Discrete element modelling of the effect of aspect ratio on compaction and

shear behaviour of aggregatess

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Abstract

Coarse aggregates are essential for constructing railways and highways, as they affect structural performance through their compacted state and shear strength. Particle geometry influences these properties, but little research has quantitatively investigated how shape indexes impact mechanical indicators. This study addresses this gap by exploring the effect of particle aspect ratio on coarse aggregate compaction and shear behavior using the discrete element method (DEM). The study's key contribution is the development of novel equations that describe the correlation between packing porosity, inter-particle contact state, and aspect ratio control thresholds in a practical format. To do so, first, a point cloud database is compiled from laser scans of 700 natural aggregate particles. Each particle is classified using three aspect-ratio parameters: elongation, flatness, and flatness-elongation index (FEI). They are then digitized as rigid block particle models and compared against actual point clouds. Next, nine aggregates of representative shapes are assessed for their macro and mesoscopic mechanical responses using DEM-based vibro-compaction and direct shear tests. The compaction simulations indicate an exponential relationship between porosity and inter-particle coefficient of friction and show that aggregates with $FEI \approx 0.5$ are a good choice. The direct shear simulations consider the same initial porosity, and show that the relationship between peak shear strength and vertical stress follows a power function. Finally, the analysis of contact forces and fabric tensors implies that $FEI \approx 0.5$ may also facilitate particle fragmentation control.

Keywords: granular aggregates; aspect ratio; railway-highway; discrete element method; rigid block; laser scanning aggregates

1 Introduction

Coarse aggregates are used for a wide range of construction applications, including highway and railway sub-bases and rockfill dams (Xu and Wang, 2016; Xiao et al., 2020; Guo et al., 2022; Fu et al., 2022). Granular aggregates are usually irregular and form complex granular systems connected to surrounding fluid media and engineering structures (Mitchell and Soga, 2005; Cheng and Wang, 2018; Ngo and Indraratna, 2020). Researchers have demonstrated how the shape influences material behaviour in both laboratory and field investigations. There is extensive literature on this subject, such as packing density, shear strength, stiffness and permanent deformation (Shin and Santamarina, 2013; Cook et al., 2017; Lee et al., 2017; Payan et al., 2017). However, there is uncertainty in the conclusions drawn from the experimental study because natural or crushed mineral grains were employed, in which case variability exists in control variables and experimental results. To overcome this challenge, the discrete element method (DEM) has proven a valuable tool for analyzing the mechanical response of granular media (Cundall and Strack, 1979; Bono et al., 2014; Dai et al., 2016; Wu et al., 2021). Using it, grain morphology can be customized to reduce experimental complexity.

To maximise the resolution and contact detection efficiency in DEM modeling, a common assumption is that the granular particles can be approximated using discs and spheres (Cundall and Strack, 1979; Abbireddy and Clayton, 2010). However, their geometries can also be modelled using more complex shapes, including polygons (Fraige et al., 2008; Xiao and Tutumluer, 2017) and super-quadric geometries (Rothenburg and Bathurst, 1992; Lin and Ng, 1995; Zhao and Zhou, 2017). A shortcoming of these approximations is that as particle sizes increase (i.e. coarser aggregates), geometry simplifications reduce accuracy because particle shape has a dominant role on the behavior of the overall granular matrix. While these drawbacks are acknowledged, mathematical expressions are adequate for describing and generating complex particle shapes, such as the rotation-invariant spherical harmonic analysis (Garboczi, 2011; Zhou et al., 2015; Su and Yan, 2018) and Fourier mathematical method with random field theory (Bowman et al., 2001; Mollon and Zhao, 2014).

Optical microscopy, laser beam systems, and digital holography can also be used to obtain realistic grain morphology (Zhang, 2017; Nie et al., 2021; Lu et al., 2022). Further, clump or rigid blocks (Itasca Consulting Group, 2017) can be used in DEM approaches, with particle surface information used to represent the actual aggregate shape.

Particle shape can be classified into three independent descriptors (Barrett, 1980; Cho et al., 2006): form (such as aspect ratio and sphericity), angularity or roundness (Wadell, 1935), and roughness. The packing fraction for form scale parameters has been estimated by (Donev et al., 2004; Ng, 2009), who investigated the macro- and micro-behaviors of ellipsoids with varying aspect ratios. Meanwhile, (Azéma and Radjaï, 2010) suggested an elongation parameter to distinguish between rounded-cap rectangles in two dimensions before exploring the stress-strain behavior of these particles. To qualify particle shape, sphericity (Cho et al., 2006; Zhang et al., 2020) has been used to study its correlation with mechanical properties. The global shape parameters of aggregate assemblies remains the focus of many works with regards to their influence on packing density, shear strength, and mesoscopic characteristics (Fang et al., 2022; Kuhn et al., 2015; Zhao et al., 2020). Similarly, angularity has been the subject of much attention due to its significant impact on particle mechanical properties (Lu et al., 2022; Nie et al., 2020; Wu et al., 2021). However, it has been noted that the literature primarily focuses on investigating shape effects while providing limited straightforward guidelines for engineering practitioners.

Prior research in developing mathematical functions to explain the correlation between shape indexes and mechanical parameters has been limited. Although aspect ratios remain prevalent in engineering applications and technical guidelines, current specifications do not offer uniform values for the limits of aspect ratios. For instance, ASTM (American Society of Testing and Materials, 2010) suggests a long/medium aspect ratio of 2.0, medium/short aspect ratio of 3.0, and a ratio of 5.0 for fill selection, while the Australian Standard (Australian Standard, 2007) recommends an optimal aspect ratio of 2.0 and 3.0 for fill particles. Similarly, Chinese standards (National Railway Administration of

PRC, 2008, 2017) advocate a maximum to minimum axial dimension ratio of approximately 3:1. Using DEM, it may be plausible to optimize this ratio or generate more precise recommendations regarding the optimal shape indexes for specific mechanical performance.

In an attempt to study this relationship, this study uses a 3D DEM approach to investigate how aspect ratios affect coarse aggregates' packing characteristics and shear behavior. First, a laser scanner is employed to compile a point cloud database of 700 coarse aggregates. For each point cloud information, a rigid block unit is constructed using particle flow code. Based on the axial dimensions, elongation (*EI*), flatness (*FI*), and flatness-elongation index (*FEI*) are selected to quantify the aspect ratios of the point clouds and rigid blocks as a representation of the coarse aggregates. Then, a novel numerical protocol is used to simulate the aggregate compaction. Vibro-compaction creates a series of compaction levels by modifying the inter-particle coefficient of friction. Following this, numerical direct shear tests are performed to map aspect ratios with vertical pressure and shear strength. A mesoscopic perspective is gained by examining the contact forces and fabric tensor between particles. Finally, based on the particle aspect ratios, approaches to control compaction quality and prevent particle fragmentation are discussed.

2 Methods

2.1 Shape characterization

Aspect ratio is commonly measured using three orthogonal axial dimensions ($P_1 > P_2 > P_3$), calculated using principal component analysis (Zhou and Wang, 2017). Two orthogonal surfaces of a particle are used to calculate the elongation and flatness indices based on three axial dimensions. (Zingg, 1935; Zhao and Wang, 2016), expressed by:

$$EI = \frac{P_2}{P_1} \tag{1}$$

$$FI = \frac{P_3}{P_2} \tag{2}$$

95   where *EI* is the elongation index ranging from 0 to 1, and *FI* is the flatness index ranging from 0 to

96   1. A particle becomes more prolate when *EI* approaches 0, while the particle becomes more oblate

97   when its *FI* approaches 0.

98   The shape indexes *EI* and *FI* help measure particle shape irregularity in three dimensions. To

99   visualize the combined effect of particle shape and to facilitate subsequent analysis, the flatness-

100   elongation index (*FEI*) (Rajan and Singh, 2017) is also chosen for quantification, with the aim of

101   establishing a relationship between it and both compaction and shearing properties indicators. The

102   definition of *FEI* is given as:

103
$$FEI = EI \cdot FI = \frac{P_3}{P_1} \tag{3}$$

104   where *FEI* ranges from 0 to 1. Particles with a high maximum orthogonal axial dimension compared

105   to their minimum dimension result in a lower *FEI* value (*FEI*→0), and thus are more irregular in shape.

106   Alternatively, particles with a maximum orthogonal axial dimension are only slightly larger in

107   comparison with their minimum dimension, resulting in a higher *FEI* value (*FEI*→1). These particles

108   are more spherical in shape.

