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Adaptive and intelligent prediction of deformation time series of high rock excavation slope①

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Abstract: Deformation of high rock excavation slope has nonlinear evolution characters. It is very difficult to build mechanical model to describe this nonlinear evolution. A genetic-neural network model has been initially proposed for adaptive and intelligent prediction of deformation of slopes, which used artificial neural network to represent nonlinear evolution of slope deformation. Number of history points of displacement inputted to the model, topologies of neural network, and learning process of model were adaptive and automatically determined using genetic algorithm. The obtained model was thus optimal at global range, and gave predictions of horizontal displacement at succedent three months for the three measurement points with average relative error of 1.4% compared with the measured values. Results from one step prediction and multi-step prediction were combined with the measurements.

Key words: slope; displacement; adaptive; genetic algorithm; neural network **Document code:** A

1 INTRODUCTION

For high rock excavation slope, the deformation is generally intrinsic nonlinear evolution of time dependence. If we know well about this, we can make reasonable and timing decisions on whether adjustment or reinforcement measures should be performed or not according to dynamic evolution law. Therefore, it is necessary to establish dynamic evolution model on the deformation. The traditional methods are all based on mathematical time series analysis such as auto-regression, GMDH, etc. However, in most cases, it is very difficult to find a reasonable mathematical model in global space. Alternatively, neural network provides a strong tool for it[1~5]. In order to obtain optimal solution in global range, this paper use genetic algorithm[6], and extrapolating algorithm[7~10] to combine neural network to make adaptive prediction of displacement of high rock excavation slope.

2 GENETIC-NEURAL NETWORK MODELING OF DISPLACEMENT OF HIGH ROCK SLOPE

2.1 Methodology

Modeling on displacement time series is to find the following description:

$$x_{i+p} = f(x_i + x_{i+1} + \cdots + x_{i+(p-1)}) \qquad i = 1,2,\cdots \quad (1)$$

where p is number of displacement history points, representing the history of displacement evolution of the slope; x_{i+p} is displacement value at current time $i+p$; x_i, x_{i+1}, $\cdots$, $x_{i+(p-1)}$ are previous displacement values at times i, $i+1$, $\cdots i+(p-1)$; f is a nonlinear relationship between them.

It is often difficult to represent f using certain mathematical equations. Considering neural

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networks have strong capability to learning and nonlinear dynamic processing, a multi-layer feed-forward neural network is thus used to represent the function f. The neural network can be learned by training with historical displacement values of the slope. There exist two most important problems to be solved for this representation, one is how to get a reasonable value of p, the other is how to get the best network topology to describe the relationship f. For the former, it is often determined artificially in all existing time series analysis, in this paper, genetic algorithm is used to search it in global space, thus the obtained solution is optimal globally. For the latter, genetic algorithm is used again to search the best topology in global opinion. An extrapolating algorithm is also used to train the selected network to overcome the "over-train" problem. The neural network model thus obtained can give the best predictions for future. The proposed genetic-neural network algorithm can be described as follows.

Step 1 Initialize genetic space, number of parameters to be determined (e.g. p and number of nodes in each hidden layer), and evolution generations of network topologies, population size (number of network topologies at each evolution generation), length of binary string for representing a chromosome, probability of crossover, probability of jump mutation per chromosomes (bits), probability of creep mutation per parameter, number of random seeds and value range of per parameter to be determined.

Step 2 Produce a set of initial network structures and regard them as parent generation. Per set of network topology is represented as a chromosome with a binary string.

Step 3 Historical values of displacement are used to train the neural network with the reselected topology. The connection weights of the network are modified by using delta rules. Calculate fitness of per chromosome (network topology) which represents applicability of the selected topology for the network to the given displacement prediction problem. The fitness F can be calculated as

$$F = \frac{1}{n}\sum_{i=1}^{n}(x_i - x'_i)^2 \tag{2}$$

where n is number of multi step prediction, x_i is predicted value of displacement at ith time step, x'_i is measurement of displacement at ith time step.

