

Construction of the discrete element bonding models for columnar granular organic fertilizers with different water contents

Longzhu Ke^{1,2†}, Quanchun Yuan^{1†}, Xiaolan Lyu¹, Jin Zeng^{1*}

(1. Institute of Agricultural Facilities and Equipment, Jiangsu Academy of Agricultural Sciences / Key Laboratory of Modern Horticultural Equipment, Ministry of Agriculture and Rural Affairs / Southern Orchard (Peach, Pear) Fully Mechanized Research Base, Ministry of Agriculture and Rural Affairs, Nanjing 210014, China;

2. School of Automation, Nanjing University of Information Science and Technology, Nanjing 211800, China)

Abstract: In order to construct a discrete element bonding model for columnar granular organic fertilizer with different moisture contents, this study calibrated the model parameters based on the Bonding model in the EDEM software. The maximum load-displacement data of the organic fertilizer were determined through uniaxial compression tests, establishing the relationship between moisture content and maximum load. Significant parameters were screened using the Plackett-Burman design, and parameter combinations were optimized through steepest ascent and Box-Behnken experiments. A mathematical model was established relating the maximum load to the Bonding parameters (normal stiffness, tangential stiffness, critical normal stress, critical tangential stress, and bonding radius) based on uniaxial compression simulation tests. Furthermore, a model was developed to predict the Bonding parameters based on the moisture content of the organic fertilizer, and the model's accuracy was verified through experimental validation. The results show that the average error of the maximum load predicted by the model is 1.98%, which allows for the accurate construction of the bonding model for slurry granular organic fertilizer with different moisture contents, laying a foundation for the simulation study of the interaction between organic fertilizer and working components.

Keywords: columnar granular organic fertilizer, crushing, bonding model, discrete element approach

DOI: 10.25165/ijabe.20261902.9921

Citation: Ke L Z, Yuan Q C, Lyu X, Zeng J. Construction of the discrete element bonding models for columnar granular organic fertilizers with different water contents. *Int J Agric & Biol Eng*, 2026; 19(2): 49–57.

1 Introduction

Organic fertilizer plays a crucial role in improving the physical and chemical properties of soil, increasing soil organic matter, enriching the soil, enhancing the soil's nutrient supply capacity for crops, and improving agricultural product quality^[1]. With the recent implementation of policies in China promoting the reduction and efficiency improvement of chemical fertilizers and the substitution with organic fertilizers, the application technology of organic fertilizers has gradually become a focus of research^[2-4]. Granular organic fertilizers are classified into spherical and columnar types^[5]; spherical granular organic fertilizers are prone to caking under high humidity, leading to issues such as clogging of fertilizer applicator components and uneven fertilization^[6]. In contrast, columnar granular organic fertilizers naturally stack, resulting in higher porosity between particles, which enhances permeability and reduces the tendency to cake. Compared with spherical granular organic fertilizers, columnar granular organic fertilizers are less

likely to adhere, making them more suitable for use in the complex and climate-variable agricultural environments^[7]. However, during the processes of transportation and spreading, columnar granular organic fertilizers are subject to varying degrees of mechanical damage, leading to particle breakage, which in turn affects the uniformity of fertilizer application^[8-10]. Therefore, this study will investigate the construction method of the discrete element bonding model for columnar granular organic fertilizers with different moisture contents, providing a basis for the design of transport and spreading mechanisms for columnar granular organic fertilizers.

The Discrete Element Method (DEM) is widely applied to processes involving bulk particulate materials, such as filling, transportation, stirring, mixing, and crushing^[11-13]. Potyondy et al.^[14] proposed a bonding particle model, using Bonding bonds to bind small particles and simulate crushing. Landry et al.^[15] developed a DEM model for organic fertilizers and calibrated its contact parameters through shear tests. Chen et al.^[16] and Yuan et al.^[17] established a simulation model for fertilizer clumps using the bonding contact model. They calibrated the bonding parameters of organic fertilizer through a combination of uniaxial compression physical tests and simulation tests, and verified the calibrated bonding parameters through load-displacement and deformation tests of organic fertilizer. These studies laid the foundation for the calibration of bonding parameters for columnar granular organic fertilizers, but the issue of quickly calibrating the bonding parameters when the moisture content of organic fertilizer changes has not yet been resolved.

To address the aforementioned issue, this study focuses on columnar granular organic fertilizers with different moisture contents, obtaining the basic parameters of the fertilizer's discrete

Received date: 2025-05-20 **Accepted date:** 2026-04-15

Biographies: Longzhu Ke, MS candidate, research interest: precision fertilization technology, Email: 202312570020@nuist.edu.cn; Quanchun Yuan, PhD, assistant researcher, research interest: intelligent nutrient diagnosis and precise fertilization technology equipment for orchards, Email: yuanquanchun@jaas.ac.cn; Xiaolan Lyu, PhD, Researcher, research interest: orchard mechanization technology and equipment, Email: xlanny@126.com.

†These authors contribute equally to this research.

***Corresponding author:** Jin Zeng, PhD candidate, Assistant Researcher, research interest: mechanisms of interaction between orchard mechanization and the environment. Institute of Agricultural Facilities and Equipment, Jiangsu Academy of Agricultural Sciences, Nanjing 210014, China. Tel: +86-18013832806, Email: j-zeng@jaas.ac.cn.

element through physical experiments. The maximum load-displacement data for columnar granular organic fertilizers with different moisture contents were obtained through uniaxial compression tests. By establishing a simulation model identical to the physical experiment, and utilizing the Plackett-Burman design, steepest ascent, and Box-Behnken experiments, the significant bonding model contact parameters affecting the maximum load were determined, and a mathematical model correlating the maximum load with these parameters was established. Finally, a predictive model was developed to relate the moisture content of the organic fertilizer to the bonding model contact parameters. The accuracy of the simulation parameters obtained through this model was validated through both physical and simulation experiments.

2 Materials and methods

2.1 Experimental materials

This study selected columnar granular organic fertilizers produced by MacroBio Biotechnology Co., Ltd. (Changzhou, China) as the research object. The main raw material is fermented and matured chicken manure, with an organic matter content of 45% or more and a total nutrient (N-P₂O₅-K₂O) content of 5%. This fertilizer is produced using an extrusion granulation process and takes on a cylindrical shape after drying and screening. To reflect the range of moisture content encountered during actual field application^[18], five different organic fertilizer samples were prepared, with moisture content ranging from 7.4% to 18.9%, as shown in Figure 1. Subsequently, discrete element simulation parameter measurement experiments were conducted on the moisture content of these five organic fertilizer samples.

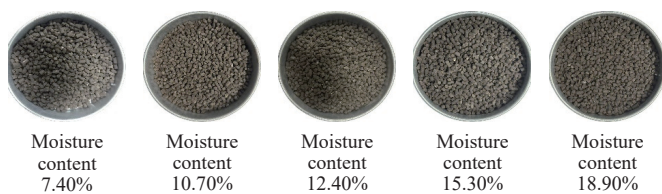


Figure 1 Organic fertilizer samples with different moisture content

A random sample of 200 column granules of organic fertilizer was selected, and their size parameters were measured using a Vernier caliper with an accuracy of 0.01 mm. As shown in Figure 2, the length of the organic fertilizer granules ranges from 6 to 15 mm, with an average diameter of 6 mm.

