Research Article

Parameter Determination Method of Soil Constitutive Model Based on Machine Learning

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In order to better determine the model parameters and improve the safety and stability of construction, an optimized identification method of constitutive model parameters with improved RCGA is proposed by combining the current optimization theory. The experimental results indicate that the improved RCGA algorithm proposed in the study has stronger recognition capabilities and optimization effects than the traditional NSGA-II algorithm and determine the parameters of the constitutive model more accurately. Moreover, it is found that the parameters obtained by the proposed improved algorithm have validity and accuracy, when parameter $P_0 = 50 \text{kPa}$, comparing the obtained optimal parameters with the real laboratory clay parameters.

1. Introduction

With the development of national policies and infrastructure, an increasing number of geotechnical projects have various drawbacks due to soil quality and other external factors, thus causing safety accidents. Unlike structural engineering, the main material of geotechnical engineering is soil. The soil is complex in nature and highly variable and is extremely susceptible to external factors such as environment and weather. It was found that there are 3% of accidents caused by design errors [1, 2]. Instead, the soil itself is the cause of accidents in geotechnical engineering. The soil intrinsic model is obtained, through which the geotechnical engineering can be better analyzed and designed. Large numbers of scholars and experts have conducted numerous researches on soil constitutive mode [3–9]. However, the soil is complex, so there are some limitations for each model to accurately identify and classify it. Furthermore, the selection of the intrinsic model plays a crucial role. At present, to obtain more accurate soil constitutive models, few studies have been conducted to determine the parameters of the current models. For example, Payne and Pochiraju proposed an optimization method of constitutive model parameter based on improved niche genetic algorithm, suspicious peak point judgment strategy, and local precision search technology, which greatly improved the sensitivity of the constitutive model [10]. Zhou et al. constructed a smoother error function to fit the target parameters and the physical properties of the material [11]. Among the above methods, the inverse analysis method based on optimization theory is widely used in the geotechnical field and has achieved good application results [12, 13]. Different methods have their own advantages and disadvantages. Based on the above research results, an optimized identification method based on improved RCGA for the parameters of constitutive model is proposed in order to better determine the parameters of the soil constitutive model. This approach can solve geotechnical engineering problems and enhance the computing capabilities of existing algorithms, thus improving the efficiency and accuracy of soil parameter identification.

2. Crossover Real Coded Genetic Algorithm

The application probabilities of the first and second crossover operators and mutation operators are defined as $P_c, P$
s, and \( P_M \), so as to sort out the implementation process of the improved RCGA, as shown in Figure 1.

Analyzing the Figure 1, the first is to generate the initial populations; the second is to use the tournament selection algorithm to select appropriate individuals from the parent population for crossover and mutation. So the new individual offspring is formed, which improves the diversity of the population. Bhosale and Pawar, Shah and Singh, and other scholars have confirmed that the tournament selection algorithm plays a key role in the implementation of RCGAs in different ways [14–16]. It should be noted that too many tournaments may harm the diversity of the population. Therefore, it was decided to execute 2 rounds of the tournament.

The improved RCGA adopts a new crossover strategy to generate offspring: that is, according to the probability of two crossover operators (\( P_c \) or \( P_r \), the appropriate crossover operator is selected to generate offspring individuals. In addition, the simulated binary crossover operator (SBX) and simplex crossover operator (SPX) are introduced in the improved RCGA algorithm. Da Ronco and Benini created the SPX operator, which can effectively solve the maximum value problem of multimodal function, and it has been confirmed by the experiment. The improved RCGA algorithm introduces a variety of crossover operators to entrust it with powerful searching ability [17]. In order to effectively avoid the search process into local optimization, the improved RCGA algorithm uses another excellent mutation operator—dynamic random mutation operator (DRM), whose application advantage is that it can greatly improve the diversity of the population. Chuang et al. developed the DRM operator, which is an adaptive mutation operator, which can be introduced in the evolution process to effectively improve the global search efficiency [18]. In the evolution process based on RCGA algorithm, as the population number is constant, it is very crucial to select excellent individuals from the parents and children. That is, whether the most effective individuals can be retained in the evolution process determines the success or failure of the whole evolution process to some extent. To this end, the improved RCGA algorithm introduces the elite retention strategy created by Aggarwal et al. Under this strategy framework, the parent and offspring compete with each other in the process of crossover and mutation. And the competitive winner forms a new population, thus improving the final optimization result.