The fitness F indicates that applicability of the network topology. Considering the prediction performance of the network is up to the training process, the minimum fitness shall be found for per network topology.

Step 4 The process is halted if a suitable solution has been found, or if the available computing time has expired; otherwise, the process proceeds to Step 5 where the new chromosomes are scored and cycle is repeated.

Step 5 Select randomly two parent's individuals i_1 and i_2 whose fitnesses are smaller than average value.

Step 6 Carry out a crossover operation on the individuals i_1 and i_2 to produce a new chromosome. Per bit of the chromosome binary string is mutated at probability to produce a new chromosome.

Step 7 Repeat Step 5 and Step 6 until finishing production of N new individuals that is considered as offspring.

Step 8 An individual of offspring is replaced randomly by the best individual of parent.

Step 9 The parent individuals are replaced by the offspring individuals. Go to Step 3.

2.2 Acquisition of neural network model

For a time series of slope displacement $\{x\} = (x_1, x_2, \cdots, x_n)$, the training samples can be constructed as follows: for the first training sample, $x_1, x_2, \cdots, x_p$ are used as input of the network and the network gives its output for x_{p+1}; for the second training sample, $(x_2, x_3, \cdots, x_p, x_{p+1})$ are used as input of the network and the network gives its output for x_{p+2}; and so on.

When the extrapolating prediction algorithm[7] is adopted, it needs some testing samples to test applicability of the networks. As the same way of training sample construction, the testing samples can be built as: for the first testing sample, $x_{1+N}, x_{2+N}, \cdots, x_{p+N}$ are used as input of the network and the network gives its output for x_{p+1+N}, in which N is number of training samples; for the second testing sample, x_{2+N}, x_{3+N}, $\cdots$, x_{p+N}, x_{p+1+N} are used as input of the network and the network gives its output for x_{p+2+N}; and so on.

The network models obtained using genetic-neural network algorithm mentioned above are tested by testing samples. The model with the minimum fitness is the best one.

2.3 Extrapolating prediction

The prediction of displacement in future was carried out in two ways. One is called to be prediction for only one time step (for example, one month or day), i.e., the foregone p points of measured value was input to the model for predicting displacement of approaching month. The other is the extrapolating prediction for multiple time steps, called multi-step-extrapolating prediction. It is that displacements at the succeeding times were predicted by using feedback of the foregone predictions (not measurements) as inputs.

3 ADAPTIVE AND INTELLIGENT PREDICTION OF DISPLACEMENT

The deformation evolution characters of three measurement points at an important high rock excavation slope were respectively modeled. For the point No. 1, the measured data of displacement of the foregone 26 months were used to build model. The best neural network model, with input nodes of 10 and hidden nodes of 5, were automatically recognized by using genetic algorithm. The model is called NN(10, 5, 1) in briefly (Table 1). The most reasonable history point number is recognized to be 10. The network gave the best-extrapolated prediction for displacement of coming three months (Fig. 1) when learning process was finished at system error of 0.004 578. The average relative error in three months is 2%.

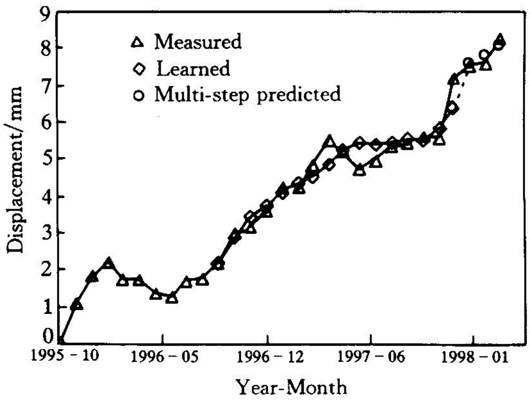

Fig. 1 Comparison between predictions and measurements of displacement at point No. 1

