Geotechnical Aspects of Underground Construction in Soft Ground, Kastner, Emeriault, Dias, Guilloux (eds)
© 2002 Spécifique, Lyon. ISBN 2-9510416-3-2

Study of optimal soft rock replacement scheme for excavation of large-scale cavern group using parallel evolutionary neural network FEM method

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ABSTRACT: For ensuring the stability of a large-scale cavern group constructed in soft rock masses, in some cases, partial replacement of soft rocks is necessary during excavating the cavern group. In order to minimize the damage zone and economic costs caused by excavation and replacement, it is important to find out an optimal soft rock replacement scheme. In this paper, a new parallel evolutionary method is provided to solve this problem. The neural network with optimal structure for prediction is trained to replace the time-consuming finite element method (FEM). Moreover, under the consideration of the nonlinear characteristics and multi-extremum of relevant parameter and scheme optimization, a method of global optimization and parallel computing is adopted. As an example, the method is applied and the optimal scope and sequence of soft rock replacement are derived for Shuibuya engineering. It indicates that the new method is rational and has a great advantage of global searching and quick convergence.

1 INTRODUCTION

There usually exist a large number of sequences of the excavation in the construction of underground cavern group. In addition, for ensuring the stability of large-scale cavern group constructed in soft rock masses, in some cases, partial replacement of soft rocks is necessary during excavating the cavern group. In order to minimize the damage zone and economic costs caused by excavation and replacement, it is important to find out an optimal soft rock replacement scheme and sequence of excavation.

The methods used in optimization and stability analysis of large cavern groups can be broadly divided into two types, namely, traditional method and intelligent method(Zhu, 1997). By numerical analysis, the traditional method is to establish a series of schemes of excavation sequence and structure assignment, and an optimal solution is selected by comparison. The intelligent method, such as that pointed out by Zhu(1997),has ability of solving the problems smoothly. Zhu proposed a method to search the optimal result using dynamic programming. For the principle of dynamic programming turns the n-dimension optimizing problem into n optimizing problems of one dimension which are in turn solved one by on, it's difficult to find the global optimum resolution. An & Feng (2001) proposed a method using genetic algorithm(GA) combined with FEM to solve the problem. The method can get a global solution. But, resulting from the consuming calculation by FEM, especially for large models, the efficiency and reliability are low.

Recent combination researches of GA and neural networks(NN) show the potential of combination of genetic algorithms and neural networks for quick global optimization in geotechnical engineering(Feng, 2000). A back-propagation neural network was used to replace the time-consuming finite element method and was embodied in GA program to evaluate the fitness of each individual. Due to global optimum advantage the genetic algorithms is used to determine connection weights of the neural networks and its topology(Feng, 1999), thus makes the neural networks more accurate to recognize the parameters and constitutive models of rock mechanics and engineering. Even if GA is a kind of non-numerical parallel computing methods, parallel realization of the algorithms is also necessary to obtain higher efficiency.

Therefore, a new scheme optimization method is proposed in this paper. The method combines genetic algorithms, neural networks and parallel computing method. The stability and optimization of replacement schemes of soft rock mass at a large cavern group is illustrated.

2 PARALLEL EVOLUTIONARY NEURAL NETWORK FEM METHOD

The parallel evolutionary neural network FEM method combines intelligent method (e.g. GA and NN), parallel computing and FEM. The new method is designed and performed according to the following procedure. In the first step, samples are constructed by finite element method. In the second step, the mapping relationships between the maximal displacement and the volume of damage zones, as well as the calculated schemes are established using parallel evolutionary neural network. In the third step, a group of initial feasible schemes is randomly generated by Genetic Algorithms and evaluated by the fitness index which equals to weighted summation of the increment ratios between the maximal displacement of key points and volume of the damage zones, and reference values. In the final step, GA is applied to this group of schemes and the next generation of feasible schemes is created. The above procedures are circularly operated until the minimum fitness value is found out. The scheme corresponding to the minimum fitness value will be the optimal scheme to be chosen.

