SOIL PARTICLE MODELING AND PARAMETER CALIBRATION FOR USE WITH DISCRETE ELEMENT METHOD

**Collection
Research**

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HIGHLIGHTS

- Soil particle shapes were statistically analyzed, and four representative particles were obtained.
- A particle model was established using three-dimensional non-contact surface topography.
- This study used a response surface design method to calibrate significant soil parameters.
- The simulation parameters were verified by rotary tiller experiment.

ABSTRACT. *The discrete element method (DEM) has broad prospects for application in soil-tool simulations. To ensure the reliability of simulations, appropriate simulation parameters and particle modeling are essential. Therefore, in this article, a method combining simulation and actual tests is proposed to calibrate the critical soil parameters. First, the effect of soil particle shape on particle contact was considered. Soil particle shapes were statistically analyzed using an improved GrabCut algorithm and k-means algorithm. Four representative soil particles were obtained. Second, a soil particle model was established by microscope and three-dimensional non-contact surface topography. Finally, taking the angle of repose as the response value, the three parameters with significant effects on the angle of repose, i.e., soil shear modulus, Hertz-Mindlin with Johnson-Kendall-Roberts contact model (JKR), and soil-soil restitution coefficient, were obtained via a Plackett-Burman experiment. The optimal value intervals of the significant parameters were determined by the steepest climbing test. A polynomial regression model between the angle of repose and the three significant parameters was established with a Box-Behnken experiment using three factors and three levels. The interactions between the three significant parameters were not significant, as revealed by response surface analysis. The optimal values of the significant parameters were obtained by taking the actual angle of repose as the target and resulted in a soil shear module of 9.8 MPa, JKR of 0.063, and soil-soil restitution coefficient of 0.478. To verify the reliability of the calibrated parameters, the soil angles of repose from the simulation and from actual tests were compared and analyzed. For a simulated angle of repose of 38.5°, the actual angle of repose was 38.6°, and the relative error was 0.26%. DEM was also used to simulate a rotary tiller with the calibrated parameters. The maximum error of the simulated soil throwing angle was less than 10% when compared with the actual throwing angle. The experimental results showed that the calibrated parameters were accurate and can provide a reference for the selection of soil discrete element parameters.*

Keywords. *Angle of repose, Numerical simulation, Parameter calibration, Shape survey, Soil.*

When studying the interaction between agricultural machinery and soil, forces applied during the movement of soil particles cannot be observed in a field experiment from a microscopic perspective. In addition, the accuracy of a numerical simulation needs to be verified separately. Both simulation and experiment have their advantages and disadvantages. At

present, the combination of testing and simulation is widely applied.

The discrete element method (DEM) can simulate the macroscopic and microscopic deformation of soil particles. It saves time and labor, has low cost, and the results can be visualized. DEM has been widely used in research (Asaf et al., 2007; Hamza et al., 2008). The accuracy of DEM depends on the particle modeling and parameter calibration. Improper simulation parameters will lead to large deviations in the results. Accurate particle models and parameters can simulate field trials more realistically, and tools can be improved based on simulation. Therefore, in simulations in which soil is the discrete element, calibration of the soil

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parameters and the soil particle shapes are the main issues that require further study.

In terms of the calibration of soil parameters, Qi et al. (2019) used the angle of repose to study the accuracy of particle parameters in a soil flow process. Zeng et al. (2017) used sensitivity analysis to determine the most critical model parameters that affect soil dynamic properties and used response surface optimization of the model parameters for calibration. Ucgul et al. (2018b) used the angle of repose to calibrate the rolling friction coefficient, coefficient of restitution, and cohesive energy density between soil particles to predict top soil burial. Horabik et al. (2017) determined the coefficient of restitution of peas, soybeans, and canola using high-speed photography. De Pue et al. (2019) used a model to verify that kriging is an accurate prediction method for material parameters. Coetzee and Els (2009) used laboratory shear tests and compression tests to determine the internal friction angle and stiffness of granular material.

Few researchers have tried to determine microscopic parameters through experiments. In recent years, researchers have proposed calibration methods by measuring the macroscopic volume behavior of a large number of particles before performing reverse calibration (Xia et al., 2019). These calibration methods include experimental design (Suliman et al., 2016; Yoon, 2007), artificial neural network, backpropagation (BP) algorithm, and radial basis function neural network based on optimal Latin hypercube sampling (Rackl and Hanley, 2017; Zhou et al., 2018; Sankhadeep et al., 2018; Ji et al., 2020). Among these methods, experimental design based on response surface analysis has been widely used (Yoon, 2007). The other methods have high accuracy but complex modeling. The response surface method is easy to perform, can find optimal values quickly, and has high reliability. The current study used a response surface method to calibrate soil parameters.

