Inversion of permanent deformation parameters of neural network based on bee colony optimization algorithm

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Abstract. In this research, a method of artificial bee colony algorithm was proposed to optimize BP neural network parameters and then introduced to parameter inversion of geotechnical engineering. The method is based on the research and analysis of permanent deformation of geotechnical earthquake engineering and aimed at addressing the shortages of BP neural network which is slow to converge and may easily get minimum value. This method not only strengthens the global optimization ability of bee colony optimization algorithm, but also reflects the high accuracy of predicting nonlinear problems of BP neural network and the strong generalization ability. The proposed method also improves the prediction accuracy. This new proposed method was validated by using the earthquake data of Zipingpu concrete faced rockfill dam in WenChuan earthquake. The results showed that this method can better solve the problem of permanent deformation parameters and can be extended to inversion predict of the same kind.

1. Introduction
The seismic safety of earth-rock dams is mainly determined by the dynamic response and permanent deformation results of the dam. The dynamic parameters of rockfill are the basic premise for the seismic response analysis of earth-rock dams. The dynamic parameters of traditional rockfill materials are mainly determined by methods like indoor dynamic single shear, dynamic three-axis and on-site wave velocity test. However, these test methods are difficult to guarantee accuracy due to equipment cost and other constraints. Therefore, the method of inverting the dynamic parameters of rockfill materials by using observation data such as permanent deformation of dam body has received much attention from many people. For the inversion of dynamic parameters of rockfill materials, the direct method [1, 2] is often used to convert the inversion problem of soil parameters into those of optimization. Since the inversion of the dam permanent deformation parameters is a large spatial search problem with multi-parameter combination, it is impossible to strip out relatively independent quantities from highly correlated influencing factors. However, adopting the inversion method of the powerful neural network based on data fitting and function approximation has a powerful advantage in solving complex nonlinear problems between geotechnical parameters and displacements [3]. At present, some scholars [4] have already applied neural network to inverse analysis of geotechnical permanent deformation parameters, but neural network algorithms have problems such as being susceptible to initial values, slow convergence, and extremely easy to fall into local minimum values. However, many optimization algorithms combined with neural network [5,6] have been presented. The frequently used optimization algorithms at present are mainly ant colony algorithm (ACO), genetic algorithm (GA), particle swarm...
optimization (PSO). The ant colony algorithm is aimless and inefficient, with slow convergence speed and limited information-update ability, and it is easy to fall into the local optimal solution. The genetic algorithm is easy to prematurely converge, and its convergence speed is slow in the late iteration. Particle swarm optimization (PSO) is easy to fall into the local optimal solution, mainly because it is difficult to ensure the diversity of the population in the late iteration. The artificial bee colony algorithm (ABC) [7] is an optimization algorithm based on the behavior of bee collecting honey, which has better optimization performance than the above optimization algorithms [8]. Its main advantage is that the global optimization ability is strong. The positive feedback behavior when using bees to search for honey sources can speed up the overall optimization speed, especially useful for solving combinatorial optimization and continuous optimization as well as complex optimization problems. Therefore, in this paper, using artificial bee colony algorithm to optimize the threshold and weight of BP neural network, a new method was proposed and introduced into the field of geotechnical engineering parameter inversion, and the permanent deformation parameter inversion model was established. Moreover, this new method was validated by the observation data of Zipingpu Dam collected in the 5.12 Wenchuan earthquake.

2. BP neural network optimized by artificial bee colony algorithm

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The initial weight and threshold of the BP neural network [9] are randomly determined, and it is easy to fall into local minimum values during training, resulting in poor prediction consistency. However, the threshold and weight of BP neural network optimized by artificial bee colony algorithm can accelerate the learning and convergence of BP neural network, and reduce the possibility of falling into local minimum value.

The artificial bee colony algorithm [7] is a method to find the feasible solution of complex problems by using the artificial bee colony to search for honey sources, which was proposed by Dervis Karaboga [10] in 2005, who was inspired by the intelligent behavior of bee collecting honey. In the artificial ant colony algorithm, the artificial bee colony is divided into observation bees, honey-collecting bees and scout bees. The search process of artificial bee colony is as follows. Honey-collecting bees determine a honey source in the area of its memory honey source, then they pass the information to observation bees, and observation bees select one honey source from the information; the selected honey source enter into the next round of selecting, while those haven’t been selected becomes random new honey sources for scouting bees to search. Here, the position of a honey source represents a possible optimization solution to the problem, and the possible stored value of the nectar existing in the honey source represents the fitness of the solution.