With the increase of computational algebra, the search range gradually shrinks. At the initial stage of optimization, the population diversity is high, and the CLS technology can be used to significantly accelerate the convergence rate. However, in the process of increasing computational algebra, the populations gradually tend to the optimal solution, and the application effect of CLS technology is not significant at this stage. Therefore, in order to ensure both optimization effect and convergence rate, this paper only uses the CLS technology to assist the search in the first 1/3 stage of the evolution process.

The optimization process based on CLS technology is listed as follows:

1. Start
2. Set the calculation algebra gen-0
3. Initialize and generate initial population \( P \) (gen)
4. Solve the fitness of initial generation
5. Check convergence criteria. If convergence has been confirmed, the optimization process is terminated; otherwise, perform Step 6 in sequence
6. Select \( m \) individuals from initial generation \( P(gen) \) to perform crossover operator
7. If (\( \text{rand} < p_c \)), SBX operator is executed; if (\( \text{rand} < p_s \)), SPX operator is executed
8. Introduce the DRM operator into the crossover process to generate a new offspring \( p'(\text{gen}) \)
9. According to elite retention strategy, the parent generation is allowed to compete with its offspring to obtain a new population offspring \( p''(\text{gen}) \)
10. CLS technology is applied to population offspring \( p''(\text{gen}) \), so as to conduct optimization more efficiently
11. Gen = gen + 1; then, \( p(\text{gen} + 1) = p''(\text{gen}) \)
12. Jump to Step 5

3. Improvement of the Main Optimization Operators in RCGA

3.1. Main Operators

3.1.1. Simulated Binary Crossover Operator. After introducing SBX operator, the offspring are generated as follows:

\[
\xi_i = 0.5 \left[ (1 + \beta_i) x_i^1 + (1 - \beta_i) x_i^2 \right],
\]

\[
\eta_i = 0.5 \left[ (1 - \beta_i) x_i^1 + (1 + \beta_i) x_i^2 \right],
\]

\[
\beta_i = \begin{cases} 
(2u)^{1/(\eta+1)} & \text{if } u \leq 0.5 \\
\frac{1}{2(1-u)}^{1/(\eta+1)} & \text{if } u > 0.5 
\end{cases},
\]

where \( \xi_i \) and \( \eta_i \) represent two offspring individuals generated based on SBX operator, \( X_i^1 \) and \( X_i^2 \) represent the two parent individuals used to produce offspring, which is selected through the tournament, \( u \) represents the uniformly distributed random number within the range of [0,1], and \( \beta_i \) represents the extension factor; \( \eta = 20 \).

3.1.2. Simplex Crossover Operator. Offspring based on SPX operator is generated as follows:

\[
\xi_i = (1 + \text{Re fI}) \cdot M - \text{Re fI} \cdot x_i^1.
\]

Here, \( M \) represents the center of the parent \( x_i^1 \) space.
Initial populations set
generation = 0