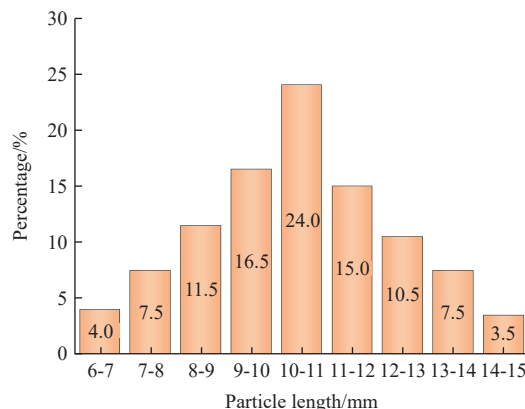


Figure 2 Distribution of organic fertilizer lengths

2.2 Measurement of column granule organic fertilizer parameters

2.2.1 Intrinsic parameter measurement

Density reflects the compactness of fertilizer accumulation^[19].

In this study, the density of the organic fertilizer was measured using the displacement method. First, a certain mass of fertilizer was weighed using a balance, and the mass of the fertilizer was recorded. Then, the fertilizer was poured into a graduated cylinder containing 100 mL of water, and the change in water level was quickly recorded after the addition of the fertilizer. This procedure was repeated 10 times. The density of the organic fertilizer was calculated using the following equation:

$$\rho = \frac{M}{V} \quad (1)$$

where, ρ represents the particle density, g/cm³; M is the mass of the fertilizer sample, g; and V is the volume of the fertilizer sample, cm³.

According to the standard for material compression performance measurement (GB/T 1041-2008)^[20], a texture analyzer (TMS-Pro) was used to perform a compression deformation test on the organic fertilizer. By measuring the axial and lateral deformations of the organic fertilizer before and after loading, its Poisson's ratio was calculated. During the experiment, axial compression was applied to the organic fertilizer at a rate of 0.1 mm/s, and loading was stopped when the granules fractured, as shown in Figure 3b. The Poisson's ratio can be calculated as,

$$\varepsilon = \frac{b/B}{l/L} = \frac{(H_1 - H_2)/B}{(A_1 - A_2)/L} \quad (2)$$

where, ε represents the Poisson's ratio of the organic fertilizer; B is the lateral deformation, mm; D is the diameter of the sample, mm; l is the axial deformation, mm; L is the length of the sample, mm; H_1 and H_2 are the lateral dimensions of the sample before and after compression, respectively, mm; A_1 and A_2 are the axial dimensions of the sample before and after compression, respectively, mm.

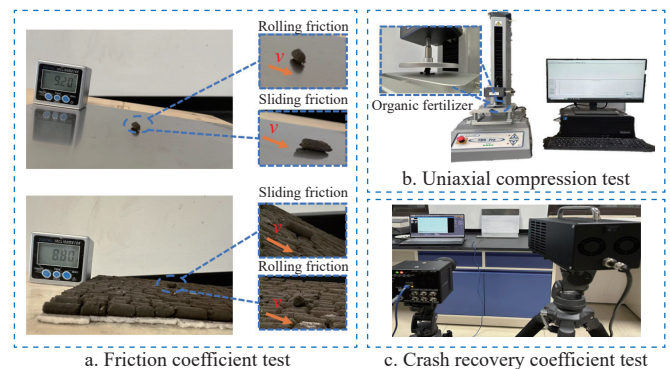


Figure 3 Discrete meta-parameter measurement test of organic fertilizer

The elastic modulus of the organic fertilizer sample can be calculated as^[21],

$$E = \frac{FL}{S\Delta l} \quad (3)$$

where, E represents the elastic modulus, MPa; F is the maximum pressure that the sample can withstand during the compression phase, N; S is the cross-sectional area of the sample, mm².

The intrinsic parameters of the Column organic fertilizer are listed in Table 1.

Table 1 Intrinsic parameters of columnar organic fertilizers

Test material	Poisson's ratio	Elastic modulus/MPa	Density/kg·m ⁻³
Column organic fertilizer	0.30	260	1000.32

2.2.2 Measurement of the coefficient of restitution

The coefficient of restitution characterizes the material's ability to recover after an impact^[22]. In this study, the device shown in Figure 3c (which includes a computer, grid paper, UX100 high-speed camera, and light source) was used to measure the coefficient of restitution between organic fertilizer granules and between the organic fertilizer and a steel plate. The UX100 high-speed camera has a maximum capture rate of 4000 frames per second, with an image resolution of 1280×1024 pixels, which meets the experimental requirements. Based on the measurement of the coefficient of restitution for materials in literature^[8], the release height of the organic fertilizer for testing was set to 200 mm. The high-speed camera recorded the free-fall process of the granules and their maximum rebound height. A total of 20 tests were conducted, with the vertical rebound height after impact selected as the valid data whenever possible. The formula for calculating the coefficient of restitution is as follows:

$$e = \sqrt{h_1/h_0} \quad (4)$$

where, e is the coefficient of restitution; h_1 is the maximum rebound height, mm; and h_0 is the release height of the granule, mm.

2.2.3 Measurement of the coefficient of friction

The coefficient of friction of granular organic fertilizer is determined by the properties and roughness of the contact surface^[23,24]. In this study, the inclined plane method was used for measurement. The experimental setup is shown in Figure 3a, which includes the inclined plane device, an inclinometer, a steel plate, and other equipment. It measures the static coefficient of friction between organic fertilizer particles and between organic fertilizer and the steel plate. The organic fertilizer is placed axially on the contact material, and the angle of the inclined plane device is gradually increased. The inclinometer is used to record the angle at which the organic fertilizer begins to slide. The experimental process is shown in Figure 3a. A total of 20 tests were conducted, and the static coefficient of friction can be calculated as,

$$\mu = \tan \theta \quad (5)$$

where, μ is the static coefficient of friction; and θ is the angle of the inclined plane, (°).

The experimental setup for measuring the rolling coefficient of friction is the same as that for measuring the static coefficient of friction. The organic fertilizer is placed transversely on the inclined plane, and the angle is gradually increased, recording the angle at the moment the organic fertilizer starts to move. The measured physical properties of the organic fertilizer are listed in Table 2.

Table 2 Range of physical property parameters of organic fertilizer granules

Moisture content/ %	Organic fertilizer and organic fertilizer			Organic fertilizer vs. steel plate		
	Collision recovery coefficient	Static friction coefficient	Rolling friction coefficient	Collision recovery coefficient	Static friction coefficient	Rolling friction coefficient
7.40	0.25-0.33	0.66-0.92	0.10-0.14	0.22-0.37	0.32-0.41	0.11-0.18
10.70	0.26-0.31	0.59-0.89	0.06-0.12	0.27-0.42	0.29-0.43	0.10-0.19
12.40	0.23-0.32	0.73-0.94	0.07-0.16	0.21-0.39	0.36-0.41	0.13-0.17
15.30	0.21-0.29	0.69-0.98	0.09-0.14	0.25-0.43	0.31-0.47	0.11-0.18
18.90	0.20-0.27	0.75-0.99	0.09-0.15	0.31-0.46	0.40-0.53	0.14-0.22

2.3 Modeling of columnar granular organic fertilizer

2.3.1 Bonding model

The column granule organic fertilizer model is composed of multiple small particles. To incorporate fracture characteristics into

the model, the Hertz-Mindlin with Bonding contact model^[25,26] is used in the EDEM2024 software. This contact model bonds the particles together using finite-sized bonding links and characterizes the mechanical properties of the column granule organic fertilizer through bonding parameters such as unit area normal stiffness, unit area tangential stiffness, critical normal stress, critical tangential stress, and bonding radius. The bonding breaks when the stress on the column granule organic fertilizer reaches the limit values of normal and tangential shear stress, as shown in Figure 4.

