Merging Model of Dam Deformation Analysis Based on Neural Network

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ABSTRACT:

Dam deformation analysis is one of the main tasks in dam safety monitoring. Regression analysis model is often used in dam deformation analysis in early days. At present, the statistical model, which divides the dam deformation into three parts, hydraulic pressure component, thermal component and ageing component, according to the causes of deformation, has been widely adopted in dam deformation analysis. The BP neural network model and the merging model based on BP neural network algorithm of dam deformation analysis are mainly discussed in this paper, and finally, the four models mentioned above are calculated and analyzed according to a specific project instance. The precisions are respectively ±1.19mm, ±0.38mm, ±0.34mm, and ±0.28mm for single linear regression model, statistical model, BP neural network model and merging model. So it is shown that the merging model is better than the others according to the results.

1. INTRODUCTION

The star-studded reservoir dams have played an irreplaceable role in accelerating the development of social economic, such as controlling flood, ensuring water supply, ensuring energy sources, shipping, protecting the environment and so on. Meanwhile, the safety management of reservoir dams is now a worldwide problem. Dam deformation is one of the important factors which affect dam security, and deformation monitoring and deformation analysis are important components of dam safety monitoring. So it is always one of the research hotspots in the world water conservancy domain for dam deformation analysis using the long-term aspect monitoring data of the dam (Zhao, 2010).

Before the 1950s, research and analysis of the observation data were mainly qualitative descriptions and explanations for measured values (Tonini D, 1956). Statistical regression method was applied for quantitative analysis of dam deformation by Rocha from Portugal and Faneli from Italy by 1955 (Rocha, 1958; Faneli, 1979). Deterministic model and mixed model of concrete dam deformation were put forward by Bonaldi (Bonaldi, 1980). Finite element method was first used to calculate hydraulic pressure component, thermal component and ageing component, and establish regression model by Marazio (Marazio, 1980). Principal component regression analysis was adopted to model the monitoring data of Idukki arch dam by Luc E. Chouinard (Luc E. Chouinard, 1996). And several other scholars did some research in mathematical models of dam safety monitoring (Oliver Crepon, 1999; A.De Sortis, 2007). In China, the studies were mainly qualitative analysis before the 1970s. Statistical regression method was applied in analysis of safety monitoring data by Chen Jiuyu in 1974, which started the quantitative research in China (Chen, 1987). The expression of ageing displacement on top of dam body was deduced by Wu Zhongru, and principles and methods of deterministic model of dam displacement were put forward in the corresponding period (Wu, 1989, 1992). From the 1980s, analysis on dam observation data at home and abroad gradually developed to the depth direction. Grey theory, fuzzy mathematics, neural network, chaos theory, statistical learning theory was applied to dam deformation analysis. New theory and new methods were introduced into the analysis of dam safety monitoring data. The fuzzy clustering analysis method was adopted to analyse and forecast the displacement of concrete dam by Liu Guanbiao (Liu, 1989). The grey system theory was introduced to the field of dam safety monitoring data analysis by Li Zhenzhao (Li, 1992). The fuzzy control theory was used to model and forecast the uplift pressure of dam foundation by Gu Chongshi (Gu, 1996). The fuzzy mathematics and the artificial neural network were combined to predict the deformation of earth dams by Chen Jiguang (Chen, 2000). The non-linear grey model of earth-rock dam deformation was established by Yang Jie (Yang, 2001). The wavelet neural network was used for fitting and forecasting of dam deformation monitoring by Gao Ping (Gao, 2003). BP neural network model was used for fitting analysis and forecasting of dam deformation monitoring data by Deng Xingsheng (Deng, 2004). BP neural network was applied to calculate the correction parameters of dam foundation by CeVik A. (Cevik A., 2008). Artificial neural network model was used for forecasting of dam relative displacement by Yong-Seong Kim (Yong-Seong Kim, 2008). The wavelet analysis and gray model were combined for decomposition detection of the dam observation data by Jiao Minglian (Jiao, 2009).

Over the past 60 years, great progress has been made in dam deformation analysis. The study above enriches the dam deformation analysis models and makes important contribution to the study of dam safety monitoring models. But now we are still not entirely clear for the rules of dam deformation, and the model accuracy of dam deformation analysis also remains to be further improved. This paper mainly discusses the establishment of dam deformation analysis models using the dam deformation monitoring data. Based on the regression analysis model, the statistical model and the BP neural network model, a merging model of dam deformation analysis is put forward. And the four models are contrasted and analysed according to a project instance.