Covergence ?
The best
solution

Selection

Crossover2
Crossover1

Generation = Generation +1
Random (0, 1) < pM
Random (0, 1) < ps

Mutation

Random (0, 1) < pc

Replacement

Local search

**Figure 1**: Implementation process of the improved RCGA.

**Table 1**: Parameter settings for different RCGA combinations.

<table>
<thead>
<tr>
<th>RCGA</th>
<th>Crossover (probability)</th>
<th>Mutation (Probability)</th>
<th>CLS</th>
<th>Tournament size</th>
<th>Elitism</th>
</tr>
</thead>
<tbody>
<tr>
<td>AC + SPX + DRM</td>
<td>AC (0.9) + SPX (0.5)</td>
<td>DRM (0.05)</td>
<td>No</td>
<td>2</td>
<td>Yes</td>
</tr>
<tr>
<td>LX + SPX + DRM</td>
<td>LX (0.9) + SPX (0.5)</td>
<td>DRM (0.05)</td>
<td>No</td>
<td>2</td>
<td>Yes</td>
</tr>
<tr>
<td>BEX + SPX + DRM</td>
<td>BEX (0.9) + SPX (0.5)</td>
<td>DRM (0.05)</td>
<td>No</td>
<td>2</td>
<td>Yes</td>
</tr>
<tr>
<td>SBX + SPX + DRM</td>
<td>SBX (0.9) + SPX (0.5)</td>
<td>DRM (0.05)</td>
<td>No</td>
<td>2</td>
<td>Yes</td>
</tr>
<tr>
<td>SBX + SPX + DRM + Chaotic</td>
<td>SBX (0.9) + SPX (0.5)</td>
<td>DRM (0.05)</td>
<td>Yes</td>
<td>2</td>
<td>Yes</td>
</tr>
</tbody>
</table>

**Table 2**: Benchmark mathematical functions of evaluating the new RCGA.

<table>
<thead>
<tr>
<th>Benchmark function</th>
<th>Range of variable</th>
<th>Optimal solution</th>
</tr>
</thead>
<tbody>
<tr>
<td>( f_1 = -20 \exp \left( -0.02 \sqrt{1/n \sum_{i=1}^{n} x_i^2} \right) - \exp \left( 1/n \sum_{i=1}^{n} \cos(2\pi x_i) \right) )</td>
<td>(-30 \leq x_i \leq 30)</td>
<td>( \min f(x^<em>) = 0 ) and ( x^</em> = (0, 0, \ldots, 0) )</td>
</tr>
<tr>
<td>( f_2 = -\exp \left( -0.5 \sum_{i=1}^{n} x_i^2 \right) )</td>
<td>(-1 \leq x_i \leq 1)</td>
<td>( \min f(x^<em>) = 1 ) and ( x^</em> = (0, 0, \ldots, 0) )</td>
</tr>
<tr>
<td>( f_3 = 1 + 1/4000 \sum_{i=1}^{n} x_i^2 - \prod_{i=1}^{n} \cos \left( x_i/\sqrt{i} \right) )</td>
<td>(-600 \leq x_i \leq 600)</td>
<td>( \min f(x^<em>) = 0 ) and ( x^</em> = (0, 0, \ldots, 0) )</td>
</tr>
<tr>
<td>( f_4 = \sum_{i=1}^{n-1} \left[ 100(x_{i+1} - x_i^2)^2 + (x_i - 1)^2 \right] )</td>
<td>(-30 \leq x_i \leq 30)</td>
<td>( \min f(x^<em>) = 0 ) and ( x^</em> = (1, 1, \ldots, 1) )</td>
</tr>
<tr>
<td>( f_5 = -\sum_{i=1}^{n} x_i \sin \left( \sqrt{</td>
<td>x_i</td>
<td>} \right) + 418.98288n )</td>
</tr>
</tbody>
</table>
**Figure 2**: Continued.
Figure 2: Difference of different RCGA combinations on the mathematical benchmark function.

Figure 3: Parameter identification process.

Table 3: The main constitutive relation of NLMC model.

