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THE GA-ANN METHOD FOR DETERMINING CALCULATION PARAMETERS FOR DEEP EXCAVATION*

XU Ri-qing(徐日庆)
(*Department of Civil Engineering, Zhejiang University, Hangzhou 310027, China*)
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Abstract: This paper presents a new method (GA-ANN) developed by combining genetic algorithm (GA) and artificial neural networks (ANN) for determining parameters of soils and retaining walls of deep excavation. This method has the advantages of nonlinear projection of neural networks, networks reasoning, prediction and good overall characteristics. It was first used for back analysis of the problem of mechanics parameters for excavation. Case studies showed that the GA-ANN method is effective and practical for back analysis of determining parameters.

Key words: excavation, diaphragm wall, genetic algorithm, artificial neural networks
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INTRODUCTION

In excavation, normal analysis is not good enough to meet engineering needs due to the uncertainty of forces applied on brace structures, soil characteristics, and soil model used. To guarantee that the construction process can be smoothly performed, measurements in situ are usually performed and the data obtained are used to back analyze mechanics parameters. Furthermore, the characteristics of soils and structures in the following stage can be forecasted. By doing so, the rationality of a design can be examined and the tendency of deformations of diaphragm walls can be better monitored. Engineering schedule can be adjusted if necessarily and the design can be changed to achieve safer, more economic and more reasonable results. More and more attention is being paid to so-called information based construction in recent years in China. It is used in more and more engineering constructions.

A crucial problem in back analysis is to determine the mechanics parameters of both soils and diaphragm walls since the accuracy of the following stage forecast is dependent on the parameters back analyzed. So developing a quick and accurate back analysis method is a very important requirement in engineering construction.

There are two methods to back analyze parameters (Xu, 1996). They are contrary-back analysis, and normal-back analysis. In contrary-back analysis. mechanics parameters are directly obtained by solving a group of equations. This analysis is aimed to find a way to rearrange new equations for different mechanics parameters and different constitutive models. In the normal back-analysis method, the mechanics parameters are obtained by optimal technique, not requiring rearrangement of different equations for different parameters and different models. So it is more suitable because it effectively achieves the desired results and so, is widely used in practice. However, it needs much more calculation time than contrary back-analysis. Its main disadvantage is the user of the method cannot be sure if the minimum obtained is the overall minimum.

In order to employ the advantages and overcome the disadvantages of normal back-analysis, Genetic Algorithm (simply called GA) and Artificial Neural Networks (simply called ANN) are combined to form the new method, GA-ANN (Xiao, 1997) reported in this paper. The method utilizes the functions of nonlinear projection and network resoning of ANN to help GA optimal technique to find the overall minimum of objec-

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tive functions.

FUNDAMENTAL PRINCIPLE OF GENETIC ALGORITHM GA

Genetic algorithm, GA(Holland, 1975; Shi, 1992), is an algorithm of self-adapting optimization based on the principle of biological evolution. It emulates the law of the biological genetic process, in which the concepts of propagation, hybridization, variation, competition, and selection, etc. lead to the algorithm. By maintaining one group of the feasible solutions and then recomposing them to improve their moving locus or tendency, the overall optimal solutions can be finally obtained. Its process is described below:

1. Define an objective function, calculate its value, which shows the suitability of the feasible solution.

2. In the initial feasible solutions under certain constraints, each solution is expressed by one vector which stands for one chromosome and a component of the vector stands for a gene that corresponds to a variable of the feasible solution.

3. Decode chromosomes in solution group X_i ($i = 1,2,3,\cdots,n$) into evaluation form and give them suitable value F_i, evaluate the feasible solution quality according to F_i. If the optimal objective function is to find the minimum of F_i, the smaller the value of F_i, the better is the quality of the feasible solution.

4. Unsuitable chromosomes are discarded according to the principle of optimum seed method. Those who have the ability to form a new group are chosen on the principle that a chromosome has bigger choice probability P_i if it has smaller value of F_i. That means the chromosome will more likely give rise to a next generation.

5. In hybridization, two chromosomes (parents) are chosen stochastically and the genes of one or both of them are exchanged to form two new chromosomes while the genes variation of one or more chromosomes are changed suddenly to form mutations and giving rise to new varieties.

6. Repeat steps (3) - (5) to let the filial generation group undergo a new process of genetic evolution until the most optimal solutions are obtained.