2. DAM DEFORMATION ANALYSIS MODELS

2.1 Single Linear Regression Analysis Model

Suppose the dam deformation δ is only related to the reservoir water level H, and for the linear relationship:

$$\delta = a + b \cdot H \tag{1}$$

Certain amount of learning sample values can be substituted into the formula (1) to establish the error equation. Then the undetermined coefficients a and b in the single linear regression analysis model can be calculated according to the least square method. And after a and b are calculated, the single linear regression analysis model can be built up.

2.2 Statistical Model

Under the loads of water pressure and temperature, the deformation δ at any point in the concrete dam can be divided into three main parts according to the causes of formation: hydraulic pressure component δ_H , thermal component δ_T and ageing component δ_θ (Wu, 1989). Use the model below:

$$\begin{aligned}\delta &= \delta_H + \delta_T + \delta_\theta \\ &= a_0 + \sum_{i=1}^{4} a_i H^i + \sum_{i=1}^{2}\left(b_{1i}\sin\frac{2\pi i t}{365} + b_{2i}\cos\frac{2\pi i t}{365}\right) + c_1\theta + c_2\ln\theta\end{aligned} \tag{2}$$

Where a_i = hydraulic factor regression coefficient (i=0~4)

H = water depth in front of the dam, namely the reservoir water level

b_{1i}, b_{2i} = thermal factor regression coefficient (i=1~2)

t = the cumulative number of days between the observation day and the first observation day of the modeling time

c_1, c_2 = ageing factor regression coefficient

θ = the cumulative number of days between the observation day and the first measuring day divided by 100, for each additional day, θ increased to 0.01

Similarly, certain amount of learning sample values can be substituted into the formula (2) to establish the error equation. Then the 11 undetermined coefficients in the statistical model can be calculated according to the least square method. Thus, the statistical model is also built up.

2.3 Conventional BP Neural Network Model

The principle of neural network and BP algorithm can be found in the references (Hu, 2006). Make each influence factor which works on the deformation of concrete dam (ten factors of hydraulic pressure component, thermal component and ageing component in this paper): H , H^2 , H^3 , H^4 , $\sin\frac{2\pi t}{365}$, $\cos\frac{2\pi t}{365}$, $\sin\frac{4\pi t}{365}$, $\cos\frac{4\pi t}{365}$, θ , $\ln(\theta)$, as the input vector of the neural network model, and make the value of dam deformation as the output vector of the model. Therefore, the model structure of BP algorithm is: 10×P×1, where P is the number of hidden layer nodes.

For the project instance in this paper, after many experiments by the author, the parameters selected for BP neural network are: the learning rate η =1.2, the smoothing factor α =1.5, the number of hidden layer nodes P=15, the learning error ε =0.01.

3. NEURAL NETWORK MERGING MODEL

Based on statistical model and BP neural network model of dam deformation analysis, a neural network merging model is put forward in this paper. The BP network structure of the merging model is (n+1)×p×1. The specific network structure is shown in Fig. 1.

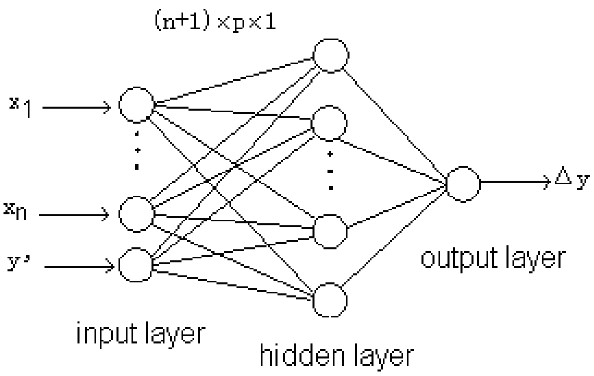

Figure. 1. Neural network structure of merging model

The BP structure of the merging model is 11×P×1 according to the project instance in this paper. The specific explanations are as follows:

①The input layers of the merging model are n factors (n=10 in this paper) which effect the dam deformation and the fitted value of statistical model y', in this instance they are: H, H^2, H^3, H^4, $\sin\frac{2\pi t}{365}$, $\cos\frac{2\pi t}{365}$, $\sin\frac{4\pi t}{365}$, $\cos\frac{4\pi t}{365}$, θ, $\ln(\theta)$ and the deformation fitted value y', namely: the number of input layer nodes of the neural network in this instance is (n+1) = 11.

②The number of hidden layer nodes is P, which is always determined by the results of the tests.

③The number of output layer nodes is 1: The difference Δy between the measured displacement value y0 and the fitted value of the statistical model y', Δy = y0 — y'.

④The fitted result of the merging model is: $y = y' + \Delta y$, where y' = the fitted value of the statistical model, Δy = the simulated value of neural network.

