

Article

Simulation Analysis and Multiobjective Optimization of Pulverization Process of Seed-Used Watermelon Peel Pulverizer Based on EDEM

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Abstract: To enhance the utilization of seed-used watermelon peel and mitigate environmental pollution, a hammer-blade seed-used watermelon peel crusher was designed and manufactured, and its structure and working parameters were optimized. Initially, the seed-used watermelon peel crusher and seed-used watermelon peel model were constructed, and the model's parameters were calibrated. Subsequently, the discrete element method (EDEM2022) was employed to investigate the effects of spindle speed (MSS), the number of hammers (NCB), and feeding volume (FQ) on the pulverizing process. Multivariate nonlinear regression prediction models were developed for the percentage of pulverized particle size less than 8 mm (P_{sv}), pulverizing efficiency (G_e), and power density (P_{pd}), followed by the analysis of influencing factors and prediction models using ANOVA. The multiobjective optimization of the prediction model utilizing the improved hybrid metacellular genetic algorithm CellIDE resulted in solutions of 90.02%, 89.57%, and 8.35×10^{-3} t/(h-kw) for P_{sv-opt} , G_{e-opt} , and P_{pd-opt} , respectively. The corresponding optimal interaction values of MSS, NCB, and FQ were determined to be 1500 r/min, 108, and 150 kg/min. Finally, a prototype test was conducted by combining the optimal factor interaction values, yielding statistically calculated values of 96.63%, 92.37%, and 7.76×10^{-3} t/(h-kw) for P_{sv-pr} , G_{e-pr} , and P_{pd-pr} , respectively. The results indicate that the optimized values of P_{sv-opt} , G_{e-opt} , and P_{pd-opt} models have an error of less than 8% compared to the statistically calculated values of the prototype test and outperform the values of P_{sv-ori} , G_{e-ori} , and P_{pd-ori} obtained under the original parameters.

Keywords: hammer grinder; EDEM2022; multiobjective optimization; power density; prototype experiment



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1. Introduction

The seed-used watermelon, an annual herb of the Cucurbitaceae family, originates from the Kalahari Desert in southwestern Africa and was brought to China through the Silk Road during the Tang Dynasty. It currently covers over 80% of the planting area in the country and contributes more than 90% to the national total output, making it the world's leading producer. Its cultivation is primarily concentrated in the arid northwestern regions of China, including Gansu, Ningxia, Qinghai, Xinjiang, and Inner Mongolia [1–3]. The seed-used watermelon peel is abundant in essential amino acids, vitamins, and various crucial nutritional trace elements. It can be utilized as dietary fiber, as well as a feed for

poultry and a raw material for deep processing products. The seed-used watermelon primarily comprises three parts: the rind, flesh, and seeds. The rind bears resemblance in shape to that of a watermelon, while the flesh of the seed melon appears white or yellowish. Currently, seed-used watermelons are primarily used for extracting seeds and flesh to produce seed-used watermelon water, juice, and other products, while the peel, which constitutes 25% of the weight of seed-used watermelon peel, is often discarded in fields and river gullies, leading to environmental pollution and resource wastage [4]. The crushing of seed-used watermelon peel is a crucial step in the deep processing of seed-used watermelon due to its high water and cellulose content, which makes the refinement process more challenging. Currently, there is limited research on the crushing of melon peel materials both domestically and internationally. Thus, the comprehensive development and utilization of seed melon hold great significance for its industrial development.

It seems there is a lack of research on melon peel material crushers compared to extensive research on crushers for fruits and vegetables. Xu et al. [5] developed a simulation method for a straw-crushing process using the discrete element method (DEM). The study deduced differential equations for the movement of straw particles on the hammer, integrating force and kinematics analyses. This led to deriving the formation mechanism of the material circulating layer. A one-factor simulation test was conducted using EDEM2022 software to determine the impact of the hammer quantity, hammer thickness, and the gap between the hammer and sieve on particle crushing and energy consumption. However, the study did not account for the interaction of these factors. In their research, Ya et al. [6] investigated the impact of several parameters, such as the distance between the hammer blade and the screen, the material and distribution density of the hammer blade, and the rotational speed of the main shaft, on the size of straw-crushing particles. Their study primarily focused on the theoretical analysis and factors influencing the size of straw crushing. They also proposed an overall design scheme for the crushing chamber. However, the study did not present a clear optimization plan for enhancing crushing efficiency and reducing power consumption. Iskenderov R et al. [7] developed a horizontal impact crusher and conducted multifactorial experiments to ascertain the optimal design and operational parameters. They suggested that the designed impact crusher is versatile and can crush various types of feeds by adjusting the operating parameters. Additionally, it was reported that the energy consumption per unit could be reduced by 50%. However, the study did not precisely define the optimum parameter values for crushing various types of feeds. Zhang, T. et al. [8] utilized the Hertz-Mindlin and Bonding contact model to develop multiple particle replacement and bonding programs using Visual Studio. These programs were integrated into EDEM to create a model for crushing corn stover, which underwent parameter calibration. The accuracy of the numerical computation of the discrete elements was enhanced by refining the physical parameters and the model structure. Subsequently, the error of the proposed DEM model for corn stover, incorporating optimal parameter combinations, was confirmed to be within acceptable limits through experimental testing. Zhai and colleagues [9] developed a functional model for fatigue fracture failure, hammer blade wear failure, and resonance failure modes commonly found in feed crushers. They computed the marginal distribution function for each failure mode and established a reliability model for the hammer rotor under multiple failure modes based on their correlation. By optimizing the structure and operational parameters, they enhanced the reliability of the silage crusher. The absence of consideration for the optimization method in the process of multiobjective optimization in the aforementioned studies could compromise the authenticity of the optimization results. Zhang and colleagues [10] employed the acoustic–solid coupling method to numerically predict the combined air and mechanical noise of the forage crusher, enabling the identification of the primary noise sources. The feasibility of the numerical prediction method for the coupled noise of the forage crusher was verified, and the prediction results were validated through tests, establishing their credibility. While the results offer insights for low-noise grass crusher design, the crushing performance of the grass crusher has not been correspondingly investigated and analyzed.

Marczuk, A. et al. [11] presented a design for a rotary centrifugal grain mill aimed at addressing issues related to uneven particle size distribution and high dust content in milled products. They utilized a multifactor experimental method to construct a prediction model of factors and indicators, enabling the determination of optimal parameter combinations. The reasonableness of these parameters was validated through operational experiments. However, the study did not delineate a specific method for multiobjective optimization. Wang and colleagues [12] endeavored to enhance the operational efficiency of the hammer mill by designing hammer blades with both tip and slant hammer shapes. They utilized a blend of the discrete element method (DEM) and experimental techniques to explore the crushing processes of corn particles using different hammerheads. The study found that the experimental results align with the simulation outcomes and theoretical analysis, indicating that the tip and slant hammers can enhance the mill's working performance. Furthermore, the findings can serve as a valuable reference for designing new types of hammerheads and simulating the crushing process of various agricultural materials. O.C. Chukwuezie and colleagues [13] examined the comminution performance of a hammer mill for three different materials, focusing on the modified hammer blades' shape and arrangement. Mugabi R. and team [14] assessed the hammer mill performance using a modified central composite design (CCD) hierarchical design of experiments to determine optimal operational conditions. Braun Michaela and colleagues [15] conducted a study to analyze the impact of hammer mill tip speed, auxiliary airflow, and sieve diameter on hammer mill throughput and maize-crushing characteristics.

For the research and analysis of a crusher's crushing mechanism, the crushing mechanism of ore and coal crushers can also be studied with reference to the crushing mechanism of ore and coal crushers. For example, Chen Z, et al. [16] combined the use of the discrete element method (DEM) and the response surface method to construct a prediction model for the crushing performance of an ore crusher, optimized the prediction model using the Matlab toolbox, and verified the model experimentally. Quist et al. utilized the discrete element method (DEM) to optimize the particle size distribution of ore in a cone crusher's crushing chamber. They employed a bonded particle model [17,18] and compared the results with the experimental values. It can be concluded that the particle size distribution of the simulated particles is consistent with the experimental values within an acceptable error range. Wu F et al. [19] developed a mathematical model to optimize both the productivity and product quality of a cone crusher. They investigated the influence of key parameters on the crusher's performance and simulated the dynamic characteristics of the C900 cone crusher using the discrete element method (DEM). The simulation results were largely consistent with the numerical analysis results. Cheng J. et al. [20] developed a real-time dynamic model using multibody dynamics (MBD) and the discrete element method (DEM) to investigate the crushing performance of a steel slag crusher. They examined how the fixed cone mass and the moving cone mass impact the operational crushing force, amplitude, and average power consumption.

Previous researchers have made some improvements in the methods and conclusions regarding the crushing performance of crushers. However, their focus has mostly been on a single factor or indicator, with limited attention given to the simultaneous consideration of multiple indicators in the research. The research on the pulverizing performance of seed-used watermelon peel pulverizing machinery is lacking. Therefore, this paper draws on and refers to the crushing mechanism of fruits and vegetables, materials, and ore crushing and incorporates viscoelastic theory to conduct research and exploration. This study analyzed the crushing process of watermelon rind using a hammer-type pulverizer as its specific focus. The physical and mechanical properties of the watermelon rind were determined through experimental testing, and the model parameters for the watermelon rind were calibrated. The entire comminution performance of the machine, including the percentage of particle sizes less than 8 mm (P_{sv}), comminution efficiency (G_e), and power density (P_{pd}), was analyzed using the EDEM2022 simulation method. The study explored the impact of spindle speed (MSS), the number of hammers (NCB), and feeding

amount (FQ) on the comminution performance and established a predictive model for the pulverizing performance of the pulverizer. Subsequently, the multiobjective optimization of the comminution performance was conducted using the improved hybrid metacellular genetic algorithm, CellDE. Finally, the validation of the optimization results was confirmed through EDEM2022 simulations and prototype testing.