From the algorithm discussed above, we can conclude that the optimal procedure of GA begins from the group of initial solution, emulates the process of biological evolution, chooses better solution based on the optimal seeding method. The quality of the new group would be improved by choosing better chromosomes with better choice probability. New variety is produced by hybridization, variation offers materials for choosing better solution. So the GA method can bypass the partial minimum problem to find the overall minimum.

FUNDAMENTAL PRINCIPLE OF ARTIFICIAL NEURAL NETWORKS (ANN)

ANN has strong ability for nonlinear projection, and does not require that data obey any distribution rules and that the variables have any relationship. It can find the relationship between input and output by learning and remembering but not supposing. The method is somewhat similar to the "black box" method. In ANN models, multi-layer front feedback neural network is widely used at present because the model can approach any nonlinear projection(Dong, 1995)

Back Propagation Learning Algorithm (simply called BP algorithm) can function as a multilayer front feedback neural network and yield weighted value. The steps in the learning procedure of BP algorithm are given below.

1. Set up a network topological structure, choose rational network learning parameters;

2. Set stochastic number of initial weighted value $W_{ij}(0)$ and initial valve value $\theta_i(0)$ of a network at domain $[-1,1]$.

3. Add learning sample, input a vector $X_p(p = 1,2,\cdots,k)$ and output expectation $Y_p(p = 1,2,\cdots,k)$;

4. In order to calculate the practice output of the network and state of elements of hidden layers, take Sigmoid function as an excitative function

$$O_{pj} = f_j(\sum W_{ji}O_i - \theta_j) = \frac{1}{1 + \exp[-\sum W_{ji}O_i - \theta_j)]} \quad (1)$$

5. Calculate output error of the network:

$$E_p = \frac{1}{2}\sum (Y_{pj} - O_{pj})^2$$
$$E = \frac{1}{K}\sum_{p=1}^{K} E_p \tag{2}$$

6. If $E < E_s$ (allowable limit of the system mean error) or $E_p \leqslant E_s$ (allowable limit of single sample error) or reach the maximum of iteration steps, stop learning. Otherwise errors resort to back propagation;

7. Calculate exercise error of the network

$$\delta_{pj} = O_{pj}(1 - O_{pj})(Y_{pj} - O_{pj}) \quad \text{(output layer)} \tag{3}$$

$$\delta_{pj} = O_{pj}(1 - O_{pj})\sum_k \delta_{pk} W_{jk} \quad \text{(hidden layer)} \tag{4}$$

8. Modify the weighted value and the valve value

$$W_{ji}(n+1) = W_{ji}(n) + \eta\delta_{pj}O_{pj} + \alpha(W_{ji}(n) - W_{ji}(n-1)) \tag{5}$$

$$\theta_j(n+1) = \theta_j(n) + \eta\delta_{pj} + \alpha(\theta_j(n) - \theta_j(n-1)) \tag{6}$$

9. Turn to (3).

GA-ANN METHOD FOR DETERMINING MECHANICS PARAMETERS OF SOILS AND RETAINING WALLS

In normal back analysis, the deviation between measured values (e. g., displacements and stresses, etc.) and calculated values is usually taken as an objective function.

$$F = \min\sum_{i=1}^{n}(s_i - s_i^*)^2 \tag{7}$$

In which n is the number of measured values; s_i^* is ith stage measured value; s_i is ith stage calculated value. Generally, s_i is a function of the mechanics parameters $\{p\}_m$ (m is the number of parameters) of soils and retaining walls, that is

$$s_i = \phi(p_1, p_2, \cdots, p_m) \tag{8}$$

The objective function is also the function of $\{p\}_m$. So the purpose of back analysis is to find the minimum of the objective function.

The objective function, expressed by Eq. (7), is a nonlinear complicated function whose analytical solution is very difficult to obtain. Usually, in order to obtain an optimal solution, we combine optimal methods and numerical analysis method to search for parameters $\{p\}_m$. After finding one group of parameters, normal analysis can be done to obtain s_i for substitution into Eq. (7) to get the value of F. The magnitude of F will determine whether the search direction should be modified. When F reaches the minimum of the objective function, $\{p\}_m^{\text{opt}}$ is an optimal solution. The traditional optimal method mentioned requires much time to obtain a solution and cannot easily yield the overall solution. But ANN can establish a relationship between parameters $\{p\}_m$ and an objective function F while GA can search for $\{p\}_m$ and input them to the network trained well. The network would match automatically with the knowledge learned, and use reasoning to predict parameters related to the objective function F. Use of the principles of genetics and variation will finally yield an overall optimal solution. The method is called GA-ANN method here. Its procedure is as follows:

1. Set learning sample by numerical analysis. That is, choose n_1 group of parameters $\{p\}_m^j$, calculate s_i^j and $F^j (j = 1, 2, \cdots, n_1)$;

2. Exercise a neural network by using n_1 sample $(\{p\}_m^j, F^j)(j = 1, 2, \cdots, n_1)$, in which parameter $\{p\}_m$ is input while F is output. Generally, taking one hidden layer is enough. The network structure is shown in Fig. 1. the knowledge is obtained by learning following the procedure discussed above.