<table>
<thead>
<tr>
<th>Model</th>
<th>NLMC</th>
<th>MCC</th>
</tr>
</thead>
<tbody>
<tr>
<td>Elasticity</td>
<td>$\varepsilon_p = (1 + \nu/E)\varepsilon_p^i - (\nu/E)\varepsilon_p^i \delta_{ij}$</td>
<td></td>
</tr>
<tr>
<td>Yield surface</td>
<td>$f = q/p - H = 0$</td>
<td>$f = (q^2/M^2) + p'(p' - p_c) = 0$</td>
</tr>
<tr>
<td>Potential function</td>
<td>$\partial g/\partial g' = M_{pd} - \left(q/p\right)$ with $\partial g/\partial q = 1$</td>
<td>$g = f$</td>
</tr>
<tr>
<td>Hardening law</td>
<td>$H = \left(M_{pd}^p + \varepsilon_p^i\varepsilon_p^i\right)$ with $M_p = 6 \sin \vartheta_p \left(3 \sin \vartheta_p - \sin \vartheta_p\right)$</td>
<td>$dp_c = p_{ac}(1 + \varepsilon_p/\lambda - k)de_p$</td>
</tr>
<tr>
<td>Number of parameters</td>
<td>6</td>
<td>5</td>
</tr>
</tbody>
</table>
variable, which can be solved by the following formula:

\[ M = \left( \frac{1}{n} \right) x_i^1. \]  

It can be seen from the formula that \( x_i^1 \) and \( x_i^2 \) represent the two parent individuals used to generate offspring, which is selected through the tournament, and there are differences in fitness between them. \( n \) represents the total number of individuals excluding the worst individuals; \( \xi \) represents the random number in the range of \([0,1]\). Meanwhile, this paper sets \( n = 2 \).

Meanwhile, there are three kinds of functions adopted to check the optimal performance of RCGA and evaluate several other excellent crossover operators, including the bounded exponential crossover operator (BEX), Laplace operator (LX), and arithmetic operator (AC). The performance advantages of the new RCGA algorithm are confirmed by comparison. The following is an introduction to these types of cross operators.

### 3.1.3. Bounded Exponential Crossover (BEX)

The expression is as follows:

\[ \xi_i = x_i^1 + \beta_i^1(x_i^2 - x_i^1), \]
\[ \eta_i = x_i^1 + \beta_i^2(x_i^2 - x_i^1). \]  

Here, the \( \beta_i^1 \) and \( \beta_i^2 \) are expressed as follows:

\[
\beta_i^1 = \begin{cases} 
\lambda \log \left( \exp \left( \frac{x_i^1 - x_i^2}{\lambda (x_i^1 - x_i^2)} \right) + u \left( 1 - \exp \left( \frac{x_i^1 + x_i^2}{\lambda (x_i^1 - x_i^2)} \right) \right) \right), & \text{if } r_{0.5} < \xi^t, \\
-\lambda \log \left( 1 - u \left( 1 - \exp \left( \frac{x_i^1 - x_i^2}{\lambda (x_i^1 - x_i^2)} \right) \right) \right), & \text{if } r_{0.5} > \xi^t. 
\end{cases}
\]

\[
\beta_i^2 = \begin{cases} 
\lambda \log \left( \exp \left( \frac{x_i^1 - x_i^2}{\lambda (x_i^1 - x_i^2)} \right) + u \left( 1 - \exp \left( \frac{x_i^1 + x_i^2}{\lambda (x_i^1 - x_i^2)} \right) \right) \right), & \text{if } r_{0.5} < \xi^t, \\
-\lambda \log \left( 1 - u \left( 1 - \exp \left( \frac{x_i^1 - x_i^2}{\lambda (x_i^1 - x_i^2)} \right) \right) \right), & \text{if } r_{0.5} > \xi^t. 
\end{cases}
\]  

Among them, \( x_i^1 \) and \( x_i^2 \) mark the upper and lower limits of variables in individuals; \( r_i \) and \( u_i \) represent the uniformly randomly distributed variables in the interval \([0,1]\); \( \lambda \) represents the scale parameter, and \( \lambda > 0 \).

### 3.1.4. Laplace Crossover (LX)

The LX operator is a parent midpoint crossover operator, and its path to generate offspring is as follows: First, two uniformly distributed parameters \( u_i \) and \( u_i' \in [0,1] \) are randomly set; second, generate a random number \( \beta_i \) that follows the Laplace probability distribution through the following:

\[
\beta_i = \begin{cases} 
-a - \log \left( u_i \right), & u_i' \leq 0.5, \\
-a + \log \left( u_i \right), & u_i' > 0.5, 
\end{cases}
\]

where \( a \) and \( b \) are constants.