Soil particle shape is one of the most sensitive factors for discrete elements. Establishing accurate soil particle shape can improve the accuracy of simulation. Some simulations use only standard spherical shapes; in reality, soil particles tend to have irregular shapes. Establishing accurate soil particle models is necessary to ensure the validity of the simulation results (Hang et al., 2017). Ucgul et al. (2017, 2018a) proposed the use of normal size or irregularly shaped particles in DEM to improve the results of future simulations. Zhao et al. (2015) established a rice seed model using multi-ball filling (Ma et al., 2017). Ding et al. (2018) used the equivalent diameter to approximate fertilizer particles as spheres. Coetzee (2016) used crushed stone particles in 2-sphere, 4-sphere, and 8-sphere clumps. Hang et al. (2017, 2018) divided the soil particle model into three shapes: massive, nutty, and columnar particles.

Previous studies have performed multi-sphere characterization of crop seeds, stones, soil particles and other particles, but the relevant particle shapes were obtained from experience or microscope observations. There is no ideal method to determine the number of shapes that particles have. Representing the three-dimensional shapes of particles is difficult with a two-dimensional model established from a single image, particularly for irregular particles such as soil.

The shape modeled from a single image often deviates greatly from the actual shape.

Establishment of a discrete element model for the soil surface of a cotton field in Xinjiang, China, where there is a large cotton planting area, is of great value because it can provide a simulation basis for subsequent farm operations and plant protection. Successful modeling can also ensure the accuracy of later farming simulations, which is conducive to the optimization of tools and reduces the cost and time required for field tests. For the modeling and simulation of soil particles, this study mainly comprised the following steps:

1. Soil particle shapes were statistically analyzed using an improved GrabCut algorithm and *k*-means algorithm.
2. A soil particle model was established by microscope and three-dimensional non-contact surface topography.
3. The experimental design method was used to determine the optimal simulation parameters for this type of soil.
4. To explore whether the soil model established in this study is suitable for simulating the operation of a rotary tiller, the angle of repose of the soil was simulated, and the simulation results were compared with actual tests.

MATERIALS AND METHODS

EXPERIMENT METHOD

In this study, the parameters of a discrete element model for the local soil were calibrated using a combination of simulations and actual tests (Coetzee, 2017; Rackl and Hanley, 2017). The tests were conducted to measure soil particle size, angle of repose, and bulk density. The simulations were run using EDEM 2017 (DEM Solutions Ltd., Edinburgh, U.K.). The optimal value of each significant parameter was obtained by the experimental design method. The simulations were conducted using the calibrated parameters. Errors of the simulated soil parameters, relative to parameters determined during the actual tests, were examined to verify the accuracy of the calibrated parameters of the discrete element model.

TEST MATERIALS

A field was randomly selected from the 145th Regiment in Shihezi City, Xinjiang, China, where cotton planting had been practiced for at least ten years. Soil augers was used to sample the surface soil at 0 to 5 cm depth. The soil is a sandy loam with a moisture content of $5\% \pm 1\%$. The collected soil samples were pulverized to obtain a uniform soil particle distribution for the subsequent experiments.

SOIL ANGLE OF REPOSE EXPERIMENT

The soil angle of repose, which was used as a test index (Dai et al., 2019), was determined using the funnel method (fig. 1). During each test, a funnel was suspended from a tripod, soil was manually poured into the fixed funnel, and the soil flowed down through the funnel and onto a horizontal steel plate.

To measure the angle of repose more accurately and reduce the error caused by manual measurements, an image processing method was adopted (Xia et al., 2019). The angle

Figure 1. Apparatus to determine soil angle of repose: 1 = tripod, 2 = funnel, 3 = soil falling from funnel, and 4 = accumulated soil.

of repose was photographed using a camera, as shown in figure 2f, to observe the actual shape of the accumulated soil. The outline of the accumulated soil was not straight but was composed of irregular curves. We used a Gaussian distribution to fit the contour of the accumulated soil to determine the angle of repose because Gaussian fitting can achieve a smoother curve, which is more accurate than straight-line fitting. The main idea was to extract the contour point coordinates of the accumulated soil by image processing and then fit them to a Gaussian distribution. The acute angle between the fitting curve and the horizontal plate was the angle of repose.

The method was performed as follows. The original image of the accumulated soil (fig. 2a) was obtained with a camera (Sony ILCE-6400L). MATLAB 2016 was then used to perform grayscale processing (fig. 2b) and binarization (fig. 2c). With generation of the contour, the working path was generated as the accumulated soil outline, producing figure 2d. The image was imported into Origin graphing and data analysis software to obtain the contour point coordinates through the image file digitizer. The curve was fit to a Gaussian distribution, and the left half of the image was selected. The angle of repose (green angle in fig. 2e) was obtained by measuring the angle between the straight outline and the horizontal line after Gaussian fitting. The test was replicated ten times to calculate a mean angle of repose of 38.6°.

PARTICLE SIZE DISTRIBUTION AND MASS FRACTION

Soil samples of 400 g were used for particle size analysis. A three-dimensional sieve shaker (SZS, Nanjing, China) and standard sieves were used for particle classification (Zhang et al., 2017). An electronic scale was used to determine the mass of each particle size range to obtain the soil particle size distribution and corresponding quantities and proportions. The tests were repeated ten times to produce six particle size ranges (table 1 and fig. 3).