The steps of using the artificial bee colony algorithm to optimize the BP neural network are as follows:

- Determine the structure of the BP neural network, as well as the input vector and output variables, and the number of input, output, and hidden layer nodes. A typical structure of neural network is shown in Figure 1. The connection weight between the hidden layer and the input layer is $W_{ij}$, the connection weight between the hidden layer and the output layer is $W_{jk}$, and the threshold of each neuron in the hidden layer is $a_j$ ($j=1, 2, \ldots, l$), and the threshold of each neuron in the output layer is $b_k$ ($k=1, 2, \ldots, f$).
Figure 1. BP neutral network model.

- Initialize the network structure based on the training data, and determine the length and range of the initial weight threshold.
- The initial weight threshold of the sample is encoded into a real string individual, and the optimization of the bee colony algorithm is performed for the individual.
- The bee colony is initialized. The honey source is a solution vector of the optimization problem. Each $X_m$ contains n parameter variables, and $x_{mi}$ ($i=1, 2, ..., N$) is the parameter combination that minimizes the target parameters. The initial process was presented by Eq: $x_{mi}=l_i+\text{rand}(0.1)*(u_i-l_i)$, where $l_i$ is the upper and lower bounds of the parameter $x_{mi}$.
- When honey-collecting bees operate, the current honey source $x_{mi}$ (problem solution) and the fitness of the adjacent honey source $v_{mi}$ are calculated, and the greedy mechanism is used to choose a better honey source. Fitness
  $$f_{it}(x_m) = \begin{cases} 
\frac{1}{1+f_{si}(x_m)}, & f_{si}(x_m) \geq 0 \\
\frac{1+\text{abs}(f_{si}(x_m))}{f_{si}(x_m)}, & f_{si}(x_m) < 0
\end{cases}$$
- When observation bees operate, according to the honey source information (fitness) given by the honey-collecting bees, they would select the honey source as the probability of being selected.
  $$P_m = \frac{f_{it}(x_m)}{\sum_{m=1}^{SN} f_{it}(x_m)}$$
  The selected honey source then calculates the fitness through step 5, and uses roulette and greedy mechanisms to select, forming a positive and negative feedback mechanism.
- Operation of scout bees. If the honey source represented by the honey-collecting bees is not selected, the honey-collecting bee will turn into a scouting bee to randomly search for a new honey source, and a bad honey source will be discarded to generate a negative feedback mechanism.
- Record the best solution so far, judge whether the termination condition is satisfied, if not, return to step 6 to continue execution; if satisfied, the feedback of the optimal result will send to the BP neural network as the initial weight threshold.
- Error calculation. Calculate the network prediction error $e$ based on the network prediction output $O$ and the expected output.
- Update of weight threshold. Update the network connection weights $W_{ij}, W_{jk}$, and thresholds $a, b$ according to the network prediction error.
- Determine whether the condition of finish is satisfied. If it is not satisfied, return to step 9. If it is satisfied, save the network.
- Using the well-trained network, the actual observed displacement is used as the input vector to invert the permanent deformation parameters of the dam.

3. Inversion of permanent deformation parameters of BP neural network based on artificial bee colony algorithm optimization
The steps for inversion analysis of permanent deformation parameters are as follows:
According to the existing data, the static and dynamic response of the dam are analyzed to provide the necessary data for the subsequent calculations — the stress level $S_i$ of each unit, and the dynamic shear strain $\gamma_d$.

- Determine the inversion range of the parameter, perform permanent deformation calculation, and conduct the parameter sensitivity analysis.
- Generate a sample set. The training set samples are generated by the central combination experimental design and the orthogonal experimental design, and the verification set and the test set samples are randomly generated. The vertical permanent deformation displacement value of the dam is the input sample, and the permanent deformation parameter value is the output sample.
- Perform network training with training set and verification set samples.
- Perform the inversion of the permanent deformation parameters of the dam with setting the actual observation displacement of the dam as the input vector.
- The forward calculation is performed by using the dam parameters obtained by the inversion, and the calculation results are compared with the actual permanent deformation.

4. Inversion of permanent deformation parameters of Zipingpu Dam

4.1. Project Overview
Zipingpu Dam [11] is the water retaining structure of Zipingpu Water Conservancy Project. Its dam crest elevation is 884.00m, the maximum dam height is 156.00m, the minimum construction elevation of panel toe is 728.00m, and the axial length of dam crest is 663.77 m, the upstream dam slope ratio is 1:1.4, and the downstream dam slope ratio is 1:1.5~1:1.4. The design flood level is 871.20m, the normal water level is 877.00m, the check flood level is 883.10m, and the reservoir water level elevation is 828m and the water depth is 100.00m.