109   **2.2 Particle geometry modelling**

110   First, 3D laser scanning technology was used to obtain the natural shape characteristics of the

111   coarse aggregates (see Fig. 2). In DEM simulations, clumps often serve as non-spherical particle

112   models. These are formed by fusing two or more spherical units or 'pebbles' (Ferellec and McDowell,

113   2010; Li et al., 2015). The surface of a clump is defined by the position and radius of each constituting

114   pebble. The closer the number of pebbles is to infinity, the more the clump shape approximates natural

115   particles, resulting in a trade-off between precision and computational efficiency. As an alternative to

116   the clump concept, rigid block models (Rblocks) within the DEM framework (Itasca Consulting Group,

117   2017) simulate actual particles without the use of spheres. By employing scanned point clouds, an

118   Rblock mirrors a convex polyhedron, comprised of triangular facets. Literature (Lu et al., 2022)

119   supports the Rblocks' ability to robustly and effectively characterize irregular surfaces while retaining

120   computational efficiency. A comprehensive analysis of this is forthcoming in Section 3. The Gilbert–

121   Johnson–Keerthi (GJK) algorithm (Gilbert et al., 1988) offers a potential avenue for maximizing

122   computational efficiency in contact detection and resolution by utilizing a single contact between two

123   convex objects. Figure 1 illustrates an iterative approach using the Minkowski difference to determine

124   convex shape overlap. The Minkowski difference of two convex sets in mathematics refers to the set

125   of pairwise differences between all points from the two sets. This mathematical concept facilitates a

126   straightforward determination of contact between two particles: if the Minkowski difference contains

127   the origin, the two particles are in contact. The entire process can be expressed as:

$$m(A, B) = \{x - y; x \in A, y \in B\} \tag{4}$$

$$d(A, B) = |min\ m(A, B)| \tag{5}$$

130   where $m(A, B)$ denotes the Minkowski difference, x and y are any of the two points on A and B, and

131    $d(A, B)$ denotes the distance between convex polyhedral A and B.
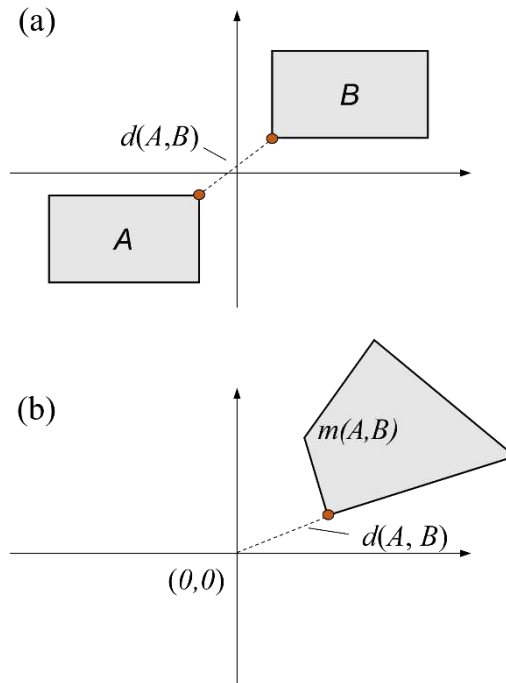
Fig. 1. Schematic of GJK algorithm for Rblocks contact: (a) the distance between convex A and B in

a real coordinate system; (b) Minkowski difference of two convex sets (A and B) and its distance to

135 the origin.

136 This study focuses on coarse, cohesionless grains (aggregates), and thus interparticle adhesion is

137 not considered. To represent interactions between particles, a linear-based contact model is used, which

138 uses linear springs acting in parallel. Linear springs at the contact location provide the particles' linear

139 elastic (tensionless) frictional properties (Cundall and Strack, 1979).

3 Materials and shape characterization

3.1 Reconstruction of realistic aggregate

142 The particles under study were coarse aggregates sampled from an in-situ subgrade fill on a high-

143 speed rail line in the Sichuan Province of China. These aggregates typically have a particle size range

144 of 2.36 to 31.5 mm. The particle size range was divided into seven groups to ensure each group's

145 minimum to maximum particle size ratio exceeded 0.50. One hundred particles were selected from the

146 respective groups, totaling 700 coarse aggregate particles. The acquisition of genuine 3D morphology

147 from the samples was accomplished using a Range7 laser scanner (Figure 2), manufactured by Konica

148 Minolta Inc.

149 The scanning procedure (Figure 2) was as follows:

150 a) To ensure precise measurements, the scanner was stationary on a stable surface, firmly secured

151 by a tripod to minimize vibrations. The particles under investigation were arranged on a revolving

152 platform. The internal environment was carefully controlled and maintained within specified

153 parameters (10 to 40 °C, 65% relative humidity or lower) compatible with the equipment's operation.

154 b) The optical lens served as a focal point, measuring the particles at a distance of 450 to 800 mm.

155 Subsequently, lasers enabled the acquisition of the point clouds on the surface of the particles. The

156 device had a scanning accuracy of approximately $\pm$ 40 μm, sufficient for describing the morphological

157 traits of the particles.

158 c) Controlling the rate of particle rotation involved the use of a fixed stepping angle of 60°,

159 determined by the size of the particle and the scanner's precision. The scanner captured the upper

160 portion of the particle at a full angle before inverting it to align the unscanned region with the scanner

161 for rescanning. The upper- and lower-point clouds were combined and aligned to create a high-fidelity

162 representation of the particle's surface. Through this process, point clouds and correlated DEM Rblocks

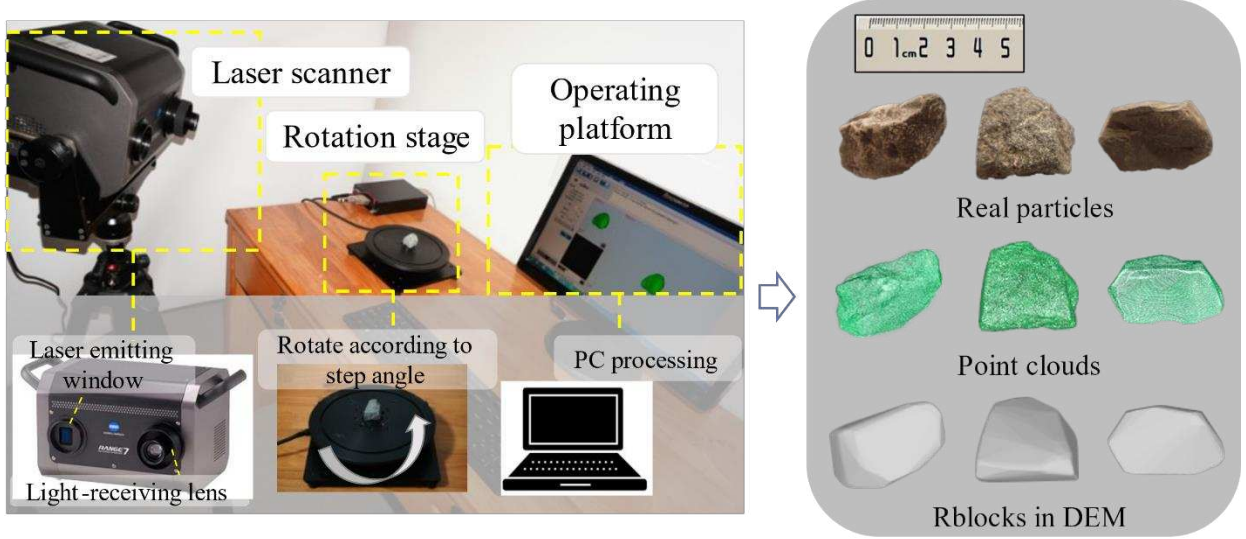163 were generated, ensuring accuracy in the description of the coarse aggregates.

164

165 Fig. 2. 3D laser scanning system and an illustration of real coarse aggregates, point clouds, and Rblocks.

166 **3.2 Statistical analysis of shape indexes**

167 Previous studies have demonstrated the significance of shape indices for describing granular

168 materials (Xiao et al., 2020; Zhao and Wang, 2016). These statistical shape indicators offer an

169 extensive understanding of the coarse aggregates' shape characteristics, which aid in the selection of

170 representative particle samples for analysis. Figure 3 depicts the frequency distribution histogram of

171 the calculated *EI* and *FI* for 700 coarse aggregates, comprising both real particles and Rblocks. The

172 aspect ratio distribution was in close proximity to the Weibull distribution, as indicated by the

173 histogram. Hence, a fitting method was used to determine the corresponding curvature of the

174 probability density distribution function. The resulting function is expressed as follows:

175
$$f(x; a, b) = \begin{cases} \dfrac{k}{\lambda}\left(\dfrac{x}{\lambda}\right)^{k-1} e^{-\left(\frac{x}{\lambda}\right)^{k}} & x \geq 0 \\ 0 & x < 0 \end{cases} \tag{6}$$

176 where x denotes the *EI* or *FI*, k is the shape parameter, and λ is the scale parameter.