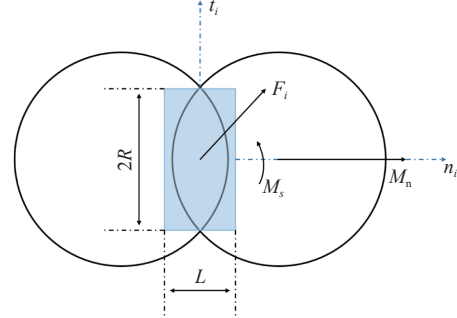


Figure 4 Hertz-Mindlin with bonding contact model

$$\begin{cases} \delta F_n = -v_n S_n A \delta t \\ \delta F_t = -v_t S_t A \delta t \\ \delta M_n = -\omega_n S_n J \delta t \\ \delta M_t = -\omega_t S_t \frac{J}{2} \delta t \end{cases} \quad (6)$$

in which,

$$\begin{cases} A = \pi R_B^2 \\ J = \frac{1}{2} \pi R_B^4 \end{cases} \quad (7)$$

where, δF_n is the normal force, N; δF_t is the tangential force, N; v_n is the normal velocity, m/s; v_t is the tangential velocity, m/s; S_n is the normal stiffness, N/m; S_t is the tangential stiffness, N/m; δt is the simulation time step, s; A is the contact area between particles, m²; δM_n is the normal torque, N·m; δM_t is the tangential torque, N·m; ω_n is the normal angular velocity, rad/s; ω_t is the tangential angular velocity, rad/s; J is the particle's moment of inertia, mm⁴; R_B is the bonding radius, mm.

When the force and torque reach their limit values or the distance between particles exceeds the set contact radius, the bonding link breaks. The formulas for calculating the normal and tangential shear forces are as follows:

$$\begin{cases} \sigma_{\max} < \frac{-F_n}{A} + \frac{2M_t}{J} R_B \\ \tau_{\max} < \frac{-F_t}{A} + \frac{M_n}{J} R_B \end{cases} \quad (8)$$

where, $\sigma_{\max}$ is the maximum normal shear force, N; and $\tau_{\max}$ is the maximum tangential shear force, N.

2.3.2 Discrete element modeling of fertilizer particles

The column granule organic fertilizer studied in this paper has a length range of 6 mm to 15 mm, with an average diameter of 6 mm. Fertilizer granules with an average length of 10 mm are selected for discrete element modeling. To study the crushing characteristics of the fertilizer granules, the Bonded Particle Method (BPM) is used to establish the discrete element model of the fertilizer particles (Figure 5). Multiple smaller spherical particles with equal diameters are bonded into a larger particle using Bond links^[16,27,28].

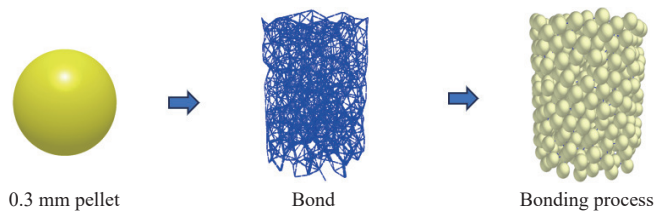


Figure 5 Particle bonding process

2.4 Uniaxial compression test

2.4.1 Physical tests

column granule organic fertilizer with a diameter of 10 mm is selected for the uniaxial compression test using a texture analyzer (TMS-Pro). Organic fertilizer particles with different moisture contents are tested at a loading speed of 0.5 mm/s until the sample fractures, at which point the loading is stopped. The loading process in the uniaxial compression test is shown in Figure 4. The test is repeated 20 times, and the average value is taken. The displacement-load curve of the fertilizer particles is shown in Figure 6.

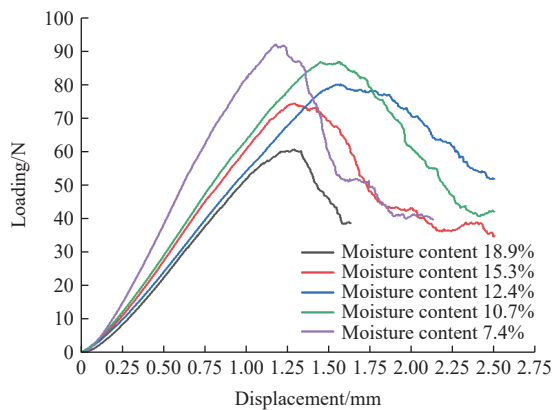


Figure 6 Displacement-load diagrams of organic fertilizers with different water content

2.4.2 Simulation test

The simulation parameters in the uniaxial compression test are listed in Table 2, with the contact parameters taken to be the median value common to each of their moisture content determination ranges. The intrinsic parameters of the organic fertilizer are listed in Table 1. The density of the steel plate is 7.85 g/cm^3 , the Poisson's ratio is 0.3, and the shear modulus is $7.9 \times 10^4 \text{ MPa}$. The uniaxial compression simulation test is shown in Figure 7. The upper and lower plates are made of steel, and they move at a constant speed of 30 mm/min to simulate the compression of the organic fertilizer block sample by the compression plates. The fixed time step is 10%, and the target save interval is 0.01 s. The lower plate is in a dormant state with no relative motion. The level value range of the bonding parameters for the column granule organic fertilizer is preliminarily determined based on references^[27-30].

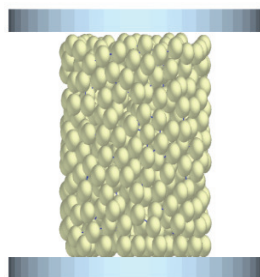


Figure 7 Uniaxial compression test simulation

2.5 Simulation parameter calibration

2.5.1 Plackett-Burman experiment

The Plackett-Burman experiment determines the significance of factors by examining the relationship between the objective response and the factors, and comparing the differences between the two levels of each factor^[29]. The maximum displacement Y_1 and maximum load Y_2 are taken as the objectives, while the unit area normal stiffness A , unit area tangential stiffness B , critical normal stress C , critical tangential stress D , and bonding radius E are the five factors for the Plackett-Burman experiment, with each factor selected at two levels. A Plackett-Burman design with $N=11$ is used, reserving six dummy terms for error analysis. The levels of the experimental factors are listed in Table 3.

Table 3 Plackett-Burman factor level table

Level	Unit area normal stiffness $A/(\text{N/m}^2)$	Unit area tangential stiffness $B/(\text{N/m}^2)$	Critical normal stress C/Pa	Critical tangential stress D/Pa	Bonding radius E/mm
-1	2.24×10^{10}	1.28×10^{10}	1.60×10^7	2.40×10^6	0.24
1	3.36×10^{10}	3.20×10^{10}	2.40×10^7	3.60×10^6	0.36

2.5.2 Steepest ascent experiment

The steepest ascent test helps to study the effect of factor levels on the evaluation target and further narrow the range of factor levels. Based on the results of the Plackett-Burman experiment, significant parameters are selected for the ascent experiment to further narrow the range of these significant parameters. In the simulation experiments, the values of non-significant parameters are taken from the median values in Table 3, while the values of significant parameters are determined according to the step sizes and directions of each parameter in the Plackett-Burman experiment results^[30].