4.2. Generation and processing of data sample set

4.2.1 Forward calculation model. After the static and dynamic response of the dam was analyzed according to the engineering data modeling [12], the necessary data for permanent analysis, namely the stress level $S_i$ and the dynamic shear strain $\gamma_d$ of each unit were obtained. The static calculation of the rockfill was carried out by the Duncan hyperbolic E-B model. The concrete panel was calculated using a linear elastic model with a density of $2.4 \text{ g/cm}^3$, a strength of C25, an elastic modulus of $E = 28 \text{ GPa}$, and a Poisson's ratio of $\nu = 0.165$. The calculation equation of the tangential elastic modulus $E_t$ and the elastic modulus $E_{ur}$ at the time of unloading and loading are as follows:

$$E_t = K p_s \left( \frac{\sigma_1}{p_s} \right)^{m} \left[ 1 - \frac{R_f (\sigma_1 - \sigma_s) (1 - \sin \phi)}{2 c \cos \phi + 2 \sigma_1 \sin \phi} \right]^2$$

$$E_{ur} = K_{ur} p_s \left( \frac{\sigma_1}{p_s} \right)^{n}$$

(1)

(2)

In the above equations $K, m, K_{ur}, n_{ur}$ are test constants; $R_f$ is the failure ratio; $c$ and $\phi$ are the cohesive force and internal friction angle of the material respectively.

The dynamic calculation of dam rockfill material was based on Shenzhujiang equivalent viscoelastic model [13]. The relationship among dynamic shear modulus $G$, damping ratio $\lambda$ and dynamic shear strain $\gamma_d$ is as follows:

$$G = \frac{k_2}{1 + k_1 \gamma_d} p_s \left( \frac{\sigma_1}{p_s} \right)^{n}$$

(3)
In the above equations, \( \sigma_0 \) is the confining pressure; \( k_1, k_2, \) and \( n \) are the test constants; \( \gamma_d \) is the normalized shear strain. The static and dynamic parameters were based on the rockfill test results of the Zipingpu Dam in the literature [14]. Since the measured acceleration record of the bedrock of Zipingpu Dam wasn’t obtained during the earthquake, the input acceleration curve of the Zipingpu Dam bedrock was obtained from the research results of the literature [15] by using the equal-scale method to adjust the measured seismic waves of the Maixian station.

The permanent deformation analysis uses the improved Shenzhujiang model that considers residual body strain [16]:

\[
\Delta \varepsilon_{vr} = c_1 (\gamma_d)^{c_2} \exp(-c_3 S_i^{c_4}) \frac{\Delta N}{1 + N},
\]

(5)

\[
\Delta \gamma = c_4 (\gamma_d)^{c_4} S_i^{c_5} \frac{\Delta N}{1 + N}.
\]

(6)

In the above equations, \( \Delta \gamma \) and \( \Delta \varepsilon_{vr} \) are the residual shear strain increment and residual body strain, respectively. \( S_i \) is the stress level; \( \gamma_d \) is the dynamic shear strain amplitude; \( N \) is the vibration frequency; \( \Delta N \) is the vibration increment, and \( c_1, c_2, c_3, c_4, c_5 \) are the test parameters. It is assumed in this model that the stress level \( S_i \) does not affect \( \varepsilon_{vr} \), i.e. \( c_3 = 0 \) in the equation.

4.2.2. Parameter sensitivity analysis and parameter inversion range. Sensitivity analysis was carried out for the four parameters \( c_1, c_2, c_4, \) and \( c_5 \) involved in the permanent deformation analysis [17], and the influence of parameter changes on the model output results was analyzed. This method calculated the influence value of the output value on the independent variable by randomly changing a certain variable within a threshold range while the other parameters remaining unchanged. Its expression equation is as follows:

\[
S_k = \left| \frac{\Delta P}{P} \right| \left| \frac{\Delta x_k}{x_k} \right| = \left| \frac{\Delta P}{x_k} \right| \left| \frac{x_k}{P} \right|.
\]

(7)

The range of the permanent deformation parameters given in literature [17] to determine the level of factors in the sensitivity analysis and the calculated sensitivity of each parameter are shown in Table 1. That is, the vertical permanent deformation displacement of the dam increases with the increase of \( c_1 \) and \( c_4 \), and decreases with the increase of \( c_2 \) and \( c_5 \).

| Table1. Range of inversion parameters and sensitivity |
|-----------------------------------------------|
| \( c_1 \) | \( c_2 \) | \( c_4 \) | \( c_5 \) |
| Range    | 0.005~0.01 | 0.50~1.0 | 0.10~0.2 | 0.75~1.5 |
| sensitivity | 0.2 | 0.3 | 0.8 | 2.6 |

