Environmental Informatics Archives, Volume 1 (2003), 394-399
EIA03-040
ISEIS Publication #002
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Study on the Optimum Design of Landslide Stabilization by Parallel Evolutionary Neural Network Method

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Abstract A new method for the optimum design of slope stabilization was presented in this paper. Firstly, the particular treatment method was determined in term of the detailed condition of the slope. Using finite element method, combined with limit equilibrium method, the slope stability was analysed and the stresses of treatment structures were calculated; upon this basis, a group of design parameters were given, and correspondingly the safety factor of the slope after stabilized and the cost of the treatment engineering was estimated. Secondly, dozens of design parameters, safety factors and costs were given, which can act as learning samples for neural networks. Then an evolutionary neural network model whose network structure was optimized by genetic algorithm was made to map the complex nonlinear relationship between the design parameters and safety factors and engineering costs. Thirdly, embedding the above evolutionary neural networks model into the genetic algorithm, take the cost as the fitness function, the safety factor as restriction, an optimum model was made. Thus, the design parameters can be optimized in the whole spectrums, and the most economic result is obtained. Lastly, the above process was programmed in parallel environment, and the searching efficiency and accuracy were both improved. This thought was practiced in Muzishuping landslide treatment engineering of Three Gorges Projects, and the excellent economic result was made.

Keywords: landslide stabilization, optimum design, finite element method, evolutionary neural network, genetic algorithm, parallel computation

1. Introduction

By the increasing extension of the human activities, landslides are more harmful to mankind as a major kind of geology catastrophe, and still are threatening the life and property safety of people. In recent 20 years, the total damage due to the landslides in the main countries where disasters occur is up to 12 billion dollars a year. In China, the damage caused by geology disasters reach 20 billion RMB a year, and from 1996 to 2000, 1156 people died in landslides, so the landslides reinforcement is an important project among the disaster prevention all along in china. With the development of the West and the reservoir sluice of the Three Gorges Project, the research on landslides is more urgent. How to search the most economic scheme for landslides reinforcement precisely and efficiently is important problem to solve, that is, making the cost of the reinforcement project the lowest while ensuring the safety of the project.

However, traditional method for landslides reinforcement always can not make the optimum design and waste investment to some extent. In fact, landslides reinforcement is a complex geotechnical problem and the design for landslides reinforcement is a complicated system. Economically, the cost of the projects varies with the parameters of certain design scheme; For safety, it is controlled by the technological index of certain scheme. Many reinforced landslides depend on conservative design, sacrificing the economy. Since the landslides reinforcement is a large complex system in which many factors are restricted each other and change, and traditional methods can not efficiently solve it, we can think about using the hybrid intelligent method。

Some researchers have done some work in this area. Xia Yuanyou uses Analytic Hyerarch process and comprehensive evaluation methods to select the best design scheme for unstable slope reinforcement; Zhang Shaobo uses grey theory to optimize the reinforcement scheme; Although these approaches made some satisfactory results, essentially these methods can not ensure the scheme selected is the best globally, for the selection is made from

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limited schemes in these studies. This paper present a new method similar to back analysis to solve this problem in global spectrum. This method has been applied successfully in optimization of reinforcement schemes for landslides at Three Gorges reservoir zone.

2. the model for schemes optimization

2.1 evolutionary neural network

Artificial Neural Network（ANN）is a kind of dynamic info-processing system simulating the structure and basic function of human brain. It has the strong ability to map the non-linear function, and has been extensively used to solve many geotechnical problems. Among all types of neural networks, the back propagation neural network is most popular and has been proved a very efficient neural network, however, it two main faults that influence the prediction ability of the network, one of which is the structure of the network, the other is "overtraining" problem.