SHAPES OF SOIL PARTICLES

Soil particles of different sizes were placed under an electron microscope for observation. Figures 4 and 5 show the shapes of soil particles with sizes of 1 to 2 mm and >2 mm, respectively. These observations revealed that most of the soil particles were non-spherical (the observed particles are soil aggregates). For accurate representation, non-sphere modeling should be considered in addition to standard sphere modeling.

Table 1. Soil particle size ranges (total mass = 400 g).

	Particle Size (mm)					
	>2	1 to 2	0.5 to 1	0.25 to 0.5	0.075 to 0.25	<0.075
Quantity (g)	81.86	154.93	31.18	45.43	62.56	23.84
Proportion	20.47%	38.73%	7.80%	11.36%	15.64%	5.96%

Figure 2. Angle of repose process: (top row) accumulated soil profile and (bottom row) camera response (1 = soil; 2 = camera).

Figure 3. Screened soil particles.

Figure 4. Soil particles of 1 to 2 mm (scale denotes 50 pixels).

Figure 5. Soil particles >2 mm (scale denotes 50 pixels).

PARTICLE SIMULATION MODEL

For the selected soil samples, the quantities of particles of 1 to 2 mm and >2 mm accounted for 59.2% of the total mass (table 1). In the process of parameter calibration, if the modeling is performed according to the real particle size distribution, the difficulty and computational time for the simulation will be increased substantially, and the simulation efficiency will be reduced. To improve the simulation speed, the

particles with the largest mass fraction in the particle size distribution (i.e., 1 to 2 mm and >2 mm particles) were selected for analysis and simulation.

The shape of soil particles varies, and it is impossible to include each shape in discrete element modeling. At present, there is no ideal method for measuring the shapes of soil particles. In this study, an image processing method was used for the particle shape statistics. The specific steps (image segmentation and *k*-means classification) are presented in the following sections.

Image Segmentation of Soil Particles

Image segmentation of soil particles under the microscope was used to extract the particle contours. Conventional image segmentation methods include fixed threshold methods (Roy et al., 2014) and the Otsu method (Otsu, 1979). As a result of the light source of the optical microscope, a shadow of the soil particles was produced. Therefore, conventional image segmentation, which allows the background to blend with the foreground, was not accurate enough. Figure 6 shows a single soil particle. To separate the particle from its shadow, an improved interactive image segmentation method (GrabCut; Rother et al., 2004) was investigated in this study. The original GrabCut algorithm determined the target area (blue box in fig. 7) by selecting the position of the soil particle and manually increasing the number of iterations to determine the best value of the segmentation effect. As shown in figure 7a, the original GrabCut algorithm failed to separate the shadow completely. The improved GrabCut algorithm manually selects the shadow pixels as the background on an iteration basis and can better recognize the shadow. After iteration, the soil particle and shadow were completely segmented (fig. 7b). Threshold segmentation and morphological closure of the segmented soil particle were performed to obtain the final binary image of the soil particle shape (improved GrabCut image in fig. 6).

K-Means Classification of Soil Particle Images

As an unsupervised method, the *k*-means algorithm divides a large quantity of data into predefined clusters (where the *k* value is the number of clusters) using a distance function to detect the similarity between sample points. According to the distance between clusters, points in the same cluster are connected as closely as possible, and the distance between different clusters is as large as possible (Sun et al., 2019; Bagwari et al., 2017; Kishor, 2016). The distance function used in this study was Euclidean distance. The equation is as follows:

$$d(x, y) = \sqrt{\sum_{i=1}^N (x_i - y_i)^2} \quad (1)$$

The implementation of the algorithm was as follows:

1. Cluster the data to achieve *k* groups by inputting the *k* value.
2. Select data points randomly from the data set as the initial cluster centers (with the number of *k*).
3. Assign each sample point to the cluster centers closest to them to generate *k* clusters.

Figure 6. Binary images of a single soil particle obtained by different methods.

Figure 7. Segmentation of soil particle and shadow using (a) original GrabCut algorithm and (b) improved GrabCut algorithm.

4. Calculate the mean distance of all the sample points for each cluster as new cluster centers. The equation is as follows:

$$u_j = \frac{1}{N_k} \sum_{i=1}^{N_k} data_{ki} \quad (2)$$

where u_j is the cluster center of the j th cluster, $data_{ki}$ is the i th sample in cluster k , and N_k is the number of samples in the corresponding cluster center.

5. The iterative method is applied repeatedly between steps 3 and 4. When the position of the cluster centers no longer changes, the iteration stops, and the clustering is completed.

The soil particles were clustered by the k -means clustering algorithm. The circularity, compactness, rectangularity, and slighthness were obtained by calculating the values of these shape features for subsequent k -means clustering (table 2).

For a soil particle image, operations such as rotation and magnification do not change its clustering characteristics. The classification of soil particles was not affected by the location and size of the particles. To judge whether the clustering was reasonable, the image of a soil particle shape was rotated by 90° , 180° , and 270° and magnified by $1.5\times$ (fig. 8).