The methodology can be described as follows:

2.1 *Parallel evolution of neural networks*

The prediction ability of the neural networks is very important for recognizing unknown coefficients. The Genetic algorithm can be used to obtain the global optimal structure, including topology and connection weights. The evolution operations are done in parallel. Currently the GA is paralleled mainly in three ways: master-slave model, coarse-grained (or distributed) island model and fine-grained parallel model (Chen,1999). The master-slave has been universal and easily carried out, and it has high efficiency and good load balance when each individual has the same evaluation volume. Therefore we take master-slave for consideration of parallel computing (Figure.1).

In this paper a two-hidden-layer neural network is adopted. The GA is applied to search the numbers of hidden layers of the neural networks. Considering that the computation of the individuals' fitness was the most time-consuming, the paper takes this part into parallelism. The algorithms can be described as follows:

Step 1: Generate randomly an initial tentative group of schemes, in which each scheme has a corresponding hidden topology of neural network;

Step 2: Initialize the network with the topology of the above group, and divide them into N fractions. Each fraction has m_1,m_2,...,m_N topology structures separately and is sent to one of the N slave processors. The individuals in each fraction can be expressed as $p_1,p_2, \ldots p_{m\_N1}$(m_N1 is selected from m_1 to m_N). The neural networks was trained in each slave processor and used to predict the given samples. Then the slaves start to evaluate their individuals in each fraction and return the evaluations to the master as soon as they finish, where the evaluation is the minimal prediction error of each neural network with different topology.

Step 3: The master processor executes the GA operations (selection, recombination and mutation) after receiving the evaluations, and generates a next generation. Replace randomly an individual in the

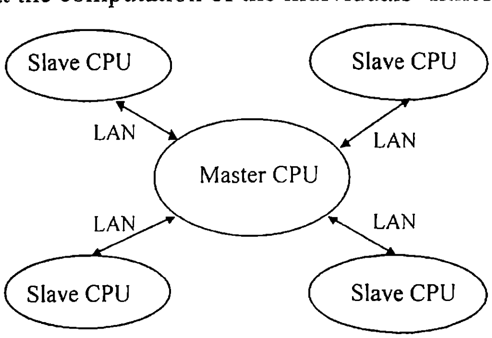

Figure.1 Master-slave parallel model

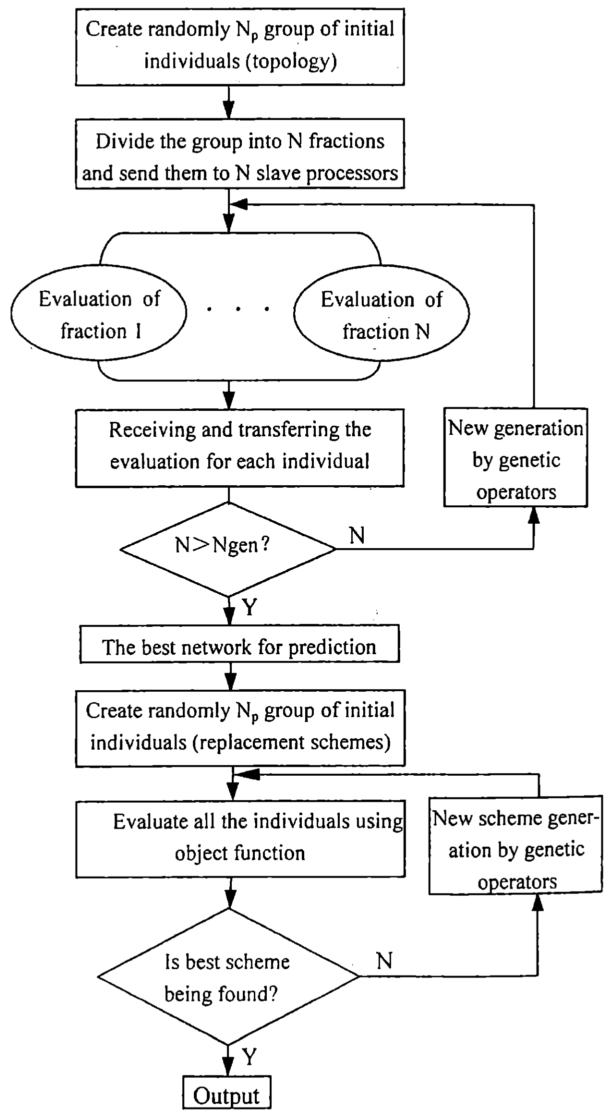

Figure.2 The evolutionary Neural Network FEM method

offspring generation using the best parent's individual. Take the offspring as parent and go to Step2. The process continues until the optimal topology was found.