Finally, calculate the offspring through the following:

\[
\xi_i = x_i^1 + \beta_i \left( x_i^1 - x_i^2 \right), \\
\eta_i = x_i^1 + \beta_i \left( x_i^1 - x_i^2 \right). 
\]

### 3.1.5. Arithmetical Crossover (AC)

The AC operator of generating the offspring is as follows:

\[
\xi_i = \lambda x_i^1 + \left( 1 - \lambda \right) x_i^2, \\
\eta_i = x_i^1 \left( 1 - \lambda \right) + \lambda x_i^2. 
\]

Here, \( \lambda \) represents the random number uniformly distributed in interval \([0,1]\).

### 3.2. Mutation Operator

Introducing the DRM operator into the evolution process can greatly improve the diversity of population, and the mutation process of DRM operator is as follows:

\[
\xi_i^t = x_i + s_m \Phi_0 \left( x_i^U + x_i^L \right),
\]

where \( x_i^U \) and \( x_i^L \) are the upper and lower limits of optimization variables, \( x_i^t \) is the offspring produced by the variation, \( s_m \) is the spacing of variation, and \( \Phi_0 \) means a random perturbation variable in \( n \)-dimensional space \([-\varphi, \varphi]^n\).

To realize the optimization process, the variation step should be flexibly set, which is as follows:

\[
S_m = \left( 1 - \frac{k}{k_{\max}} \right)^b. 
\]

Here, \( k \) stands for the current algebra, \( k_{\max} \) stands for the maximum optimization algebra, and \( b \) stands for the decay rate of regulation \( S_m \). Based on previous research results, this paper sets \( b = 2 \) and \( \Phi_0 = 0.25 \).

### 3.3. Chaotic Local Search (CLS)

The chaotic local search is as follows:

\[
x_i^{t+1} = (1 - \lambda)x_i^t + \lambda \beta_i^t.
\]

As can be seen from the formula, \( x_i^{t+1} \) represents the individual generated from \( x_i^t \) processed through CLS technology, and \( \beta_i^t \) can be obtained from \( \beta_i^t = x_i^t + \beta_i^t \left( x_i^U - x_i^L \right) \); here, \( \beta_i^t \) represents a chaotic variable.
The expression of shrinkage measure is

\[ \lambda = 1 - \frac{FE_s - 1^m}{C_12/C_12/C_12/C_12} \]

where \( FE_s \) represents the fitness of current individual and \( m \) can control the shrinkage speed, \( m = 1000 \). In addition, the larger its value is, the slower the shrinkage speed is.

This paper generates the logical chaos function referenced by the chaos chain, as follows:

\[ \beta_{t+1}^j = \mu \beta_t^j \left( 1 - \beta_t^j \right), \quad t = 1, 2, \ldots; \beta_t^j \neq 0.25, 0.5, \text{ and } 0.75. \]

Under the condition of \( \mu = 4 \), the above formula can reach the state of chaos. Select any value except 0.25, 0.5, and 0.75 from the interval \([0,1]\) and set it as the initial value \( \beta_1^j \). Therefore, the chaotic trajectory can traverse all points in the interval \([0,1]\).

3.4. Optimal Performance and Behavior of the Algorithm.

The newly constructed RCGA algorithm is named according to the cross operator combination form, namely, AC + SPX + DRM, LX + SPX + DR, SBX + SPX + DRM, BEX + SPX + DR, and SBX + SPX + DRM + Chaotic.

In order to guarantee the rationality of comparative research, after removing the cross operators, the other operators in the new RCGA algorithm use the same combination of parameters, which are listed in Table 1.