2.5.3 Box-Behnken experiment

To obtain the optimal combination of bonding parameters, a four-factor, three-level Box-Behnken Design (BBD) experiment was conducted using Design-Expert 13 software based on the results of the steepest ascent experiment. The Box-Behnken experiment can fit the functional relationship between parameters and response values to determine the interactions between parameters^[27-31]. A solver is used to find the optimal values for the effective parameters. The values for significant parameters are determined based on the results of the steepest ascent experiment, while the values for non-significant parameters are taken from the median values of the Plackett-Burman experiment levels.

3 Results and discussion

3.1 Plackett-Burman test

The Plackett-Burman experimental plan and results are listed in Table 4. Analysis of variance (ANOVA) and t -tests for the effects of each factor were performed using Design-Expert 13 software, and the results are shown in Figure 8 and Table 5.

From Table 5 and Figure 8, it can be seen that the factors affecting the maximum displacement Y_1 , ranked from largest to smallest, are B , D , E , C , and A . The p values for B , D , and E are less than 0.05, indicating that these factors have a significant impact on the target. The same conclusion can be drawn from the t -value test of the Pareto Chart, where B and E have a positive effect on the target, while D has a negative effect on the target. Similarly, the factors affecting the maximum load Y_2 , ranked from largest to smallest, are E , D , B , A , and C , with p values for A , B , D , and E being less than 0.05, indicating a significant impact on the target.

The t -value test of the Pareto Chart also confirms the same conclusion, with E , D , A , and C having a positive effect on the target.

3.2 Steepest ascent test

Based on the results of the Plackett-Burman experiment, C has no significant effect on the results; therefore, C is set to 20 MPa. The initial values for factors A , B , D , and E are selected as 2.24×10^{10} N/m³, 3.2×10^{10} N/m³, 2.4×10^6 Pa, and 0.24 mm, respectively, with step sizes of 5.6×10^9 N/m³, -9.6×10^9 N/m³, 6×10^5 Pa, and 0.03 mm. A steepest ascent experiment is conducted to further find the parameter combination that approximates the true values. The steepest ascent experimental plan and results are listed in Table 5.

As can be seen from Section 1.4.1, the maximum load from the physical test of column granule fertilizer is 80.1 N (with a moisture content of 12.4%). According to Table 6, the error between the maximum load in the simulation test and the real value first decreases and then increases. Test 3 has the smallest error, so the parameters from Test 3 are used as the center point for subsequent

experiments, while the parameters from Tests 2 and 4 serve as the lower and higher levels, respectively, for further testing.

Table 4 Plackett-Burman test results

Test number	$A/\text{N} \cdot \text{m}^{-3}$	$B/\text{N} \cdot \text{m}^{-3}$	C/Pa	D/Pa	E/mm	Displacement/mm	Loading/N
1	2.24×10^{10}	3.20×10^{10}	2.40×10^7	3.60×10^6	0.36	1.21	80.50
2	2.24×10^{10}	1.28×10^{10}	1.60×10^7	3.60×10^6	0.24	2.05	62.81
3	2.24×10^{10}	3.20×10^{10}	2.40×10^7	2.40×10^6	0.24	1.01	40.60
4	3.36×10^{10}	1.28×10^{10}	2.40×10^7	2.40×10^6	0.36	1.44	86.90
5	3.36×10^{10}	3.20×10^{10}	1.60×10^7	3.60×10^6	0.24	1.29	60.02
6	2.24×10^{10}	3.20×10^{10}	1.60×10^7	2.40×10^6	0.36	1.04	62.21
7	3.36×10^{10}	1.28×10^{10}	2.40×10^7	2.40×10^6	0.24	1.63	56.71
8	2.24×10^{10}	1.28×10^{10}	1.60×10^7	2.40×10^6	0.24	1.57	50.53
9	3.36×10^{10}	3.20×10^{10}	2.40×10^7	3.60×10^6	0.24	1.29	60.21
10	3.36×10^{10}	3.20×10^{10}	1.60×10^7	2.40×10^6	0.36	0.97	63.94
11	3.36×10^{10}	1.28×10^{10}	1.60×10^7	3.60×10^6	0.36	1.75	98.01
12	2.24×10^{10}	1.28×10^{10}	2.40×10^7	3.60×10^6	0.36	1.76	93.31

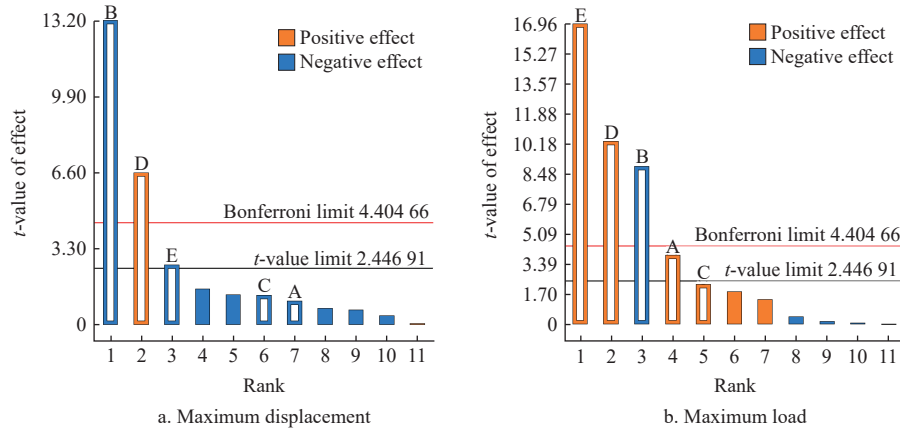


Figure 8 Pareto chart

Table 5 Significance analysis of Plackett-Burman test results

Source of variance	Y_1					Y_2				
	Square sum	Degree of freedom	Mean square	F	p	Square sum	Degree of freedom	Mean square	F	p
model	1.2500	5	0.2496	45.41	0.0001*	3402.40	5	680.48	98.84	<0.0001*
A	0.0061	1	0.0061	1.11	0.3336	105.61	1	105.610	15.34	0.0078*
B	0.9577	1	0.9577	174.21	<0.0001*	546.75	1	546.75	79.41	0.0001*
C	0.0091	1	0.0091	1.65	0.2462	35.36	1	35.36	5.14	0.0640
D	0.2380	1	0.2380	43.30	0.0006*	733.20	1	733.20	106.49	<0.0001*
E	0.0374	1	0.0374	6.80	0.0402*	1981.47	1	1981.47	287.80	<0.0001*
Residual	0.0330	6	0.0055			41.31	6	6.88		
Total	1.2800	11				3443.71	11			

Note: * Denotes significant difference ($p < 0.05$); same as below.