Genetic algorithm is able to overcome the above difficulty nicely. Genetic algorithm operates on the Darwinian principle of "survival of the fittest". An initial population of size *m* is created from a random selection of the parameters in the parameter space. Each parameter set represents the individual's chromosomes. Each individual is assigned a fitness based on how well each individual's chromosomes allow it to perform in its environment. Through selection, crossover, and mutation operations, with the probabilities P_s, P_c, P_m respectively, the next generation is created. Fit individuals are selected for mating, whereas weak individuals die off. Mated parents create a child with a chromosome set that is some fix of the parent's chromosomes. The process of mating and child creation is continued until an entire population of size *m* is generated, with the hope that strong parents will create a fitter generation of children. Successive generations are created until very fit individuals are obtained. Using genetic algorithm to optimize the structure of neural networks not only can decrease the blindness of selection by experience, but also can avoid the "overtraining" in the process of network learning, so the learning effect and the prediction ability are enhanced.

2.2 model for mapping the nonlinear relationship of the design parameters *vs* stability and cost

Firstly, the particular reinforcement method was determined in term of the specific circumstance of the slope.

Secondly, Using finite element method, combined with limit equilibrium method, the slope stability was analysed and the stresses of treatment structures were calculated; upon this basis, a group of design parameters were given, and correspondingly the safety factor of the slope after reinforced and the cost of the treatment engineering was estimated.

Thirdly, dozens of design parameters, safety factors and costs were given, which can act as learning samples for neural networks. Then an evolutionary neural network model whose network structure was optimized by genetic algorithm was made to map the complex nonlinear relationship between the design parameters and safety factors and engineering costs.

Based on the above evolutionary neural network model, for each group of given design parameters, the safety factor and cost of the reinforcement project can be obtained through the prediction of the network correspondingly.

2.3 Parallel genetic algorithm model

Since recognition of parameters is carried out from evolutionary of *m* individuals at *M* generations, *m* individuals at each evolutionary generation can be created through genetic operation and appraised on several personal computers at the same time. A computing task distributed to each computer can be finished at the almost the same. If the load is discovered imbalanceable during the process, the system can adjust automatically distribution of computing task among the connected computers. The strategy provides a grantee of enough high efficiency.

To deal with the parallel computing in geotechnical problems, Feng Xiating developed a parallel computing environment, RsmVPC. It is based on personal computer under Windows platform, such as Windows 98/2000, Windows NT, etc. With the environment, a group of personnel computers are connected through LAN to form a virtual parallel machine. Every personnel computer has a substantive environment in the parallel virtual machine; the RsmVPC daemon runs in each PC and is responsible for communication and process management. The information between processes depends on WinSocket of Windows to transfer. The protocol is similar to BSD standard; the TCP service and UDP service are provided on the top of IP layer.

With this parallel environment, a complex geotechnical engineering task can be solved by many CPUs at the same time, not only single CPU. Therefore, the high performance computing (large scale, high velocity, and high accuracy) can be realized to satisfy needs of a true problem.

2.4 search the best scheme using parallel genetic algorithm model

Based on the above evolutionary neural network, GA-NN, take the safety factor in output parameters as $\boldsymbol{F}$（*GA-NN*）, and take the cost of reinforcement as $\boldsymbol{M}$（*GA-NN*）,thus, the optimization of landslides reinforcement schemes can be reduced to such a mathematical model as following:

$\min f = \boldsymbol{M}$（$GA\text{-}NN$）

$s.t.\ \boldsymbol{F}$（$GA\text{-}NN$）$\geq Fs$

Where f is the cost of the reinforcement project, and Fs is the safety factor that satisfies the demand of the practical project.

The specific steps for optimizing the reinforcement schemes can be summarized as follows:

Step1: Initialize space of genetic parameters such as generation number N_{gen}, population size P_{size}, crossover probability , mutation probability.

Step2: Create P_{size} group of initial values of design parameters at interval. Each individual is represented by a chromosome.

Step3: Compute the fitness of each individual.

Step4:If the best parameter values are found for the given parameters,then the search processs ends. Otherwise, go to step 5.

Step 5:Select randomly two individuals to create a new individual through a crossover operation at certain probability and a mutation operation at certain probability.