Ten soil particle images were subjected to the operations mentioned above to obtain their shape features. Comparison showed that the $1.5\times$ magnified image had a maximum roundness error of 3%. The equation is as follows:

$$e = \frac{|E_0 - E_1|}{E_0} \quad (3)$$

where e is the error, E_0 is the particle image before magnification, and E_1 is the magnified particle image. The deviation for magnified images may have occurred because the edge pixels of the contour changed after the image was magnified, while the calculation results for the remaining features did not change. The 3% error was ignored in this study. Finally, the four features (circularity, compactness, rectangularity, and slighthness) were selected as the k -means clustering features.

The silhouette coefficient is the evaluation index of the k -means clustering algorithm (Rousseeuw, 1987), and the equation is as follows.

$$S_{(i)} = \frac{b_{(i)} - a_{(i)}}{\max\{a_{(i)}, b_{(i)}\}} \quad (4)$$

Figure 8. (a) Original image, (b) rotated 90° clockwise, (c) rotated 180° clockwise, (d) rotated 270° clockwise, and (e) magnified by $1.5\times$.

Table 2. Shape features.

Feature	Definition	Equation ^[a]
Circularity (E)	Degree to which the boundary of the soil particles approximates a circle	$E = 4\pi A/C^2$
Compactness (J)	Ratio of soil particle diameter to long axis	$J = D/L$
Rectangularity (T)	Ratio of soil particle area to the area of the smallest circumscribed rectangle	$T = L/S$
Slighthness (R)	Ratio of the length and width of the smallest circumscribed rectangle of soil particles	$R = A/(L \times S)$

^[a] A = particle area, and C = particle perimeter (determined by summing the boundary pixels of the soil particle sample image), L = long axis of the smallest circumscribed rectangle of the particle area, S = short axis of the smallest circumscribed rectangle of the particle area, and D = diameter of the circle equal to the particle area and is calculated as: $D = 2\sqrt{A/\pi}$.

Figure 9. Values of silhouette coefficient for each k value.

where $a_{(i)}$ is the mean distance between point i and other points in the cluster, $b_{(i)}$ is the mean distance between point i and a different cluster point, and the mean $S_{(i)}$ value of the entire data set represents the overall clustering effect. The range of $S_{(i)}$ is $[-1,1]$, and values closer to 1 indicate that the clustering of the data points is more appropriate. A total of 100 particle images were selected for extracting and saving the relevant shape features of each image. The optimal number of clusters was obtained by comparing the $S_{(i)}$ values for different k numbers. The $S_{(i)}$ values are shown in figure 9. When the clustering result was four clusters, the $S_{(i)}$ value was highest, so the soil particles were determined to be of four types. Soil particles of each type were randomly selected as representative soil particles for subsequent modeling.

SOIL PARTICLE MODELING

In view of the irregular shapes of actual soil particles, non-standard spherical particles were used to fill soil particles of the four representative types measured above to resemble actual particles. To create the irregular shapes of the particles, we used a particle modeling method. The specific steps are described in the following paragraphs.

A 3D non-contact surface topography instrument (Nano-vea Inc., Irvine, Cal.) was used to scan a soil sample to obtain a three-dimensional topographic map of each soil particle (fig. 10a) with a certain height. The cross-section of this height was taken as a cross-sectional view of the soil

Figure 11. Particle filling results.

particle, although only the upper section (fig. 10b) or the lower section (fig. 10c) could be obtained with this surface topography instrument. To obtain a complete cross-section, the upper and lower sections were combined using the graphics editor in Adobe Photoshop, and the image was grayed and binarized using MATLAB. Figure 10d shows a binarized image, and figure 10e shows a soil particle divided into ten sections.

Binarized maps of the ten sections of each analyzed soil particle were obtained using the above process. The ten binary images were then imported into SolidWorks and placed according to their divided distance (fig. 10f). Corresponding sketches of the ten sections were created using the tracing function in SolidWorks. A three-dimensional map of the soil particle shape was then established using the “lofting surfaces” function. The map was applied to EDEM 2017 as a template for particle fill.

Standard spheres were selected to fill the irregular shapes. According to the results of the k -means algorithm, the selected soil particle shapes were chunk, crutch, square, and triangle. Four standard sphere arrays were selected for the chunk, crutch, and square shapes according to the particle contours (figs. 11a to 11c). For the triangle shape, triangular arrays of three standard spheres were applied (fig. 11d).

PLASTIC FUNNEL AND STEEL PLATE SIMULATION

Before the simulation, a three-dimensional model of the plastic funnel and steel plate (fig. 1) was created in SolidWorks and imported into EDEM 2017 as the test bench model. The parameters of the funnel and steel plate were obtained by testing and consulting the relevant literature (table 3).

Figure 10. Soil particle modeling process.

Table 3. Parameters used in modeling plastic funnel and steel plate.