2. The Calibration of the Model Parameters of Seed-Used Watermelon Peel and the Construction of the Simulation Model

In order to establish an accurate discrete element model of seed-used watermelon peel, the TA.XT plus-type mass tester (including computer mainframe, computer monitor, vernier calipers, knife, thermometer, hygrometer, and electronic balance) was mainly used to conduct two kinds of tests, namely, puncture and TPA cyclic compression tests on each structural layer of seed-used watermelon peel to derive the parameters of the mechanical properties of each structural layer of seed-used watermelon peel. Secondly, the simulation test was used to calibrate the mechanical parameters and contact parameters of the seed-used watermelon peel crushing device.

Figure 1 depicts the preparation process for the experimental seed-used watermelon samples. Variations in the microcellular structure and fiber content of each structural layer of the seed gourd rind result in differences in their respective mechanical properties. Figure 1a,b depict the structure and model of a longitudinally cut seed-used watermelon, achieved using a knife to mitigate the effect of fiber anisotropy originating from the melon peel tissue [21]. Subsequently, the tissues of the green, emerald, and white layers were separated and sampled based on their structure. The determination of the mechanical properties was completed within 12 h of sampling, and the specimens are illustrated in Figure 1c.

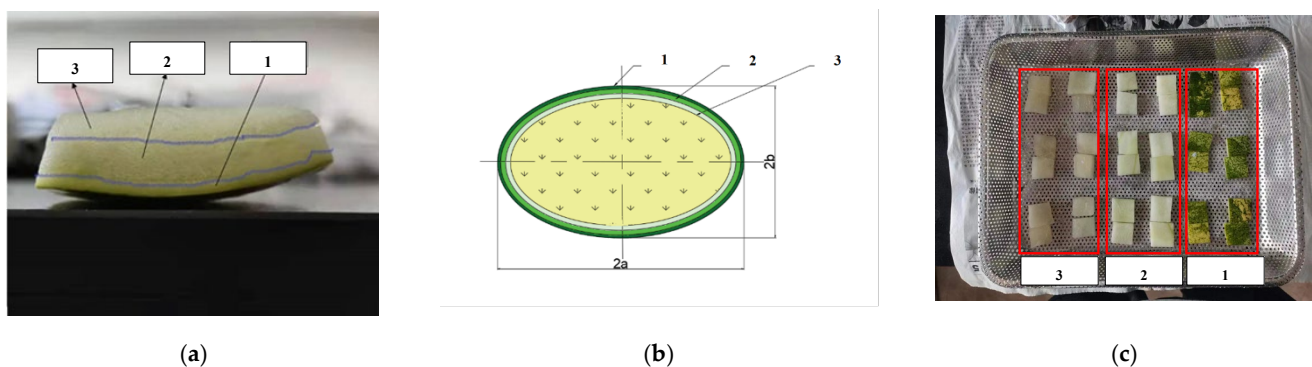


Figure 1. Test sample: (a) seed-used watermelon peel structure diagram, (b) seed-used watermelon model diagram, (c) seed-used watermelon peel sample. (1) Outer layer of seed-used watermelon peel, (2) seed-used watermelon peel middle layer, (3) seed-used watermelon peel lining.

The entire experiment was conducted in the laboratory of the School of Mechanical and Electrical Engineering at Gansu Agricultural University. The laboratory was maintained at a temperature of 22 ± 1 °C and a humidity of $20 \pm 1\%$. The “Jingyuan 1” variety of melon seeds, sourced from Gaowan Town, Baiyin City, Gansu Province, China, was chosen as the main subject of the study, focusing on its melon rind. The basic components and biological characteristics are presented in Table 1.

Table 1. Biological characteristics of seed-used watermelon.

Ingredient	Parameter
Moisture content %	≥94
Ash percentage %	0.29
Density of outer layer of seed-used watermelon peel g/mL	0.79
Density of inner and middle layers of seed-used watermelon peel g/mL	0.75~0.77
Total carbohydrate %	2.1~3.0
Thickness of outer layer of seed-used watermelon peel mm	1.5~3.0
Thickness of the middle layer of seed-used watermelon peel mm	4.0~5.0
Thickness of the inner layer of seed-used watermelon peel mm	4.0~5.0

2.1. The Calibration of Model Parameters of Seed-Used Watermelon Peel

2.1.1. Mechanical Performance Tests

(1) Puncturing test: The puncture test was conducted on samples of the outer layer of seed-used watermelon peel, the inner layer of seed-used watermelon peel, and the middle layer of seed-used watermelon peel using an SMS P/5 probe at a pretest speed of 1 mm/s. Due to the thinner nature of the outer layer of seed-used watermelon peel samples compared to the other two, the midtest speeds were adjusted to 0.2 mm/s for the outer layer and 0.5 mm/s for the inner and middle layers. The post-test speed remained at 1 mm/s, and the triggering force was set at 0.1 N to ensure data accuracy. Subsequently, the force–displacement curves of the samples were calculated and are depicted in Figure 2. The force–displacement curves of the puncture test were analyzed using Texture Exponent software2019, yielding five relevant parameter eigenvalues: the force (F_p), fracture deformation (D_p), cut line modulus ($E_p = \tan \alpha$), fracture work (W_p), and total fracture work (W_t) necessary for the fracture of seed-used watermelon peel, where α represents the angle between the curve and the x -axis. The specific calculation formula and results can be found in Table 2.

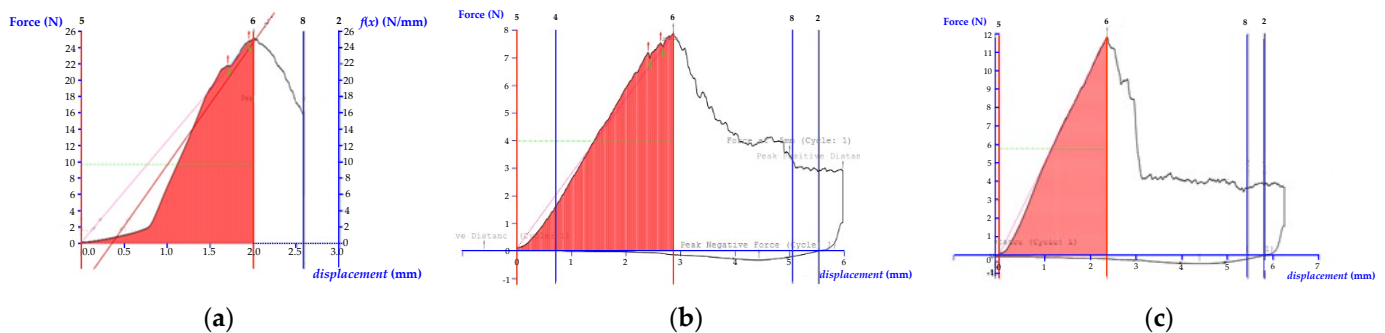


Figure 2. Seed–used watermelon peel puncture test force–displacement diagram. (a) Outer layer of seed-used watermelon peel, (b) seed–used watermelon peel middle layer, (c) seed–used watermelon peel lining.

(2) The circulating compression test of TPA: Texture profile analysis (TPA) is a common instrumental analytical method employed for evaluating the textural properties of fruits and vegetables. The TPA compression test was conducted on seeded melon peel samples with distinct structural layers, and the force–time curves of the seeded melon peel compression test were extracted, as depicted in Figure 3. Through the utilization of Texture Exponent software, six pertinent TPA test parameters were obtained, as illustrated in Table 3. Notably, the modulus of elasticity can be derived from Equation (1):

$$E = \frac{F_{1.5s} - F_{0.5s} / S_p}{D_{1.5s} / D_p} \quad (1)$$

where the variables in the equation are defined as follows: $F_{1.5s}$ represents the force of the probe at 1.5 s, $F_{0.5s}$ is the force of the probe at 0.5 s, S_p denotes the cross-sectional area of the sample, $D_{1.5s}$ indicates the displacement of the probe's movement at 1.5 s, and D_p represents the length of the sample.

Table 2. Characteristic values of seed-used watermelon peel puncture test.

Parameter Eigenvalues	Definition and Formula	Outer Layer of Seed-Used Watermelon Peel	Seed-Used Watermelon Peel Middle Layer	Seed-Used Watermelon Peel Lining
Rupture stress (MPa)	F_p	1.31 ± 0.1^a	0.40 ± 0.1^b	0.61 ± 0.1^b
Fault deformation (mm)	D_p	2.01 ± 0.4^a	2.86 ± 0.8^a	2.36 ± 0.6^a
Fracture slope (N/mm)	$E_p = \tan \alpha$	12.48 ± 0.5^a	2.79 ± 0.8^c	5.07 ± 1.2^b
Fracture work (N·mm)	$W_p = \int_0^{\epsilon_f} \sigma d\epsilon$	19.32 ± 1.3^a	11.41 ± 1.6^b	13.89 ± 1.7^b
Total fracture work (N·mm)	$W_t = \int_0^{\epsilon} \sigma d\epsilon$	25.37 ± 4.3^a	24.28 ± 3.7^b	25.81 ± 4.4^b

Note: Six samples were obtained from each tissue of the seed-used watermelon peel, and the results are presented as mean $\pm$ standard deviation. Distinct letters within the same row denote significant differences ($p < 0.05$) for that parameter.

