Mesoscopic Simulation Method for Uniaxial Compression Test of RCC Dam Material Based on DEM

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1. Introduction

Roller compacted concrete (RCC) dam has become one of the most competitive dam types due to its fast construction speed, low cost, and strong adaptability [1–3]. However, the current research is mostly on the RCC dam vibration compaction mechanism from a macro-perspective through physical means such as rolling tests or laboratory tests, which fails to consider the mesoscopic structure of concrete fully. Undoubtedly, the mesoscopic structure of RCC is closely related to its mechanical properties such as strength, impermeability, and frost resistance. The roller compaction tests on the macroscale commonly used in construction are difficult to reflect the effect of mesoscopic structure on the compaction characteristics of RCC. RCC cannot be regarded as a continuum system due to the amount of large pores and the omission of fine aggregates in its structure. Hence, only methods that can handle the discontinuous features of this material are generally suitable. Therefore, it is necessary to find a numerical simulation method to study the rolling characteristics of RCC dam materials.

Scholars typically employ discrete models at the mesoscale. Mesoscale models directly simulate the material structure and therefore may be used to comprehensively study the mechanism of the initiation, growth, and formation of micro- and macroracks. They may also be applied for studying different local phenomena at the particles level (e.g., force chains, vortex structures, and bottlenecks) [4, 5]. The classical continuum mechanics assumes that a material is a composition of an infinite number of particles each of which is a point that can only move and interact with its nearest neighbors. For RCC material continua in macroscale sizes, the material particle is small enough compared to the continuum size. Hence, RCC material particle can be modeled as a mass point and thus the classical theory of elasticity can be applied. It is the macroscale behavior of the modeled material that will be observed as a result of the interactions and movements of rigid particles and mesoscale components in the mesoscale models [6–9].
The commercial discrete element particle flow code (PFC) [10] is an effective discrete element method (DEM) for analyzing the mesoscopic mechanical behavior of granular media materials, which is suitable for simulating the vibration compaction process of RCC materials with granular properties, as well as the interlayer aggregate movement and embedding problems. The advantages of the DEM have made it well-suited for investigating the mesoscale behavior of concrete. Discrete element models might even replace costly experimental tests once validated. To generate a mesoscale model, the calculation process is dynamic along with the motion of representative particles (spheres or cylinders). It is classified as a time-stepping, explicit scheme, which makes it possible to compute the nonlinear interaction of numerous particles without needing excessive computer memory. During each calculation step, Newton’s second law is applied to the particles and the force-displacement law is applied at the contacts. The analysis comprises a number of repetitions of this cycle until the desired condition is reached [11]. Based on the above mesoscale modeling approach, Liu and Zhang [12] simulated the compaction process of the RCC materials and analyzed the compaction mesoscopic mechanical characteristics reflected by particle motion and porosity using the PFC 3D software. Li et al. [13, 14] discussed the impact of particle size distribution on the compaction quality from a mesoscopic perspective and analyzed the particle movement law, density distribution, and compaction characteristics during the compaction process. Wang et al. [15] used the DEM to simulate the fracture process of concrete specimens under compression. All these studies provided valuable guidelines for developing a numerical simulation model for RCC materials.

Nevertheless, most of the developed DEM models so far are deficient from the in-depth details of the mesoscale model in the RCC structure with regard to the following: (1) the spherical aggregates are used to simulate the aggregates of the actual RCC materials in most simulation studies. In particular, the coarse aggregates in RCC dam materials are mostly artificial stones with irregular shapes, which are fundamentally different from regular spherical materials in terms of anisotropy, resistance, vibrational movement, etc. (2) The performance of RCC dam material (similar to the ordinary concrete) would widen with the filling time. After hardening to a certain stage, it will not be able to achieve better interlayer bonding quality, even if the roller’s vibration force is strong enough. In the numerical simulation research of RCC dam materials, the mechanical properties of RCC at different filling times need to be simulated accurately to control the dam’s construction organization. However, mesoscopic parameters of RCC materials at different ages are commonly determined using the trial method [16, 17], which is not only tedious and time-consuming but also subject to human factors impact. Considering all the above discussed aspects, there is still considerable scope to further improve PFC modeling methods.