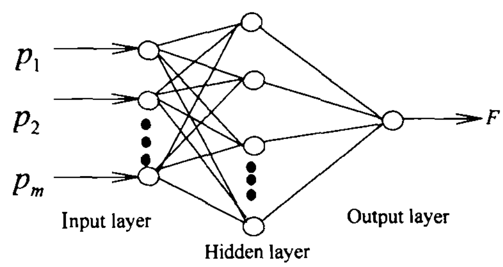

Fig. 1 Neural network structure

3. Constitute one seed group of the initial solution. Stochastically choose n_2 group to obtain the feasible solution group $\{p\}_m^j$, where each $\{p\}_m^j$ stands for one chromosome, in which p_i^j stands for i th gene ($i = 1, 2, \cdots, m$; $j = 1, 2,$

$\cdots, n_2)$;

4. Input each feasible solution into $\{p\}_m^j$ the network trained well, which forecasts automatically the objective function F^j ;

5. Disregard chromosomes corresponding to bigger F , propagate other chromosomes based on the probability to form n_2 new ones;

6. Hybridize and vary the new group to produce a new filial generation, stochastically choose $n_2/4$ pair chromosomes, exchange genes of each pair of chromosomes (this is called hybridization); stochastically choose $n_2/2$ chromosomes, add stochastic amount to some genes to produce new chromosomes (this is called variation);

7. Repeat steps (4) – (6) to produce a new filial generation, that will genetically evolve anew till optimization parameters $\{p\}_m^{opt}$, that are overall minimum, are finally found.

From the procedure introduced above, we can understand that the GA-ANN method combines advantages of both GA method and ANN method.

APPLICATION OF GA-ANN METHOD

The Shenmao International Building is located in the Pudong financial opening district of Shanghai. Its plan area is 10423 m^2 while architecture area is 113000 m^2. It is 192 m high. There are 46 storeys aboveground and 4 storeys underground. Design excavation depth was 17.82 m and semi-back construction was adopted. Parameters of soil mechanics and physics are listed in Table 1. The diaphragm wall was used as retaining structure with 4 braces at 4.1 m, 8.5 m, 11.7 m and 17.85 m respectively in the design. The plan shape of excavation is shown in Fig. 2 and the depth of each excavation is shown in Fig. 3, in which 4 th brace used was a temporary column of steel and concrete and the other braces were permanent ones of the floors. In the construction, measurements are made which included displacements and moments of the diaphragm wall, axial forces of brace structures.

Table 1 Parameters of soil mechanics and physics

Soil layer	Soil type	Thickness (m)	Water content (%)	Density (g/cm^3)	e	I_p	φ (°)	c (kPa)
1	Fill soil	1.5						
2	Silty clay	0.6	32	1.88	0.92	1.50	14.0	13
3	Mucky silty clay	0.8	38	1.83	1.17	13.6	14.5	8
4	Mucky clay	5.1	49	1.71	1.39	20.0	7.2	10
5	Mncky clay	9.8	32	1.86	0.95	14.7	13.8	9
6	Silty clay	6.7	23	1.99	0.68	15.0	13.6	40
7	Sandy clay	5.5	32	1.87	0.90	24.6	2	