Material	Poisson's Ratio	Shear Modulus (Pa)	Density (g cm ⁻³)
Plastic funnel	0.39	7.89×10^8	10.2
Steel plate	0.3	7.94×10^{10}	7.85

SETTING OF SIMULATION PARAMETERS

Soil particles have a certain viscosity due to the influence of their moisture content, electrostatic force, and other factors. To express the viscosity of the soil particles, we chose the “Hertz-Mindlin with Johnson-Kendall-Roberts” contact model (JKR) for the simulation (Johnson et al., 1971). In the simulation, the particle factory generated 60,000 particles at a rate of 3000 particles s⁻¹. The total simulation time was 22 s, the fixed time step was 20% of the Rayleigh time step, the data storage interval was 0.1 s, and the grid size was 2R.

SIMULATION AND VERIFICATION

SELECTION OF SIGNIFICANT PARAMETERS

Not all parameters in the discrete element simulation had a significant influence on the angle of repose. Parameters without a significant influence should not be calibrated based on the angle of repose; otherwise, the calibrated parameters would not be accurate (Guerrini et al., 2019; Moss et al., 2019). We used the Plackett-Burman design in Design-Expert 8.0.6 to select parameters with significant effects on the soil angle of repose. The parameters investigated included intrinsic soil parameters (shear modulus and Poisson's ratio), contact parameters (soil-soil restitution coefficient, soil-soil static friction coefficient, soil-soil rolling friction coefficient, soil-steel restitution coefficient, soil-steel static friction coefficient, and soil-steel rolling friction coefficient), and contact model parameters (JKR).

The relevant ranges of the parameter values were derived from published data on similar soils (Dai et al., 2017, 2019; Fang et al., 2016). The soil shear modulus varied from 1 to 10 MPa with a Poisson's ratio between 0.15 and 0.3, the soil-soil static friction coefficient varied between 0.30 and 0.70, the soil-soil rolling friction coefficient varied between 0.14 and 0.40, the soil-soil restitution coefficient varied between 0.20 and 0.60, the soil-steel static friction coefficient varied between 0.30 and 0.60, the soil-steel rolling friction coefficient varied between 0.04 and 0.20, and the soil-steel restitution coefficient varied between 0.28 and 0.60. Simulation of the preliminary experiments confirmed that the JKR value ranged from 0.01 to 0.1 J m⁻². The Plackett-Burman design factors are shown in table 4. There were nine factors, each having a low, intermediate, and high level. The test design and results are shown in table 5. Thirteen tests were conducted, and two additional factors (*K* and *L*) were included for error analysis.

Analysis of variance (ANOVA) was conducted using Design-Expert 8.0.6, and the effects of the nine parameters on the angle of repose were obtained (table 6). Parameters that significantly affected the angle of repose ($p < 0.05$) included soil shear modulus (factor *A*), JKR (factor *B*), and soil-soil restitution coefficient (factor *C*). These three parameters had a positive effect on the angle of repose, that is, the angle of repose increased with an increase in each of the parameters.

Table 4. Plackett-Burman design factors.

Factors and Definitions		Levels		
		-1	0	1
<i>A</i>	Soil shear modulus (MPa)	1	5.5	10
<i>B</i>	JKR (J m ⁻²)	0.01	0.055	0.1
<i>C</i>	Soil-soil restitution coefficient	0.2	0.4	0.6
<i>D</i>	Soil-soil friction coefficient	0.3	0.5	0.7
<i>E</i>	Soil-soil rolling friction coefficient	0.14	0.27	0.4
<i>F</i>	Soil-steel restitution coefficient	0.28	0.44	0.6
<i>G</i>	Soil-steel friction coefficient	0.3	0.45	0.6
<i>H</i>	Soil-steel rolling friction coefficient	0.04	0.12	0.2
<i>J</i>	Poisson's ratio of soil	0.15	0.225	0.3

Table 5. Plackett-Burman test design and results for soil angle of repose (factors *K* and *L* were included for error analysis).

Test	Factors											Angle of Repose
	<i>A</i>	<i>B</i>	<i>C</i>	<i>D</i>	<i>E</i>	<i>F</i>	<i>G</i>	<i>H</i>	<i>J</i>	<i>K</i>	<i>L</i>	
1	1	1	-1	1	1	1	-1	-1	-1	1	-1	43.8°
2	-1	1	1	-1	1	1	1	-1	-1	-1	1	38.9°
3	1	-1	1	1	-1	1	1	1	-1	-1	-1	42.1°
4	-1	1	-1	1	1	-1	1	1	1	-1	-1	29.7°
5	-1	-1	1	-1	1	1	-1	1	1	1	-1	29°
6	-1	-1	-1	1	-1	1	1	-1	1	1	1	30.1°
7	1	-1	-1	-1	1	-1	1	1	-1	1	1	36.1°
8	1	1	-1	-1	-1	1	-1	1	1	-1	1	38.8°
9	1	1	1	-1	-1	-1	1	-1	1	1	-1	43°
10	-1	1	1	1	-1	-1	-1	1	-1	1	1	33.8°
11	1	-1	1	1	1	-1	-1	-1	1	-1	1	41.8°
12	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	26.7°
13	0	0	0	0	0	0	0	0	0	0	0	39.1°

Table 6. ANOVA for Plackett-Burman test for soil angle of repose.