Step 6:Perform Step5 repeatedly until all new individuals are created.

Step 7:Go to step 3 to appraise these new individuals as before.

In this paper, RsmVPC is used to realize parallel computation, in which Master-Slave model of visual parallel program is adopted.

3. Case Studies

Muzishuping Landslide is in the west of Guojiaba at Three Gorges reservoir zone and is supposed to fail after the sluice of Three Gorges reservoir. Once it fails, it will destroy the building of a company and residence of local people .So it is urgent to reinforce the landslide.

As the designer of this reinforcement project, we were determined to set 2 rows of anti-slide piles to reinforce the landslide, and designed 60 schemes based on the different groups of parameters of anti-slide piles. These parameter include the length of pile, the width and length of the section of certain pile, the distance between piles, the number of reinforcing steel bar. We also calculated the safety factor after reinforced and the cost of project according to different parameters. These data is summarized as follows:

Table 1 the safety and economic index of each sample scheme

No.	Pile Length (m)	Pile Section		Distance (m)	Steel	Pile	Section		Distance	Steel	Safty	Cost of Project (10^4yuan)
		Width (m)	Length (m)		Bar	Length (m)	Width (m)	Length (m)	(m)	Bar	Factor	
1	35	2.1	2.6	4.8	103	36	2.4	2.9	6.3	119	1.1345	825.44273
2	35	2.3	2.7	5.2	98	36	2.4	2.8	5.2	119	1.14	878.11607
3	33	2.2	2.6	5.3	96	34	2.2	2.6	5.1	100	1.1271	742.54839
4	34	2.3	2.7	5	109	37	2.4	2.8	5.2	128	1.1456	945.83601
5	37	2.1	2.5	5	127	37	2.1	2.4	5.3	130	1.1328	954.96561
6	38	2.4	2.8	5.7	138	38	2.5	2.8	5.5	140	1.1504	1043.1566
7	36	2.8	3.1	6	127	37	2.2	2.6	4.6	128	1.1502	1027.4436
8	37	2.5	3.1	5.6	126	35	2.2	2.5	4.2	106	1.1508	995.94479
9	39	2.5	2.8	5.2	148	35	2.5	2.9	5.7	113	1.151	1027.7722
10	37	2.5	2.9	4.6	127	37	2.2	2.6	5.5	125	1.1513	1048.147
11	38	2.2	2.5	5.5	139	38	2.6	3.2	5.7	136	1.1515	1036.9867
12	39	2.3	2.5	5.5	154	39	2.4	2.7	5.1	149	1.1498	1156.9676
13	34	2	2.4	4.2	94	39	2.5	3	5.5	147	1.1496	1008.3887
14	37	2.1	2.6	6.2	123	40	2.7	3.1	5.7	156	1.1494	1014.8472
15	37	2.6	2.9	5.5	114	39	2.5	3.1	6.1	138	1.1492	984.25588
16	34	2.4	2.9	5.3	103	36	2.4	2.9	5.6	120	1.1437	863.65457
17	36	2.5	2.9	5.6	121	37	2.5	2.8	5.4	131	1.1493	971.7926
18	37	2.4	2.8	5.4	130	37	2.6	3.2	5.7	115	1.1511	979.06299