9

177   Table 1 showcases the fitted λ and k values, along with statistical indicators such as mean,

178   coefficient of variation (C_v), skewness (SK), and kurtosis (KU), derived from the data in Figure 3. The

179   results suggest that the Rblocks closely resemble the aspect ratio characteristics of the natural

180   aggregates. Thus, it can be inferred that Rblocks preserve the natural aggregates' aspect ratio features.

181   According to (Lu et al., 2022), particle angularity can be more accurately represented using

182   Wadell's roundness of Rblocks when the number of facets (which is the unit of Rblocks) is

183   approximately 300. Thus, Rblocks were set to 300 to ensure the simulation's realism. Roundness was

184   initially delineated by Wadell (1935) as the ratio between the radius of a particle projection's corner

185   portion and the maximum radius of its inscribed circle. Methods to automate Wadell's roundness

186   evaluation process efficiently through digital image processing have been proposed (Nie et al., 2020;

187   Zhao and Wang, 2016; Zheng and Hryciw, 2016). Further details on angular scale are available in the

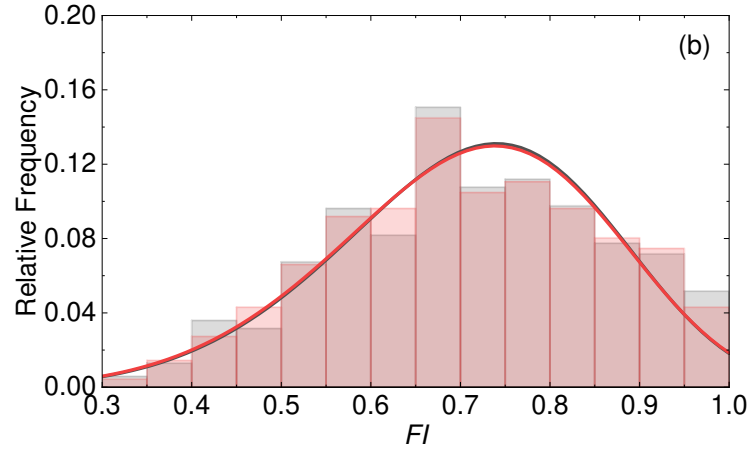188   aforementioned literature.

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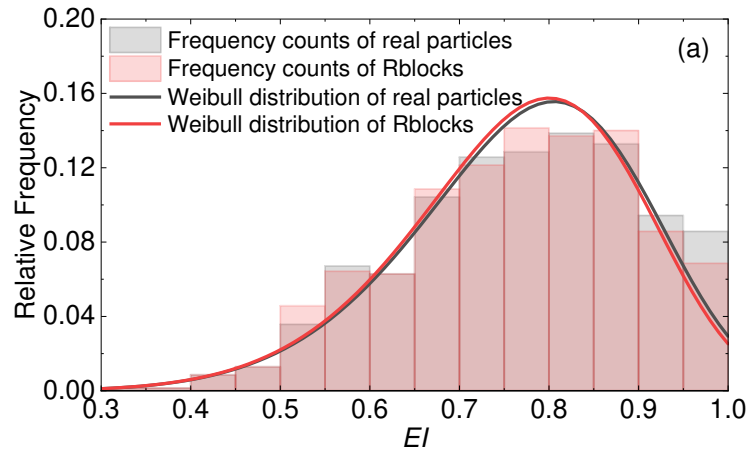
Fig. 3. Frequency histograms of *EI* and *FI* and the fitted Weibull distributions: (a) real particles; (b) Rblock model.

Table 1. Fitted parameters under Weibull distribution and statistical indicators of aspect ratios.

	EI		FI	
	Real particles	Rblocks	Real particles	Rblocks
Mean	0.769	0.764	0.708	0.707
C_v	0.173	0.172	0.215	0.216
SK	−0.383	−0.391	−0.212	−0.183
KU	−0.485	−0.420	−0.507	−0.465
k	6.984	6.393	5.319	5.380
λ	0.824	0.819	0.768	0.769

3.3 Particle sample selection

According to Zingg (1935), the *EI* and *FI* of coarse aggregates can be divided into three groups: prolate, oblate, and scalene. Following the known *EI* and *FI* values ranges, nine representative particle samples were selected at *EI*s of approximately 0.95, 0.75, and 0.55, and *FI*s of approximately 0.95, 0.75, and 0.55. DEM simulations were then used to analyze these samples, which are illustrated in Figure 4. As *EI* decreases, the particle prolate becomes more pronounced; as *FI* decreases, the particle oblate becomes more apparent. There is a greater degree of scalene when the values of *EI* and *FI* are both small, meaning that there is a significant difference between the three axial dimensions (P_1, P_2 and P_3) of a particle.

The DEM specimens corresponding to these nine Rblocks are named according to their shape characteristics. As shown in Fig. 4.
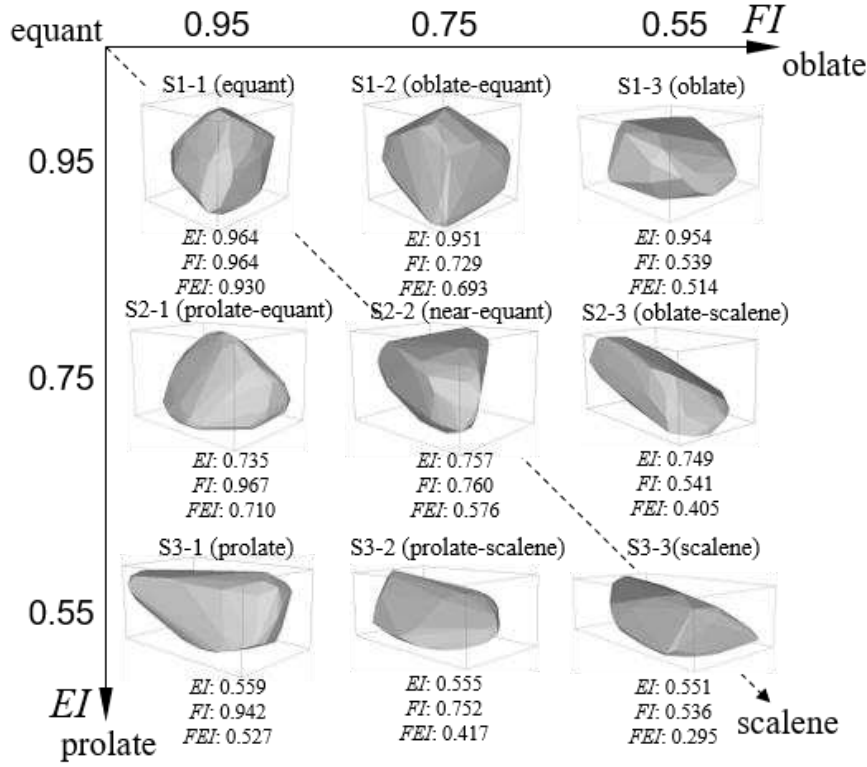
Fig. 4. Particle shape classification using Zingg's bivariate method (Zingg, 1935).

4 Models and calibration

4.1 Vibro-compaction model

Using gravitational deposition and additional compression, the inter-particle friction coefficient μ_p is usually set to zero in DEM to achieve dense specimens (Abbireddy and Clayton, 2010; Gong et al., 2019; Nie et al., 2021). According to this method, a larger value of μ_p means the particles are less likely to slide between one another. A smaller μ_p means particle sliding is easier, and thus particle rearrangement happens more easily under external forces, resulting in a denser aggregate.

Compaction simulations were performed for each of the nine typical Rblocks. A variety of packing densities were obtained based on the initial values of $\mu_p = 0, 0.1, \cdots, 1$. Since vibro-compaction is a dynamic process, the DEM simulation employed a blend of viscous and local damping (refer to Table 2). The damping coefficients employed in the numerical model were calibrated as per the findings of (Zhou and Sun, 2013). Other DEM contact parameters were set based on the calibration results

218   described in Section 4.3. Compression was achieved using surface vibration compaction (Figure 5),

219   via the following steps:

220   a) The randomly generated Rblocks were placed in a cuboidal domain with a length, width, and

221   layer thickness of 150 mm. The equivalent particle size of the Rblocks was 20 mm.

222   b) A rigid load plate compacted the specimen after the Rblocks had been subjected to gravitational

223   deposition and reached stability. The vibration frequency was 50 Hz , cycling the force between 2.88

224   kN (18 kPa), and 52.88 kN (330.5 kPa) (National Railway Administration of PRC, 2010). The

225   compaction process was considered complete after the porosity of each specimen reached stability.

226   c) Steps a and b were repeated three times, and particles above 350 mm in height removed. Note

227   that the final specimens had the exact dimensions as the direct shear box in the physical tests (Zhang,

228   2017).