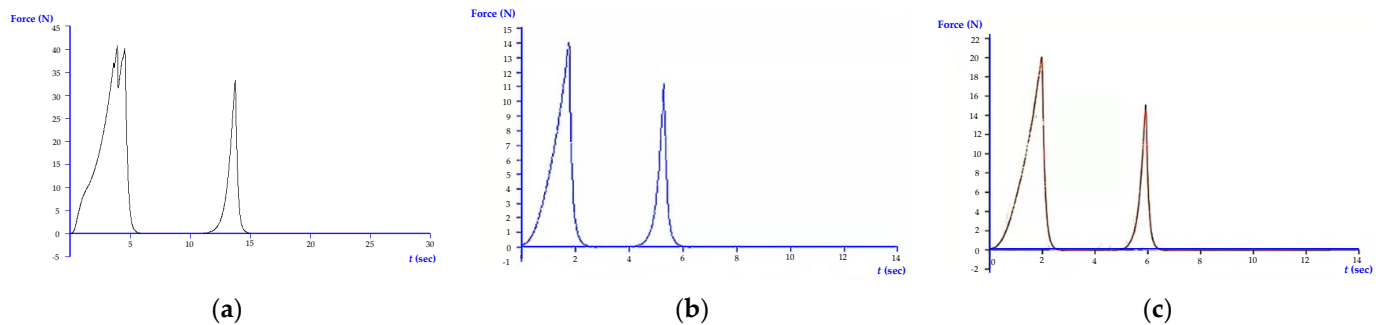


Figure 3. TPA compression force–time plot. (a) Outer layer of seed-used watermelon peel, (b) seed–used watermelon peel middle layer, (c) seed–used watermelon peel lining.

Table 3. Analysis of circulating compression characteristic values of seed-used watermelon peel.

Parameter Eigenvalues	Outer Layer of Seed–Used Watermelon Peel	Seed–Used Watermelon Peel Middle Layer	Seed–Used Watermelon Peel Lining
Hardness 1 (N)	41.50 ± 2.5^a	14.04 ± 1.5^c	21.06 ± 2.0^b
Hardness 2 (N)	33.25 ± 2.3^a	11.26 ± 1.4^b	14.12 ± 1.7^b
Elasticity	0.33 ± 0^b	0.68 ± 0.01^a	0.70 ± 0.1^a
Cohesiveness	0.26 ± 0.0^a	0.36 ± 0.03^a	0.20 ± 0.01^a
Reversion	0.50 ± 0^a	0.22 ± 0.01^b	0.12 ± 0^b
Initial modulus of elasticity (MPa)	1.37 ± 0.3^a	0.29 ± 0.1^b	0.31 ± 0.1^b

Note: Six samples of each tissue were taken, and results are expressed as mean $\pm$ standard deviation. Different letters in the same row represent significant differences ($p < 0.05$) for that parameter. Hardness 1, the peak of the curve during the first compression; Hardness 2, the peak of the curve during the second compression; elasticity, the ratio of the time required to reach Hardness 1 initially to the time required to reach Hardness 2 after recovery; cohesion, the ratio of the area under the second compression curve to the area under the initial compression curve; chewiness, which is equal to Hardness 1 $\times$ Cohesion $\times$ Elasticity; reparability, the area under the first recovery curve to the area under the second recovery curve.

2.1.2. The Calibration of Mechanical Parameters

To accurately represent the mechanical properties of the BondingV2 model for seeded melon peel, it is imperative to calibrate the pertinent parameters of the model prior to simulation. As this paper centers on the crushing characteristics of seeded melon peels within the crushing chamber, the bonding parameters of the seeded melon peel model in this section, specifically, the normal stiffness per unit area (NSPUA), shear stiffness per

unit area (SSPUA), critical normal stress (CNS), and critical shear stress (CSS), were determined through calibration. The bonding parameters were calibrated using the following procedure: A rectangular calibration model ($60 \times 60 \times 20$ mm) was established, figure in Section 2.2.2, and a uniaxial compression test was conducted. The height-to-width ratio ($H/A_1, A_2$) was 5. The platen compression speed was 1.0 mm/s. The bonding parameters were calibrated by comparing the simulated compressive strength with the experimental values of TPA cyclic compression (1.37 ± 0.3 MPa) (Figure 4a). The parameter values are reported in Table 4.

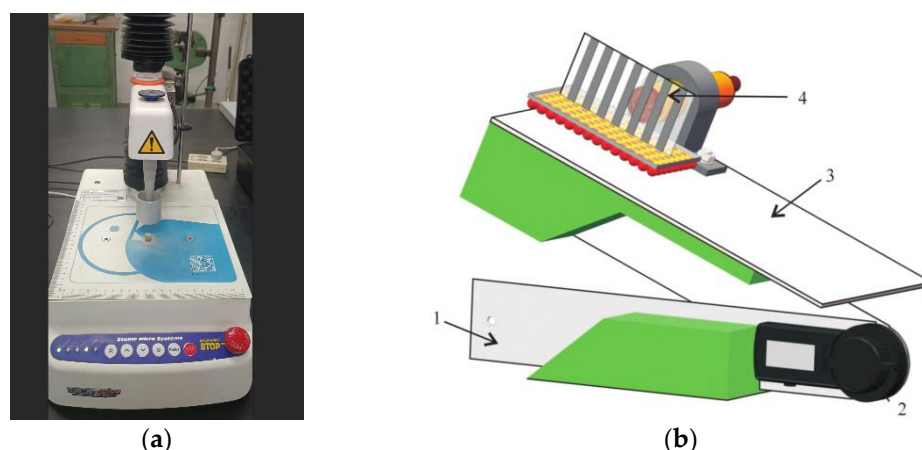


Figure 4. The parameter calibration test. (a) TPA cyclic compression test, (b) self-made photoelectric inductive measuring stage for static friction coefficient. (1) Bottom plate; (2) protractor; (3) tilt plate ($800 \text{ mm} \times 600 \text{ mm}$); (4) photoelectric switch.

Table 4. The bonding parameters.

Parameter	Parameter Value
The normal stiffness per unit area (N/m)	16,437
The coefficient of tangential stiffness (N/m)	11,815
Critical normal stress (MPa)	1.37
Critical tangential stress (MPa)	1.1
Bonding radius (mm)	3.0

2.1.3. The Calibration of Contact Parameters

The contact parameters, including the coefficients of static friction (seeded melon peel and seeded melon peel, seeded melon peel and hammer blade, seeded melon peel vs. inner wall), rolling friction (seeded melon peel and seeded melon peel, seeded melon peel and hammer blade, and seeded melon peel vs. inner wall), and recovery (seeded melon peel and seeded melon peel, seeded melon peel and hammer blade, and seeded melon peel vs. inner wall), were also determined through calibration. This study determined the static and rolling friction coefficients, along with the coefficient of recovery, using a custom photoelectric inductive measuring platform (Figure 4b). Each test group was repeated 10 times, and the results were then averaged. The simulation tests were conducted in EDEM2022 software, involving the creation of a simplified geometric model based on the tilt test device. Subsequently, the seed-used watermelon peel slip test was utilized for calibrating parameter values, which are detailed in Table 5.

Table 5. Contact parameters.

	Recovery Coefficient	Static Friction Coefficient	Coefficient of Rolling Friction
Seeded melon peel and seeded melon peel	0.30	0.25	0.05
Seeded melon peel vs. inner wall	0.52	0.50	0.03
Seeded melon peel and hammer blade	0.49	0.50	0.03

2.2. Whole Machine Structure of Pulverizer and Discrete Element Modeling of Seeded Melon Peels

2.2.1. Whole Machine Structure

The seed-used watermelon peel crusher, as illustrated in Figure 5, primarily comprises the crushing chamber, crushing device, power unit, and machine base. The crushing chamber includes the screen, box, feed port, discharge port, and various other components. Meanwhile, the crushing device consists of the crushing hammer blade and the rotor assembly, which comprises the pin, hammer spacer, shaft sleeve, hammer supporting plate, and spindle. The power unit for the seed-used watermelon peel crusher is a three-phase asynchronous motor. For further details on the main technical parameters of the seed-used watermelon peel crusher designed in this paper, please refer to Table 6.

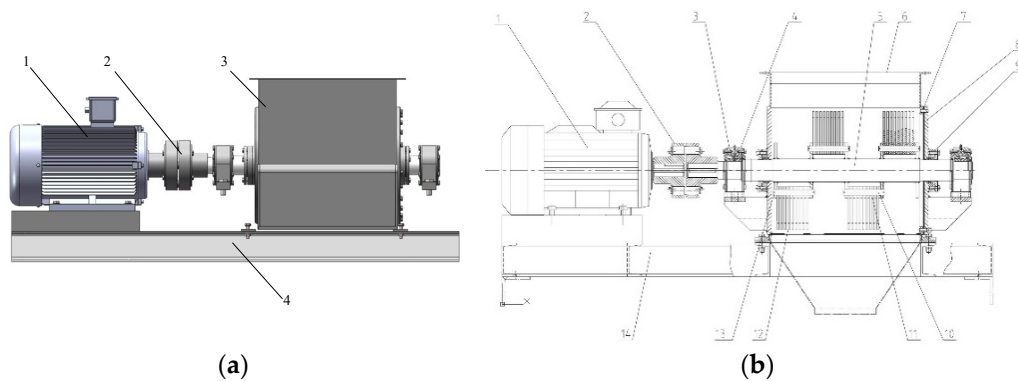


Figure 5. Structure diagram of the whole machine. (a) Three-dimensional diagram: (1) power plant, (2) transmission shaft, (3) crushing chamber, (4) machine base; (b) two-dimensional diagram: (1) motor, (2) elastic pin coupling, (3) bearings, (4) bearing seat, (5) principal axis, (6) airframe structure, (7) sealing gasket, (8) active end cover, (9) gland cover, (10) axis pin, (11) spacer of crushing hammers, (12) hammers, (13) circlip for shaft, (14) base support.