For the point No. 2, the measured data of displacement of the foregone 28 months were used to build model. The best neural network model was recognized by NN(7, 9, 1) (Table 2). The model gave its extrapolated predictions for succedent three months with an average relative error of 1.6% (Fig. 2). In this case, the learning process was finished when system error

Table 1 Network connection weights for point No. 1 obtained at learning rate of 0.20, momentum rate of 0.20, learning iterations of 6 829, and system error of 0.004 578

	Input node										T
	1	2	3	4	5	6	7	8	9	10	
H_1	−2.571 056	−2.371 901	−2.287 198	2.879 383	2.524 701	1.556 788	−4.640 572	−4.459 610	−3.743 047	−1.311 150	−0.604 958
H_2	−0.892 310	−2.890 160	−4.563 337	−2.452 960	−6.164 756	−0.940 371	−3.759 381	−3.493 139	−3.310 608	−0.814 219	0.106 198
H_3	−0.930 877	−2.771 086	−3.354 400	−2.755 471	−5.385 030	−0.566 963	−4.523 244	−4.588 775	−4.199 772	−1.327 737	−0.978 387
H_4	−0.900 972	−3.326 949	−4.658 839	−3.516 110	−6.335 795	−0.909 315	0.436 920	0.972 134	0.375 406	−1.480 794	−0.628 515
H_5	0.119 360	0.223 910	1.342 886	0.412 653	2.185 788	2.585 075	0.399 393	0.525 898	0.690 266	−0.783 685	−0.880 810

Weight of hidden node i to output node				
1	2	3	4	5
−0.172 989	0.928 560	0.814 126	0.505 678	1.747 142
Threshold of output node: 2.547 504				

T: Threshold of hidden node, H_i node i at hidden layer ($i = 1, 2, \cdots, 5$)

Table 2 Network connection weights for point No.2 obtained at learning rate of 0.20, momentum rate of 0.20, learning iterations of 270 000, and system error of 0.001 818

Weights		Input node 1	2	3	4	5	6	7	Threshold of node
Hidden node	1	-1.326 441	-1.462 338	-1.018 822	5.908 441	-1.306 099	2.431 231	-1.433 767	-1.585 980
	2	6.374 451	1.116 657	-4.925 531	-2.394 282	-2.018 339	-2.633 850	-2.296 708	-3.314 130
	3	-5.846 640	-0.832 948	-4.275 996	-1.944 191	-2.394 292	-2.100 098	-3.031 571	-3.875 398
	4	-5.706 339	-1.151 190	-3.689 262	-2.041 232	-2.255 008	-2.554 525	-2.697729	-3.593 282
	5	-5.376 954	-0.457 580	2.875 009	-1.724 090	-1.423 209	-1.110 188	-0.326 029	0.471 047
	6	5.633 148	5.732 262	-4.512 120	-1.986 218	-1.513 087	-2.402 166	-2.383 893	-3.275 465
	7	-5.553 760	-0.756 462	0.528 134	0.291 847	-0.208 527	-0.777 912	0.191 229	1.050 950
	8	1.770 184	1.818 255	-4.451 853	-2.899 446	-2.135 082	-2.485 939	-3.043 012	-3.677 103
	9	-6.511 381	-1.272 552	-3.401 183	-1.471 546	-1.249 787	-1.977 117	-2.514 302	-2.678 843

Weight of hidden node i to output node

1	2	3	4	5	6	7	8	9
-5.269 279	-0.691 227	2.907 712	-1.631 822	-0.891 247	-1.130 763	-0.647 544	0.467 083	6.019 415

Threshold of output node: 6.411 163

of 0.001 818 arrived (see Table 4 below).

By the same way, for the point No.3, the measured data of displacement of the foregone 18 months were used to build model. The best neural network model was recognized by NN(6, 7, 1) (Table 3). The model gave its extrapolated predictions for succedent three months with an average relative error of 0.45% (Fig. 3) when the learning process was finished at system error of 0.002 793 (Table 4). The obtained models and their applicability are shown in Table 4.