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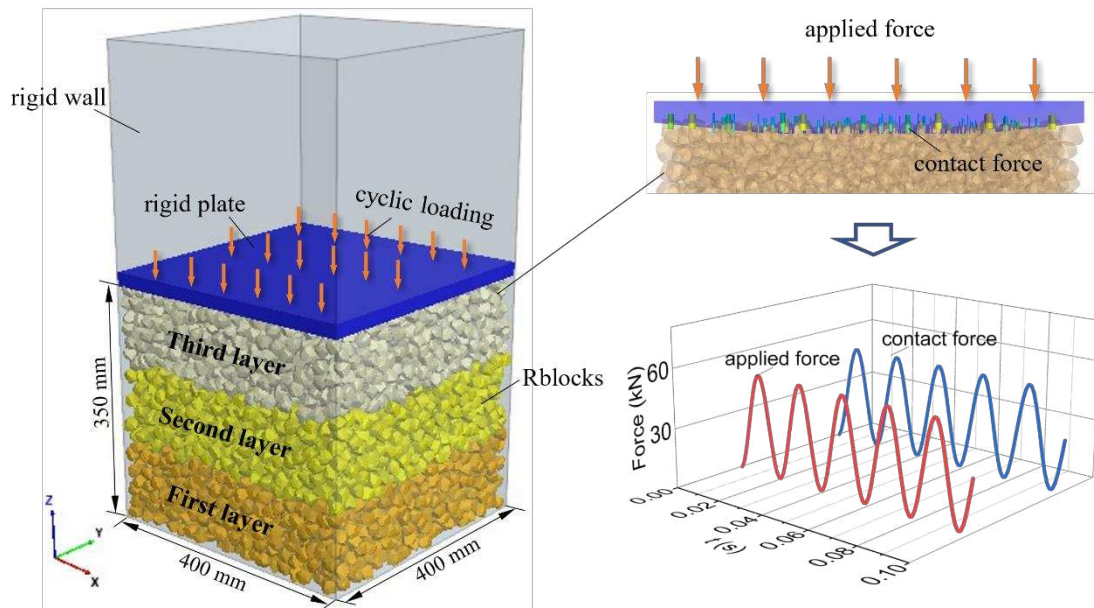
230   Fig. 5. Schematic of the surface vibratory compaction method for achieving target packing density of coarse

231   aggregates: the applied force on the specimen from the rigid plate was equal to and synchronized with the

232   contact force received by Rblocks.

233   **4.2 Direct shear test on compacted samples**

234   Direct shear simulations were also performed for homogenous particle matrices consisting of each

235   of the nine Rblock types. Note that the vertical stresses σ_n applied to each specimen are 20, 50, 100,

236 and 150 kPa. Using the calibration results in Section 4.3, the other DEM contact parameters were be

237 set. As noted in Section 6.1, the initial condition of each specimen was determined through compaction

238 simulation, but the corresponding packing density remained unchanged.

239   The shear strength of the coarse aggregates was investigated using direct shear tests. Similar to

240 the container for the post-compaction specimens, the dimensions of the direct shear device in the

241 numerical test were 400×400×350 mm, with a 5 mm shear gap in the middle (Figure 6). During the

242 shear process, the upper part of the shear box was fixed, and the lower part was sheared along the

243 horizontal direction at a specific rate. The upper and lower walls maintained the load applied to the

244 specimens until the shear displacement reached 80 mm (20% of the length of the shear box), at which

245 point the test was terminated. Figure 6 illustrates the final state of the compacted aggregates in shear.
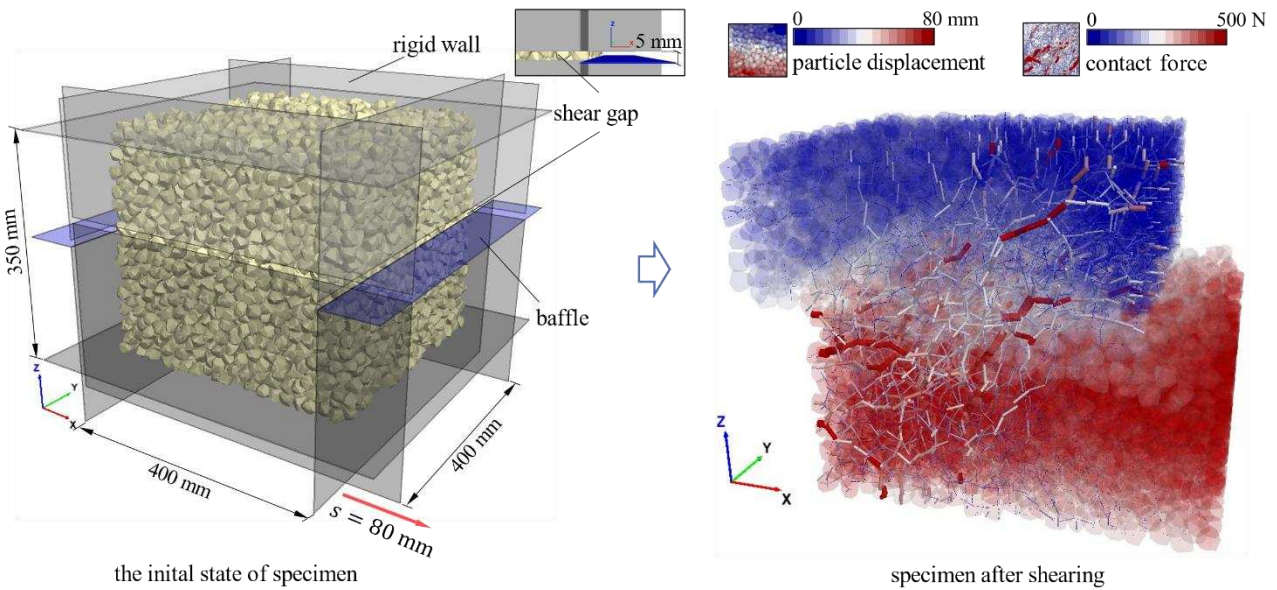
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247 Fig. 6. Schematic of DEM simulations for the direct shear test: baffle prevents particles from spilling out during

248 the shearing process.

249 **4.3 Parameter calibration**

250   The DEM parameters were calibrated by comparing them with experimental data (Zhang, 2017).

251 The experimental setup for direct shear is illustrated in Figure 7. The shear box had a volume of 400

252 mm×400 mm×350 mm and housing coarse aggregates with porosity of 0.4. The tests utilized

14

253 maximum hydraulic actuator loads of 300 kN and 100 kN in the vertical and horizontal directions,

254 respectively.

255
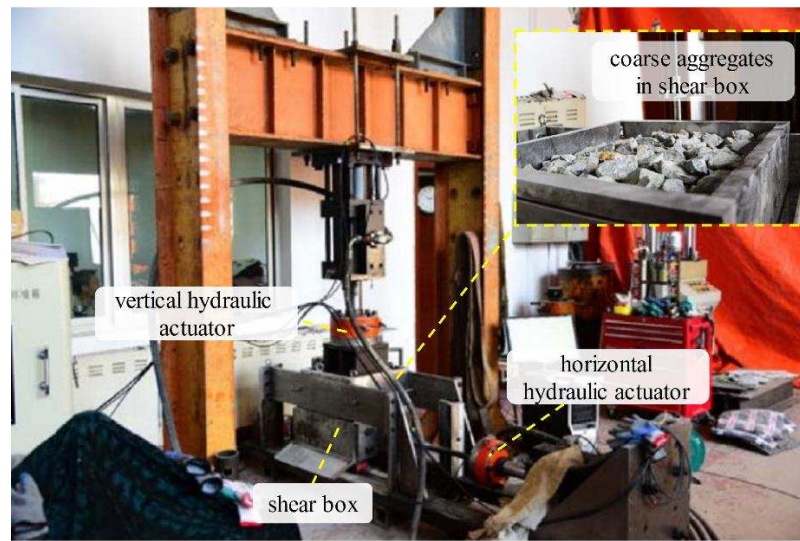
256 Fig. 7. Overview of the direct shear testing system (Zhang, 2017).

257   Note that the particles employed in the study by Zhang (2017) were sourced differently from the

258 scanned particles currently under scrutiny. Despite this, several compelling reasons justify the use of

259 these experiments for calibration. Predominantly, both aggregates - frequently applied in railway

260 construction - originate from crushed rocks with similar strengths and shapes. Additionally, the direct

261 shear device featured in the numerical experiments aligns with the methodology documented in the

262 experimental study. The preparation of the numerical specimen was executed as follows: first, non-

263 overlapping balls were generated within a shear box of predetermined porosity, and the three-

264 dimensional coordinates and volumes of each ball were calculated. The porosity and gradation of the

265 balls were kept consistent with literature (Zhang, 2017). Second, the balls were removed and Rblocks

266 of coarse aggregate were generated at the original coordinates of each ball, with equal volumes and

267 random angles. The particle shape profile used for each Rblock was randomly selected from the

268 scanned 700 coarse particles. Lastly, the final state was determined by conducting sufficient time

269 steps to ensure a stable equilibrium between the Rblocks.