Source	Effect	Mean Square	p-Value
<i>A</i>	9.57	274.56	0.0031
<i>B</i>	3.7	41.07	0.0426
<i>C</i>	3.9	45.63	0.0373
<i>D</i>	1.47	6.45	0.2710
<i>E</i>	0.8	1.92	0.5161
<i>F</i>	1.93	11.21	0.1742
<i>G</i>	1	3	0.4265
<i>H</i>	-2.47	18.25	0.1086
<i>J</i>	-1.5	6.75	0.2625

STEEPEST CLIMBING TEST FOR OPTIMAL VALUE INTERVAL OF SIGNIFICANT PARAMETERS

The premise of using response surface analysis to establish a regression model for determining the optimal value of a parameter is that the optimal value is between the selected high and low levels of the parameter. The steepest climbing test can quickly determine the interval where the optimal value is located (Duineveld and Coenegracht, 1995; Yan and Yan, 2008; Yan et al., 2017). According to the results of the Plackett-Burman test design, only three significant parameters gradually increased with the selected step size (i.e., the parameter influence was positive): soil shear modulus (factor *A*), JKR (factor *B*), and soil-soil restitution coefficient (factor *C*).

The remaining parameters at their intermediate levels (soil-soil static friction coefficient of 0.5, soil-soil rolling friction coefficient of 0.27, soil-steel restitution coefficient of 0.44, soil-steel static friction coefficient of 0.45, soil-steel rolling friction coefficient of 0.12, and Poisson's ratio of 0.225) were chosen for the steepest climbing test. The relative error between the simulated soil angle of repose and the actual angle of repose was calculated. The test design and results are shown in table 6. Table 7 shows that as the soil shear modulus (factor *A*), JKR (factor *B*), and soil-soil

Table 7. Steepest climbing test design and results.

		Shear Modulus (MPa)	JKR (J m ⁻²)	Soil-Soil Restitution Coefficient	Angle of Repose (°)	Relative Error (%)
(1)	Plackett-Burman design level 0	5.5	0.055	0.4	-	-
(2)	Step in Plackett-Burman design	4.5	0.045	0.2	-	-
(3)	Slope of the model	4.78	1.85	1.95	-	-
(4)	(2) × (3)	21.51	0.08	0.39	-	-
(5)	Step length = (4) × 0.1 ^[a]	2.151	0.008	0.039	-	-
	Test group 1	5.5	0.055	0.4	37.6	2.6
	Test group 2	7.65	0.063	0.439	39.3	1.8
	Test group 3	9.8	0.071	0.478	39.9	3.4
	Test group 4	11.95	0.079	0.517	43.7	13.2
	Test group 5	14.1	0.087	0.556	46.2	19.7
	Test group 6	16.26	0.095	0.595	49	26.9

^[a] The 0.1 factor in (5) was determined experimentally based on process knowledge and other practical considerations (He et al., 2006).

restitution coefficient (factor *C*) increased, the simulated angle of repose increased continuously, and the relative error of the simulated angle of repose decreased and then increased. The relative error for the second group of tests was the smallest, so the optimal interval for the three significant parameters was near the level selected by the second group of tests. The relative error (e_r) was calculated as follows:

$$e_r = \frac{|A0 - A1|}{A0} \quad (5)$$

where *A0* is the actual angle of repose, and *A1* is the simulated angle of repose. Therefore, the selected surfaces of the first, second, and third groups of tests were selected for the response surface analysis. A regression model was established to determine the optimal value of the significant parameters.

BOX-BEHNKEN TEST DESIGN AND ANALYSIS

According to the results of the Plackett-Burman test, a three-factor and three-level Box-Behnken test was performed to obtain the relationship between the angle of repose and the three significant parameters (Fernandes et al., 2018). Table 8 shows the Box-Behnken test factors determined with Design-Expert 8.0.6, and table 9 shows the Box-Behnken test design and results. The three parameters with significant influence on the angle of repose were considered, i.e., soil shear modulus (factor *A*), JKR (factor *B*), and soil-soil restitution coefficient (factor *C*). The intermediate levels of the non-significant parameters were as follows: the soil-soil static friction coefficient was 0.5, the soil-soil rolling friction coefficient was 0.27, the soil-steel restitution coefficient was 0.44, the soil-steel static friction coefficient was 0.45, the soil-steel rolling friction coefficient was 0.12, and the soil Poisson's ratio was 0.225. Design-Expert 8.0.6 was used to establish the quadratic polynomial regression equation between the angle of repose and the three significant parameters:

$$\begin{aligned} \text{Angle of repose} = & 38.88 + 1.44A - 1.18B + 0.24C \\ & + 0.27AB + 0.85AC + 0.025BC \\ & + 2.09A^2 + 1.56B^2 - 0.91C^2 \end{aligned} \quad (6)$$

The coefficient of determination (R^2) was 0.9145, and the correction coefficient (R^2_{adj}) was 0.8046, which was close to 1. Table 10 shows the ANOVA results for the quadratic

polynomial regression model for soil angle of repose. The model p-value was 0.0054, while the lack-of-fit p-value was 0.0655. The model was well fitted with high reliability and can be used to predict the angle of repose.