The benchmark function is shown in Table 2. The benchmark functions referenced in this paper contain 30 variables, which set the initial population to be 10 times the number of variables and the maximum optimization algebra to be 100. Therefore, this paper matches the uniformly distributed random initialization method for all five RCGA algorithms, namely, SOBOL method, to generate initial population.

Optimization performance of genetic algorithm is mainly reflected in the accuracy and efficiency. And the efficiency of genetic algorithm depends on convergence speed of its optimization process. Moreover, the accuracy of the genetic algorithm can be represented by the spacing between the optimization result and the global optimal solution. Changes of the minimum objective error in each generation during the process of optimizing the increment of the algebra are shown in Figure 2.

It can be seen that BEX + SPX + DRM performs best in question 2, AC + SPX + DRM performs best in question 6, and SBX + SPX + DRM performs best in problems 1, 3, 4, and 5. So SBX + SPX + DRM has the ability to handle complex optimization problems. In addition, although SBX + SPX + DRM has no outstanding performance on problem 2, it has a small gap with other RCGAs. In general, when dealing with complex optimization problems, SBX + SPX + DRM has comparative advantages in convergence speed, optimization accuracy, and so on.

However, according to the evaluation results of various benchmark functions, SBX + SPX + DRM still has a large space for improvement in the convergence speed. To this end, introducing CLS technology into SBX + SPX + DRM can greatly improve the convergence speed and save the convergence time. The improved algorithm is SBX + SPX + DRM + Chaotic. Based on the test results, compared with

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**Table 5: Optimal parameters of NLMC model.**

<table>
<thead>
<tr>
<th>Parameter</th>
<th>( E_0 )</th>
<th>( \xi )</th>
<th>( k_p )</th>
<th>( \varphi' )/°</th>
<th>( \psi' )/°</th>
</tr>
</thead>
<tbody>
<tr>
<td>Value</td>
<td>180</td>
<td>0.55</td>
<td>0.00031</td>
<td>36.4</td>
<td>5.9</td>
</tr>
</tbody>
</table>

---

Figure 4: The results of isotropic compression test and triaxial drainage tests.

(a) Deviatoric stress versus axial strain

(b) Void ratio versus axial strain
SBX + SPX + DRM, SBX + SPX + DRM + Chaotic has significantly improved the convergence speed, and the optimization accuracy in questions 4 and 5 has also been improved. It can be seen that using CLS technology in the new RCGA can not only improve the convergence speed and save the convergence time but also improve the optimization performance of new RCGA algorithm.

Therefore, the proposed RCGA algorithm has significant advantages in convergence and search ability, which makes it more excellent to deal with the complex optimization problems.

4. Application of New RCGA for the Identification of Soil Parameters

In the laboratory environment, new RCGA algorithm is used to identify the constitutive parameters of sand and clay, respectively, so as to find a set of optimal model parameters and test the optimization performance of the new RCGA algorithm.

4.1. Parameter Identification Method. The optimal parameter combination can be found by means of experiment, and the new RCGA algorithm can be used to determine a set of optimal model parameters. In contrast, the parameter combination provided by the latter can achieve the most ideal simulation effect. To evaluate the merits of parameter combination, an error function needs to be set in advance to calculate the deviation between predicted and measured value. In this paper, the error function used is proposed by C. Rechea et al. [19] based on the least square method, which has been described in detail in the first chapter.

In describing the mechanical properties of soil, the deformation and strength characteristics of soil are usually concerned. In the laboratory triaxial test, the sample is first subjected to anisotropic or isotropic compression and then subjected to shear tests while remaining in the current state. During the experiment, the experimental curves that can reflect the mechanical properties of soil are recorded in real time, and the specific model parameters, including the critical state line parameter $M$, are extracted from them. In addition, the force-displacement curves can be obtained by other field tests (cross plate shear test, penetration test, pressure-meter test, etc.), so as to reveal soil properties of the sample, such as dilatancy or shrinkage, hardening, or softening. Although it is not possible to measure specific parameters directly by test curve, it can use the valuable information contained in the test curve to determine the optimal parameters by using the appropriate optimization algorithms. The optimization problem studied in this paper is a single-objective optimization problem in nature, the special feature of which is that there are two subobjectives in a single objective. One of which is related to the soil strength, and the other is related to the soil deformation.

$$\min \frac{\text{Error}(x)}{\text{Error}(q)\text{orError}(\Delta u)}$$

where Error($q$), Error($e$), and Error($\Delta u$) are the errors between predicted and the measured value of deviator stress, void ratio, and excess pore water pressure, respectively.