This study will develop a novel method to construct numerical models of RCC materials using the three-dimensional PFC [11] based on RCC samples obtained under typical construction conditions. The major contribution of the work relates to the following:

(1) Aiming at the problem of discrete element refinement simulation of the physical properties of RCC dam materials, the dominant shape of the RCC aggregates were statistically determined, and a simulation method of the dominant aggregate shape and ratio of RCC materials was proposed.

(2) Based on the adaptive differential evolution (ADE) algorithm, an inversion method of microparameters of RCC dam material was proposed. Taking the minimal difference of stress-strain characters of RCC dam material from uniaxial compressive test and PFC model as the optimized objective, the overall process of inverting mesoscopic parameters of dam materials with ADE was given to obtain the contact parameters of RCC dam materials with different filling time.

(3) Validation analysis was performed, which indicated that the RCC material simulated by this research was well conformed to the real RCC material mechanical behavior.

2. Mesoscopic Model Establishing for RCC Materials Using PFC Software

2.1. Aggregate Characteristics of RCC Dam Material. In the RCC mixing of practical dam projects, the fine aggregates (that is, the sand) are mostly spherical with regular shape, but coarse aggregates are generally crushed stones, and convex polygons on cross-section are shown in Figure 1. The irregular shape of coarse aggregate has a significant impact on the performance of RCC, especially when the size of the aggregate is larger, the greater impact it has [18]. For example, a large proportion of flat or narrow aggregates in RCC mixing will not only increase the internal porosity, but also cause the mortar to be difficult to wrap and fill, resulting in structural weaknesses. Furthermore, these irregular aggregates will increase the mechanical occlusal force of concrete and increase the compressive and shear properties of concrete significantly. Therefore, the influence of the irregular shape of coarse aggregate particles on the macroperformance should be fully considered when establishing the PFC 3D model of RCC dam materials.

2.2. Modeling Method of Irregular Aggregate of RCC Dam Material. Considering the characteristics of the actual RCC dam material, this paper simplified the RCC dam material into a two-phase body of coarse aggregate and mortar (nonaqueous) and then used two types of particles with different material properties to simulate [12, 19]. In the PFC 3D simulation, the mortar can be simulated by spheres with a certain particle size range, and the coarse aggregates can be simulated by super-granular CLUMP with irregular shapes. The specific steps of modeling method of irregular aggregate in this paper are as follows:
2.2.1. Statistics of Typical Aggregate Shape. There are many coarse aggregates with irregular shapes in RCC dam materials. The real simulation of each coarse aggregate will bring a lot of work to the modeling. In order to simplify the modeling process, the shape statistics were performed on the actual coarse aggregate and several typical aggregate shapes were summarized. Then, the targeted modeling of these shapes could not only ensure the authenticity of the simulation but also improve the modeling efficiency.

Taking the RCC with two graded aggregate as an example, this paper used a square-mesh sieve to screen coarse aggregate stones and classifies the remaining stones into five typical aggregate shapes, as shown in Figure 2.

2.2.2. Description of the Irregular Shape of Aggregate. Gram [20] pointed out that the shape and size of any convex polygon particle could be roughly defined by a ratio of maximum thickness, maximum height, and maximum length (i.e., $a:b:c$), and the diameter of the particle could be approximately defined as the smaller value in $a$, $b$, and $c$, as shown in Figure 3. In order to reflect the angular characteristics of actual coarse particles, a vernier caliper was used to measure accurately multiple representative sections along the direction of the maximum length $c$ of each typical particle to obtain the maximum thickness $a$ and the maximum height $b$ of each section. Finally, the size and shape of each typical particle could be described by a set of $(a_i:b_i:c_i)$, where $i$ represents the number of cross-section measurements taken along the longest side.

2.2.3. 3D Geometric Modeling of Aggregate Shape. The sketch lofting function in CATIA software [21] was used to draw the contour lines of different representative sections along the longest side to establish a coarse aggregate shape control section, and then the multisection solid command was used to fill the geometric model between each section. The three-dimensional modeling process of a typical coarse aggregate is shown in Figure 4.

