Research Article

Parameter Identification of 3D Elastic-Plastic Model for Tunnel Engineering Based on Improved Genetic Algorithm

Xiaoma Dong and Lifei Chen

Yangzhou Polytechnic Institute, Yangzhou, Jiangsu 225127, China

Correspondence should be addressed to Xiaoma Dong; 2016123730@jou.edu.cn

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In order to overcome the deficiencies of the existing intelligent displacement back analysis methods, the authors propose a parameter identification method for the 3D elastic-plastic model of tunnel engineering based on an improved genetic algorithm. An improved SVR algorithm is introduced, which solves this problem by transforming the multidimensional output variable regression into a multilayer standard one-dimensional output variable regression; combined with the decimal-coded genetic algorithm, an improved GA-SVR algorithm is formed, and genetic algorithm is used to search for optimal SVR model parameters, in order to establish the optimal nonlinear mapping relationship between the parameters to be identified and the displacement. The genetic algorithm is used to carry out the optimal identification of the parameters to be identified. In order to compare the effect of this improved GA-SVR algorithm, the genetic algorithm is combined with the BP neural network to form the GA-BP algorithm and compile the corresponding calculation program. The two algorithms are applied to the intelligent identification of the parameters of the 3D elastic-plastic model of the same tunnel engineering. The experimental results show that the maximum relative error of the 6 parameters to be identified is 18.51%, only 2 are over 15% and 1 4 are within 10%, and the average relative error of the 6 parameters is only 10.32%, the minimum is 2.63%; for the GA-BP algorithm, the maximum relative error of identification is 22.73%, 4 are more than 15% and 9 are within 10%, and the average relative error of 6 parameters’ identification is up to 13.91%, and the minimum is 4.64%. The improved GA-SVR algorithm can achieve higher identification accuracy and better calculation efficiency than the GA-BP algorithm and can be used in the identification of similar geotechnical engineering parameters.

1. Introduction

With the development of the economy and the progress of the society, many people’s behaviors, such as mining production, water conservancy development, national defense construction, and transportation, have an increasingly close relationship with the stability of the caverns in the rock mass and the surrounding rock of the tunnel. Underground engineering has played a pivotal role in water conservancy and hydropower, road traffic, and mining engineering [1]. Various engineering geological problems caused by the interaction between the rock and soil mass and engineering activities, which are the occurrence environment of various projects, have also received more and more attention; the stability of large-scale underground engineering caused by a large number of rock and soil excavation has become an important problem faced by human engineering activities [2]. Because of the complexity and diversity of natural rock mass structures, people’s understanding of the stability of surrounding rocks has encountered great obstacles; therefore, the research on the stability of the surrounding rock and its influencing factors is of great significance to the in-depth understanding of human engineering activities and the stability of the surrounding rock.

The study of rock mass structural plane characteristics is a complex and hot issue in the field of rock mechanics and has always been paid close attention by academic circles and engineering application units. The rock mass structural plane is a geological interface or zone with a certain direction, relatively low mechanical strength, and two-way
extension (or a certain thickness) in the rock mass formed in the long geological history development process. Because of the existence of the structural plane, it not only destroys the integrity of the rock mass but also directly affects the mechanical properties and stress distribution state of the rock mass and greatly affects the penetration path and failure mode of the rock mass. The existence of structural planes affects the stability of rock mass engineering [3]. Therefore, at present, in the fields of engineering geology, rock mechanics, and hydrogeology, much attention is paid to the study of rock mass structure.

2. Literature Review

Li et al. conducted detailed research on the elastic-plastic damage constitutive model of rock and other materials [4]. Namazi et al. used the transverse isotropic constitutive relation to simulate the local deformation behavior of geomaterials in triaxial symmetric compression test, which considered the case of shear zone and pure compression zone [5]. Raghavan et al. established an elastic-plastic damage model of geological materials under the framework of continuous thermodynamics, the tensile stress damage is considered in the model, the plastic potential function is based on the Drucker–Prager criterion, and the damage is a function of volumetric strain [6]. Anirban has conducted a lot of systematic research on the elastic-plastic damage constitutive model of rock materials; considering the hydraulic properties of rock under saturated and unsaturated states, an elastic-plastic damage coupled constitutive model of semibrittle materials is established and compared with the experimental results [7]. Arbabsiar et al. proposed a statistical damage constitutive model for rock softening based on the Weibull distribution of mesoscopic element strength, in order to describe the entire continuous change process of microcracks from damage to fracture, and the influence of strength criterion and residual strength on the softening-type statistical damage model was studied [8]. Tushavina et al. established an elastic damage model based on fracture mechanics theory, which can be used to describe the stress-strain relationship of rock-like materials under uniaxial compression, since macroscopic plastic deformation is not considered in the model establishment process; therefore, the effect of confining pressure on rock plasticity cannot be reflected [9].