Table 6 Steepest ascent test program and results

Number	$A/\text{N} \cdot \text{m}^{-3}$	$B/\text{N} \cdot \text{m}^{-3}$	D/Pa	E/mm	Y_1/mm	Y_2/N
1	2.24×10^{10}	3.20×10^{10}	2.40×10^6	0.24	1.00	40.32
2	2.80×10^{10}	2.72×10^{10}	3.00×10^6	0.27	1.28	60.51
3	3.36×10^{10}	2.24×10^{10}	3.60×10^6	0.30	1.42	79.40
4	3.92×10^{10}	1.76×10^{10}	4.20×10^6	0.33	1.51	98.12
5	4.48×10^{10}	1.28×10^{10}	4.80×10^6	0.36	1.72	110.81
6	5.04×10^{10}	8.00×10^9	5.40×10^6	0.39	1.79	112.93

3.3 Box-Behnken test

Based on the results of the Plackett-Burman experiment, the Box-Behnken experimental plan and results are listed in Table 7, and Table 8 presents the analysis of variance.

The experimental results are analyzed using multiple linear regression with Design-Expert 13 software, with Y_1 and Y_2 as

response variables and A , B , D , and E as independent variables. A second-order polynomial equation is established to fit the maximum load displacement:

$$Y_1 = 1.79 - 3.33 \times 10^{-12} A + 1.36 \times 10^{-11} B + 1.03 \times 10^{-6} D - 13.27 \times E + 9.30 \times 10^{-23} AB - 1.49 \times 10^{-18} AD + 1.49 \times 10^{-11} AE(9) - 1.04 \times 10^{-17} BD - 8.68 \times 10^{-11} BE + 5.56 \times 10^{-7} DE + 4.52 \times 10^{-23} A^2 + 3.87 \times 10^{-22} B^2 - 1.07 \times 10^{-13} D^2 \quad (9)$$

$$Y_2 = 80.26 - 1.52 \times 10^{-10} A - 5.22 \times 10^{-10} B + 1.2 \times 10^{-5} D - 3.32 E + 1.02 \times 10^{-20} AB + 9.67 \times 10^{-17} AD + 2.97 \times 10^{-9} AE - 2.6 \times 10^{-16} BD - 4.51 \times 10^{-9} BE + 5 \times 10^{-5} CE + 6.48 \times 10^{-21} A^2 + 4.19 \times 10^{-20} B^2 - 1.9 \times 10^{12} D^2 + 642.59 E^2 \quad (10)$$

Analysis of variance (ANOVA) is used to assess the

significance of the model and the interaction between factors. The results are listed in Table 8. The F value for the Y_2 model is 72.94, and the p value is low (<0.0001), confirming the significance of the model at the 95% confidence level. The F value for the lack of fit term is 3.71, indicating that the lack of fit term is not significant relative to the pure error. The same applies to Y_1 .

The coefficient of determination (R^2) for the regression equation of Y_2 is 0.9867, indicating that 98.67% of the experimental variance is explained by the model, which shows a high fit with the actual data. The adjusted R^2 of 0.9735 is very close to 1, further indicating a high fit and good correlation with the actual data. The difference between R^2_{adj} and the predicted R^2 is less than 0.2, suggesting that the model fits well. The experimental coefficient of variation (CV) is 1.44%, indicating a high correlation between the actual and predicted values. The precision is 34.1108, indicating that the accuracy of the model is very good, making it suitable for predicting the maximum load of the organic fertilizer.

To ensure the validity of the regression model, its residuals need to be verified. Figure 9 shows the residual diagnostic plots of the model. Among them, Figure 9a is the residual normality test plot. All residuals fit along a straight line, with 85.7% of the residuals lying on the regression line, indicating that the model errors exhibit high randomness and meet the assumptions of normality and homoscedasticity. This suggests that the regression model is likely to reach an ideal state. Figure 9b shows the dispersion of the residuals within a range of ± 2.5 . The more dispersed the distribution, the better the predictive performance of the model. Figure 9c shows the fit between the predicted and actual maximum load values. The residuals are closely distributed around the regression line, and the coefficient of determination (R^2) reaches 0.9932, indicating that the model has a high predictive accuracy for the maximum load.

Table 7 Box-Behnken test program and results

Number	$A/N \cdot m^{-3}$	$B/N \cdot m^{-3}$	D/Pa	E/mm	Y_1/mm	Y_2/N
1	3.92×10^{10}	2.24×10^{10}	4.20×10^6	0.30	1.47	86.80
2	3.36×10^{10}	2.24×10^{10}	3.00×10^6	0.27	1.31	65.21
3	2.80×10^{10}	2.24×10^{10}	4.20×10^6	0.30	1.42	80.80
4	2.80×10^{10}	2.72×10^{10}	3.60×10^6	0.30	1.29	74.53
5	2.80×10^{10}	1.76×10^{10}	3.60×10^6	0.30	1.55	80.10
6	3.36×10^{10}	2.72×10^{10}	4.20×10^6	0.30	1.31	80.72
7	3.36×10^{10}	2.72×10^{10}	3.00×10^6	0.30	1.22	69.80
8	3.36×10^{10}	2.24×10^{10}	3.60×10^6	0.30	1.38	77.10
9	3.92×10^{10}	1.76×10^{10}	3.60×10^6	0.30	1.51	84.21
10	3.36×10^{10}	2.24×10^{10}	3.00×10^6	0.33	1.23	76.70
11	3.36×10^{10}	1.76×10^{10}	3.00×10^6	0.30	1.42	73.60
12	2.80×10^{10}	2.24×10^{10}	3.00×10^6	0.30	1.26	69.10
13	3.92×10^{10}	2.24×10^{10}	3.60×10^6	0.33	1.36	87.31
14	2.80×10^{10}	2.24×10^{10}	3.60×10^6	0.33	1.35	83.50
15	3.92×10^{10}	2.24×10^{10}	3.60×10^6	0.27	1.53	72.30
16	3.36×10^{10}	1.76×10^{10}	3.60×10^6	0.33	1.57	91.71
17	3.36×10^{10}	2.24×10^{10}	3.60×10^6	0.30	1.43	78.80
18	3.36×10^{10}	2.24×10^{10}	4.20×10^6	0.33	1.45	93.30
19	3.36×10^{10}	2.24×10^{10}	4.20×10^6	0.27	1.49	78.23
20	3.36×10^{10}	1.76×10^{10}	3.60×10^6	0.27	1.63	74.30
21	3.36×10^{10}	2.24×10^{10}	3.60×10^6	0.30	1.44	78.11
22	3.92×10^{10}	2.24×10^{10}	3.00×10^6	0.30	1.33	73.82
23	3.92×10^{10}	2.72×10^{10}	3.60×10^6	0.30	1.26	79.70
24	3.36×10^{10}	2.72×10^{10}	3.60×10^6	0.27	1.32	68.90
25	3.36×10^{10}	2.72×10^{10}	3.60×10^6	0.33	1.21	83.73
26	3.36×10^{10}	2.24×10^{10}	3.60×10^6	0.30	1.37	78.55
27	2.80×10^{10}	2.24×10^{10}	3.60×10^6	0.27	1.53	70.50
28	3.36×10^{10}	2.24×10^{10}	3.60×10^6	0.30	1.42	77.81
29	3.36×10^{10}	1.76×10^{10}	4.20×10^6	0.30	1.63	87.51