2.2.4. Introduction of Three-Dimensional Shape of Aggregate in PFC. The established coarse aggregate 3D models were saved in .stl or .dxf format, and the FISH language programming was used to make the PFC software read the aggregate shape .stl or .dxf file (FISH was a programming language embedded within PFC that enables the users to define new variables and function). The coarse aggregate shape parameters could be imported into the model to make the CLUMP particles with corresponding shape and size. The CLUMP particles were made up of basic sphere particles, which could overlap arbitrarily without generating contact force and would not disintegrate and break during interaction with other particles. Therefore, it is especially suitable for simulating irregular aggregates in RCC dam materials.

In summary, the process of establishing irregular coarse aggregates in PFC 3D is shown in Figure 5. It can be seen from the figure that the established aggregate models have a high similarity with the actual stone particles, and the modeling method can reflect the irregular characteristics of the actual coarse aggregates.

2.3. Determination of Particle Proportion of RCC Dam Material Based on Screening Statistics. The simulation of the RCC mix proportion is the key to whether the simulation results are authentic, as the RCC mix proportion affects the compaction performance of the dam. The number of particles at each gradation is usually calculated according to the conventional target porosity [22] in the PFC model. There is a certain gap between the number of particles generated in the PFC model and the number of particles in the real RCC dam materials, especially if the target porosity is small.

In order to simulate the mix proportion of actual RCC dam materials, this paper proposed a method of determining the number of particles at each gradation based on the statistical results of screening. As shown in Figure 6, the specific steps are as follows:

1. The RCC dam material is mixed using the proportion and the aggregate materials of an actual RCC dam project.

2. The cube standard test specimens are prepared according to “test code for hydraulic roller compacted concrete” (Chinese standard specification no.
aggregate particles; $v_w$ is the volume of water in the model; $R_j$ is the average radius of mortar particles; and $n_j$ is the number of mortar particles in the modeling.

2.4. Determination of Mesoscopic Parameters Contact Model of RCC Dam Material. As described in Section 2.2, the RCC dam material is simplified into a two-phase body consisting of coarse aggregate and mortar. The coarse aggregate particles mainly played the role of skeleton in the two-phase body, and the linear contact model [12, 24] is used to simulate the contact between particles; the mortar mainly plays the role of filling the pores between the coarse aggregates, and the linear bonding model is used to simulate the viscosity of mortar in related studies.

The linear bonding model is composed of two parts in PFC software, namely, the linear part and the viscous part. The linear part gives the elastic relationship between the contact force and relative displacement, which can be used to represent the rigid characteristics of RCC coarse aggregate particles; the viscous part defines the solid connection behavior between contact elements, which can be used to simulate the viscosity characteristics of RCC mortar mixture.

As one of the linear bonding models, the linear parallel bonding model has been used in some studies to simulate the mechanical properties of concrete materials. For example, Lian et al. [18] used the linear parallel bonding model to describe the mechanical behavior of permeable concrete under static load. Cao [24] used a linear parallel bonding model to describe the mortar composition of newly mixed concrete. Xiao [25] used a linear parallel bonding model to simulate the connection behavior of particles when simulating the uniaxial compression behavior of concrete.

Based on the abovementioned theoretical analysis and other people’s research experience, this paper adopts a combined contact model, that is, a linear contact model is selected to simulate the contact between coarse aggregates and coarse aggregates in the RCC mixture, and a linear parallel bonding model is selected to simulate the adhesion performance between mortar particles and coarse aggregates and within mortar particle.

2.5. Determination of Initial Mesoscopic Parameters of RCC Dam Materials. As described in Section 2.4, the linear contact model is used between the coarse aggregates, and a linear parallel bonding model is used to express the viscosity of mortar mixture. However, whether using the traditional trial algorithm or the parameter inversion method proposed in this paper, it is necessary to determine initial mesoscopic parameters of the above selected models, which directly affect the efficiency of subsequent trial calculations or inversions.

The mesoscopic variables of the linear parallel bonding model are mainly divided into two parts: (1) the normal contact stiffness $k_n$ (N/m), the tangential contact stiffness $k_s$ (N/m), and the friction coefficient $fric$ of the linear contact part; (2) the normal bond stiffness $p_b$ (Pa/m), the normal
bond stiffness $p_b \_ks$ (Pa/m), the normal bond strength (tensile strength) $p_b \_ten$ (Pa), tangential bond strength (shear strength) $p_b \_coh$ (Pa), and the bonding radius $R_{bond}$ (m). The linear contact model is equivalent to the linear parallel bonding model with nonadhesive, so the linear contact behavior between coarse aggregate particles is only defined by three variables: $k_n$, $k_s$, and $fric$. In PFC software, the mesoscopic parameters can be established some relationships with the macroparameters through the relationship between deformation and strength of elastic beam [11].