The parameter identification of geotechnical numerical calculation model based on the displacement inverse analysis method has been paid more and more attention. However, based on the research results at home and abroad, the current displacement inverse analysis still has the following problems: (1) the inverse analysis model is generally concentrated on the homogeneous material and the linear elastic model, although it can achieve good results, is obviously still a little bit deviated from the actual situation; (2) the direct optimization and inversion of the current stage all use two-dimensional plane calculation to shorten the calculation time to meet the engineering requirements, but many projects cannot actually be approximated as two-dimensional problems (Figure 1); (3) whether the adopted optimization method can guarantee the convergence to the optimal solution in the parameter search interval; (4) the mechanical behavior of geotechnical engineering is affected by many uncertain factors, and the relationship between these factors and the basic information of back analysis is also highly uncertain and nonlinear; errors are difficult to avoid with any definite computational model; (5) the complexity of geotechnical materials and the harsh construction environment of geotechnical engineering bring two problems: (1) the information obtained from monitoring is inaccurate; (2) large-scale and high-density monitoring is also impossible.

The author applied this improved support vector regression algorithm to the inverse analysis of the three-dimensional elastic-plastic displacement of the tunnel in order to overcome the shortcomings of the existing intelligent displacement inverse analysis methods.

3. Research Methods

3.1. Improved GA-SVR Algorithm. The so-called improved GA-SVR algorithm refers to the use of genetic algorithm to optimize the network parameters of the improved SVR algorithm; in order to establish the optimal nonlinear mapping relationship between the parameters to be inverted and the displacement, the following descriptions will be made separately.

3.1.1. Improved GA-SVR Algorithm. The improved GA-SVR algorithm draws on the idea of the support vector multiclass classification algorithm and converts the multidimensional output regression problem into a multilayer standard one-dimensional SVR algorithm to solve. The same tunnel shotcrete support design comparison shows that this improved algorithm is better than BP neural network. The network generalization performance is better and the prediction accuracy is higher, which verifies its effectiveness in the field of geotechnical engineering [10]. Some people have elaborated on the standard one-dimensional SVR algorithm. The flowchart of the improved SVR algorithm is shown in Figure 2.

The training steps are as follows:

(1) The input parameter X of the learning sample is used as the training input of the network, and the sample value y1 of the first output parameter is used as the training output of the network; after machine learning, predict the input variable X′ of the test sample to obtain the first output parameter y1′ of the test sample, denoted as j = 1.

(2) Judge whether j reaches the number n of regression output parameters; if so, output the yj of the test sample, otherwise the calculation goes to Step (3), and record j = j + 1.

(3) Take X and y1 as the training input of the network and the sample value y2 of the second output parameter as the training output of the network; after machine learning, the input variables X′ and y1′ of
the test sample are predicted to obtain the second sample value of the test sample, an output parameter \( y_2' \).

(4) \( X, y_1, \) and \( y_2 \) are used as the training input of the network, and the sample value \( y_3 \) of the third output parameter is used as the training output of the network; after machine learning, predict the input variables \( X', y_1', \) and \( y_2' \) of the test sample to obtain the third output parameter \( y_3' \) of the test sample.

(5) Repeat the above steps in the same way until the condition of Step (2) is satisfied.

3.1.2. Genetic Algorithm. In order to speed up the searching speed of genetic algorithm, the author adopts decimal coding genetic algorithm, and its genetic operation operator is described below.

(1) Selection Operator. Using the queuing selection method, after calculating the fitness of each individual, the individuals are sorted in the group according to the size of the fitness, and then the predesigned probability table is assigned to the individuals in sequence as their respective selection probabilities. According to the standard geometric distribution selection method, the selection probability of each individual is defined as the following formula:
\[ P = q' (1 - q')^{r' - 1}, \]  

(1)

where

\[ q' = \frac{q}{1 - (1 - q)^P}, \]  

(2)

In the formula, \( q \) is the probability of selecting the best individual; \( r' \) is the rank of the individual, 1 is the best; \( P \) is the population size.