Table 8 Analysis of variances

Source of variance	Y_1					Y_2				
	Square sum	Degree of freedom	Mean square	F	p	Square sum	Degree of freedom	Mean square	F	p
model	0.3780	14	0.0270	14.7300	$<0.0001^*$	1322.8000	14	94.4900	74.3800	$<0.0001^*$
A	0.0003	1	0.0003	0.1637	0.6919*	54.6100	1	54.6100	42.9900	0.0251*
B	0.2408	1	0.2408	131.3800	$<0.0001^*$	96.9000	1	96.9000	76.2800	$<0.0001^*$
D	0.0833	1	0.0833	45.4600	$<0.0001^*$	521.4000	1	521.4000	410.4500	$<0.0001^*$
E	0.0341	1	0.0341	18.6200	0.0007*	627.8500	1	627.8500	494.2500	$<0.0001^*$
AB	0.0000	1	0.0000	0.0136	0.9087	0.3025	1	0.3025	0.2381	0.6331
AD	0.0001	1	0.0001	0.0546	0.8187	0.4225	1	0.4225	0.3326	0.5733
AE	0.0000	1	0.0000	0.0136	0.9087	1.0000	1	1.0000	0.7872	0.3899
BD	0.0036	1	0.0036	1.9600	0.1829	2.2500	1	2.2500	1.7700	0.2045
BE	0.0006	1	0.0006	0.3410	0.5686	1.6900	1	1.6900	1.3300	0.2681
DE	0.0004	1	0.0004	0.2182	0.6476	3.2400	1	3.2400	2.5500	0.1326
A^2	0.0000	1	0.0000	0.0071	0.9340	0.2682	1	0.2682	0.2111	0.6530
B^2	0.0005	1	0.0005	0.2813	0.6041	6.0500	1	6.0500	4.7600	0.0466*
D^2	0.0097	1	0.0097	5.2700	0.0377*	3.0400	1	3.0400	2.3900	0.1444
E^2	0.0017	1	0.0017	0.9537	0.3454	2.1700	1	2.1700	1.7100	0.2123
Residual	0.0257	14	0.0018			17.7800	14	1.2700		
Lack of fit	0.0218	10	0.0022	2.2500	0.2263	16.0500	10	1.6100	3.7100	0.1092
Total	0.4036	28				1340.0000	28			
R^2	0.9364					0.9867				
Adjusted R^2	0.8728					0.9735				
Predicted R^2	0.6741					0.9290				
Adeq precision	14.6141					34.1108				
CV	3.0500					1.4400				

As seen in Table 8, the factor terms A , B , D , and E have a highly significant effect on Y_2 (maximum load) ($p < 0.01$); the

quadratic term B^2 has a significant effect ($p < 0.05$). By ensuring the overall significance of the model and removing insignificant terms,

the second-order regression model can be optimized, resulting in the following regression equation for the maximum load:

$$Y_2 = 80.26 - 1.52 \times 10^{-10} A - 5.22 \times 10^{-10} B + 1.2 \times 10^{-5} D - 3.32E + 642.59E^2 \quad (11)$$

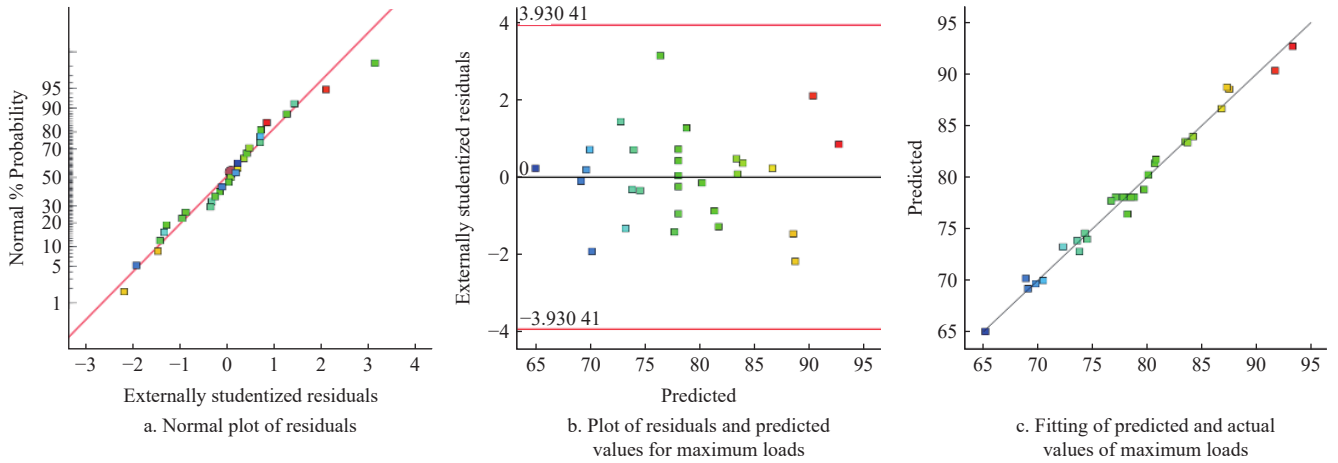


Figure 9 Residual diagnostics for the second-order regression model

3.4 Construction of the moisture content-bonding parameter model

The physical test results show that organic fertilizers with moisture content ranging from 7.8% to 18.5% can form a stable and measurable maximum load. As shown in Figure 6, there is no obvious linear relationship between the maximum displacement and the moisture content of the fertilizer, and the maximum displacement is around 1.38 ± 0.20 . Therefore, in this study, a mathematical model relating the moisture content of the organic fertilizer to the maximum load was established through six sets of physical experiments. The curve fitting was determined with a coefficient of determination R^2 of 0.9921, as shown in Figure 10.

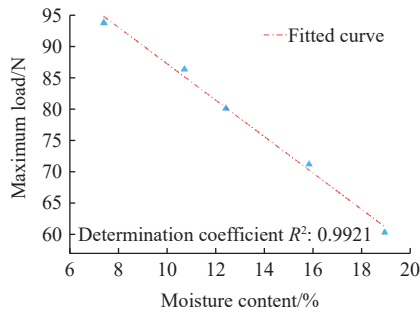


Figure 10 Fertilizer moisture content versus maximum load curve

Within this range of moisture content, as the moisture content of the fertilizer increases, the breaking force decreases. The linear fitting equation is as follows:

$$Y = -2.9M + 116.193 \quad (12)$$

Combining Equations (11) and (12), the relationship model between the moisture content of the organic fertilizer and the bonding parameters is as follows:

$$M = 12.39 + 5.2 \times 10^{-11} A + 1.8 \times 10^{-10} B(13) - 4.1 \times 10^{-6} D - 1.15E - 2.221.58E^2 \quad (13)$$

3.5 Model validation

3.5.1 Maximum load bonding parameter model validation

To verify the reliability of the maximum load and bonding parameter contact model, physical experiments were conducted with five sets of organic fertilizers at different moisture contents. Using the maximum load as the validation criterion, the bonding parameters of the fertilizer (A , B , D , E) were optimized and

calibrated using Design-Expert 13 software. The results are listed in Table 9.