270   As described in Section 2.2, there was no adhesion between the coarse aggregates meaning a linear

271   contact model was a suitable assumption. Combining the mesoscopic parameters related to the direct

272   shear tests (Bian et al., 2015; Xiao and Tutumluer, 2017; Zhang, 2017) and the experimental data

273   (Zhang, 2017), the calibration results and the microscopic parameters are presented in Table 2 and

274   Figure 8.

275   Table 2. The DEM parameters of the direct shear simulation after calibration.

	Micro-parameters	Unit	Value
	Normal stiffness of particle	MN/m	20
	Tangential stiffness of particle	MN/m	10
	Normal stiffness of wall	MN/m	100
	Tangential stiffness of wall	MN/m	100
	Wall–particle frictional coefficient	/	0.40
Vibro-compaction	Interparticle frictional coefficient	/	0, 0.1 ···, 1.0
	Local damping	/	0.05
	Normal viscous damping	/	0.20
	Tangential viscous damping	/	0.20
Direct shear	Interparticle frictional coefficient	/	0.60
	Local damping	/	0.7

276   **Note:** As the direct shear test is a quasi-static process, local damping of 0.7 is used for the contact.
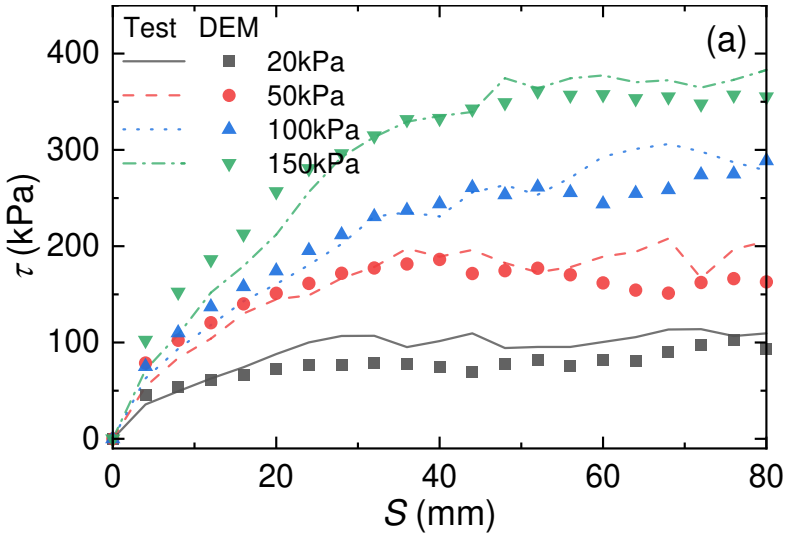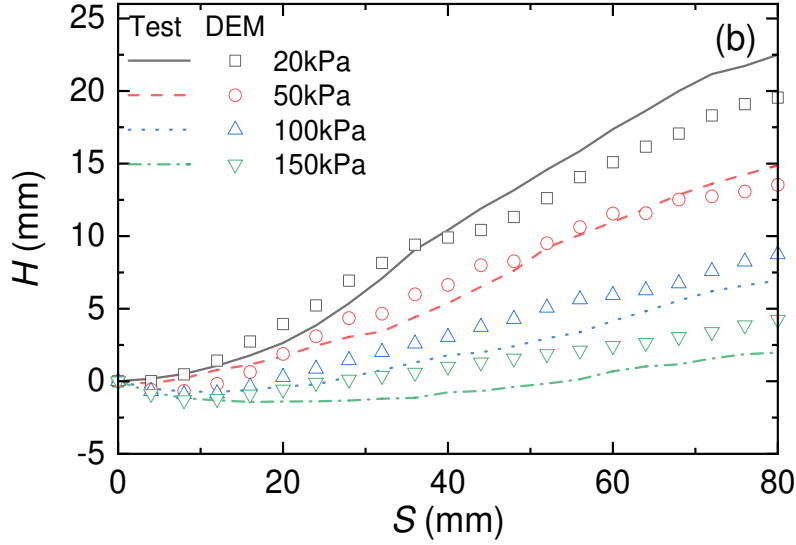

277

Fig. 8. DEM calibration results compared to (Zhang, 2017): (a) shear strength; (b) vertical displacement (τ is the shear strength, H is the vertical displacement, and S is the shear displacement).

5 Analysis of compaction characteristics

5.1 Effect of particle shape on porosity

The final compacted state of each specimen was measured using measuring spheres (Itasca Consulting Group, 2017) for porosity determination. The measuring sphere reflects the percentage of void volume within the sphere, meaning it reflects the porosity of a region inside it. Figure 9 shows the porosity of nine specimens after compaction for a series of μ_p values ($\mu_p = 0, 0.1, \cdots 1.0$). The porosity of the specimens increases with increasing μ_p within the same sample, but the rate slows when approaching $\mu_p = 1$. All particle aspect ratios exhibit the same pattern, which is similar to that observed in particle porosity with inter-particle friction coefficient (Abbireddy and Clayton, 2010; Huang et al., 2015). The relationship between porosity n_p and μ_p of specimens with different particle aspect ratios can be fitted using an exponential function:

$$n_p = \zeta - \alpha_1 \cdot \alpha_2^{\mu_p} \tag{7}$$

where ζ, α_1 and α_2 denote the regression coefficients respectively, as shown in Table 3.
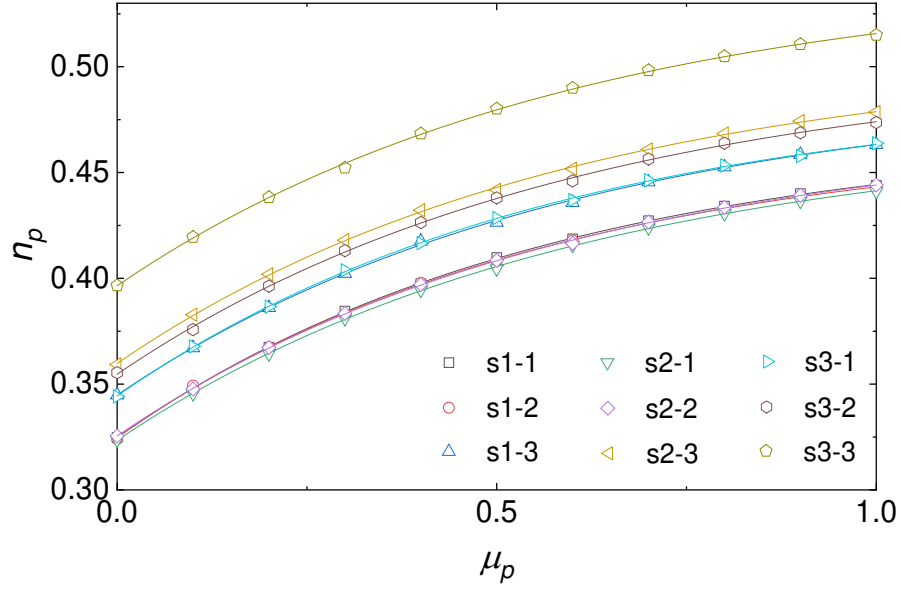
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295 Fig. 9. Variation on the porosity of specimens under different shapes and different interparticle-friction

296 coefficients.

297   Table 3 shows that the curve fit is more sensitive to ζ compare to α_1 and α_2. For example,

298 considering all samples, the range of $\Delta\zeta$ is 0.07, while for $\Delta(\alpha_1 \cdot \alpha_2{}^{f_p})$ the range is 0.005. This is

299 because ζ is primarily affected by the particle aspect ratio, while α_1 and α_2 are related to the

300 gradient of the fitted curve which is similar for all particles. Therefore, in the subsequent analysis, α_1

301 and α_2 are set as constants, with values 0.145 and 0.18, respectively.

302   Table 3. The corresponding regression coefficient data after the fitting of Eq. (4).

ID	ζ	α_1	α_2	R^2
S1-1	0.469	0.144	0.171	99.35%
S1-2	0.468	0.143	0.171	99.52%
S1-3	0.491	0.146	0.189	99.51%
S2-1	0.469	0.146	0.190	98.99%
S2-2	0.471	0.146	0.187	99.66%
S2-3	0.506	0.146	0.185	99.19%
S3-1	0.488	0.144	0.174	99.73%
S3-2	0.502	0.148	0.191	99.19%
S3-3	0.543	0.147	0.189	99.86%

303 **Note**: R^2, Goodness of fitting.