19	35	2.2	2.7	6.3	109	36	2.3	2.8	6.2	117	1.1263	737.05332
20	35	2.2	2.5	5.2	101	37	2.5	2.9	4.6	127	1.1496	984.11942
21	38	2.2	2.5	5.5	139	36	2.1	2.9	6	110	1.1326	874.63227
22	34	2.1	2.4	4.5	101	37	2.6	2.9	5.5	114	1.1378	896.85263
23	38	2.4	2.8	6.3	137	40	2.5	3	5.6	146	1.1504	1040.2346
24	36	2.8	3.1	6	127	37	1.9	2.5	5.2	121	1.1408	919.26867
25	37	2.4	2.7	4.9	125	38	1.9	2.4	4.5	134	1.1452	1089.2952
26	34	2.4	2.8	4.9	105	39	2.2	2.6	5	146	1.1482	1028.5469
27	35	2.2	2.5	5.2	101	35	2.2	2.5	5	112	1.1295	821.65564
28	33	2	2.6	5.3	88	40	2.3	2.6	5	151	1.1317	945.65151
29	36	1.8	2.4	5.3	108	40	2.3	2.5	4.9	159	1.1361	1030.3962
30	36	1.8	2.4	5.5	110	41	2.7	3.4	5.8	152	1.1506	1009.5434
31	36	2.3	2.9	6.2	117	35	2.2	2.5	4.2	106	1.1395	892.34953
32	37	2.6	3.1	5.6	124	37	1.9	2.5	5.2	121	1.1417	944.55703
33	37	1.9	2.5	5.2	121	39	2.5	3.1	6.1	138	1.1447	953.12149
34	40	2.5	3.1	5.3	147	37	2.1	2.6	6.2	123	1.1465	1019.2257
35	40	2.6	3.1	5.4	151	35	2.3	2.8	6.1	109	1.1502	1004.6485
36	40	2.6	3.1	5.4	153	38	2.3	2.6	5.4	141	1.1585	1162.7582
37	41	2.5	2.8	5.4	159	40	2.6	3.3	6.2	150	1.1641	1206.5575
38	38	2.3	2.6	5.4	140	40	2.7	3.2	5	149	1.1678	1217.762
39	39	2.5	3.1	6.1	138	35	2.3	2.8	5	109	1.1491	961.08942
40	41	2.5	2.8	5.4	159	42	3	3.5	6.2	166	1.1752	1324.1776
41	42	3	3.4	6.3	164	42	3	3.4	6	162	1.1825	1344.6118
42	38	2.2	2.9	5.4	130	41	1.9	2.7	4.8	140	1.1496	1106.9846
43	41	2.8	3.4	6.5	155	36	2.3	2.8	6	117	1.15	989.20479
44	36	2.5	2.9	5	116	39	2.4	2.9	6.3	147	1.15	999.83438
45	35	2.4	2.8	5.8	112	40	2.5	3.2	5.9	144	1.1502	964.18417
46	38	2.2	2.6	5.3	136	41	2.4	2.8	5.3	151	1.1503	1135.286
47	35	2.3	2.8	6.1	109	41	2.8	3.4	6.5	155	1.15	954.93165
48	37	2.4	2.8	5.6	130	39	2.6	2.9	6	154	1.1513	1034.194
49	35	2.4	2.7	6.4	113	40	2.8	3.4	6.3	152	1.1504	943.35325
50	36	2.7	3.3	5.6	117	36	2.3	2.7	5.4	118	1.1511	938.09472
51	36	2.3	2.6	6.1	121	41	2.6	3.1	5.6	155	1.1503	1033.643
52	37	2.3	2.6	6.7	129	41	2.7	3.2	5.7	154	1.1503	1026.5466
53	38	2.2	2.5	5.8	139	37	2.7	3.1	5.5	136	1.1504	1017.6329
54	38	2.2	2.4	5.7	146	39	2.6	3.1	5.7	149	1.1502	1070.5587
55	39	2.2	2.4	5.7	159	40	2.5	3	5.5	151	1.1501	1141.8677
56	39	2.2	2.4	5.6	160	39	2.5	3	5.5	146	1.1504	1125.8611
57	37	2.1	2.7	5.5	121	39	2.7	3.1	6	152	1.1505	1009.8758
58	37	2.2	2.7	5.6	125	39	2.6	3.2	6.2	146	1.1502	985.22715
59	36	2.3	2.7	5.4	120	37	2.7	3.2	6	133	1.1506	952.1764
60	36	2.3	2.7	6.5	119	42	2.8	3.5	6.5	156	1.1504	980.88472

Take the above data as the learning sample for neural network, where *the length of pile, the width and length of the section of certain pile, the distance between piles, the number of reinforcing steel bar* are taken as input data, and

the safety factor after reinforced and the cost of project according to different parameters are taken as output data. We used these groups of parameters to train the neural network.