As shown by the p-values for the interaction factors in table 10, the three interaction effects were not significant,

Table 8. Box-Behnken design factors.

Factors and Definitions		Levels		
		-1	0	1
<i>A</i>	Soil shear modulus (MPa)	5.5	7.65	9.8
<i>B</i>	JKR (J m ⁻²)	0.055	0.063	0.071
<i>C</i>	Soil-soil restitution coefficient	0.4	0.439	0.478

Table 9. Box-Behnken test design and results.

Test	Soil Shear Modulus (MPa)	JKR (J m ⁻²)	Soil-Soil Restitution Coefficient	Angle of Repose (°)
1	5.5	0.055	0.439	42.4
2	9.8	0.055	0.439	45.6
3	5.5	0.071	0.439	38.9
4	9.8	0.071	0.439	43.2
5	5.5	0.063	0.4	39.1
6	9.8	0.063	0.4	39.4
7	5.5	0.063	0.478	39
8	9.8	0.063	0.478	42.7
9	7.65	0.055	0.4	40.7
10	7.65	0.071	0.4	39
11	7.65	0.055	0.478	40.1
12	7.65	0.071	0.478	38.3
13	7.65	0.063	0.439	38.6
14	7.65	0.063	0.439	38.6
15	7.65	0.063	0.439	38.9
16	7.65	0.063	0.439	39.8
17	7.65	0.063	0.439	38.5

Table 10. ANOVA for Box-Behnken test of soil angle of repose using quadratic polynomial regression.

Source	Sum of Squares	Degrees of Freedom	Mean Square	p-Value
Model	63.45	9	7.05	0.0054
<i>A</i>	16.53	1	16.53	0.0031
<i>B</i>	11.05	1	11.05	0.0086
<i>C</i>	0.45	1	0.45	0.4892
<i>A</i> × <i>B</i>	0.30	1	0.30	0.5690
<i>A</i> × <i>C</i>	2.89	1	2.89	0.1072
<i>B</i> × <i>C</i>	0.0025	1	0.0025	0.9582
<i>A</i> ²	18.30	1	18.30	0.0023
<i>B</i> ²	10.25	1	10.25	0.0103
<i>C</i> ²	3.53	1	3.53	0.0807
Residual	5.93	7	0.85	-
Lack-of-fit	4.78	3	1.59	0.0655
Pure error	1.15	4	0.29	-
Sum	69.38	16	-	-

Figure 12. Response surface for the influence of JKR (*B*) and soil shear modulus (*A*) on angle of repose.

Figure 13. Response surface for the influence of soil-soil restitution coefficient (*C*) and shear modulus (*A*) on angle of repose.

and the corresponding response surfaces are shown in figures 12 to 14. The angle of repose first decreased and then increased with the increases in shear modulus and JKR, while the angle of repose increased before decreasing with the increase in the soil-soil restitution coefficient.

Previous studies (Haervig et al., 2017) pointed out that using a smaller shear modulus can reduce the simulation time. However, our results (table 10) showed that changes in the shear modulus affected the simulation of the angle of repose. Calibration of the soil particle shear modulus should be considered in future simulations. The interactions of the three factors were not significant, and the reason may be that each single factor had a large impact on the test results, resulting in a small effect of the factor interactions. In summary, the optimal parameter values determined by the response surface analysis were as follows: soil shear modulus of

Figure 14. Response surface for the influence of soil-soil restitution coefficient (*C*) and JKR (*B*) on angle of repose.

9.8 MPa, JKR of 0.063 J m^{-2} , and soil-soil restitution coefficient of 0.478. With these parameter values, the simulated angle of repose was almost equal to the actual value.

ANGLE OF REPOSE VERIFICATION TEST

To verify the optimal values of the three significant parameters, the three parameters were set to their optimal values (soil shear modulus = 9.8 MPa, JKR = 0.063 J m^{-2} , and soil-soil restitution coefficient = 0.478). The non-significant parameters were set to their intermediate levels (soil-soil static friction coefficient = 0.5, soil-soil rolling friction coefficient = 0.27, soil-steel recovery coefficient = 0.44, soil-steel static friction coefficient = 0.45, soil-steel rolling friction coefficient = 0.12, and soil Poisson's ratio = 0.225). The particle factory was set to generate 60,000 particles at a rate of $3000 \text{ particles s}^{-1}$. No particles were generated after 20 s. The total simulation time was 22 s (after 22 s, a small number of particles on the angle of repose surface began to roll, which did not affect the overall angle). The fixed time step was 20% of the Rayleigh time step, and the data storage interval was 0.1 s with a grid size of 2R. The soil angle of repose was simulated using EDEM 2017. The simulated angle of repose was 38.5° , the actual repose angle of 38.6° (measured using the apparatus shown in fig. 1), and the relative error was 0.26%.