Table 6. The main technical parameters.

Technical Index/Units (mm × mm × mm)	Numerical Value
Boundary dimension (length × width × height)	1750 × 620 × 900
Equipment total weight/kg	728
Size and number of hammer pieces (length × width × thickness)	(150 × 50 × 6) 108
Feed inlet size	250 × 528
Seed-used watermelon peel size range	<300
Motor power/kW	18.5
Mesh size	6
Diameter of fragment room	520

2.2.2. The Discrete Element Method (DEM)

The discrete element method (DEM) is a specialized approach for analyzing the dynamics of granular materials. It is founded on Newton's second law and Euler's equations. This method has gained widespread adoption in agricultural machinery research due to its unique technological advantages and enhanced performance [22–24]. In order to simplify the simulation process, only the hammer blade, rotor spindle, casing, and other

key components within the crushing chamber structure were considered in establishing the simulation model, as depicted in Figure 6a. The hammer blade is made of 0Cr18Ni9 food-grade stainless steel, while the other contact materials are 40Cr food-grade stainless steel. The pertinent mechanical parameters of the materials are provided in Table 5. The simplified model of the crushing chamber was imported into the EDEM2022 simulation platform. The seeded melon peel was then simulated using the Bonding V2 model of EDEM2022. A discrete metamodel of the seeded melon peel contained circular particles connected by physical, 2 mm-radius bonds (see Figure 6b).

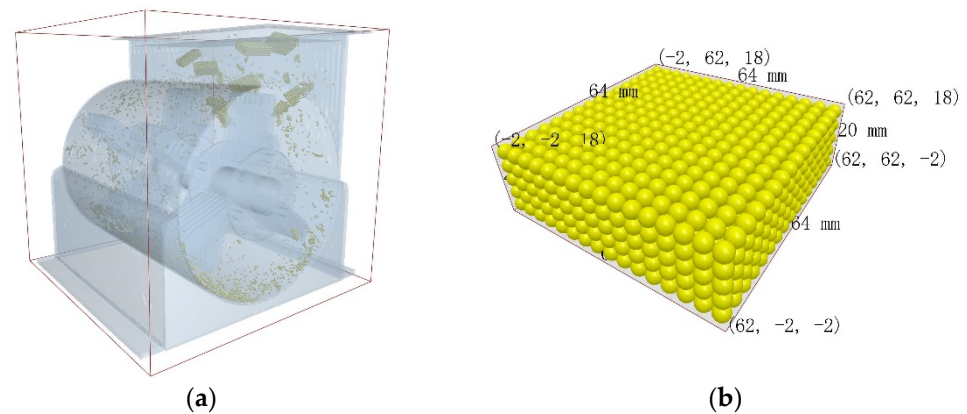


Figure 6. Seed-used watermelon peel discrete element model. (a) Crushing model, (b) model of the particles to be crushed generated by bonding.

3. Design of Pulverization Performance Simulation Test

3.1. The Simulation Testing and Validation

The pulverizer's operational process is simulated using EDEM2022 software, as depicted in Figure 7. The structural parameters of the pulverizer are detailed in Table 7, while the bonding key and contact parameters are outlined in Tables 4 and 5. The simulation utilizes a time step of 1.98×10^{-5} s for 1 s, and the results are presented in Table 7. To validate the adopted model's reliability, a comparative analysis is conducted between the discrete element simulation test of the pulverizing process of seeded melon rinds under different parameters and the one-factor test.

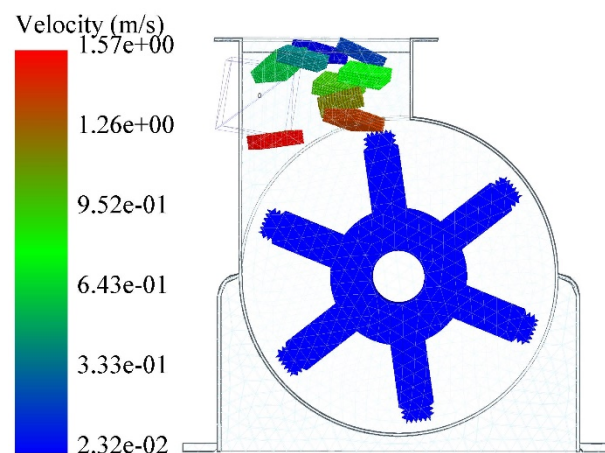


Figure 7. Crushing simulation process.

Table 7. Comparison of the results of the measured and simulated experiments.

Parameters	Test Values for Percentage of Particle Size Less Than 8 mm	Simulated Values for Percentage of Particle Size Less Than 8 mm	Relative Error %
Spindle speed n (r/min)	83	85	2.41
Hammer number x	84	87	3.57
Feeding quantity t (kg/min)	81	85	4.93

In the simulation test, it is difficult to define the power density index, and the observation and calculation of crushing efficiency are challenging in the measured test platform. Therefore, compare and analyze the proportion of consistent index particle size less than 8 mm in the simulation test and the measured test. The relative error between the measured value and the simulated value is utilized for this judgment.

Take the measured experiments and the simulation of the largest difference between the value of a group of test data statistical analysis. Tests are the crushed particle size less than 8 mm as a percentage of the response, respectively, to the spindle speed, the number of hammers, and feed as a factor; the simulation test and the measured relative error values are listed in Table 7. It can be seen that the relative error values are relatively small and belong to the experimental allowable error, so the discrete element model can be used for the seed—used watermelon peel crushing process of the discrete element simulation test.

3.2. RSM Test Scheme Design

In this chapter, the spindle speed (MSS, n), the number of hammers (NCB, x), and the feeding volume (FQ, t) are considered as the influencing factors, with their respective values detailed in Table 8. The response surface modeling (RSM) optimization test method is utilized to examine the impacts of these factors on the percentage of particles crushed to less than 8 mm (P_{sv}), the crushing efficiency (G_e), and the power consumption (P_{pc}), with the test scheme outlined in Table 8. The power consumption is calculated according to Formula (2):

$$P_{pc} = T_{Ms} \cdot n / 9550 \quad (2)$$

where n represents the spindle speed, and T_{Ms} denotes the torque of the spindle, which signifies the resisting moment experienced during the crushing of the seeded melon peels and is acquired through postprocessing upon the completion of the simulation.

Table 8. The values of the influencing factors.

Level	MSS, n (r/min)	NCB, x	FQ, t (kg/min)
1	1000	60	100
0	1500	84	150
−1	2000	108	200

Referring to the national standard GB/T 6971-2007 “Test Methods for Feed Mill,” the power density of the mill is chosen as the evaluation index for the test. The formula for determining the power density is as follows:

$$P_{pd} = Q_c / P_{pc} \quad (3)$$

where P_{pd} is the power density, Q_c is the operating volume during the working time, and P_{pc} is the power consumption during the working time, which is calculated by Equation (2) to obtain the postprocessing acquisition (Table 9).

Table 9. The experiment scheme of the response surface methodology.

Test No.	Influence Factor			Evaluation Indexes of Crushing Performance		
	x_1	x_2	x_3	y_1	y_2	y_3
	(MSS, n)/(r/min)	(NCB, x)	(FQ, t)/(kg/min)	P_{sv} (%)	G_e (%)	$P_{pd} \times 10^{-3}$ (t/h·kw)
1	1	0	−1	97	92	13
2	0	1	1	95	82	23
3	0	0	0	76	72	29
4	0	−1	1	75	65	17
5	−1	0	1	95	85	55
6	0	0	0	71	61	29
7	0	0	0	71	61	29
8	0	1	−1	85	69	13
9	−1	0	−1	85	64	73
10	1	−1	0	76	71	12
11	0	−1	−1	69	64	20
12	−1	−1	0	62	72	19
13	1	1	0	96	96	18
14	0	0	0	71	61	29
15	−1	1	0	81	76	58
16	0	0	0	71	61	29
17	1	0	1	98	97	18

Based on this foundation, a prediction model for the crushing cavity performance is developed using the principles of multivariate nonlinear regression [25], and it can be represented in the coding space by Equation (4).

$$y = (x_1, x_2, x_3) = b_0 + \sum_{j=1}^4 b_j x_j + \sum_{i < j}^4 b_{ij} x_i x_j + \sum_{j=1}^4 b_{ij} x_j^2 \quad (4)$$

where y is the evaluation index; x_1 , x_2 , and x_3 are MSS, NCB, and FQ, respectively; and b is the regression coefficient, which can be expressed as:

$$\begin{cases} b_0 = \frac{1}{N} \sum_{k=1}^N y_k \\ b_0 = \frac{\sum_{k=1}^N x_{kj} y_k}{\sum_{k=1}^N x_{kj}^2} \\ b_{ij} = \frac{\sum_{k=1}^N x_{ki} x_{kj} y_k}{\sum_{k=1}^N (x_{ki} x_{kj})^2} \\ b_{ij} = \frac{\sum_{k=1}^N (x_{kj}^2 - \frac{1}{N} \sum_{k=1}^N x_{kj}^2) y_k}{\sum_{k=1}^N (x_{kj}^2 - \frac{1}{N} \sum_{k=1}^N x_{kj}^2)} \end{cases} \quad (5)$$

where N is the number of simulations.