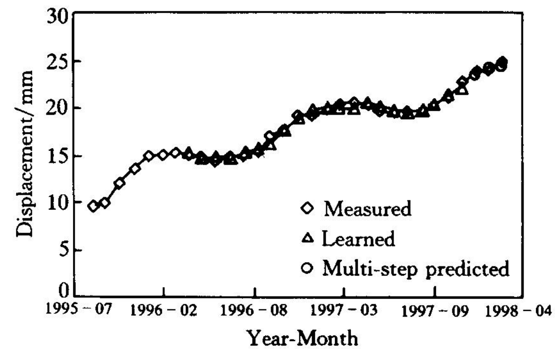

Fig.2 Comparison between predictions and measurements of displacement at point No.2

4 CONCLUSIONS

(1) Evolution characters of steep and high slopes are nonlinear. It is effective to use neural network to represent it. Genetic algorithm is adopted to learn and search the topologies of the network in global space, which provides a feasibility that the obtained network will have the best performance for extrapolating predictions for slope displacement.

(2) Failure of slopes is progressive. This indicates that its evolution history has influence on its further deformation. In this paper number of historical points, p, is adaptive determined by using genetic algorithm. This overcomes inaccuracy of man-made.

(3) The predicted values of displacement are fed back to be input of the model to obtain

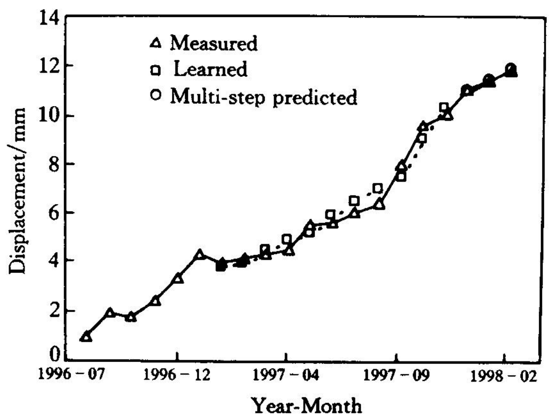

Fig.3 Comparison between predictions and measurements of displacement at point No.3

Table 3 Network connection weights for point No.3 obtained at learning rate of 0.20, momentum rate of 0.20, learning iterations of 11 670, and system error of 0.002 793

Weights		Input node 1	2	3	4	5	6	Threshold of node
Hidden node	1	-1.795 402	-1.354 019	-2.241 843	3.311 488	-1.726 332	-1.041 248	-1.69 1313
	2	0.697 101	-0.777 616	-4.774 743	-3.688 976	-3.288 467	-5.036 647	-10.131 194
	3	-0.095 657	0.966 802	-2.270 329	-1.437 545	-1.281 913	-2.774 647	-6.518 713
	4	-0.567 926	-1.718 766	-5.386 236	-3.780 338	-4.317 080	-6.083 877	-11.593 781
	5	-0.574 924	-2.661 492	0.759 703	-0.193 892	-0.585 093	1.068 807	3.365 463
	6	2.183 428	0.655 316	-1.897 594	-1.011 000	-1.420 524	-2.291 870	-6.103 319
	7	-1.666 079	-0.034 704	-2.148 395	-2.211 417	-1.879 339	-3.498 095	-7.248 581

Weight of hidden node i to output node

1	2	3	4	5	6	7
-0.586 132	0.748 127	-1.111 925	-0.222 245	-0.246 251	-1.446 142	-2.890 550

Threshold of output node: 0.389 203

Table 4 Obtained models and their predictions for horizontal displacement of three measurement points for succedent three months

Measurement point	Data length used for building model/months	The most reasonable learning error	The obtained neural network model	Average related error of predictions
No.1	26	0.004 578	NN(10,5,1)	2%
No.2	28	0.001 818	NN(7,9,1)	1.6%
No.3	18	0.002 793	NN(6,7,1)	0.45%

future of prediction. Use of extrapolating prediction algorithm can result in obtaining more reasonable predictions for future.

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