Figure 4: Modeling process of 3D geometric model. (a) Description of aggregate shape. (b) Sketch of representative section. (c) Shape control section. (d) Coarse aggregate model.

Figure 5: Modeling process of irregular particles in PFC 3D.
Figure 6: Determining process of the particles number in each gradation in RCC.

bonding behavior can be regarded as a series of springs evenly distributed in the contact surface and centered on the contact point, whose mechanical behavior is similar to a beam with a length of $L$, closing to zero, and the force and bending moment acting on both ends of the beam. The following parameters can be used to define geometric parameters: beam length $L$, bonding radius $R_{bond}$, cross-sectional area $A$, inertia moment $I$, and polar inertia moment $J$; contact elastic modulus $E_c$, parallel bonding modulus $E_p$, and Poisson’s ratio $\nu$; strength parameters: normal strength $\sigma$ and tangential strength $\tau$. If the two contact spheres are encoded with 1 and 2, the geometric parameters of the beam can be expressed as follows [11]:

\[
L = R(1) + R(2),
\]

\[
R_{bond} = \lambda \min (R(1), R(2)),
\]

\[
A = \pi (R_{bond})^2,
\]

\[
I = \frac{\pi}{4} (R_{bond})^4,
\]

\[
J = \frac{1}{2} \pi (R_{bond})^4,
\]

where $\lambda$ is the parallel bonding radius coefficient.

2.5.1. Mesoscopic Contact Parameters of Contact Model. When pure axial force and pure shear force are applied, the normal and tangential behaviors are not coupled. The normal and tangential contact stiffness can be expressed as follows:

\[
kn = \frac{AE_c}{L},
\]

\[
ks = \frac{12IE_c}{L^3}.
\]

2.5.2. Mesoscopic Contact Parameters of Parallel Bonding Model. Similar to equation (1), the normal and tangential behaviors are not coupled under the action of pure axial force and pure shear force. The normal and tangential stiffness of parallel bonding is expressed by the contact stiffness per unit area:

\[
pb_{kn} = \frac{E_p}{L},
\]

\[
pb_{ks} = \frac{12IE_p}{AL^3}.
\]

It is worth noting that equations (7), (8), (9), and (10) do not contain Poisson’s ratio $\nu$, indicating the lack of relationship between Poisson’s ratio and contact stiffness at the microscopic level. However, the macroscopic Poisson’s ratio is related to the ratio of the normal and tangential stiffness for any dense particle system when using the parallel bond model [27].

Therefore, the consistent process for estimating the deformation mesoscopic parameters is ① obtaining the contact modulus and parallel bonding modulus between particles; ② setting the ratio of the normal stiffness and tangential stiffness of particle contact and parallel bonding, namely, $kn/ks$ and $(pb_{kn}/pb_{ks})$; ③ calculating the $kn$ and $pb_{kn}$ referring to equations (7) and (9), respectively, and then calculating the $ks$ and $pb_{ks}$ referring to the set stiffness ratio.

2.5.3. Mesoscopic Intensity Contact Parameters. As shown in Figure 7, the relative motion of the spheres causes the normal force $F_i^n$, tangential force $F_i^\tau$, normal torque $M_i^n$, and tangential torque $M_i^\tau$ of the parallel bonding. The maximum normal stress and maximum tangential stress that the parallel bond undergoes can be expressed as follows:

\[
\sigma_{\text{max}} = \frac{F_i^n}{A} + \frac{|M_i^n|}{I} R_{\text{bond}}^d,
\]

\[
\tau_{\text{max}} = \frac{F_i^\tau}{A} + \frac{|M_i^\tau|}{J} R_{\text{bond}}^d.
\]

When the maximum normal stress exceeds the normal strength or the maximum tangential stress exceeds the
3. Adaptive Differential Evolution Algorithm for Inversion of Mesoscopic Parameters of RCC Dam Materials