⑤For the project instance in this paper, after many experiments by the author, the parameters selected for BP neural network are: the learning rate η =1.2, the smoothing factor α =1.5, the number of hidden layer nodes P=15, the learning error ε =0.01.

4. A CASE STUDY

4.1 Project Overview

The CC dam is a comprehensive medium-sized water conservancy and hydropower hub project in China. It is built mainly for power generation, and for flood control, irrigation, farming, shipping and other benefits simultaneously.

4.2 Explanation for Deformation Observation Data

The in-situ observation data is used for deformation analysis. At present, there are two ways for collection of CC dam prototype observation data, manual collection and automatic collection. Large amount of statistical data shows that there are many problems in the reliability of manual observation data, and compared with the manual monitoring data, the automatic monitoring data has largely improved in precision and efficiency. Therefore, before analysis and processing of the data, the reliability of the monitoring data must be tested and the effect of gross error must be eliminated so as to ensure that the monitoring data is accurate and reliable.

After data preprocessing, the vertical displacement data of an observation point in CC dam between January 1999 and December 2006 is shown in Table 1. There are totally 107 samples in the observation point. In order to compare the effects between different deformation analysis models, the 107 samples are divided into three parts:"learning samples", "test samples" and "forecast samples". For the detail: 60 samples are randomly selected as "learning samples" from 90 samples between 1999 and 2005 (the 60 samples are used to establish deformation analysis models), and the other 30 samples as "test samples" (the 30 samples are used to test the effect of the established deformation analysis models), and the 17 samples in 2006 are selected as "forecast samples" (the 17 samples are used to test the prediction effect of the established deformation analysis models).

Date	H/m	y/mm
1999-1-11	14.12	0.62
1999-2-6	13.01	1.01
1999-3-17	13.73	1.78
1999-4-13	17.90	1.29
1999-5-17	17.92	0.11
1999-6-15	19.92	-0.35
1999-7-12	26.04	-0.30
1999-8-10	24.20	-1.11
1999-9-14	26.18	-1.78
1999-10-12	23.59	-1.39
1999-11-16	20.43	-0.94
1999-12-13	18.39	-0.36
2000-1-19	16.54	1.47
2000-2-16	16.23	1.75
2000-3-13	16.26	2.04
2000-4-18	12.92	1.03
2000-5-16	11.71	0.02
2000-6-20	16.48	-0.59
2000-7-11	17.45	-1.35
2000-8-15	15.73	-2.14
2000-9-19	17.29	-1.96
2000-10-16	17.20	-1.46
2000-11-14	15.54	-0.56
2000-12-11	15.85	0.04
2001-1-15	15.6	0.96
2001-2-20	17.09	1.58
2001-3-13	16.84	1.43
2001-4-17	13.68	0.95
2001-5-15	18.20	0.14
2001-6-12	19.01	-0.30
2001-7-16	20.59	-1.35
2001-8-14	20.95	-1.6
2001-9-18	19.26	-1.98
2001-10-16	17.31	-1.58
2001-11-19	13.35	-0.98
2001-12-24	14.18	0.56
2002-1-21	14.65	1.14
2002-2-18	15.26	1.19
2002-3-19	18.79	1.18
2002-4-17	20.45	0.61
2002-5-15	23.68	0.76
2002-6-18	19.51	-0.66
2002-7-16	24.01	-1.14
2002-8-20	25.10	-1.35
2002-9-24	22.78	-1.85
2002-10-22	20.95	-0.95
2002-11-19	19.98	-0.65
2002-12-24	21.29	0.44
2003-1-14	21.01	1.09
2003-2-18	20.85	1.81
2003-3-25	23.65	1.64
2003-4-22	22.81	1.27
2003-5-13	23.04	0.65
2003-6-24	17.37	-0.68
2003-7-15	20.60	-1.26