304   Next, a function for correlating the shape parameters EI, FI and ζ was constructed. As show

18

305   in Figure 10a, the relationship between EI, FI, and ζ satisfies the quadratic equation (refer to Eq.

306   (8)). Concerning Eq. (7), n_p can be derived using Eq. (9). In particular, when $EI = 0.869$ and $FI =$

307   0.839, there exists a minimum value, $\zeta_{min} = 0.472$.

$$\zeta(EI, FI) = 1.09 - 0.68EI - 0.77FI + 0.29EI^2 + 0.35FI^2 + 0.21EI \cdot FI \qquad (8)$$

308

$$n_p = \zeta(EI, FI) - \alpha_1 \cdot \alpha_2{}^{\mu_p} \qquad (9)$$

309

310   To corroborate the aforementioned calculations, the published work (Donev et al., 2004) was

311   examined. In their study, a modified Lubachevsky-Stillinger algorithm was utilized to estimate the

312   packing fraction of randomly jammed frictionless hard ellipsoids in three dimensions. The algorithm,

313   which incorporated controlled particle growth, is an event-driven molecular dynamics simulation

314   (Donev et al., 2005a, 2005b). The packing fraction of ellipsoids with three orthogonal axial dimensions

315   α: 1: 1 (prolate for $\alpha > 1$, oblate for $\alpha < 1$) and α: 1: α^{-1} (aspherical) as a function of α was determined.

316   It was found that the n_p of ellipsoidal aggregates decreased and then increased with increasing *FEI*,

317   with the densest state ($n_p \approx 0.29$) for prolate and oblate ellipsoidal particles at a *FEI* of 0.67 and the

318   densest state ($n_p \approx 0.265$) for aspherical ellipsoidal particles at a *FEI* of 0.64. Similarly, for coarse

319   aggregates, n_p decreased and then increased with increasing *FEI*, reaching the densest state ($n_p \approx 0.326$)

320   at an *FEI* of approximately 0.72 ($EI = 0.869$ and $FI = 0.839$), as determined by Eq. (9) when $n_p = 0$

321   (Figure 10b). This was attributed to the increase in the number of contacts resulting from the additional

322   degrees of freedom of the ellipsoids. The denser packing of the particles was a consequence of the

323   need for more contacts per particle to eliminate all local and collective degrees of freedom. However,

324   the increase in porosity for large *FEI* was due to exclusion volume effects. It is worth noting that the

325   results for coarse aggregates differ somewhat from the literature (Donev et al., 2004) due to the

326   Rblocks model's ability to characterize the angularity of the particles. (Cho et al., 2006) concluded that

327   as the particle roundness decreases (angularity increases), the corresponding void ratio also increases.

328   Furthermore, standard balls were compacted under identical conditions, yielding an n_p of

329 approximately 0.36, which is identical to the reported results (Donev et al., 2004).

330   Regarding porosity, Figure 10b shows that EI and FI have approximately equal influence. For

331 instance, the n_p value for an oblate-equant specimen ($EI = 0.95, FI = 0.75$) is 0.330 and for a

332 prolate-equant specimen ($EI = 0.75, FI = 0.95$) is 0.332, equating to a 0.6% difference. Similarly,

333 n_p for an oblate specimen ($EI = 0.95, FI = 0.55$) is 0.352 and for a prolate specimen ($EI = $

334   $0.55, FI = 0.95$) is 0.353 equating to a 0.28% difference; As is evident from the above cases, the

335 effect of EI and FI on n_p of the coarse aggregates is approximately the same. The intermediate

336 axis (P_2) of a particle exerts a minimal influence on n_p, meaning that the contribution of P_2 can be
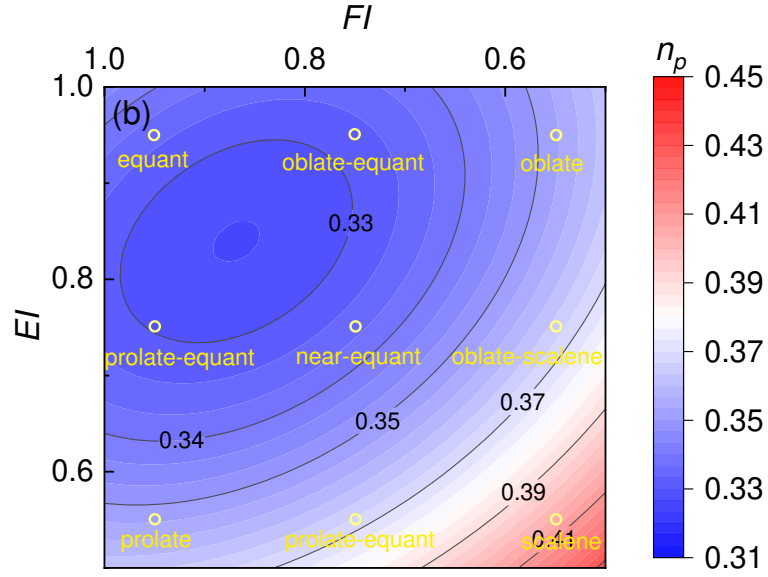
337 ignored.

338
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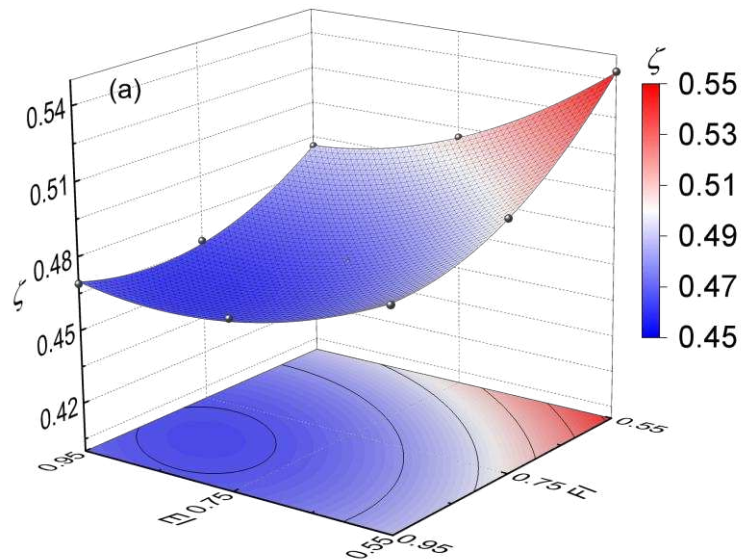
341 Fig. 10. Regression coefficients ζ and porosity n_p as a function of EI and FI: (a) ζ; (b) n_p when

342 $\mu_p = 0$.

5.2 Compaction control

344   Compaction performance refers to the ability of a body of coarse aggregate to achieve a desired

345 level of compaction under external pressure. Particles with irregular shapes are more likely to form

346 interlocking that prevents effective compaction. According to (American Society of Testing and

347 Materials, 2010; Australian Standard, 2007; National Railway Administration of PRC, 2008, 2017),

348 the maximum and minimum axial dimensions of coarse particles used as ballast or subgrade fill are

349 explicitly limited. The most rigorous requirement is that they conform to an aspect ratio of 3.0. Since

350 the ratio limits are still based on engineering experience, it remains to be seen whether there is a clear

351 threshold between the variation in particle aspect ratios and the compaction properties. Although the

352 analyses in this study are discussed for samples with different particle shapes at homogeneous particle

353 sizes, the method allows the particle shape to be controlled as a single variable, thus providing a better

354 understanding of the influence of particle shape on compaction.

355   Therefore, this section explores how to control the compaction of coarse aggregates by studying

356 the influence of FEI. Based on n_p of specimens with differing aspect ratios, the relative porosity P_r

357 is defined as:

21

$$P_r = \frac{n_{p\ max} - n_p}{n_{p\ max} - n_{p\ min}} \tag{10}$$

where $n_{p\ max}$ is the value for the scalene specimen ($EI = 0.55$, $FI = 0.55$), which is close to the aspect ratio limit requirement of coarse aggregates. $n_{p\ min}$ is the minimum value computed using Eq. (9). Note that μ_p when determining the values of $n_{p\ min}$ and $n_{p\ max}$, μ_p is 0.6.