3.1. Basic Principle of ADE Inversion. Realistic mesoscopic parameters are required when using DEM to calculate the numerical value. However, the mesoscopic parameters of the numerical model are generally adjusted by trial and error until the numerically simulated results correspond to the macroparameters of the real specimens. This method usually requires a large number of time-consuming calculations and is prone to introduce human error. Compared to the trial-and-error method, the adaptive differential evolution (ADE) algorithms have the advantages of simple control parameters, global search ability, strong robustness, fast convergence speed, and precision characteristics [28, 29]. Thus, the algorithms would also be suitable for solving the problem of parameter inversion, especially for the inversion of discontinuous, nonlinear, nondifferentiable, and analytic functions.

Suppose that the number of mesoscopic parameters inversion of RCC dam material is \( n \), that is, the dimension is \( n \). After setting the initial population number \( NP \), scaling factor \( F \), and cross probability \( CR \), the basic operation steps include encoding and initialization, differential mutation operation, cross operation, select operation, and termination judgment [28, 29]. Assuming that the \( i \)th individual of the \( t \)th population in the population can be expressed as

\[
X_i^t = (X_{i,1}^t, X_{i,2}^t, \ldots, X_{i,n}^t),
\]

where the \( i \) equals to 1, 2, \ldots, \( NP \), which is the current individual representing a combination of the mesoscopic parameters to be inverted; \( t \) equals to 1, 2, \ldots, \( t_{\text{max}} \), and \( t_{\text{max}} \) is the maximum number of iterations.

3.2. ADE Operation Process of Parameter Inversion. For RCC dam materials, the mesoscopic parameters used in the PFC simulation mainly include \( kn, ks, pb_{\text{kn}}, pb_{\text{ks}}, \text{fric}, pb_{\text{ten}}, \) and \( pb_{\text{coh}} \). The mesoscopic parameter combination can be rewritten according to equation (12) as follows:

\[
X = (kn, ks, pb_{\text{kn}}, pb_{\text{ks}}, \text{fric}, pb_{\text{ten}}, pb_{\text{coh}})^T.
\]

The overall process of inverting the abovementioned mesoscopic parameters using an ADE algorithm is as follows.

3.2.1. Construction of Primary Population Samples. Based on the initial mesoscopic parameters, appropriate adjustments are made to each of the indicators to construct the NP groups of mesoscopic parameters and the stress-strain relationship obtained under the mesoscopic contact parameters as the initial population sample of the ADE algorithm.

The adjustment of mesoscopic parameters should be determined based on the relationship between the stress-strain curve obtained from the initial mesoscopic parameters.

![Figure 7: Schematic diagram of the linear parallel bonding model [26, 27].](image-url)
and the measured stress-strain curves for different filling times of RCC. When the simulation test result is greater than the actual measurement result, the increasing \( kn, ks, pb_{kn} \), and \( pb_{ks} \) or reducing \( fric, pb_{ten} \), and \( pb_{coh} \) should be considered; otherwise, reducing \( kn, ks, pb_{kn} \), and \( pb_{ks} \) or increasing \( fric, pb_{ten} \), and \( pb_{coh} \) should be considered. The purpose is that the stress obtained by adjusting the mesoscopic parameters is close to the measured stress value of the same strain.

3.2.2. Determination of Inversion Target Value by Uniaxial Compression Physical Test. The uniaxial compression physical test of the RCC specimen is used to measure the stress-strain curve at each filling time, the measured values of the elastoplastic phase (that is, the rising section) of the physical test of the RCC specimen is used to measure the \( K_h \) uniaxial compression physical test.