The neural network with the topology found above has the minimal prediction error, and can make the predicted maximal displacement magnitude of key points and the volume of damage zone approach the computational results of FEM. The Figure.2 shows the flow of the method.

The paper adopts a new parallel computing environment, called RsmVPC, which is developed on personal computer under Windows platform (such as Windows 95/98/2000, etc). The information between processes depends on Winsocket of Windows to transfer. With the environment, a group of personal computers are connected through LAN to form a virtual parallel machine.

2.2 *The optimal scheme searching with genetic algorithms*

The evolutionary neural network obtained above has set up the correct mapping relationship between the schemes to be predicted and the output factor, i.e. the key points' maximal magnitude of displacement and the volume of damage zone. Combined with the evolutionary FEM method(An, et al., 2001), i.e., to replace the FEM by neural network, it is convenient to further proceed the schemes optimization for the practice problems (Figure.2). The optimization method can be described as follows:

Step 1: Initialize the parameters of GA and neural network, and determine the range of schemes to be optimized. The parameters of NN are set as above.

Step 2: Generate randomly *Np* group of feasible schemes. Each individual represents a scheme. Calculate the fitness of each individual. The fitness can be computed as follows:

$$fitness = \sum_{i=0}^{n-1} \left(y_{ip} - y_{ia}\right) / \, y_{ia} \qquad (1)$$

where y_{ip}, y_{ia} represents the prediction value and comparison aim value of *i*th evaluation index. The index can be key points' displacement or volume of damage zone, n is the number of evaluation index. y_{ip} is calculated by the trained NN obtained above.

Step 3: Operate on the initial scheme population with GA to generate an offspring population. Calculate the fitness of each individual of the population.

Step 4: Replace randomly an individual in the offspring generation using the best parent's individual.

Step 5: Regard the offspring as a parent and go to step3, until the best scheme is found.

The above steps of scheme optimization can be shown in Figure. 2.

3 THE CASE STUDY—OPTIMIZATION OF SOFT ROCK REPLACEMENT SCHEMES BEFORE A LARGE-SCALE CAVERN GROUP EXCAVATION USING PARALLEL EVOLUTIONARY NEURAL NETWORK FEM METHOD

3.1 *Geological condition and structure assignment of the chamber*

Shuibuya power plant locates in the right hill of the Qingjiang River. The top level of the hill is from about 540 to 550m. The axis direction of the chamber is N296°. The stratum exists with a 245° strike and 8－15° dip angle. The dimension of the main chamber is 141×23×68m(length×width× the maximum height).The geological condition consists of interlayer of soft and hard rock. In the main chamber domain, the surrounding rock is from the above to the bottom to be QiXia group(p_{1q}^4、p_{1q}^3、p_{1q}^2 and p_{1q}^1), Ma'an group(p_{1ma}) and HuangLong group separately(Figure.3). The top of the main chamber is located in hard rock of p_{1q}^4; the foundation is based on soft rock mass, where the head of outlet tunnel is located. The total height of the soft rock is up to 1/3 more of the height of main chamber, which results in much difficulty in construction. The chamber has four units for four generator sets. The dimensions of the calculation domain are 25.5 × 400 × 450m(length × width × depth). The excavation of the main chamber is carried out in one stage to simulate the worst condition after excavation. The model is divided into 9840 isoparametric space elements and 41088 nodes.

For it is a good way to ensure the stability of the main chamber, partial replacement of the soft rock mass before excavation is considered. Therefore, there is an optimal and most economic scheme of replacement. According to the actual engineering demands, it's needed to decide the optimal replacement height, depth, and width of soft rock mass on both of the main chamber sidewall and the replacement depth of the outlet tunnel sidewall.