In their simulation study, Qi et al. (2019) reported a relative error of 1.7% between simulated and actual angles of repose. The relative error in our study was 0.26%, which is better than the relative error reported by Qi et al. (2019). The main reason for this difference is the shape of the soil particles and our use of multi-sphere filling. Our results suggest that considering the shapes of the soil particles can increase the accuracy of the simulation. Coetzee (2016) also reported that the shapes of the particles affected the simulation results. The optimal values of the three significant parameters in our study were accurate and reliable. A comparison of an

Figure 15. Comparison of (a) actual test and (b) simulation of soil angle of repose.

actual test and simulation of the soil angle of repose is shown in figure 15. The outlines of the accumulated soil particles closely resemble each other.

VALIDATION WITH ROTARY TILLER

To further verify that the model (after parameter calibration) accurately reflected the dynamic characteristics of soil particles, we used a discrete element model to analyze soil movement during rotary tillage and compared the simulation with actual soil behavior. The accuracy of the discrete element model was determined by the throwing angle of the soil.

The simulated soil bed was 900 mm × 500 mm × 100 mm (length × width × height), and the particle parameters were as described in the previous section. The simulation time step was 20% of the Rayleigh time step. The simulation was performed for 10 s, and the data storage interval was 0.05 s. The particle factory produced 6.5×10^6 particles s^{-1} . Figure 16 shows the simulation results of the discrete element model.

SolidWorks was used to establish a three-dimensional model of a rotary tiller, and the blade of the tiller followed China Standard GB/T 5669-2017. To reduce the simulation time, a model with a length of 400 mm was established for the rotary tiller. This model was saved in x.igs format and imported into EDEM 2017 (fig. 17). The rotational speed of the tiller was 300 rpm (as measured in the field with an actual rotary tiller), the simulation time was 1 s, the simulation time step was 15% of the Rayleigh time step, and the data storage interval was 0.01 s. The simulation results are shown in figure 18, where images a to j show the movement of the soil every 0.01 s.

The results of a field test with an actual rotary tiller are shown in figure 19. The images were taken with a high-speed camera (TS4, Fastec Imaging, San Diego, Cal.). Images a to j were taken every 0.01 s, and a single tiller blade was selected to observe the movement of the soil under the

Figure 17. Rotary tiller simulation.

blade. The starting point was defined as the pixel in the lower left corner of the soil disturbance area under the selected blade, as shown by the origin of the blue axes in image a. The soil throwing angle is shown by the green angles in figures 18 and 19. The throwing angle error (e_t) was calculated as follows:

$$e_t = \frac{\min(P, S)}{\max(P, S)} \quad (7)$$

where P is the actual angle, and S is the simulated angle.

The throwing angle results are shown in figure 20. The throwing angle error (e_t) for images b to j was no greater than 10%. Due to factors such as tool modeling and rotational speed loss, the simulated throwing angle will have a certain error, but the overall macroscopic motion of the soil is the same. The throwing angle error is within the acceptable range, indicating that the calibration results of the relevant contact parameters were reliable.

CONCLUSION

Four representative soil particle shapes were identified with the improved GrabCut algorithm and k -means clustering. Accurate modeling of the four particle shapes was obtained by three-dimensional non-contact surface topography. Discrete element software (EDEM) was used to determine the parameters of the soil angle of repose based on response surface design and included a soil shear modulus of 9.8 MPa, JKR of 0.063 J m^{-2} , and soil-soil restitution coefficient of 0.478.

Figure 16. Simulated soil bed.

Figure 18. Simulation results of rotary tillage. Rotation is counter-clockwise.

Figure 19. Side view of rotary tiller during field test. Red machine is rotary tiller, and rotation is counter-clockwise.

Figure 20. Soil throwing angles derived from images b to j in figure 18 (simulation) and images b to j in figure 19 (field test).

Comparing the simulation and actual test results showed no significant difference between the simulated and actual angles of repose. The results showed that the soil parameter calibration was reliable, and the simulation accuracy was improved by soil shape modeling. The soil particle parameters calibrated with the actual angle of repose were also suitable for rotary tillage simulation. The error in soil throwing angle for the simulation was less than 10%. The parameters of the discrete element model were accurate and reliable.

The soil particle shapes were statistically analyzed using the improved GrabCut algorithm and *k*-means clustering. For particles with a large size range, manual segmentation requires much work, and there is a need to develop a faster particle statistical algorithm. The calculation accuracy was improved with response surface analysis and soil particle shape modeling. However, due to the influence of soil type and moisture content, accurate simulation of machine operation is still a challenge. In addition, due to the introduction of multiple particle shapes, the simulation time and complexity were greater than for spherical particles. Therefore, in the next step, we will simulate and analyze specific field scenarios and try to develop a parallel computing framework to improve the simulation speed with multiple particle shapes.

These results and conclusions are for a sandy loam soil. The moisture content of the soil was $5\% \pm 1\%$. Different soil types or different moisture contents will lead to different particle shapes and simulation parameters, which need to be studied according to their specific conditions.

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