(2) Hybrid Operator. Using arithmetic crosses, let \( P_c \) be the probability of the crossover operation, and to determine the parent of the crossover operation, repeat the following process from \( i = 1 \) to \( P \): a uniform random number \( r \) is generated from \((0, 1)\), if \( r < P_c \) is selected as a parent, \( X_i \) is selected as a parent, and \( X, Y \) is used to represent the parent selected above. The hybrid operation is carried out as follows, and two offspring are generated, that is, the following formula:

\[
X' = rX + (1 - r)Y \\
Y' = (1 - r)X + rY
\]

(3)

Check whether the newly generated offspring are feasible solutions; if feasible, use them to replace the parent; otherwise, keep the feasible ones, then generate new random numbers, and repeat the crossover operation until two feasible offspring are obtained [11].

(3) Mutation Operator. Using nonuniform mutation, the mutation method is for real number coding. Suppose \( x_i \) is an individual in the group and \( x'_i \) is the offspring produced by mutation, then we obtain the following formula:

\[
x'_i = \begin{cases} 
  x_i + (b_i - x_i)f(G), & (r_1 < 0.5), \\
  x_i - (x_i + a_i)f(G), & (r_1 \geq 0.5).
\end{cases}
\]

(4)

Among them,

\[ f(G) = \left[ r_2 \left(1 - \frac{G}{G_{\max}}\right)\right]^b. \]  

(5)

In the formula, \( r_1 \) and \( r_2 \) are uniform random numbers between \((0, 1)\), \( G \) is the current generation, \( G_{\max} \) is the maximum number in the generation, and \( b \) is the shape parameter.

3.1.3. Adaptation Function. In the training stage of the improved SVR network, the total relative error is used as the objective function as shown in the following formula:

\[ f(x) = \min \left( \frac{\sum_{j=1}^{m} \sum_{i=1}^{n} |y'_i - y_i|}{y_i} \times 100\% \right), \]  

(6)

where \( m \) is the number of network output variables, \( n \) is the number of test samples during network training, and \( y_i \) and \( y'_i \) are the sample value and network prediction value of the \( i \)-th test sample during network training, respectively.

When using the genetic algorithm to optimize the parameters of the support vector machine network, the fitness function adopts the following nonlinear acceleration form:

\[ g(x) = \exp[-0.005f(x)]. \]  

(7)

It can be seen from equations (6) and (7) that when the prediction error is 0, that is, when the prediction result is completely consistent with the sample value, the adaptation function reaches the maximum value of 1, since the objective function is nonnegative, the adaptation function cannot be greater than 1; the closer the fitness function value is to 1, the higher the accuracy of the network training.

3.1.4. Improved GA-SVR Algorithm. The implementation steps of this algorithm are as follows:

(1) Divide the training samples into two parts: one part is used as a learning sample to improve the GA-SVR network, and the other part is used as a test sample to test the network training ability.

(2) Initialize the genetic algorithm, randomly generate an initial population of SVR network parameters (kernel parameters, \( C \) and \( \varepsilon \)) with a population size of \( N_p \), and the counter is denoted as \( g = 0 \).

(3) The improved GA-SVR algorithm reads in the training samples and test samples, and at the same time, it reads the individual network parameters in the initial population for network training and prediction.

(4) The prediction result of each individual is passed to the genetic algorithm, the fitness of each individual is calculated by the fitness function of the genetic algorithm, and the fitness is evaluated.

(5) Determine whether the prespecified evolutionary algebra is reached; if so, the algorithm ends and the individual with the highest fitness is returned to decode to obtain the optimal SVM network parameters. If the evolutionary algebra is not reached, go to the next step.

(6) The selection operator selects individuals with higher fitness in the initial population and performs reproduction, crossbreeding, and mutation operations to generate a progeny population of SVR network parameters whose number of individuals is \( N_p \), and the counter is recorded as \( g = I + 1 \).

(7) Repeat Steps (3)–(6) until the specified evolutionary algebra is reached. The algorithm ends, and the optimal SVM network parameters are returned. The flowchart of the improved GA-SVR algorithm is shown in Figure 3.

3.2. Intelligent Identification of Parameters of Tunnel Engineering 3D Elastic-Plastic Model Based on Improved GA-SVR Algorithm

3.2.1. Acquisition of Training Samples: Numerical Experiments. Since the calculation model is axisymmetric, only half of it is considered in modeling, and the length of
The calculation model from top to bottom and from left to right is 60 m. The axial length of the model is set at 50 m [12, 13].