The prediction model Equation (7) in the natural space is derived by combining the factor-coding Equations (4) and (6).

$$x_j = \frac{(x_j - x_{0j})}{\Delta_j} \quad (6)$$

where x_{0j} is the level of the influencing factor, and Δ_j is the level increment of the influencing factor.

$$y = f(x_1, x_2, x_3) = \beta_0 + \sum_{j=1}^4 \beta_j x_j + \sum_{i < j}^4 \beta_{ij} x_i x_j + \sum_{j=1}^4 \beta_{jj} x_j^2 \quad (7)$$

where x is the impact factor in natural space, and β is the regression coefficient in natural space.

3.3. Multiobjective Optimization Based on Hybrid Metacellular Genetic Algorithm CellDE

This paper proposes the utilization of the hybrid metacellular genetic algorithm CellDE for solving the multiobjective optimization problem. Several researchers have extensively investigated the hybrid metacellular genetic algorithm CellDE. For example, in 2007, Alba introduced the classical multiobjective metacellular genetic algorithm CMOGA [26]. Based on its modeling principles, numerous scholars have proposed various multiobjective metacellular genetic algorithms using the cell genetic algorithm (CGA), which has led to numerous research outcomes, such as the MoCell algorithm [27] (depicted in Figure 8), the hybrid tuple–cell genetic algorithm CellDE [28] for three-objective optimization, and its enhanced version. These algorithms have demonstrated outstanding performance in addressing multiobjective optimization problems. The authors have conducted significant research on the hybrid metacellular genetic algorithm CellDE.

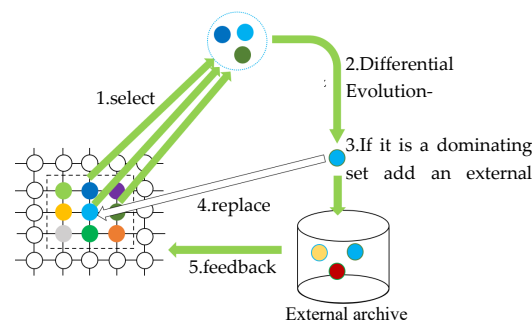


Figure 8. CellDE algorithm schematic diagram.

CellDE, an improved version of the MoCell algorithm designed for solving high-dimensional objectives, utilizes the differential evolution (DE) [29] operator, based on the MoCell algorithm framework, to generate new individuals without relying on the reproduction mechanism of crossover and mutation operators. Additionally, the introduction of the density estimation method from the SPEA2 algorithm enhances CellDE's diversity and convergence in addressing three-objective optimization problems. Empirical testing demonstrates the clear advantages of CellDE in terms of diversity and convergence [30].

Given the importance of optimizing power consumption in this paper, the performance indexes of the crushing chamber directly related to power consumption include crushing force and power density. Therefore, this section integrates the prediction model established in Section 3.2 to formulate the objective function as follows:

$$\max F_{obj}(x_1, x_2, x_3) = w_1 P_{bd} + w_2 P_{\max} \quad (8)$$

w_1 and w_2 in Equation (8) can be calculated by Equation (9):

$$\begin{cases} w_1 = 1/\max\{P_{pd}\} \\ w_2 = 1/\max\{P_{\max}\} \end{cases} \quad (9)$$

and the design variables $x = [x_1, x_2, x_3]$:

$$\begin{cases} 1000 \leq x_1 \leq 2000 \\ 60 \leq x_2 \leq 108 \\ 100 \leq x_3 \leq 200 \end{cases} \quad (10)$$

While the primary objective of this paper is to enhance the utilization efficiency of electrical energy using optimization methods, it is still necessary to ensure that the crushing efficiency cannot be reduced. Therefore, the following constraints need to be satisfied:

$$G_e \geq G_{e-ori} \quad (11)$$

3.4. The ANOVA Model

This section employs the F-test method for analysis of variance (ANOVA) [31] to ascertain the impact of influencing factors on the performance of the crushing chamber. The general process is outlined as follows:

Step 1: Calculate the sum of the squared errors Δ_{xj} and Δ_e , which can be calculated by Equations (12) and (13).

$$\Delta_{xj} = \left(\sum_{i=1}^N x_{ij} y_{ij} \right)^2 / \sum_{i=1}^N x_{ij}^2, \quad j = 1, 2, 3 \quad (12)$$

where x_{i1} , x_{i2} , and x_{i3} are the spindle speed (MSS), the number of hammers (NCB), and the feeding quantity (FQ), respectively; y_{i1} , y_{i2} , and y_{i3} are the percentage of the size of the seed-used watermelon peel less than 8 mm, the pulverizing efficiency, and the power density at the end of pulverizing, respectively.

$$\Delta_e = \sum_{i0=1}^{m_0} (y_{ij0} - \bar{y}_{j0})^2 = \sum_{i0=1}^{m_0} y_{ij0}^2 - \left(\sum_{i0=1}^{m_0} y_{ij0} \right)^2 / m_0, \quad j = 1, 2, 3 \quad (13)$$

where m_0 is the repetition times of the test center, y_{ij0} is the crushing chamber performance of the test center, and $\bar{y}_{j0}$ is the average value of y_{ij0} ;

Step 2: Calculate the freedom degrees of the influence factors f_{xj} and f_e . Here, $f_{xj} = 1$, and $f_e = m_0 - 1$;

Step 3: Calculate the statistic F_{xj} and determine the significance level. It is described as:

$$F_{xj} = (\Delta_{xj} / f_{xj}) / (\Delta_e / f_e) \bar{F}_\alpha(f_{xj}, f_e), \quad j = 1, 2, 3 \quad (14)$$

4. The Crushing Performance Simulation Test Analysis

4.1. The Simulation Analysis of the Original Working State

Figure 9 depicts the state of the seeded melon peel at various moments during the crushing simulation. The red structure represents the uncrushed model, while the blue structure represents the crushed particles, including those measuring less than 8 mm. It is evident that the dispersion degree gradually increases over time, although some individual models remain uncrushed. The determination of the size of the crushed particles is derived from measurement and statistics. Due to the large number of particles, the percentage of particles smaller than 8 mm is calculated using a $100 \times 100 \times 100$ geometry bin for statistical accuracy. Subsequently, the size distribution is established in three different locations in the crushing room using the same geometric bin for statistics.

Figure 10a–c show the time change curve of the compression force for the seed-used watermelon peel model, the normal force for the parallel bond, and the force of the hammer blade during pulverizing machine operation. It is evident from the combination of the three graphs that the peak of the curves consistently falls within the 0.3 s to 0.4 s range. The power density of the pulverizer can be derived by combining Equations (1) and (2), and the resultant values are provided in Table 8. A prototype test was conducted based on the simulation parameters. The pulverized seed-used watermelon peel particles are depicted in Section 4.4.2, and the corresponding statistical data are detailed in Table 8. The simulated values fall within the error range of the test values, indicating the validity of the simulation.

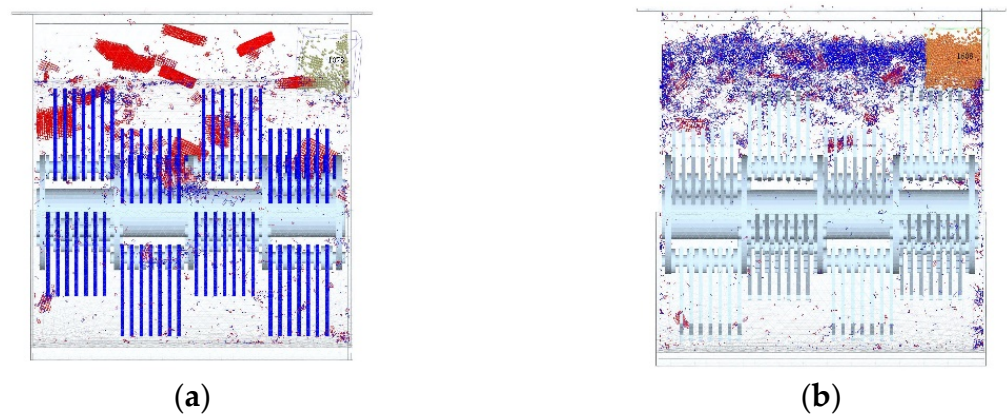


Figure 9. The crushing of seed and melon peels at different moments. (a) $t = 0.5$ s, (b) $t = 1.0$ s.

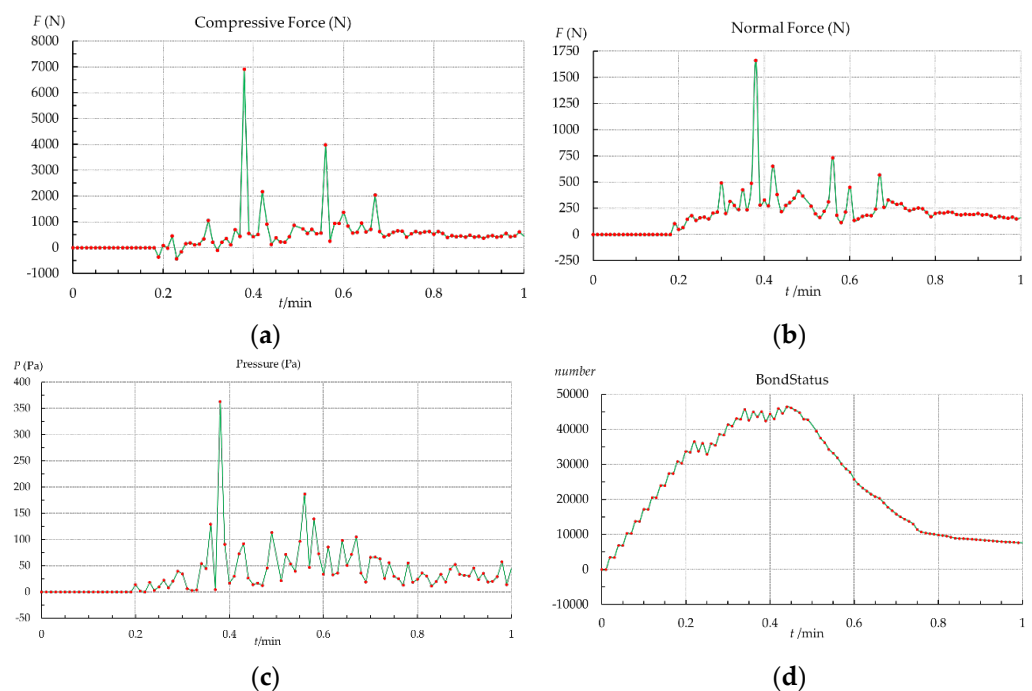


Figure 10. Time plot of each metric during simulation time. (a) Compression force–time curve of seed–used watermelon peel, (b) parallel bond normal force–time curve, (c) hammer blade pressure–time curve, (d) number of bond breaks–time curve.