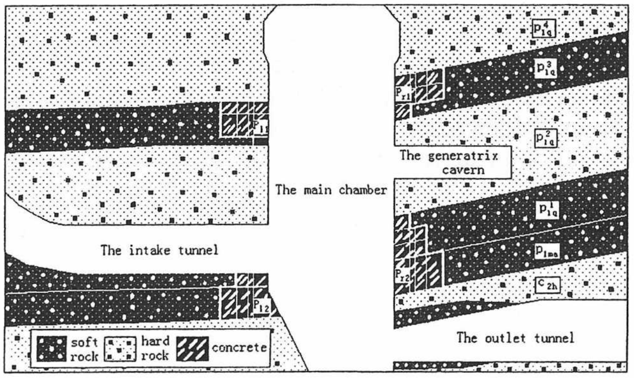

Figure.3 The main chamber and its replacement parameters

3.2 Parallel evolutionary optimization of soft rock replacement scheme

3.2.1 The design of replacement scheme

According to the practical construction condition, seven design parameters of the schemes are considered, represented by A~G, including the 3m-width replacement sequence along the chamber axial (A), the replacement height (E), width (F) and depth of each layer (B, C, D) on both sides of the sidewall, and replacement depth of the outlet tunnel sidewall (G). The parameter for upriver and lower river of main chamber is the same (Table 1).

Table1 The value of each code and its meaning

The code of the scheme	A	B C D	E	F	G
1	P_{r1} and P_{l1} first, then P_{r2} and P_{l2}	1m	2/3 height of the whole layer	One-alure width	1m
2	P_{r2} and P_{l2} first, then P_{r1} and P_{l1}	3m	The height of whole layer	Two-alure width	6m
3	P_{r1} and P_{l2} first, then P_{r2} and P_{l1}	6m			
4	P_{r2} and P_{l1} first, then P_{r1} and P_{l2}	10m			

According to the schematic theory of GA (Liu, 1995), the scheme with lower order, short defining distance and higher average fitness comparing to the population average fitness would obtain a population increment in the discipline of geometric series. So the important factor of the replacement schemes was placed in the front segment of the code chain so as to ensure the searching efficiency and stability better. For the replacement sequence of the three 3-meter allures(A) and the replacement depth(B, C and D) is more important than the other factors, the encoding scheme could be presented as ABCDEFG.

The schemes (with code shown in Table 1) could have 2048 kinds of scheme combinations. Each scheme need a two-day time for computation on PIII 600 personal computer. All the schemes consume about 4,000 days. It indicates that it is impracticable to compare more than 2000 schemes by traditional calculation methods. Through some schemes can be got rid of by referring to the engineering experiments, there are a large number of schemes which need calculation. Moreover, it is difficult to find the global solution in short period.

3.3.2 The comparison of the 16 orthogonal schemes

At first 16 orthogonal schemes are designed (as shown in Table 2). Then a comparison scheme is considered. It is provided that the soft rock mass being replaced by hard rock. It is indicated that stability can be assumed from the results (Table 2)

Table 2 16 orthogonal designs

schemes	The maximal displacement /cm							The volume of the damage zone/m^3
	Sole-plate	Side wall of the lower river	The outlet tunnel	The intake tunnel	Side wall of the upper river	Top of the main chamber	The generatrix	
1111111	2.722	1.886	1.122	1.245	0.749	1.504	1.228	13076
1444221	2.675	1.231	1.135	0.957	0.692	1.598	1.139	12131
2123221	2.672	1.263	1.227	1.145	0.742	1.497	1.223	11056
2432111	2.702	1.312	1.226	1.341	0.751	1.496	1.222	12534
3244111	2.697	1.296	1.163	1.200	0.743	1.559	1.207	14588
3312221	2.699	1.213	1.156	1.162	0.733	1.514	1.202	13100
4231221	2.697	1.267	1.225	1.293	0.737	1.516	1.208	12258
4324111	2.699	1.261	1.203	1.193	0.750	1.554	1.200	14094
2341122	2.708	1.231	1.191	1.215	0.735	1.54	1.214	13619
2214212	2.697	1.208	1.18	1.192	0.753	1.544	1.208	13625
1333212	2.71	1.269	1.199	1.269	0.726	1.546	1.191	14589
1222122	2.692	1.22	1.206	1.159	0.731	1.508	1.22	13224
3421212	2.717	1.348	0.981	1.347	0.713	1.495	1.199	12664
4142212	2.707	1.412	1.189	1.324	0.706	1.490	1.219	14123
4413122	2.688	1.154	1.186	1.324	0.702	1.545	1.197	12849
3133122	2.673	1.247	1.195	1.085	0.712	1.493	1.223	12660

The column 1 in table 2 is the encoded schemes as what ABCDEFG (Table 1) means. Column 2 to 8 is the maximal displacement at each key point. Column 9 is the volume of the damage zone in the surrounding of the main chamber.