2003-8-12	18.62	-1.97
2003-9-19	16.89	-2.04
2003-10-14	16.31	-1.51
2003-11-11	14.71	-1.11
2003-12-15	14.60	0.28
2004-1-13	14.43	0.73
2004-2-25	14.53	1.09
2004-3-23	15.31	1.37
2004-4-14	15.23	0.83
2004-5-19	20.62	0.12
2004-6-21	20.04	-0.71
2004-7-14	24.03	-1.14
2004-8-18	21.89	-1.87
2004-9-15	21.39	-1.76
2004-10-13	18.65	-1.47
2004-11-16	15.81	-1.20
2004-12-21	15.81	-0.33
2005-1-17	15.06	1.03
2005-2-20	20.25	2.01
2005-3-1	20.2	1.81
2005-3-12	17.98	1.83
2005-4-8	16.14	1.01
2005-5-1	15.7	0.37
2005-5-18	17.48	-0.07
2005-6-10	16.98	-0.61
2005-6-27	15.89	-1.02
2005-7-5	15.84	-1.21
2005-7-31	17.29	-1.82
2005-8-23	16.9	-2.08
2005-8-31	17.06	-2.02
2005-10-3	17.62	-1.74
2005-10-22	17.17	-1.43
2005-11-19	15.5	-0.56
2005-12-4	13.97	-0.31
2005-12-18	13.22	-0.15
2006-1-6	13.27	0.36
2006-1-19	14.02	0.82
2006-2-4	16.04	1.04
2006-2-28	18.14	1.41
2006-3-10	18.54	1.45
2006-4-11	18.82	0.76
2006-4-18	19.59	0.91
2006-5-15	20.85	0.19
2006-6-6	20.12	-0.31
2006-6-21	19.34	-0.78
2006-8-11	18.37	-2.11
2006-8-30	17.34	-1.81
2006-9-13	16.98	-1.71
2006-11-6	16.53	-1.77
2006-11-24	16.38	-1.11
2006-12-9	16.61	-0.54
2006-12-29	16.42	-0.39

Table 2. Deformation observation data of CC dam（H = Reservoir water level； y = Deformation value of dam）

4.3 Comparative Analysis of Different Dam Deformation Analysis Model

In order to compare the effects of different models, four models are selected in this paper for dam deformation analysis: the single linear regression model, the statistical model, the conventional BP neural network model and the neural network merging model. The simulation results of four models are shown in Table 2.

Methods	Single Linear Regression Model	Statistical Model	Conventional BP Neural Network Model	Neural Network Merging Model
RMSE of Learning Samples（60 samples）	±1.20	±0.37	±0.23	±0.19
RMSE of Test Samples（30 samples）	±1.27	±0.38	±0.32	±0.26
RMSE of Forecast Samples（17 samples）	±1.19	±0.38	±0.34	±0.28

Table 3. Comparison of different models（Unit：mm）

From the "RMSE of Forecast Samples" in Table 2, we can see that the effect of the single linear regression model is poor, and the effect of the statistical model is very good and its RMSE of forecast samples is ±0.38mm. Compared with the statistical model, the prediction effect of the conventional BP neural network model is improved, while the effect of the neural network merging model is the best. The RMSE of the forecast samples is ±0.28mm, and the prediction accuracy is improved by approximately 25% compared to the statistical model.

The prediction results of the statistical model and the neural network merging model on the 17 samples in 2006 are listed in Table 3, from which we can see that the prediction effect of the neural network merging model is improved obviously compared to the statistical model.

Observation Date	Measured Value /mm	Statistical Model		Neural Network Merging Model	
		Forecast Value /mm	Residual Error /mm	Forecast Value /mm	Residual Error /mm
2006-1-6	0.36	0.62	-0.26	0.48	-0.12
2006-1-19	0.82	1.03	-0.21	0.70	0.12
2006-2-4	1.04	1.23	-0.19	0.97	0.07
2006-2-28	1.41	1.72	-0.31	1.42	-0.01
2006-3-10	1.45	1.61	-0.16	1.50	-0.05
2006-4-11	0.76	1.49	-0.73	1.31	-0.55
2006-4-18	0.91	1.21	-0.30	1.17	-0.26
2006-5-15	0.19	0.83	-0.64	0.61	-0.42
2006-6-6	-0.31	0.21	-0.52	0.10	-0.41
2006-6-21	-0.78	-0.34	-0.44	-0.34	-0.44
2006-8-11	-2.11	-1.52	-0.59	-1.71	-0.40
2006-8-30	-1.81	-1.76	-0.05	-1.81	0.00
2006-9-13	-1.71	-1.98	0.27	-1.92	0.21
2006-11-6	-1.77	-1.44	-0.33	-1.57	-0.20
2006-11-24	-1.11	-1.26	0.15	-1.17	0.06
2006-12-9	-0.54	-0.86	0.32	-0.75	0.21
2006-12-29	-0.39	-0.09	-0.30	-0.15	-0.24

Table 4. Comparison of forecasting results

5. CONCLUSION

①The selection of dam deformation analysis models will affect the precision of deformation prediction, and the deformation prediction can affect safety judgment of the dam. Therefore, the dam deformation analysis model is very important and need to be further studied.

②As we can see from the instance, the effect of the single linear regression analysis model is general. Compared with the single linear regression analysis model, the effect of the statistical model is improved obviously. Therefore, the statistical model has been widely adopted in dam deformation analysis at present.

③Compared with the statistical model, the effect of the conventional BP neural network model has improved, but the stability of the results is poor. The effect of the neural network merging model proposed by the author is best, and the stability of the results is also very good, so the method is worthy popularizing.

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