Fig. 11 shows the exponential relationship between P_r and FEI for $\mu_p=0.6$, as described in Eq. (11). To maximise the fit, 16 additional particles within the range: 0.55 < EI < 0.95, 0.55 < FI < 0.95, were selected for calculation under the same conditions, supplementing the existing calculation results for the above representative particles. As FEI increases, P_r first increases rapidly and then gradually. The maximum curvature of this function curve is indicated as the threshold point for the variation of P_r with FEI. The maximum value of curvature occurs when $FEI = 0.469$.

$$P_r = 0.97 - 21.76e^{-10FEI} \tag{11}$$

The results suggest that coarse aggregates were difficult to compact when there was significant axial particle size difference, particularly if the aggregates had prolate, oblate, or scalene shapes. It is possible to control the packing density by keeping FEI greater than the threshold (0.469). Accordingly, the maximum and minimum axial dimensions ratio is approximately 2:1.
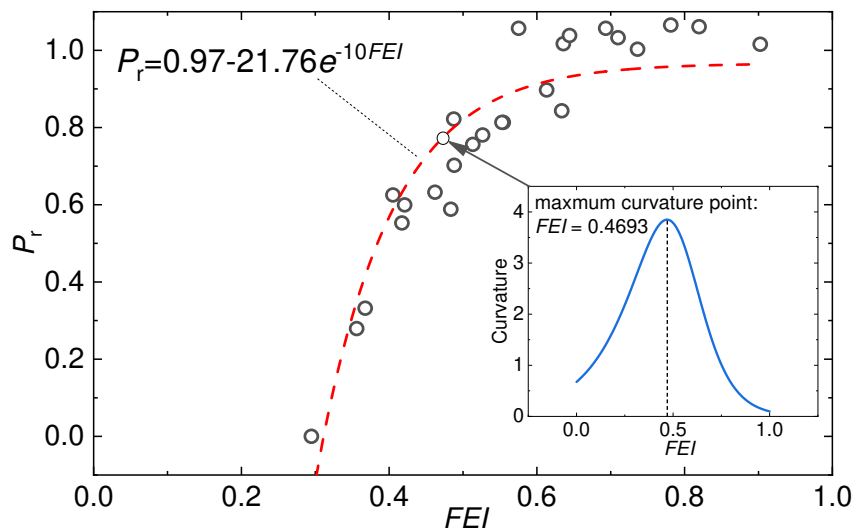
Fig. 11. Variation in n_p with FEI and the corresponding curvature value distribution at $\mu_p = 0.6$.

6 Analysis of shear behaviour

6.1 Shape effects on shear strength

Nine aggregate mixes formed from the aforementioned shapes were analyzed under controlled initial porosity conditions, with the aim of investigating the effect of aspect ratio on shear behavior. Following the above analysis, $n_p = 0.42$ was selected as the final compaction criterion. The preset friction coefficient μ_p was calculated using Eq. (9) to perform compaction on specimens. Table 4 shows the preset friction coefficient μ_p and porosity n_p for each specimen. All n_p values were close to 0.42, with a maximum difference of 0.65%.

Table 4. μ_p and n_p values derived from Eq. (4) and DEM simulations.

	μ_p	n_p	Relative error
S1-1	0.614	0.418	−0.57%
S1-2	0.626	0.419	−0.21%
S1-3	0.431	0.421	0.12%
S2-1	0.647	0.417	−0.62%
S2-2	0.627	0.418	−0.48%
S2-3	0.339	0.423	0.65%
S3-1	0.423	0.418	−0.38%
S3-2	0.367	0.422	0.49%
S3-3	0.142	0.421	0.17%

Figures 12 (a) - (i) illustrate the variation of shear strength τ and vertical displacement H of each specimen under the direct shear test conditions. The data indicates τ for each specimen exhibited strain-hardening, whereas H primarily showed a trend of small shear contraction followed by continuous shear expansion. Further, the specimens with different aspect ratios showed an increase in shear strength and vertical displacement with the decrease of EI and FI.

23
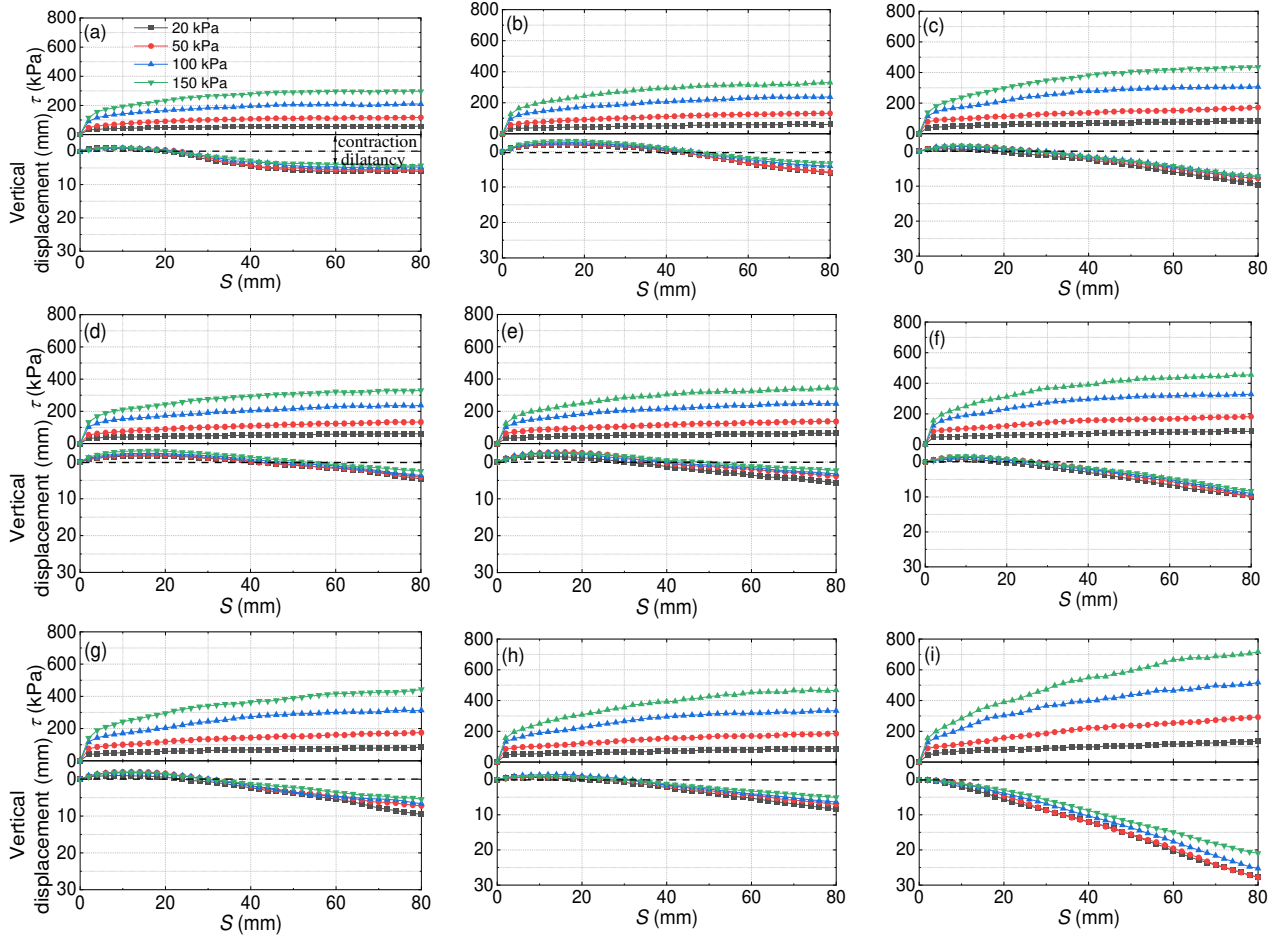
Fig. 12. Shear strength and vertical displacement of the specimens in direct shear simulations under the same porosity: (a) S1-1; (b) S1-2; (c) S1-3; (d) S2-1; (e) S2-2; (f) S2-3; (g) S3-1; (h) S3-2; (i) S3-3.

As shown in Fig. 13, the peak shear strength τ_p and the vertical stress σ_n had a non-linear relationship. A power function relationship was used to describe shear strength envelope of each specimen:

$$\tau_f = \eta \sigma_n{}^\beta \tag{12}$$

where η, β denote the regression coefficients, as specified in Table 5.

Fig. 13. Shear strength envelopes for specimens of different shapes.