Crushing efficiency can be quantified by the count of broken bonds between particles [32], as depicted in Figure 10d. Initially, the seed-used watermelon peel model is not in contact with the hammer blade, resulting in zero instances of crushing. As the operation progresses, the count of broken bonds gradually increases due to the impact and squeezing forces, indicating a positive correlation trend. After a certain level of pulverization, the number of bonds ceased to change. This is due to the centrifugal force exerted on the particles by the hammer blade, leading to the nonpulverization of the parts far from the hammer blade and maintaining stable bonds between the particles. The graph showing bond changes mirrors the crushing process, while the crushing efficiency can be quantified by comparing the pre- and postcrushing bond counts, with the final values detailed in Table 8.

4.2. ANOVA of Influencing Factors

The simulation results based on the discrete element method (DEM) simulation of the seed-used watermelon peel pulverizer under various interaction factors are presented

in Table 10. Table 11 presents the corresponding ANOVA results. The impact of the single-factor NCB on pulverization size is extremely significant, and the interaction term MSS·FQ has the most significant effect on particle size. This is attributed to the influence of spindle speed (MSS) and feed amount (FQ) on the secondary pulverization of seed-used watermelon peels in the pulverization chamber, which strongly correlates with particle size. The main and secondary effects of each factor on the pulverization size followed the order $NCB > MSS > FQ > MSS \cdot FQ > NCB \cdot FQ > MSS \cdot NCB$. This suggests that the interaction between MSS and NCB had the least impact on the size of pulverized particles.

Table 10. The result of ANOVA for performance of seed-used watermelon peel crusher.

Factor Intercept	Coefficient	P_{sv} (%)			Coefficient	G_e (%)			Coefficient	$P_{pd} \times 10^{-3}$ (t/h·kw)		
		Mean Square	F-Value	p-Value		Mean Square	F-Value	p-Value		Mean Square	F-Value	p-Value
MSS	72.00	242.00	34.75	0.0006	7.38	435.13	17.30	0.0042	−18.00	2592.00	28.94	0.0010
NCB	5.50	703.13	100.96	<0.0001	6.38	325.13	12.93	0.0088	5.50	242.00	2.70	0.1442
FQ	9.38	91.12	13.08	0.0085	5.00	200.00	7.95	0.0258	−0.75	4.50	0.050	0.8290
MSS·NCB	3.38	0.25	0.036	0.8551	5.25	110.25	4.38	0.0746	−8.25	272.25	3.04	0.1248
MSS·FQ	0.25	20.25	2.91	0.1319	−4.00	64.00	2.54	0.1547	5.75	132.25	1.48	0.2637
NCB·FQ	−2.25	4.00	0.57	0.4733	3.00	36.00	1.43	0.2705	3.25	42.25	0.47	0.5143

The individual effects of MSS, NCB, and FQ on crushing efficiency were all relatively significant, particularly MSS, which was extremely significant. The interaction term MSS·NCB also showed high significance on crushing efficiency, with a significance level of 0.0746. In contrast, the effects of MSS·FQ, NCB·FQ, etc., on crushing efficiency were relatively weak. The order of their effects was $MSS > NCB > FQ > MSS \cdot NCB > MSS \cdot FQ > NCB \cdot FQ$, indicating that the interaction of NCB·FQ had the weakest effect on crushing efficiency.

The analysis of power density variance revealed that the influence of MSS on power density was highly significant when considered as a single factor. Furthermore, the impact of MSS·NCB on power density was even more notable in the interaction factor. This can be attributed to the significant influence of the pulverizer's rotational speed and the number of hammers on the spindle's torque. Specifically, a higher spindle speed and an increased number of hammers result in a corresponding increase in torque. The primary order of influence of each factor on pulverized size was $MSS > MSS \cdot NCB > NCB > MSS \cdot FQ > NCB \cdot FQ > FQ$. This implies that the single factor FQ had the least impact on power density.

4.3. Crushing Performance Analysis

4.3.1. Analysis of the Percentage of Particle Size Less Than 8 mm

The P_{sv} variation surfaces of MSS, NCB, and FQ and their first-order interactions are depicted in Figure 11a–c. The black lines in Figure 11a–c denote the percentage of particle size less than 8 mm after pulverization, while the area enclosed by the blue dotted line represents the 95% confidence band. It is observed that P_{sv} initially decreases and then increases with the increase in MSS and FQ (Figure 11a,c), indicating that MSS and FQ have an optimal range concerning pulverized size. The change in the effect of MSS on the postcrush size is relatively substantial, whereas the change in the effect of FQ on the postcrush size is comparatively small, suggesting that the impact of FQ on the pulverized size is weaker. This is in line with the results of the analysis in Section 4.2. Concurrently, with the increase in NCB, the pulverized size gradually increases (Figure 11b), suggesting the existence of an optimal solution.

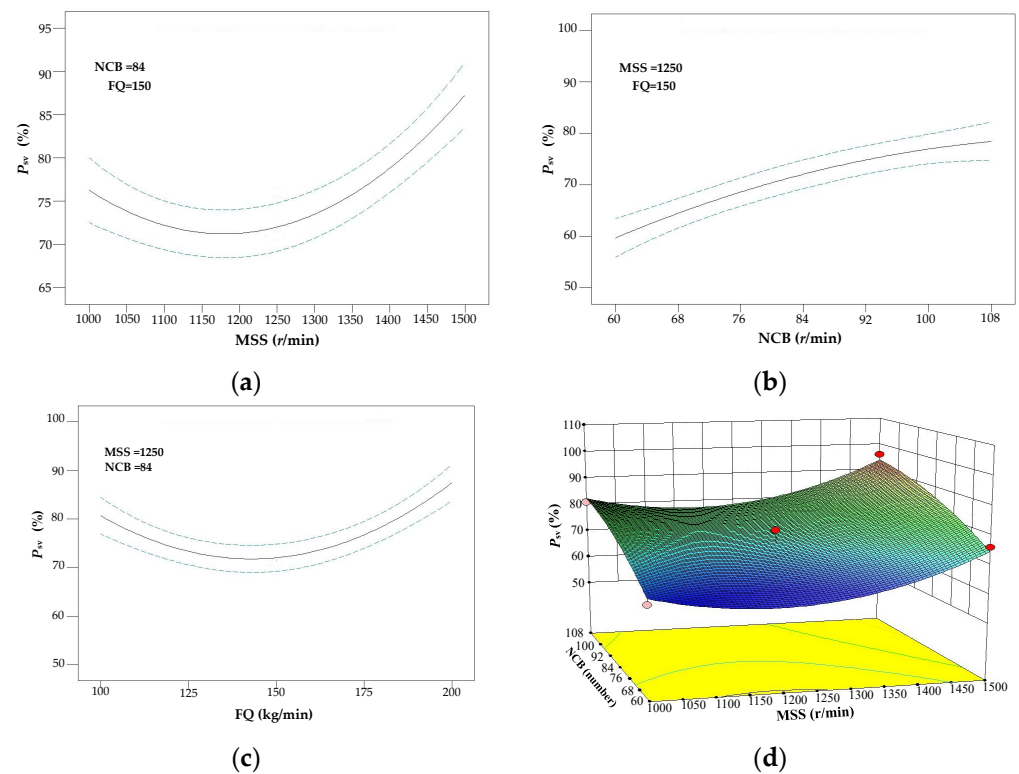


Figure 11. P_{sv} curve of percentage of particle size less than 8 mm. (a) Spindle speed, (b) hammer number, (c) feeding rate, (d) feeding rate–spindle speed.

When FQ is held constant, the impact of the interaction between MSS and NCB on the pulverized size is depicted in Figure 11d. It is evident that the pulverized size decreases and then increases with the rise in MSS. Notably, when $1300 < \text{MSS} < 1500$ or $84 < \text{NCB} < 108$, the response surface exhibits a steeper inclination, indicating a stronger interaction between MSS and NCB. This can be attributed to the higher spindle rotational speed and increased number of hammers during pulverization, resulting in a greater number of impacts and impact forces on the seeded melon peels.

4.3.2. The Analysis of Pulverizing Efficiency

The variation in comminution efficiency with MSS, NCB, and FQ is depicted in Figure 12. The black lines in Figure 12a–c represent the comminution efficiency, while the area surrounded by blue dotted lines indicates the 95% confidence band. It is evident that the comminution efficiency initially experiences a slight decrease followed by an increase with the rise in MSS. This phenomenon occurs because as the rotational speed increases, some particles are not completely crushed and are temporarily moved away from the hammer due to the airflow. However, with further increases in speed, the particles that were not initially crushed are subjected to repeated impacts by the hammer, consequently leading to an increase in crushing efficiency. As the NCB increases, the comminution efficiency rises approximately linearly, reaching a maximum value within the horizontal coordinate range. Moreover, the impact of FQ on the comminution efficiency is marginally smaller compared to MSS and NCB, aligning with the findings of the analytical results in Section 4.2.