3.2.3. Construction of Fitness Function of Inversion Algorithm. The target value of fitness under different combinations of mesoscopic parameters is defined as the minimum value of the total error between the stress value calculated by the PFC simulation and the stress value measured in the physical test, so the objective function for the inversion of the mesoscopic parameters at the \( i \)th filling time can be defined as follows:

\[
\text{Min} \ G_{ij}(X) = \sum_{k=1}^{q} (\sigma_{ik,j}(X) - \sigma_{ik}^*)^2, \tag{14}
\]

where \( i \) is the working condition represented by different filling time, \( i = 1, 2, \ldots, g \); \( j \) is the stress-strain curve number of the PFC uniaxial compression simulation test, \( j = 1, 2, \ldots, NP \); \( k \) is the group number of the stress-strain value obtained from the stress-strain curve under a certain filling time, \( k = 1, 2, \ldots, q \); \( \sigma_{ik}^* \) is the measured stress from physical test under the \( i \)th filling time corresponding to the \( k \)th point on the stress-strain curve, whose corresponding strain is \( \varepsilon_{ik}^* \); \( \sigma_{ik,j} \) (\( X \)) is the stress value from PFC simulation under the \( i \)th filling time corresponding the strain of \( \varepsilon_{ik,j} \) on the \( j \)th group of stress-strain curves. The relationship between the variables is shown in Figure 8.

Further, the fitness function of the ADE algorithm for the \( j \)th individual (that is, a combination of mesoscopic parameters) under the \( i \)th filling time condition can be constructed as follows:

\[
\text{fitness}_{ij} = \frac{1}{G_{ij}(X)} \tag{15}
\]

It can be seen that the greater the individual’s fitness is, the smaller the objective function value will be, which represents that the uniaxial stress-strain curve simulated by PFC is consistent with the measured value. This indicates that the microscopic contact parameters can reflect the real RCC dam material characteristics.

3.2.4. Realization of Inversion Algorithm for Mesoscopic Parameters of RCC. The specific steps are as follows:

1. It is supposed that the filling time conditions to be inverted are \( g \) (if the filling time condition is 1, \( g = 1 \)), the initial population number of the inversion is \( NP \), the maximum number of iterations is \( i_m \), and the inversion mesoscopic parameters are \( X = (kn, ks, pb_{kn}, pb_{ks}, fric, pb_{ten}, pb_{coh})^T \), the crossover probability is \( CR \), and the scaling factor is \( F \).

2. For the current filling time condition \( i \), each individual in the initial population \( NP \) is encoded and randomly initialized to generate the initial parent individuals according to equation (13).

3. The uniaxial compression physical test is performed to measure the stress-strain curve of working condition \( i \), and the PFC uniaxial compression simulation test is performed to calculate the corresponding stress-strain curves of all parent individuals under the working condition \( i \).

4. Take the \( (\varepsilon_{ik}^*, \sigma_{ik}^*) \) from the measured stress-strain curve of the working condition \( i \) and calculate the adaptive values of all individuals in the current parent according to equation (15).

5. Compare the fitness values of all individuals and determine whether the number of iterations has reached the target value. If so, the individual with the highest fitness is considered to be the optimal mesoscopic parameter \( X_i^* \); if not, the improved adaptive mechanisms of \( F \) and \( CR \) are used to assign different \( F_i \) and \( CR_i \) to each individual in the population, and then, the adaptation variation and crossover operation of parameter are carried out to produce offspring individuals.

6. Repeat the steps 3 to 5 until the maximum number of iteration is reached, and the individual with the largest fitness value is the corresponding mesoscopic parameter \( X_i^* \).

7. Determine whether the number of inversion times has reached the target working condition number \( g \). If so, the corresponding mesoscopic parameters \((X_{i1}^*, X_{i2}^*, \ldots, X_{ig}^*)\) of \( g \) working conditions are output; if not, the inversion operation of the next working condition is performed repeating from steps 2 to 5.

4. Case Analysis and Verification

According to Chinese standard specification (DLT-5433-2009), the interval time in the continuous construction generally does not exceed 8 hours in the actual project. The filling time of 8 hours is selected to carry out the physical and simulation tests of uniaxial compression in this paper, and then, the mesoscopic parameters of RCC dam materials are inverted based on the ADE algorithm to verify the effectiveness of the proposed method.
4.1. Physical Test of Uniaxial Compression. The RCC concrete is mixed according to the mix proportion in Table 1. According to the abovementioned testing specifications (DLT-5433-2009), a standard test specimen of 150 mm × 150 mm × 150 mm is prepared and cured in a standard curing room for a curing time of 8 h. After the curing is completed, the uniaxial compressive test is carried out with the load speed of 0.03 MPa/s until the specimen is damaged. The results show that the uniaxial compressive strength of this RCC specimen is 0.665 MPa, as shown in Figure 9.