Two core tools are used in the identification process of soil parameters, namely, RCGA optimization algorithm and single Gaussian point constitutive program. The parameter identification process is shown in Figure 3.

4.2. Parameter Identification Based on Laboratory Test. In order to verify the general effect of model, the constitutive parameters of sand soil are identified in this section. In order to simulate the target test, this paper first simulates a new sand and soil constitutive model—NLMC model, whose main constitutive relation formula is listed in Table 3.
To analyze the characteristics of the NLMC, list the Yang’s modulus expression:

\[ E = E_0 \cdot P_{at} \left( \frac{(2.97 - e)^2}{1 + e} \right)^{\zeta} \cdot \left( \frac{P'}{P_{at}} \right)^{\zeta}. \] (17)

In the formula, \( E_0 \) represents the reference Young’s modulus, \( P' \) represents the average effective stress, \( e \) stands for void ratio, \( \zeta \) is constant, and atmospheric pressure is \( P_{at} = 101.325 \) kPa.

The NLMC model contains several core parameters, which need to be measured by different methods. Elastic relevant parameters such as \( E_0 \) and \( \zeta \) are tested and determined by performing isotropic compression tests, as well as a number of plastic hardening parameters such as friction angle \( \phi' \), cohesion, plastic hardening modulus \( k_p \), and dilation angle \( \psi \). Look up the table to find the sand Poisson’s ratio \( \nu = 0.2 \). By performing the parameter identification process based on the RCGA algorithm, the parameters of the identified NLMC model are finally determined, as listed in Table 4.

In the optimization process, the initial population is randomly generated by referring to SOBOLO within the range of search values, so as to start the execution process of RCGA algorithm. Finally, the value range and interval of each parameter of the NLMC model are obtained to test the parameter identification effect of the RCGA algorithm. The sand sample used in this test is a common Fontainebleau sand. During the test, an isotropic compression test and a series of standard triaxial drainage tests are carried out. The test results are shown in Figure 4.

Considering that there is almost no cohesion in the dry Fontainebleau sand, the core parameters of the NLMC model are reduced to three plastic-related parameters and two elastic-related parameters, which are the objective of parameter identification and optimization by RCGA algorithm.

Under the established optimization process framework, the new RCGA algorithm is used to identify the parameters of the NLMC model. And in order to obtain the optimal parameter combination, the optimization process is usually performed several times under different parameter conditions. The optimal parameters of the NLMC model are listed in Table 5.

After the optimal parameters are determined, the target test is immediately organized, and the test results are shown in Figure 5.

Comparing the experimental results (curves) with the optimal simulation results, it can be found that the new RCGA algorithm proposed in this paper can produce the optimal parameters [20–22].

5. Conclusion

In summary, the improved RCGA constitutive model parameter optimization identification method proposed in the study has feasibility and effectiveness. This method can realize the accurate identification of soil constitutive model and provide data reference and technical support for geological engineering. Therefore, the obtained parameters are very close to the real values, and the error between them is small, indicating that this model is applicable to the constitutive model. And the parameters of soil constitutive model can be identified by simple experiments when a reasonable optimization process is selected. However, due to limited experimental conditions and insufficient research experience, the experimental results may have certain limitations, mainly in the sparse experimental parameters, resulting in the lack of convincing experimental results. Future improvements will be made in this area to add more soil data and improve the parameter certainty of the constitutive model.

Data Availability

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

Conflicts of Interest

The authors declared that they have no conflicts of interest regarding this work.

References