Table 9 Optimum values of bonding parameter and experimental results of organic fertilizers at different water contents

Moisture content/%	Maximum load/N	$A/N \cdot m^{-3}$	$B/N \cdot m^{-3}$	D/Pa	E/mm
7.40	93.73	2.98×10^{10}	1.86×10^{10}	4.17×10^6	0.33
10.70	86.30	3.88×10^{10}	2.57×10^{10}	3.60×10^6	0.33
12.40	80.10	3.85×10^{10}	2.42×10^{10}	3.69×10^6	0.30
15.30	71.20	3.27×10^{10}	2.23×10^{10}	3.45×10^6	0.28
18.90	60.41	2.81×10^{10}	2.65×10^{10}	3.00×10^6	0.27

Figure 11 shows a comparison between the maximum load physical tests and simulation test results. The red dashed line and red shaded area represent the maximum load physical test results and their 95% confidence interval, while the blue error bars represent the maximum load simulation test results. The yellow dashed line represents the relative error between the simulation and physical tests. From the figure, it can be seen that the results of the five simulation tests all fall within the confidence interval, and the overall relative error increases as the moisture content of the fertilizer increases. The main reason for this is that the internal space of the organic fertilizer particles becomes loose or expands at higher moisture content, leading to structural damage. Overall, the prediction error for the maximum load is distributed around 3%, with an average value of 1.98%. The overall error is small, indicating that the maximum load and bonding model parameters have good reliability.

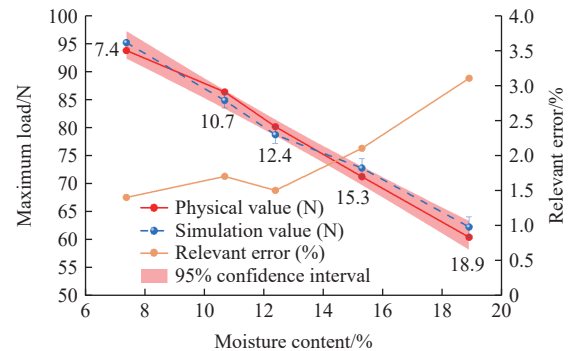


Figure 11 Comparison of maximum loads for physical and simulation tests

3.5.2 Moisture content-bonding parameter model validation

To validate the accuracy and applicability of the established moisture content and bonding parameter prediction model, 20 organic fertilizer samples with moisture contents ranging from 7.6% to 18.9% were randomly prepared. The maximum load for samples with different moisture contents was obtained using the physical testing method described in Section 1.4.1. The moisture content and bonding parameter prediction model established in Design-Expert

13 software was used. By inputting the maximum load corresponding to the moisture content into the solver, the optimal bonding parameter values for the given moisture content of the organic fertilizer were obtained. A simulation experiment was then conducted with these optimal parameter values to obtain the simulated maximum load. The comparison between the physical and simulation test results for the maximum load is shown in Figure 12.

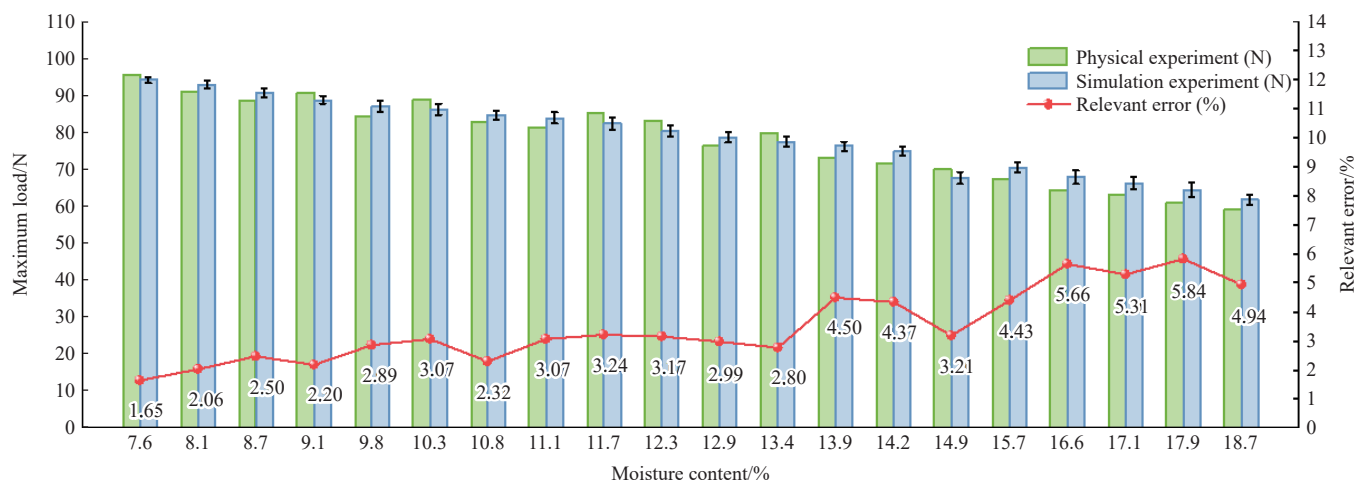


Figure 12 Comparison of maximum loads in physical and simulation tests

The overall trend of the relative error in maximum load prediction increases as the moisture content of the organic fertilizer increases. When the moisture content is below 13.40%, the average relative error of the predicted resting angle is 2.66%; for moisture contents of 13.90% and above, the average relative error is 4.82%. Overall, the average relative error for the 20 experiments is 3.51%, and the error line length variation in the predicted maximum load data is small, indicating more stable predictions. Therefore, the established moisture content and bonding parameter model is stable and reliable.

4 Conclusions

1) Physical experiments were conducted to obtain the moisture content range (7.40%-18.90%), length and diameter averages of 10 mm and 6 mm, density of 1000.32 kg/m³, Poisson's ratio of 0.30, elastic modulus of 260 MPa, and the coefficient of restitution, static coefficient of friction, and kinetic coefficient of friction for column granule organic fertilizers with different moisture contents and between the organic fertilizer and steel plate. The Hertz-Mindlin bonding model was used to establish a model for column granule organic fertilizer with a length of 10 mm.

2) Maximum load data for organic fertilizers at different moisture contents were obtained through uniaxial compression tests. The significant parameters affecting the maximum load of organic fertilizer and their optimal range were determined by combining the Plackett-Burman experiment and the steepest ascent experiment. A moisture content and bonding parameter model was established using the Box-Behnken design. The experimental results show that the model predicts the maximum load of organic fertilizer with moisture content ranging from 7.40% to 18.90%, with an average relative error of 3.51%. This indicates that the developed discrete element bonding parameter prediction model has high accuracy across a wide range of moisture contents.

3) The Hertz-Mindlin bonding contact mechanics model used in this study can accurately represent the characteristics of organic

fertilizer particles at low moisture contents. However, its accuracy significantly decreases at higher moisture contents. Therefore, future research will explore the use of a coupling between the Hertz-Mindlin bonding contact model and the JKR contact model to study organic fertilizers with higher moisture content ranges. The aim is to develop a discrete element bonding contact mechanics model suitable for various moisture content levels. This will address the issue of poor applicability of the discrete element bonding contact parameters due to changes in moisture content.

Acknowledgements

This research was funded by the National Key Technology Research and Development Program of China (Grant No. 2023YFD1702200) and China Agriculture Research System of MOF and MARA (Grant No. CARS-28-21).