4.2. Determination of Initial Mesoscopic Parameter of RCC Dam Materials. There are few pieces of literature on the values of contact elastic modulus $E_c$ and parallel bonding modulus $Ec$ for RCC dam materials; the $E_c$ and $Ec$ are determined as 40.2 GPa and 12.0 GPa, respectively, referring to the previous research about pervious concrete [18] and conventional concrete [30, 31] with PFC method. The spheres and their contact forces contacting with each other in a discrete system can be considered isotropic, so the $(ks/kns)$ of linear contact is taken as 1.0 referring to the related research [32–34]. The relationship between $p_b_{kn}$ and $p_b_{ks}$ is deduced in literature [18], as shown in the following equation:

$$\frac{p_b_{kn}}{p_b_{ks}} = \frac{2}{1 - \nu} \quad (16)$$

where $\nu$ is the Poisson’s ratio. Referring to the related literature [35], the $\nu$ of concrete material is 0.22, and $(p_b_{kn}/p_b_{ks})$ can be obtained as 2.564. The radius coefficient $\lambda$ of parallel bonding is 0.69 with reference to the pervious concrete [18].

Taking the maximum particle (40 mm) and maximum mortar particle (5 mm) in the mix proportion of prototype RCC as an example, the initial $kn = ks = 1.67 \times 10^7$ N/m of linear contact and linear parallel bonding can be obtained according to equation (7); the linear parallel bonding $p_b_{kn} = 5.11 \times 10^3$ Pa/m and $p_b_{ks} = 2.08 \times 10^4$ Pa/m can be calculated from equation (9); the bonding radius is $R_{bond} = 1.73 \times 10^{-3}$ m according to equation (3); the friction coefficient between particles is $fric = 0.5$ referring to the experience. In addition, the maximum normal stress of cement is 47 MPa according to the test results of a cement manufacturer [18]; the maximum shear stress is 30 MPa according to the empirical equations of Moosavi and Bawden [36]. Therefore, the initial value of $pb_{ten}$ of RCC dam material is 47 MPa, and the initial value of $pb_{coh}$ is 30 MPa.

Thus, all initial mesoscopic contact parameters for PFC simulation of test RCC dam material are determined, as shown in Table 2. But it is significant to point out that the mesoscopic parameters only represent the material property of some state of RCC and the initial mesoscopic parameters should be adjusted within a certain range according to the difference between the simulation results and the physical test results, until the mesoscopic parameters conforming to the RCC dam material characteristics are determined.

4.3. Inversion Samples Determination Using PFC Simulation Test. The particles in the RCC dam material model are divided into three grades: mortar (radius range 2–5 mm), small coarse aggregate (radius range 5–20 mm), and middle coarse aggregate (radius range 20–40 mm). The irregular particle generation method introduced in Section 2.2 is used to generate the irregular CLUMP units. These CLUMP units are used to simulate the small and middle coarse aggregates, and the ball units of regular particle are used to simulate mortar particles. Finally, the specimen (with a size of 150 mm × 150 mm × 150 mm) consistent with the physical experiment is established to simulate the uniaxial compression test of RCC dam material. The designed compacting density of the model is 2465 kg/m$^3$. The total number of mortar particles generated by the model is 67069, the total number of small coarse aggregates is 527, and the total number of middle coarse aggregates is 62.

Based on the established RCC model, the uniaxial compression simulation test is conducted as shown in Figure 10. The simulated stress-deformation curve adopted the initial mesoscopic parameters in Table 1 can well reflect the compression failure process of real RCC specimens, but the peak stress is larger than the actual RCC test result (the measured compressive strength is just 0.665 MPa). Therefore, the initial mesoscopic parameters should be adjusted according to the difference between the simulation results and the physical test results.

A total of 24 sets of uniaxial compression test results are obtained by using the initial mesoscopic parameters and their adjusted values in a certain range, as shown in Table 3. As the initial samples of the ADE algorithm, the results are used to calculate the fitness value of the parent individuals.