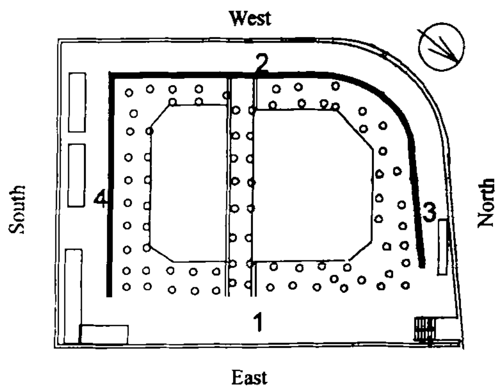

Fig. 2 The plan shape of excavation

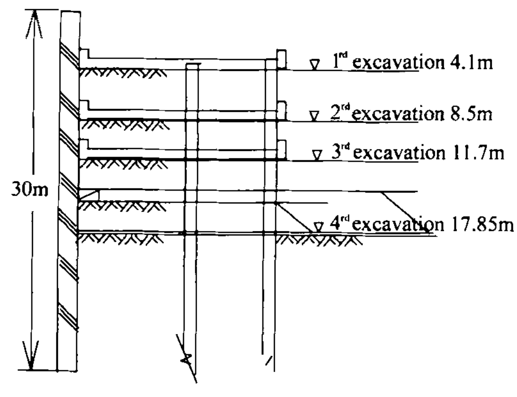

Fig. 3 Different depth of each excavation

During first layer excavation, many crevices appeared in diaphragm walls and underground water flowed from them. The maximum top displacement of diaphragm walls was more than 10 cm. After reinforcing the diaphragm wall and dewatering, the situation was under control. Following excavation stages went on smoothly. When the 3rd excavation stage was progressing, concealing the 4th brace was proposed to speed up construction and lower investment. To determine the feasibility of the proposal, back analysis of excavation characteristics was used to forecast analysis for the 4th excavation.

NUMERICAL ANALYSIS

To simplify calculation, bar system was employed in FEM analysis. The diaphragm wall was taken as a turning beam on elastic foundation. Strong springs simulated forces acting on brace structures and Winkler springs simulated foundation resistance force

$$P_s = k_s \omega \tag{9}$$

where k_s is the coefficient of Winkler spring; ω is lateral displacement of the wall.

In back analysis, Eq. (9) was changed to the following form considering that the force was not linearly distributed along the depth

$$P_s = A(z/L)^B k_s \omega \tag{10}$$

where A and B were parameters to be back analyzed; z was the depth of soil layer; L was the length of the beam.

Earth pressure acting on the beam was calculated based on the Rankine theory of active earth pressure and equivalently acted on calculation points of FEM. Fig. 4 shows the force system.

CHOICE OF PARAMETERS TO BE BACK ANALYZED

In the 1st excavation stage, it was decided that parameters A and B were to be back analyzed. In the 2nd excavation stage, the first brace spring k_1 was added to the parameters to be back analyzed. In the 3rd excavation stage, the second brace spring k_2 was added to the parameters be back analyzed.

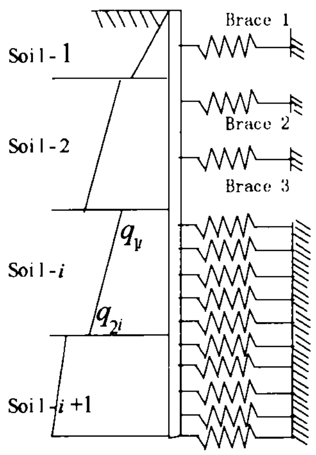

Fig. 4 Force system

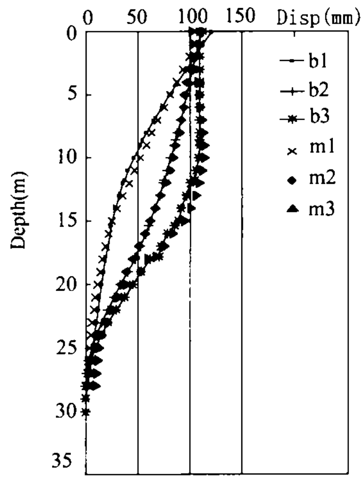

Fig. 5 Comparison of measured and calculated disp

Table 2 Results of back analysis at each excavation

Excavation stage	A	B	Coef. of first brace spring k_1 (kN/m)	Coef. of second brace spring k_2 (kN/m)	Objective function value F
1	3.620	1.141			1.0×10^{-7}
2	2.157	3.229	30000		2.0×10^{-6}
3	1.008	2.962	51375	22061	1.3×10^{-5}

RESULTS OF BACK ANALYSIS OF PARAMETERS DURING EACH EXCAVATION STAGE

Using procedures introduced above, back analysis was carried out at each excavation stage. The results are listed in Table 2. The measured and back analyzed displacements are shown in Fig. 5 indicating that m1, m2 and m3 measured displacement curves of the 1st , 2nd and 3rd excavation stages agree reasonably well with the corresponding labeled b1, b2 and b3 back analyzed displacements curves. This attests to the effectiveness of the back analysis method.

CONCLUSIONS

GA method and ANN method, two important intersecting methods, have the characteristics of emulating biological evolution, were combined to form the GA-ANN method used in this paper for back analysis of excavation parameters. This new method for back-analysis of parameters. can also be used in complex problems such as those without mathematical relation between variables and an objective function.

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