[References]

- [1] Han J Q, Dong Y Y, Zhang M. Chemical fertilizer reduction with organic fertilizer effectively improve soil fertility and microbial community from newly cultivated land in the loess plateau of China. *Applied Soil Ecology*, 2021; 165: 103966.
- [2] Yuan Q C, Xu L M, Niu C, Ma S, Yan C G, Zhao S J, et al. Development of layered backfill device for organic fertilizer deep application machine soil fertilizer mixture in orchard. *Transactions of the CSAM*, 2021; 37(5): 11–19. (in Chinese)
- [3] Tang H, Wang J W, Xu C S, Zhou W Q, Wang J F, Wang X. Research progress analysis on key technology of chemical fertilizer reduction and efficiency increase. *Transactions of the CSAM*, 2019; 50(4): 1–19. (in Chinese)
- [4] Li N, Tian Y L, Zhang L, Wang S T, Zhu C X, Li H N. Research on action and technology for reducing fertilizer usage and enhancing efficiency in China. *Journal of Agricultural Resources and Environment*, 2025; 42(1): 1–10. (in Chinese)
- [5] Huan X L, Feng M C, Wu C Y, Jia J M, Chen J N. Construction and experiment of discrete element model for tea garden soil-organic fertilizer mixture based on EDEM. *Transactions of the CSAM*, 2025; 56(12): 267–278. (in Chinese)
- [6] Xiao W L, Liao Q X, Liao Y T, Wang L, Wan X Y. Discrete elemental

- parameter calibration of the bonding model for caking compound fertilizer utilized in oilseed rape mechanized direct seeding. *Int J Agric & Biol Eng*, 2025; 18(4): 17–25.
- [7] Niu Z Y, Liu M, Niu W J, Shao K Y, Geng J, Tang Z, et al. Effects of biochar fertilizer ratio and bentonite binder on physicochemical properties and slow release properties of biochar fertilizer particles. *Transactions of the CSAE*, 2020; 36(2): 219–227. (in Chinese)
- [8] Zhang H J. Key technology and experimental research on two-row open furrow fertiliser applicator for modern apple orchards. PhD dissertation. Tai'an: Shandong Agricultural University, 2021; 129p. doi: [10.27277/d.cnki.gsdnu.2021.000032](https://doi.org/10.27277/d.cnki.gsdnu.2021.000032). (in Chinese)
- [9] Juodišius G, Zinkevičienė R, Jotautienė E, Karayel D, Mieldažys R. Investigation of granular organic fertilizer distribution uniformity in disk-type spreaders with standard and modified vane configurations. *Applied Sciences*, 2025; 15(24): 13076.
- [10] Chen M, Jian Z, Cao L W, Yin H, Zhang C, Li C S, et al. Mechanistic investigation of granular organic fertilizer discharge performance in a concentric twin-shaft screw assembly using DEM. *Powder Technology*, 2026; 474: 122307.
- [11] Wang X, Yu J, Lv F, Wang Y, Fu H. A multi-sphere based modelling method for maize grain assemblies. *Advanced Powder Technology*, 2017; 28(2): 584–595.
- [12] Gallego E, Fuentes J M, Wiącek J, Villar J R, Ayuga F. DEM analysis of the flow and friction of spherical particles in steel silos with corrugated walls. *Powder Technology*, 2019; 355: 425–437.
- [13] Chen G B, Wang Q J, Li W Y, He J, Li H W, Yu C C. Design and experiment of double roller differential speed crushing fertilizer device for block organic fertilizer. *Transactions of the CSAM*, 2021; 52(12): 65–76. (in Chinese)
- [14] Potyondy D O, Cundall P A. A bonded-particle model for rock. *International Journal of Rock Mechanics and Mining Sciences*, 2004; 41(8): 1329–1364.
- [15] Landry H, Thirion F, Laguë C, Roberge M. Numerical modeling of the flow of organic fertilizers in land application equipment. *Computers and Electronics in Agriculture*, 2006; 51(1): 35–53.
- [16] Chen G B, Wang Q J, Li H W, He J, Lu C Y, Xu D J, et al. Experimental research on a propeller blade fertilizer transport device based on a discrete element fertilizer block model. *Computers and Electronics in Agriculture*, 2023; 208: 107781.
- [17] Yuan Q C, Xu L M, Ma S, Niu C, Wang S S, Yuan X T. Design and test of sawtooth fertilizer block crushing blade of organic fertilizer deep applicator. *Transactions of the CSAE*, 2020; 36(9): 44–51. (in Chinese)
- [18] Liu H, Lu Q, Wang J, Wang N. Rapid calibration method for discrete element simulation parameters of columnar granular organic fertilizer with variable moisture content. *Powder Technology*, 2024; 448: 120354.
- [19] Fang M, Yu Z H, Zhang W J, Cao J, Liu W H. Friction coefficient calibration of corn stalk particle mixtures using Plackett-Burman design and response surface methodology. *Powder Technology*, 2022; 396: 731–742.
- [20] GB/T 1041–2008. Plastics-determination of compressive properties. Standardization Administration of China, 2008. (in Chinese)
- [21] Zhao W S, Chen M J, Xie J H, Cao S L, Wu A B, Wang Z W. Discrete element modeling and physical experiment research on the biomechanical properties of cotton stalk. *Computers and Electronics in Agriculture*, 2023; 204: 107502.
- [22] Zhang H J, Cheng X B, Li H L, Tian Y, Fan G Q, Xu J S, et al. Simulated contact parameters calibration and experiment of controlled-release fertilizer particles. *Transactions of the CSAM*, 2024; 55(6): 80–90. (in Chinese)
- [23] Li D H. Experimental study of centrifugal spreading disc fertilizer spreader. Master dissertation. Jiangsu: Nanjing Agricultural University, 2022; 88p. doi: [10.27244/d.cnki.gnjnu.2022.001319](https://doi.org/10.27244/d.cnki.gnjnu.2022.001319). (in Chinese)
- [24] Sun Y K. Design and experiment of vertical organic fertilizer spiral spreading device. Master dissertation. Harbin: Northeast Agricultural University, 2022; 56p. doi: [10.27010/d.cnki.gdbnu.2022.000334](https://doi.org/10.27010/d.cnki.gdbnu.2022.000334). (in Chinese)
- [25] Zhao P F, Jia X, Bi Y B, Song Q B, Gao X J, Yang Y W, et al. Simulation analysis of the influence of front-mounted fertilizer pipe on distribution uniformity in strip rotary tillage-fertilization device. *Results in Engineering*, 2025; 28: 107341.
- [26] Duan J P, Liu D W, Xie F P, Zhang Y R, Zheng P. Breakage simulations and experiments of granular fertilisers for optimizing a device of side-deep fertilisation by using the discrete element method. *Biosystems Engineering*, 2024; 238: 105–114.
- [27] Du X, Liu C L, Jiang M. Calibration of bonding model parameters for coated fertilizers based on discrete element method. *Transactions of the CSAM*, 2022; 53(7): 141–149. (in Chinese)
- [28] Wang L, Zhang Y L, Lu W Q, Yang L, Liu X P. Bonding parameter calibration and crushing process analysis of pellet feed based on discrete element method. *Feed Industry*, 2023; 44(1): 10–17. (in Chinese)
- [29] Wang L M, Fan S Y, Cheng H S, Meng H B, Shen Y J, Wang J, et al. Calibration of contact parameters for pig manure based on EDEM. *Transactions of the CSAE*, 2020; 36(15): 95–102. (in Chinese)
- [30] Bai J Y, Xie B, Yan J G, Zheng Y, Liu N, Zhang Q. Moisture content characterization method of wet particles of brown rice based on discrete element simulation. *Powder Technology*, 2023; 428: 118775.
- [31] Tu M, Cao T, Wan Z H, Mo H T, Zhang G Z. Calibration and shear experiments of discrete element bonding parameters for water caltrop. *Journal of Huazhong Agricultural University*, 2023; 42(4): 270–278. (in Chinese)