Firstly, we need to use genetic algorithm to search the best structure for the network. Set population size N_p=30, and generation number N_{gen}=100. Use the former 58 samples for training to set up the neural network model, and use the last 2 for checking. The search space is hidden layer *p*: 0~3, nodes of hidden layer *h*:1~30.

After the evolutionary calculation, the best structure is obtained as: *p*=2, the nodes of the first layer h_1=24, the nodes of the second layer h_2=12. So we select the evolutionary neural network as *GA-NN*(10,24,12,2).

(Y)= GA-NN（10，24，12，2）(X)

(Y)=(M，F)

(X)=(L_1，a_1，b_1，d_1，n_1，L_2，a_2，b_2，d_2，n_2)

Using the obtained neural network replacing the real calculation of the stability and the cost of the project, we can search the best design parameters in the following given space based on the practical circumstance of landslide:

The upper row of anti-slide pile: the length of pile L_1: 32~42m, the width of the section of certain pile a_1 : 1.8~3m, the length of the section of certain pile b_1: 2.2~3.5m, the distance between piles d_1 : 4~7m, the number of reinforcing steel bar n_1 : 80~150.

The lower row of anti-slide pile: the length of pile L_2: 32~42m, the width of the section of certain pile a_2 : 1.8~3m, the length of the section of certain pile b_2: 2.2~3.5m, the distance between piles d_2 : 4~7m, the number of reinforcing steel bar n_2 : 80~150.

We selected genetic parameters as follows: N_p=5；N_{gen}=100；P_{size}=10；number of bit N_{bit}=10；jump mutation rate J_r=0.1；cumulation mutation rate C_r=0.2. Adaption value is calculated as the fomula below:

$$fitness=M[GA\text{-}NN(10,24,12,2)]$$

Considering the safety rank of Three Gorges Projects, the safety factor of a landslide after reinforced can not be less than 1.15. So the restriction qulification is:

$$F[GA\text{-}NN(10,24,12,2)]\geq 1.15$$

After genetic operation of 60 generations of evolution, the final scheme searched out is:

The upper row of anti-slide pile: L_1: 35m, a_1 :2.3m, b_1: 3.0m, d_1 : 5.5m, n_1 : 101.

The lower row of anti-slide pile: L_2: 35m, a_2 : 2.6m, b_2: 3.2m, d_2 : 5.5m, n_2 : 136.

Correspondingly, the output safety factor is 1.1507, and the cost is 905.26×10^4yuan.

The optimized design parameters satisfied the intension check of anti-slide pile design. The practical calculation result using these parameters is: Safety factor equals 1.1502, and Cost equals 913.94 ×10^4yuan. The comparision is as Table 2:

Table 2 Comparison of GA-NN results and practical solutions

Output Parameters	GA-NN Results	Practical Solutions	Relative Error
the Safty Factor ***F***	1.1507	1.1502	0.045%
Costs of the Project ***M***（×10^4yuan）	905.26	913.94	0.950%

This design schemes has passed the review and being adapted in the construction, and exellent economic and social effect is made.

4. Conclusions

Starting from bionics, genetic algorithm and neural network are two kinds of methods that are robust enough for highly non-linear and multi-modal search in large space for optimization of design parameters of landslides.Because of the non-mumerical parallel advantage themselves and their parallel realization on the independently developed RsmVPC environment, the global optimum solutions can thus be obtained using the proposed algorithm. The results are verified from optimization of design parameters of Muzishuping Landslide at Three Gorges reservoir zone.

Acknowledgement.

The financial support from China National Nature Science Foundation (No.10072073) and China National Key Fundamental Research “973 Programme”(No. 2002CB412708) are grately acknowledged.

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