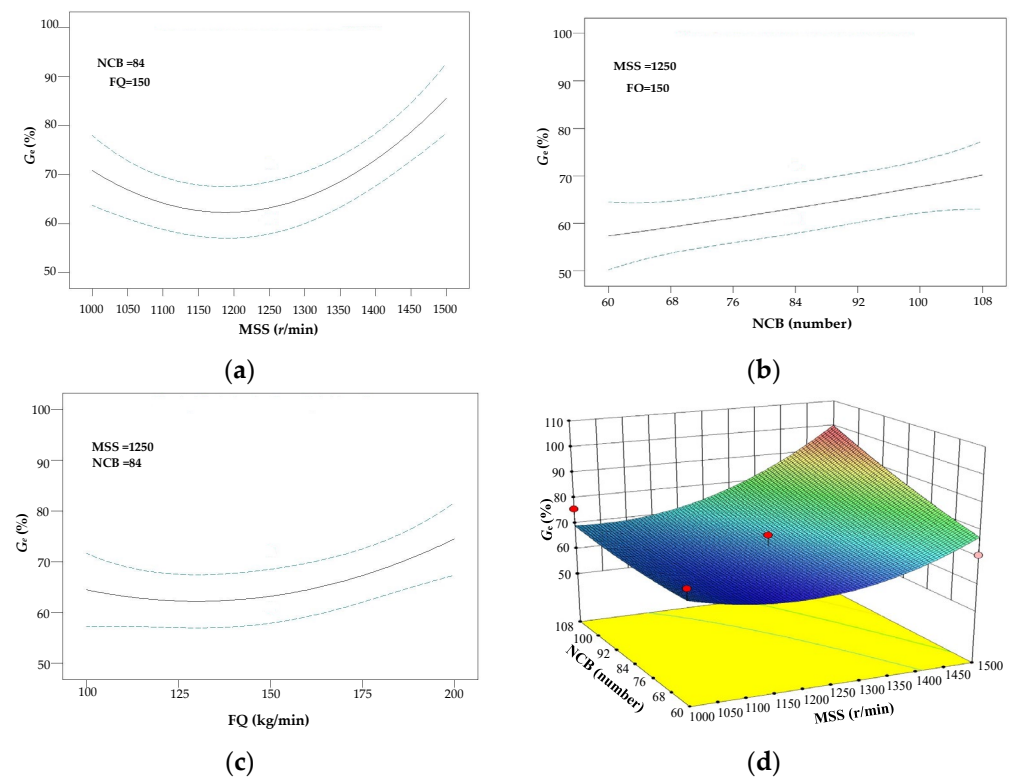


Figure 12. Crushing efficiency G_e curve diagram. (a) Spindle speed, (b) hammer number, (c) feeding rate, (d) hammer number–spindle speed.

When FQ is at level 0, the impact of the interaction between MSS and NCB on crushing efficiency is illustrated in Figure 12d. In the range of $1250 < \text{MSS} < 1500$ or $84 < \text{NCB} < 108$, the response surface exhibits a steeper gradient, signifying a stronger interaction between MSS and NCB. This phenomenon arises from the increased spindle rotational speed and the greater number of hammers, resulting in seeded melon peels being subjected to a higher impact force and an increased number of impacts per unit.

4.3.3. The Analysis of Power Density

The power density varies with MSS, NCB, and FQ, and their first-order interactions are depicted in Figure 13. The black lines in Figure 13a–c represent the power densities, while the area enclosed by the blue dotted lines denotes the 95% confidence bands. It is evident that as MSS increases, the power density gradually decreases. This is due to the increase in speed leading to a rise in torque, resulting in higher power consumption and, subsequently, a decrease in power density. Additionally, with the increase in NCB, the power density slowly increases and then gradually decreases, indicating the presence of an optimal range for NCB in terms of power density. However, the impact of FQ on power density exhibits relatively minor changes.

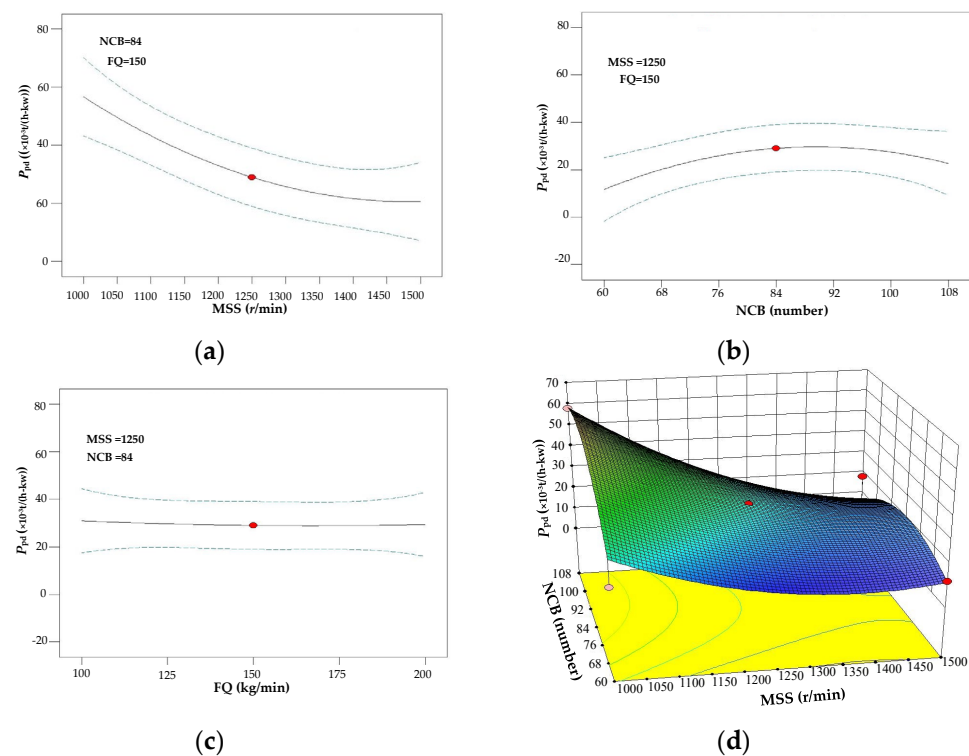


Figure 13. Power density P_{pd} curve. (a) Spindle speed, (b) hammer number, (c) feeding rate, (d) feeding rate–spindle speed.

When FQ is at level zero, the impact of the interaction between MSS and NCB on power density is depicted in Figure 13d. It demonstrates that the response surface is steeper when $1000 < \text{MSS} < 1250$ or $84 < \text{NCB} < 100$, indicating a larger variation in power density. This is attributed to the fact that the lower spindle speed and lower number of hammer blades, approximately 92, result in lower power consumption, enabling the power density to reach its maximum value.

4.4. Parameter Optimization and Verification Analysis

4.4.1. The Establishment of Prediction Model and Multiobjective Optimization Analysis

The prediction model for the three evaluation indicators was formulated by integrating the methods outlined in Section 3.2, as depicted in Equation (15). Through the combination of the ANOVA method with Sections 3.3 and 4.2, It was produced, revealing that the p -value of the three objective functions is less than 0.05. Furthermore, the coefficient of determination $R^2 \geq 0.75$ signifies significant model effectiveness and good fitting. Therefore, the model can be optimized with more than three objective values.

$$\begin{cases} y_1(x_1, x_2, x_3) = 297.68750 - 0.34450x_1 + 1.08854x_2 - 1.21750x_3 + 0.000042x_1x_2 - 0.00018x_1x_3 \\ \quad + 0.00083x_2x_3 + 0.000156x_1^2 - 0.00521x_2^2 + 0.0048x_3^2 \\ y_2(x_1, x_2, x_3) = 490.91875 - 0.59700x_1 - 1.35625x_2 - 0.46300x_3 + 0.000875x_1x_2 \\ \quad - 0.00032x_1x_3 + 0.0025x_2x_3 + 0.00024x_1^2 + 0.00091x_2^2 + 0.0025x_3^2 \\ y_3(x_1, x_2, x_3) = 62.90625 - 0.34150x_1 + 5.41146x_2 - 0.15000x_3 - 0.00137x_1x_2 + 0.000154x_1^2 \\ \quad - 0.020616x_2^2 + 0.00045x_3^2 \end{cases} \quad (15)$$

Leveraging the evaluation indices for the overall crushing performance of the machine, the multiobjective optimization function model for the seed-used watermelon peel crusher is defined as follows:

$$\begin{cases} \max y_1(x_1, x_2, x_3) \\ \max y_2(x_1, x_2, x_3) \\ \max y_3(x_1, x_2, x_3) \\ s.t. \begin{cases} 1000 \leq x_1 \leq 2000 \\ 60 \leq x_2 \leq 108 \\ 100 \leq x_3 \leq 200 \end{cases} \end{cases} \quad (16)$$

Per Equations (15) and (16), the optimal Pareto solution set of objective and parameter values can be obtained through CellDE solving, as depicted in Figure 14a,b. Upon observing Figure 14a, it is evident that the optimal values for the authors' desired seed-used watermelon peel crusher crushing performance, represented by P_{sv-opt} , G_{e-opt} , and P_{pd-opt} , are indicated by the three selected groups (red dots). These values are strategically chosen based on the actual crushing scenario, and the best among the three groups of values are delineated within the wireframe in the figure. The corresponding optimal MSS, NCB, and FQ parameter combinations are determined to be 1457.78, 108, and 152.51 (Figure 14b), aligning with P_{sv-opt} , G_{e-opt} , and P_{pd-opt} values of 90.02%, 89.57%, and 8.35×10^{-3} t/(h-kw), respectively. Considering that the actual rotational speed of the crusher lies within a fixed range, the optimized value of MSS is set at 1500 r/min for the parameter value of the prototype production experiments. To facilitate operation and data collection for feed quantity, FQ is set at 150 kg/min, while the number of hammers is fixed at 108 pieces.