The tunnel is constructed in sections with upper and lower steps, the cycle footage is 1 m, and the upper section is excavated 6 m ahead of the lower section. The excavation range of the upper section is above the line segment to the vault, and the vertical coordinate is $-0.75$ to $4.55$; after the excavation of the upper section is completed, immediately hit the bolt and spray concrete. When the distance between the upper and lower sections exceeds 6 m, the lower section is excavated and supported, and then the upper and lower sections are excavated at the same time [14]. Considering that the tunnel is excavated in II–V grade surrounding rock, the IV–V grade surrounding rock tunnel has a buried depth of 20–145 m, a shotcrete thickness of 8–20 cm, an anchor bolt length of 2–3 m, and a dilatation angle of $17.5^\circ$. The burial depth of grade II-III surrounding rock tunnel is 20–220 m, the thickness of shotcrete is 2–6 cm, the length of bolt is 1.5–2 m, and the dilatation angle is $10^\circ$–$18^\circ$. The horizontal side pressure coefficient is taken as 0.5–1.5, the bolt spacing is taken as 1 m, the bolt diameter is taken as 18–22 mm, the surrounding rocks of grades II-III are divided into 11 levels, and the surrounding rocks of grades IV-V are divided into 26 levels; according to the uniform experimental design method, 37 numerical test schemes are combined [15, 16].

Numerical simulation of excavation process is done using FLAC3D software and the Mohr–Coulomb constitutive model. In this paper, the author randomly selects the calculated absolute displacement of each measuring point in each test on the monitoring surface $Y = 16$ m when the face is advanced to $Y = 16$ m; the absolute displacement of each measuring point is converted into the relative convergence value of measuring lines EA, EB, AC, and BD, evenly and randomly. 6 test results were selected from 37 numerical tests as test samples, the last three samples of the test sample set are regarded as the “specific projects” to be inverted, and the parameters to be identified are cohesion, internal friction angle, deformation modulus, lateral pressure coefficient, Poisson’s ratio, and dilatancy angle [17].

3.2.2. Intelligent Identification of Three-Dimensional Elastic-Plastic Parameters of Tunnel Engineering Based on Improved GA-SVR Algorithm. The direct optimization method is used for intelligent identification of elastic-plastic parameters, in order to compare the effect of the improved GA-SVR algorithm proposed by the author on the three-dimensional elastic-plastic inversion; here, the GA-BP algorithm is used for the same inverse analysis, except that the regressor is changed to BP neural network [18]. The genetic algorithm uses the same real number coding and the same fitness function. In order to improve the generalization ability of the BP network, the input data are normalized. The
Levenberg–Marquardt algorithm is used to adjust the weights, and the weight adjustment rate is as follows:

\[
\Delta W = (J^T J + \mu I)^{-1} J^T e. \tag{8}
\]

In the formula, \(J\) is the Jacobian matrix of the error differential to the weight, \(e\) is the error vector, \(f\) is the identity matrix, and \(\mu\) is a scalar. The introduction of \(\mu I\) is to ensure the positive definiteness of the inverse matrix; when \(\mu\) is large, equation (8) is close to the gradient method, and when \(\mu\) is small, equation (8) is changed to Gauss–Newton method. In this method, \(\mu\) is also adaptively adjusted. Because of the use of approximate second derivative information, the algorithm has a faster convergence rate than the standard BP algorithm. A 3-layer BP neural network is used, the number of nodes in the input layer is 12, the number of nodes in the output layer is 4, and the neurons in the hidden layer use the Sigmoid transformation function. Its expression is as follows:

\[
f(x) = \frac{1}{1 + e^{-x}}. \tag{9}
\]

The neurons in the output layer adopt a linear transformation function [19, 20]. The network training convergence accuracy is 0.01. The number of neurons in the hidden layer \(m\), the learning rate \(lr\), and the number of iterations' epochs are obtained by the genetic algorithm search. The BP network computing program borrows the neural network toolbox that comes with MATLAB software [21]. The learning sample set and the first three test samples in Table 1 are read into the improved GA-SVR and GA-BP algorithm programs. The SVR kernel function adopts the RBF kernel function, the program predicts the three test samples while learning knowledge, and the network parameters are continuously adjusted by genetic algorithm, until the network parameters that can minimize the prediction error of the three test samples are found within the specified evolutionary algebra; after the network training is over, the optimal mapping relationship between the parameters to be inverted and the displacement has been established [22]. After obtaining the optimal network parameters, the displacement and weight, using the same fitness function and genetic operator, 100 generations of evolution and a population size of 30, within the search range of the parameters to be inverted that can make the predicted displacements closest to the calculated displacements of the next three samples. The identification results of the improved GA-SVR algorithm and GA-BP algorithm are shown in Tables 2 and 3, respectively.