3.3.3 The fitness function

The fitness function is defined as:

$$fitness(s) = \sum_{i=1}^{8} \left| (y_i - y_{i0}) / y_{i0} \right| \tag{2}$$

where (s) is a scheme to be evaluated. y_i is the calculated displacement of the scheme(i selected from 1 to 7) and damage zone (i=8). y_{i0} is the corresponding value of hard rock scheme calculated by FEM.

3.3.4 The optimization of soft rock replacement schemes by parallel evolutionary search

The topology and weights of neural networks is very important to the prediction of the new cases. The progress of evolution to search the optimal neural network could be very time-consuming when the problem is dealing with large-scale schemes and multi-parameters. The paper uses parallel evolutionary method to speed up the process of calculation. The computing environment is carried on Master-Slave PC networks. The steps of replacement optimization can be described as follows:

Step 1: Determine initially the parameters of NN, such as number of input and output nodes and number of hidden layers (*Np*). Then determine the parameters of GA, such as the population size (*Psize*), probability of creep mutation (*Cr*), the jump mutation (*Jr*) and evolutionary generation of topology (*Ngen*). The parameters are set as *Np*=2, *Nbit*=6, *Psize*=90, *Ngen*=40, *Cr*=0.1, *Jr*=0.2. The searching zone of hidden nodes is bounded from 2 to 25.

Four PC machines were used to parallel computation. Through 10 hours running, the optimal topology of NN is obtained to be: 7 for hidden layer 1 and 15 for hidden layer 2. Meanwhile, the minimum prediction error is obtained.

Step 2: Search the replacement schemes by GA. With the method mentioned above, the optimum scheme with coding of 2233211 was found through evolution of 500 generations with 300 individuals.

3.4 Analysis of the results

3.4.1 The comparison of the calculation results by FEM and neural networks

In order to test the learning and predicting effects, the calculation of the optimal scheme is done by FEM and compared with the predicting results by neural network. The comparison is show in table 3. The comparison shows that the results are rather according with each other. The maximal relative error is 10.8% and the average relative error is 1.2%. It indicated that the evolutionary neural network had been set up a correct mapping relationships between the replacement schemes and the maximal displacement of key points and volume of the damage zones. Consequently, the neural network can be used for a forward prediction of new cases to replace the FEM analysis.

Table 3. The comparison between the prediction of NN and the value calculated by FEM

	The maximal displacement /cm							The volume of the damage zone/m^3
	Sole-plate	Side-wall of the lower river	The outlet tunnel	The intake tunnel	Side-wall of the upper river	Top of the main chamber	The generatrix	
A*	2.687	1.229	1.020	1.177	0.748	1.522	1.217	12559
B	2.683	1.259	1.111	1.202	0.675	1.379	1.258	12053
C(%)	0.14	-2.38	-8.19	-2.08	10.8	10.36	-3.26	4.199

*A represents the prediction value of BP;

B represents the value calculated by FEM.

C represents relative error

3.4.2 The effect of the soft rock replacement

It indicates from the result that the soft rock replacement can greatly improve the stability of the main chamber. But in the same time, the replacement can make some damage to the surrounding rock when excavating. The larger the replacement scope is, the more disturbances are caused to the surrounding rock. So the optimal soft rock replacement scheme is preferably adopted before the large-scale cavern group excavation.

4 CONCLUDING REMARKS

A new intelligent and parallel method is proposed for replacement scheme optimization. The method is applied to Shuibuya power plant engineering, and the optimal scope and sequence of soft rock replacement are derived from it. Some reasonable suggestions are given for safe construction. The method is also useful to the similar kind of problem of excavation optimization.

ACKNOWLEDGEMENTS

Allied financial support from National Nature Science Foundation of China and Qingjiang water and electricity development Ltd. Co. of Hubei Province under Grant no. 59939190 is greatly acknowledged.

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