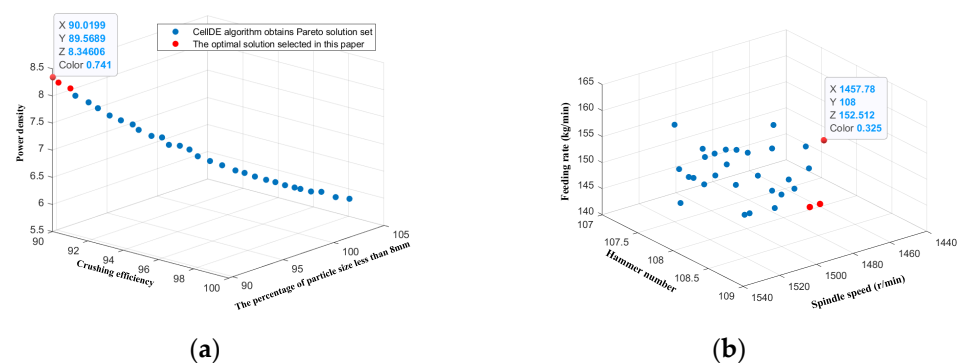


Figure 14. Pareto frontier curve: (a) The Pareto front of the target value obtained by CellDE, (b) Pareto front of parameter values obtained by CellDE.

Table 11. The results of ANOVA for prediction model.

Model	Mean Square	F-Value	p-Value	R ²
P_{sv}	237.30	34.07	<0.05	0.98
G_e	260.47	10.36	<0.05	0.93
P_{pd}	578.68	6.50	<0.05	0.83

4.4.2. Prototype Crushing Performance Test and Verification Analysis

The results from the Section 4.4.1 analysis indicate that the spindle speed was set at 1500 r/min, and there were 108 hammer blades, as illustrated in Figure 15a. As shown in Figure 15b, seeded melon peels were weighed prior to the test for spares. When the machine was running smoothly, the seed-used watermelon peels were fed into the pulverizer's working chamber at a uniform speed of 150 kg/min from the feeding port. Subsequently, the timing started, and feeding ceased after 1 min. Upon stopping the pulverization, the power was turned off, and the test results were recorded, as shown in Figure 16b. The tests were repeated three

times within each group, and the average statistical values of P_{sv-pr} , G_{e-pr} , and P_{pd-pr} were determined as 96.63%, 92.37%, and 7.76×10^{-3} t/(h-kw), respectively.

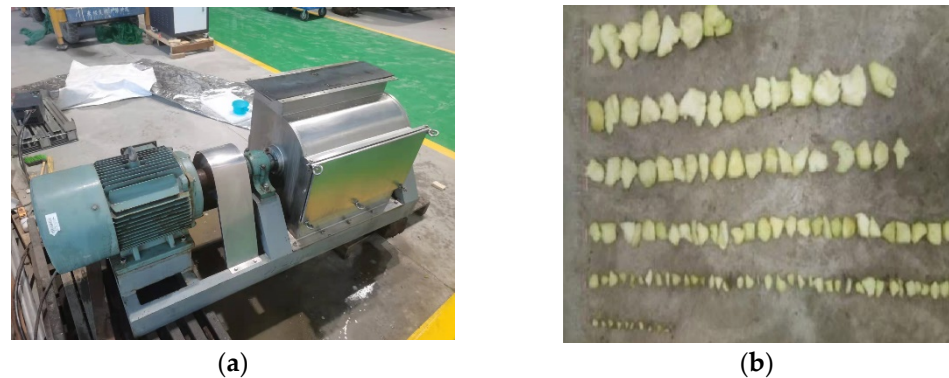


Figure 15. Experimental prototype. (a) Test prototype; (b) seed-used watermelon peels used in the experiment.



Figure 16. The crushing effect of the seed-used watermelon rind. (a) The crushing effect under the original parameters; (b) the crushing effect after parameter optimization.

The comparative analysis of the prototype test values and simulation data indicated that the P_{sv-pr} and G_{e-pr} values in the prototype tests were significantly large. This was attributed to the adjustment of the spindle speed to a high value and a slight reduction in the feed amount. Consequently, the prototype experimental results show a smaller overall crushed size, reflecting the high crushing efficiency due to the large P_{sv-pr} value. The primary factor influencing power density is the spindle speed, which results in a power density value marginally smaller than the simulated P_{pd-pr} value. In conclusion, the comparison reveals that both the simulation and the prototype experiment fall within an acceptable error range, thereby validating the simulation conducted in this paper.

The original working parameters of P_{sv-ori} , G_{e-ori} , and P_{pd-ori} are presented in Table 8. Observing the results, it is evident that the values of P_{sv-opt} , G_{e-opt} , and P_{pd-opt} have shown improvement after optimization. Therefore, the multiobjective optimization method and prediction model introduced in this study are deemed effective and provide a theoretical foundation for addressing similar industry problems.

5. Conclusions

The limited comprehensive development and utilization of seed-used watermelon rind in China has led to relatively underdeveloped research on and development of machinery for crushing melon rind. This study aimed to investigate the current utilization status and mechanization equipment of seed-used watermelons in northwest China. Following the optimization design of the seed-used watermelon peel crushing process, the seed-used watermelon peel crusher is now capable of meeting usage requirements, effectively addressing the significant waste of seed-used watermelon peel in Northwest China and

improving the efficiency of the seed-used watermelon peel crushing machinery. The main conclusions are as follows:

(1) The mechanical properties of each layer of the seed-used watermelon rind were analyzed using puncture and TPA cyclic compression tests on different tissues. The findings indicate that the outer layer of seed-used watermelon peel exhibited the highest fracture force and work of rupture, as well as a higher modulus of elasticity and hardness compared to both the seed-used watermelon peel middle layer and seed-used watermelon peel lining. Consequently, the mechanical properties of the seed peel are primarily influenced by the structure of the seed-used watermelon peel outer layer;

(2) The parameter calibration of the discrete elemental model for seeded melon peel resulted in the following values: NSPUA at 16,437, SSPUA at 11,815, and CNS and CSS at 1.37 and 1.1, respectively. Moreover, the coefficients of restitution, static friction, and rolling friction between the seeded melon peel and itself were found to be 0.30, 0.25, and 0.05, while those for the seeded melon peel in contact with Q235 were 0.52, 0.50, and 0.03, and for seeded melon peel in contact with 0Cr18Ni9 were 0.49, 0.50, and 0.03, respectively;

(3) The discrete element model was developed, and simulation tests were conducted to analyze the crushing performance of the entire machine under its original operating parameters. The comparison between the simulated values (P_{sv-ori} : 85%, G_{e-ori} : 86%, P_{pd-ori} : 7.6×10^{-3} t/h-kw) and the prototype test values (P_{sv} : 83%, G_e : 81%, P_{pd} : 7.8×10^{-3} t/h-kw) reveals that they fall within an acceptable error range, suggesting the effectiveness of the simulation;

(4) A three-factor, three-level orthogonal test was employed to analyze the variance of the factors and their impact on the pulverization performance. The impact of the factor NCB on pulverization size was notably significant, and the interaction between factors MSS and FQ had the most substantial effect on the dimensions of pulverization size, primarily due to the influence of MSS and FQ variations on the secondary pulverization of seed-used watermelon peels in the pulverization chamber. The impact of the single factor MSS on comminution efficiency (G_e) and power density (P_{pd}) was highly significant. Additionally, the interaction term between MSS and NCB had the most pronounced effect on both comminution efficiency (G_e) and power density (P_{pd}). This is because the value of the crusher speed and the number of hammers on the spindle torque have a great impact on the result; the greater the spindle speed and the greater the number of hammers, the corresponding torque increases. The p -values corresponding to each significant factor are all less than 0.05, aligning with the results of the orthogonal test analysis. This demonstrates that the orthogonal simulation test fulfills the practical requirements;

(5) A predictive model for crushing performance was developed, and the enhanced hybrid metacellular genetic algorithm, CellDE, was employed for multiobjective optimization of the crushing performance. The optimized values of P_{sv-opt} , G_{e-opt} , and P_{pd-opt} have an error of less than 8% compared to the statistically calculated values of the prototype test, outperforming the values of P_{sv-ori} , G_{e-ori} , and P_{pd-ori} under the original parameters. The optimization parameters served as input values for the prototype crushing experiments, yielding final statistical values of P_{sv-pr} , G_{e-pr} , and P_{pd-pr} at 96.63, 92.37, and 7.76, respectively. The experimental prototype value was larger than the simulation value due to the adjustment of the spindle speed and a slight reduction in the feed amount during prototype operation, resulting in an overall smaller size for seeded melon peel crushing (i.e., a larger P_{sv-pr} value). This led to high crushing efficiency. The spindle speed, being the main factor affecting power density, resulted in the power density value P_{pd-pr} being slightly smaller than the simulation value P_{pd-opt} . Nevertheless, the overall performance was superior to that of the prototype's initial parameters.

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