### 4. Analysis of Results

For the improved GA-SVR algorithm, the maximum relative error of the 6 parameters to be identified is 18.51%, only 2 parameters exceed 15% and 14 parameters are within 10%. The average relative error of 6 parameters’ identification is only 10.32% at maximum and 2.63% at minimum. For the GA-BP algorithm, the maximum relative error of identification is 22.73%, 4 are over 15% and 9 are within 10%, and the average relative error of 6 parameters’ identification is

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**Table 1: Optimal model parameters.**

| Improved SVR model | | BP model | |
|-------------------|----------------|----------|
| C | \(\sigma\) | \(\epsilon\) | \(M\) | \(lr\) | Epochs |
| 8207.5 | 171.7 | 0.2 | 14 | 0.6185 | 43 |

**Table 2: Identification results of the improved GA-SVR algorithm.**

| Side pressure coefficient | Deformation modulus relative error (%) | Poisson’s ratio | Poisson’s ratio relative error (%) | Dilation angle (°) | Relative error of dilation angle (%) |
|--------------------------|----------------------------------------|----------------|-----------------------------------|-------------------|-----------------------------------|
| Actual value | Identification value | Actual value | Identification value | Actual value | Identification value | Actual value | Identification value | Actual value | Identification value |
| 0.82 | 0.86 | 4.88 | 0.42 | 0.48 | 14.29 | 3.5 | 3.42 | 2.29 |
| 0.50 | 0.45 | 10.00 | 0.24 | 0.28 | 16.67 | 14.8 | 14.99 | 1.28 |
| 1.40 | 1.24 | 11.43 | 0.22 | 0.22 | 0.00 | 16.4 | 15.69 | 4.33 |
| 8.77 | | | | | 10.32 | | | 2.63 |

**Table 3: Identification results of GA-BP algorithm.**

| Cohesion (MPa) | Cohesion relative error (%) | Internal friction angle (°) | Relative error of internal friction angle (%) | Deformation modulus (GPa) | Actual value | Identification value |
|----------------|----------------------------|----------------------------|--------------------------------------------|--------------------------|---------------|----------------------|
| Actual value | Identification value | Actual value | Identification value | Actual value | Identification value |
| 0.20 | 0.18 | 10.00 | 23.8 | 20.05 | 15.76 | 2.0 | 2.08 |
| 1.54 | 1.33 | 13.64 | 51.6 | 45.09 | 12.62 | 22.2 | 18.11 |
| 1.82 | 1.89 | 3.85 | 55.8 | 48.35 | 13.35 | 27.6 | 31.77 |
| Average relative error (%) | 9.16 | | | | | 13.91 |

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The data used to support the findings of this study are drawn: the first 4 parameters are more obvious [23]. According to the predicted displacement situation of the subsequent excavation inversion results, under the condition that the convergence itself is small, the prediction result of the improved GA-SVR algorithm is significantly better than that of the GA-BP algorithm, and the other two examples are not much different [24]. The calculation time of the two algorithms is shown in Figure 4 (P4 dual-core 2.8G, 256M memory PC). It can be seen from Figure 4 that the calculation time of the improved GA-SVR algorithm is slightly shorter, that is, the improved GA-SVR algorithm has higher computational efficiency than the GA-BP algorithm [25].

5. Conclusion

After comparative research, the following conclusions can be drawn:

(1) It is feasible to apply the improved GA-SVR algorithm to the 3D elastic-plastic parameter identification of tunnel engineering, and the author’s example proves this.

(2) Whether it is the improved GA-SVR algorithm or the GA-BP algorithm, applying it to the identification of three-dimensional elastic-plastic parameters of tunnel engineering can achieve good results, but in contrast, the improved GA-SVR algorithm is slightly better than the GA-BP algorithm in terms of identification accuracy, computational efficiency, and convergence; it can be popularized and applied in similar projects.

Data Availability

The data used to support the findings of this study are available from the corresponding author upon request.

Conflicts of Interest

The authors declare no conflicts of interest.

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