4.4. Mesoscopic Parameter Inversion Results and Analysis. Based on the abovementioned 24 sets of initial samples and the measured stress-strain values under uniaxial compression, the mesoscopic parameters of RCC dam material with the filling time of 8 h are inverted according to the steps of ADE algorithm to inverse the mesoscopic parameters as described in Section 3.1. Referring to the model parameters...
of the previous study, the friction coefficient is set to a fixed value of 0.5 when the microscopic contact parameters are inverted in order to reduce the dimensionality and calculation amount during inversion. Therefore, the microscopic variables to be inverted are six dimensions of $kn$, $ks$, $pb_{kn}$, $pb_{ks}$, $pb_{ten}$, and $pb_{coh}$. The initial population is 24 groups of PFC uniaxial compression simulation test data, the maximum number of iterations is 30, the variation strategy is DE/rand/1 model [37, 38], the initial crossover probability $CR = 0.1$, and the variation probability $F = 0.9$. Five groups of $(\epsilon, \sigma^*)$ are taken from each measured stress-strain curve, that is $Q = 5$. Finally, the meso-parameters of RCC mixture at filling time of 8 h determined by the inversion of ADE algorithm are shown in Table 4.

Figure 11 shows the comparison between the measured stress-strain curve and the simulation stress-strain curve.
using the mesoscopic parameters obtained from inversion. The measured stress value, the calculated stress value, the absolute value of the stress error, the relative error value, and the average relative error value of the filling time 8 h are shown in Table 5.

According to the comparative results in Figure 11 and Table 5, the average relative errors of the five points are 7.16% indicating that the simulation curve fits the measured curve well. This shows that the ADE algorithm can be used to inverse mesoscopic parameters of RCC dam materials.



table 5: Error statistics of the measured and calculated values of the stress.

| Point | Measured, \( \sigma^* \) (Pa) | PFC calculated, \( \sigma \) (Pa) | Absolute error value, \( \sigma_{id} \) (Pa) | Relative error value, \( \Delta \sigma_{id} \) (%) |
|-------|-------------------------------|---------------------------------|------------------------------------------|------------------------------------------|
| 1     | \( 1.30E+05 \)               | \( 1.48E+05 \)                 | \( 1.80E+04 \)                        | 13.85                                    |
| 2     | \( 2.70E+05 \)               | \( 3.03E+05 \)                 | \( 3.30E+04 \)                        | 12.22                                    |
| 3     | \( 4.15E+05 \)               | \( 4.12E+05 \)                 | \( 3.50E+03 \)                        | 0.84                                     |
| 4     | \( 5.65E+05 \)               | \( 5.90E+05 \)                 | \( 2.50E+04 \)                        | 4.42                                     |
| 5     | \( 6.70E+05 \)               | \( 6.40E+05 \)                 | \( 3.00E+04 \)                        | 4.48                                     |

Average error relative error value, \( \Delta \sigma_i \)

5. Conclusions

This paper puts forward a numerical DEM method for the mesoscopic analysis on the compaction characteristics of RCC dam materials. The following conclusions are drawn from the study:

1. A PFC modeling method reflecting the irregular shape and composition of RCC materials is proposed. Based on the statistics of characteristic shape of RCC coarse aggregate, five types of PFC particle models of characteristic coarse aggregates are established to simulate the irregular coarse aggregate composition in RCC. The determination method of coarse particle number and the estimation method of fine particle number based on the sieves statistics are proposed to meet the requirements of mixing ratio simulation.

2. An inversion method for mesoscopic parameters of RCC dam material based on ADE algorithm is proposed. The overall flow of the ADE algorithm to invert the mesoscopic parameters of RCC dam material under uniaxial compression is given, and the corresponding mesoscopic parameters of RCC dam material under 8 h filling time are obtained by inversion.

The proposed method can effectively avoid the disadvantages of tedious and time-consumption of conventional test algorithms and provide a prerequisite for the subsequent research on the compaction characteristics of RCC with different filling time. Further research will consider conducting an in-depth study with respect to fine characterization of aggregate structure outline and boundary and optimization of calibration method for mesoscopic contact parameters.

Data Availability

The data used to support the findings of this study are included within the article. Any reader or researcher who wishes to obtain the other related data of this article can contact the author by e-mail.

Conflicts of Interest

The authors declare that there are no conflicts of interest regarding the publication of this paper.

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