2 Comparison of prediction accuracy

After modeling by the statistical model, the BP neural network model and the neural network merging model respectively for the three kinds of sample classification above, the RMSEs of the testing samples are shown in Tab. 1.

Tab. 1 RMSEs of testing samples of different models mm

Model selection	Statistical model	BP neural network model	Neural network merging model
Sample 1	0.549	0.442	0.314
Sample 2	0.504	0.385	0.328
Sample 3	0.377	0.343	0.311

From Tab. 1, we can see that the prediction accuracy of the statistical model is general. The effect of the BP neural network model is improved, while the neural network merging model is the best, since the average prediction accuracy of the merging model is improved by 33% and 18% respectively compared with the other two models. From the comparison of different sample classifications for each model, we can see that with the increase in the learning samples, the RMSEs of the statistical model reduce significantly, while the RMSEs of the BP neural network model and the merging model change slowly. This shows that the prediction accuracy of the statistical model is more dependent on the number of learning samples for modeling, which is determined by its statistical characteristics.

2.3 Analysis of generalization ability

In order to test the generalization ability of the neural network merging model, we choose sample classification 2 to compare the forecast values in 2005 and 2006 predicted by the statistical model and the neural network merging model. The results are shown in Tab. 2 and Tab. 3.

Tab. 2 Comparison of prediction results in 2005 mm

Date of observation	Measured value	Statistical model		Merging model	
		Forecast value	Residual error	Forecast value	Residual error
2005-01-17	−0.09	−0.15	0.06	−0.26	0.17
2005-02-21	0.31	−0.14	0.45	0.00	0.31
2005-03-14	0.84	0.13	0.71	0.26	0.58
2005-04-19	−0.37	−0.42	0.05	−0.31	−0.06
2005-05-16	−1.37	−1.33	−0.04	−1.20	−0.17
2005-06-14	−2.07	−2.07	0.00	−1.93	−0.14
2005-07-19	−2.58	−2.74	0.16	−2.55	−0.03
2005-08-16	−3.01	−3.01	0.00	−2.79	−0.22
2005-09-13	−2.66	−3.17	0.51	−2.92	0.26
2005-10-12	−2.36	−3.08	0.72	−2.86	0.50
2005-11-15	−2.41	−2.37	−0.04	−2.39	−0.02
2005-12-20	−0.86	−1.08	0.22	−1.03	0.17

Tab. 3 Comparison of prediction results in 2006 mm

Date of observation	Measured value	Statistical model		Merging model	
		Forecast value	Residual error	Forecast value	Residual error
2006-01-17	−0.09	−0.26	0.17	−0.24	0.15
2006-02-13	0.64	−0.06	0.70	0.11	0.53
2006-03-13	0.34	−0.30	0.64	0.02	0.32
2006-04-19	−0.31	−1.12	0.81	−0.78	0.47
2006-05-15	−1.32	−2.05	0.73	−1.68	0.36
2006-06-13	−1.95	−2.76	0.81	−2.39	0.44
2006-07-12	−2.62	−3.27	0.65	−2.85	0.23
2006-08-15	−3.38	−3.46	0.08	−3.05	−0.33
2006-09-19	−2.65	−3.48	0.83	−3.06	0.41
2006-10-17	−2.98	−3.29	0.31	−2.94	−0.04
2006-11-21	−2.26	−2.66	0.40	−2.62	0.36
2006-12-19	−1.27	−1.88	0.61	−1.78	0.51

From Tab. 2 and Tab. 3, we can see that the residual errors of the statistical model in 2005 are significantly smaller than those in 2006, and the RMSEs are ± 0.363 and ± 0.613 mm, respectively. Compared with the statistical model, the amplitude of variation of the neural network merging model is less, and the RMSEs are ± 0.277 and ± 0.373 mm, respectively. This shows that the neural network merging model has a better generalization ability.

3 Conclusion

Dam deformation observation data is important for dam safety monitoring, and dam deformation analysis is the most effective use of these data, so the quality of the deformation analysis models directly determines whether the dam can operate under a safe condition or not. From the instance in this paper, we can see that the statistical model has been widely used. But in some cases, due to the complexity of influencing factors of the dam, the fitting accuracy is often not very good. The neural network merging model has not only a higher prediction accuracy but also a stronger generalization ability, so it can be used as a good method for deformation analysis of dam monitoring data.

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神经网络融合模型在大坝变形分析中的应用

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摘要:为了提高大坝变形分析模型的预测精度并检验模型的泛化能力,研究了大坝变形分析的 BP 神经网络模型,并基于神经网络 BP 算法和传统的统计模型建立了大坝变形分析的融合模型. 结合陈村大坝多年的变形观测数据,对上述 3 种模型进行了试算及分析. 分析结果表明,统计模型的平均预测精度为 ±0.477 mm, BP 神经网络模型的平均预测精度为 ±0.390 mm,融合模型的平均预测精度为 ±0.318 mm,相比统计模型和 BP 神经网络模型分别提高了 33% 和 18% ,且泛化能力较强,具有广泛的适用性.

关键词:大坝变形分析;神经网络;统计模型;融合模型

中图分类号:TV698.1