4.2.3. Orthogonal method to determine the training set sample. The orthogonal experimental method [18] was used to design the sample set. According to the range of permanent deformation parameters in Table 1, the parameters were divided into five levels as shown in Table 2. The orthogonal table of 5 levels and 4 factors was used to determine the 25 combinations of permanent deformation parameters, which were input as the parameters of the permanent deformation numerical simulation calculation. After the permanent deformation forward calculation, the calculated displacement value of the dam deformation after the earthquake was obtained.
Table 2. Division of factors and levels

| C1  | C2  | C4  | C5  |
|-----|-----|-----|-----|
| 1   | 0.0050 | 0.500 | 0.100 | 0.75 |
| 2   | 0.0625 | 0.625 | 0.125 | 0.925 |
| 3   | 0.0750 | 0.750 | 0.150 | 1.200 |
| 4   | 0.0875 | 0.875 | 1.075 | 1.375 |
| 5   | 0.0100 | 1.000 | 0.200 | 1.500 |

4.3. Training and applying the neural network optimized by artificial bee colony algorithm

The calculation value of the maximum vertical displacement $u_0 = [u_1, u_2, u_3, u_4]$ of the D+025 section of the main monitoring deformation section inside the dam with elevations of the 850m, 820m, 790m, and 760m were set as the input sample of network analysis, while the parameters $c = [c_1, c_2, c_4, c_5]$ of different combinations designed by orthogonal experiment were used as output samples for network analysis. The BP neural network optimized by the artificial bee colony algorithm was used to train the sample set and obtain a mature neural network.

The on-site monitoring data were organized, and the maximum vertical displacement measured value $u_0 = [810.3, 417.5, 187.9, 106.5]$ of the D+025 section of the main monitoring deformation section inside with elevations of the 850m, 820m, 790m, and 760m, the unit of which is mm, as the input value band into the mature BP neural network, while the output is the inversion of the permanent deformation parameters of the dam rockfill. The results are shown in Table 3.

Table 3. Inversion results of rockfill deformation parameters

| Material | C1  | C2  | C4  | C5  |
|----------|-----|-----|-----|-----|
| Rockfill | 0.007| 0.7800 | 0.1432 | 1.4073 |

The permanent deformation parameters obtained by the inversion were brought into the forward model for permanent deformation calculation. The comparison of the settlement increment value of the D+025 section with the realmeasured value [14] is shown in Figure 2. It can be seen from the figure that the calculated settlement value increases with the increase of the elevation of the dam. The dam section gradually becomes smaller, and the upstream and downstream slopes gradually shrink inwardly, indicating that the dam rockfill has the characteristic of “shocking”. The upstream slope is affected by the water load, and the maximum horizontal deformation of the dam is directed to the downstream, but the permanent deformation of the earthquake is mainly settlement, which is consistent with the measured settlement law, and the numerical values are similar. Therefore, the reliability of the inversion can be basically confirmed, and the feasibility of analyzing the permanent deformation of the earthquake based on the node method of the improved Shenzhoujiang model is also verified.

Figure 2. Comparison of dam subsidence (unit: mm)
### 4.4. Comparison with inversion results of BP neural network optimized by genetic algorithm

In order to better analyze the inversion results of ABC-BP algorithm, the GA-BP algorithm of BP neural network [19] optimized by more mature genetic algorithm was also used to invert the permanent deformation parameters of Zipingpu concrete rockfill dam. The comparison of the prediction results of the GA-BP algorithm with the ABC-BP algorithm is shown in Table 4.

| Type of network | Network structure | Number of training steps | Accuracy (%) |
|-----------------|-------------------|--------------------------|--------------|
| ABC—BP          | 4—10—4           | 1143                     | 96.43        |
| GA—BP           | 4—10—4           | 2369                     | 91.24        |

It can be seen from Table 4 that the prediction of the ABC-optimized BP neural network is more accurate than that of the GA-optimized BP neural network, and the number of training steps is less, which saves the time of the inversion prediction.

### 5. Conclusion

In this paper, an inversion analysis model of dam earthquake permanent deformation based on BP neural network optimized by bee colony optimization algorithm was proposed. This inversion analysis model not only strengthens the global optimization ability of bee colony optimization algorithm, but also reflects the high accuracy of predicting nonlinear problems of BP neural network and the strong generalization ability, which improves the prediction performance. Through the application of the model in the inversion of the permanent deformation parameters of the Zipingpu concrete face rockfill dam, the reliability of the proposed model for the permanent deformation inversion of the earth-rock dam was verified, therefore this method can be extended to the same kind of inversion prediction.

### Acknowledgments

This research is National Key R&D Program of China (Nos.2018YFC0406803)

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