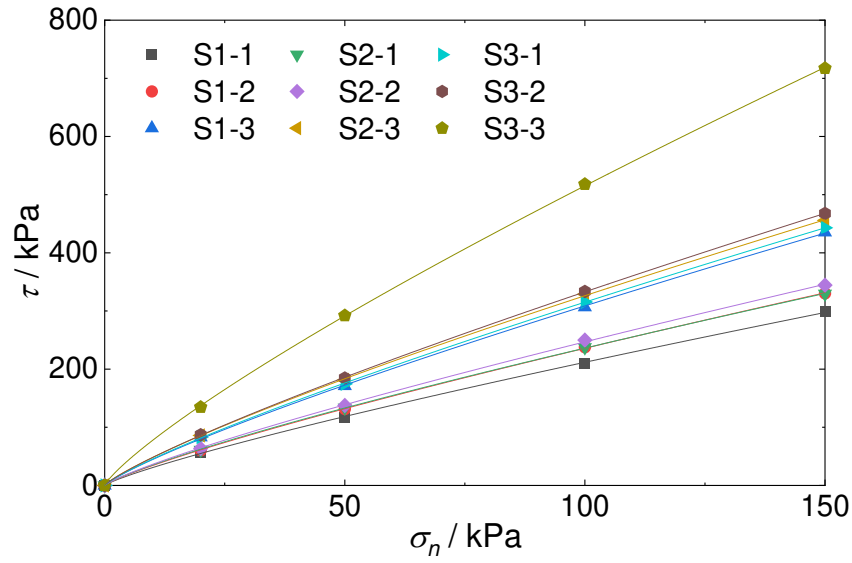399   Table 5 shows that the value of $\Delta\eta$ varied by 7.23 across all simulations while $\Delta\beta$ varied by

400   0.018. This is because the regression parameter η was mainly affected by particle shape, while β was

401   relatively constant. Therefore, a typical value of β=0.83 was assumed to be representative for all

402   samples.

403   Table 5. The regression coefficients for the fitting of Eq. (12).

ID	η	β	R^2
S1-1	4.48	0.838	99.98%
S1-2	4.99	0.837	99.99%
S1-3	6.46	0.840	99.98%
S2-1	5.25	0.827	99.99%
S2-2	5.36	0.832	99.97%
S2-3	7.12	0.831	99.98%
S3-1	6.60	0.840	99.99%
S3-2	6.97	0.840	99.99%
S3-3	11.71	0.822	99.99%

404   Next a function to describe the shape parameters EI, FI, and η was constructed. As shown in

405   Figure 14a, the relationship between EI, FI and η was quadratic in nature, described using Eq. (13).

406   Referring to Eq. (12), τ_p can be further expressed using Eq. (14). In particular, when $EI = 1.00$ and

407    $FI = 0.839$, the minima value (η_{min}) was 4.26. Fig. 14b showed the peak shear strength distribution

408　fitted using Eq. (14) at σ_n=100 kPa, where the minimum value $\tau_{p\,\min}$ was 194.63kPa.

409　　　　$$\eta(EI, FI) = 46.54 - 34.09EI - 60.92FI + 13.79EI^2 + 31.12FI^2 + 8.61EIFI \qquad (13)$$

410　　　　$$\tau_p = \eta(EI, FI)\sigma_n{}^{\beta} \qquad (14)$$

411　　　On the other hand, Figure 14b showed that there were some differences in the effects of EI and

412　FI on the shear strength of the coarse aggregates. For instance, the oblate-equant specimen had a τ_p

413　value of 232.60 kPa, while prolate-equant specimen had a τ_p value of 208.06 kPa, (a difference of

414　10.55%). Similarly, the oblate specimen had a τ_p value of 305.91 kPa, while τ_p for the oblate

415　specimen had a value of 318.43 kPa, (a difference of 4.09%). However, compared to the differences

416　in τ_p for specimens with different aspect ratios, the effect of P_2 in particle was relatively low. The

417　compacted state of the coarse aggregates or analytical bias resulting from the sample number could
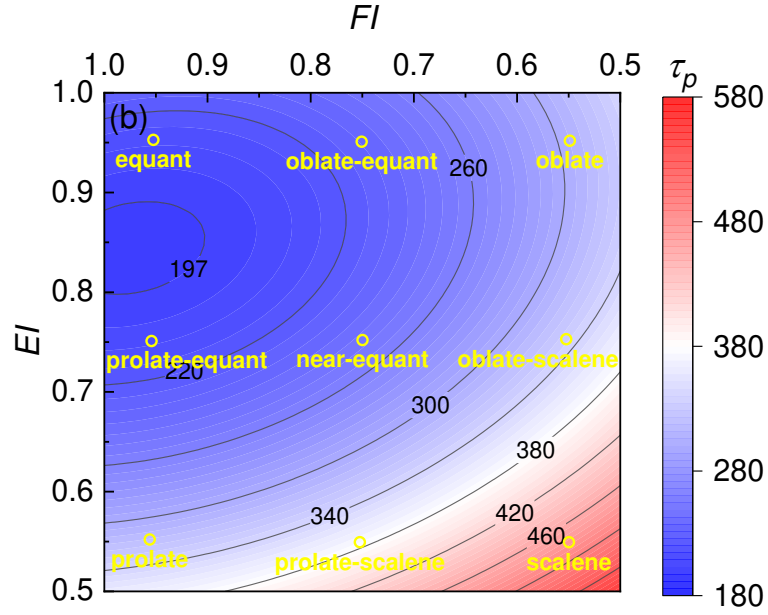
418　explain this finding.
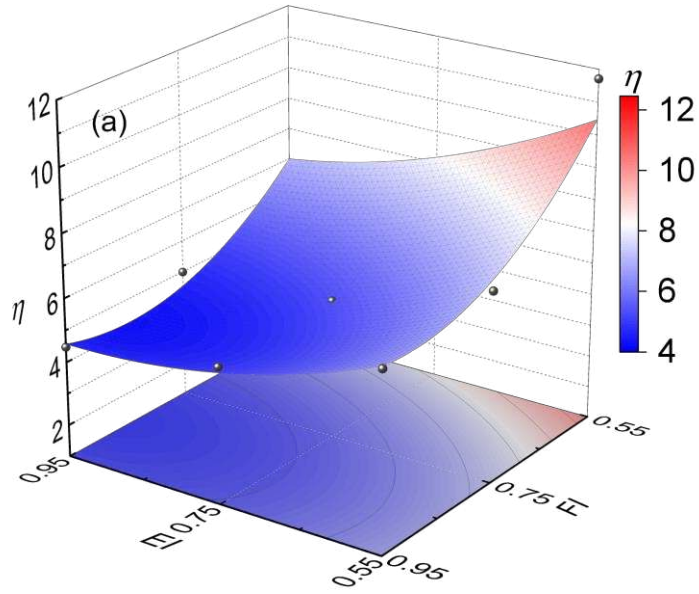
419

Fig. 14. Regression coefficients η and τ_p as a function of EI and FI: (a) η (b) τ_p when $\sigma_n = 100$ kPa.

6.2 Contact force

Particle-particle contacts in granular materials transmit external loads from one boundary to another. These contact forces are a critical factor in determining the mechanical properties of granular materials (Radjai et al., 1998). Inhomogeneity in the spatial distribution of granular materials makes it challenging to characterize their contact networks (Majmudar and Behringer, 2005). Previous investigations (Azéma et al., 2009; Thornton, 2000) show the normal contact force contributes more towards the deviatoric stress tensor than the tangential contact force. Therefore, the purpose of this section is to provide a quantitative analysis of contact force networks based on the normal contact force.

The spatial distribution of normal contact forces can be visualized intuitively using a spherical histogram in which each bar represents the local average normal contact force $\overline{f_n}$ in that direction. The local average normal contact force $\overline{f_n}$ denotes the average of the magnitudes of normal contact forces that fall in the direction intervals of the corresponding bar. The spherical histogram is an exact sphere for an isotropic distribution of normal contact forces. A non-spherical histogram implies an anisotropic distribution of normal contact forces. All specimens exhibit similar shear strength at the

438 same σ_n. Hence, the results were analyzed at σ_n=100 kPa.

439 Figure 15 shows the normal contact force histogram for specimens at different shear displacements

440 ($S = 0, 40, 80$ mm) where the corresponding local minimum average contact force $\bar{f}_{n,min}$ and local

441 maximum average contact force $\bar{f}_{n,max}$ are calculated. At the initial stage of the shear process ($S =$

442 0 mm), the distribution of the corresponding normal contact forces was approximately the same for

443 each specimen, with $\bar{f}_{n,min}$ and $\bar{f}_{n,max}$ ranging from 20 N to 50 N. As shear displacement developed,

444 each specimen gradually exhibited a horizontal distribution of normal contact forces, and the difference

445 between $\bar{f}_{n,min}$ and $\bar{f}_{n,max}$ became larger.

446 The specimens (prolate-equant, oblate-equant, near-equant) increased the aggregate matrix shear

447 strength without changing the internal contact forces compared to those with equant characteristics.

448 Increasing the particle shape's prolate, oblate, or scalene characteristics significantly increased the

449 internal contact forces, despite increased macroscopic shear strength. For instance, given $S = 80$ mm,

450 $\bar{f}_{n,max}$ of these specimens increased between 2 to 4 times compared to specimens with equant
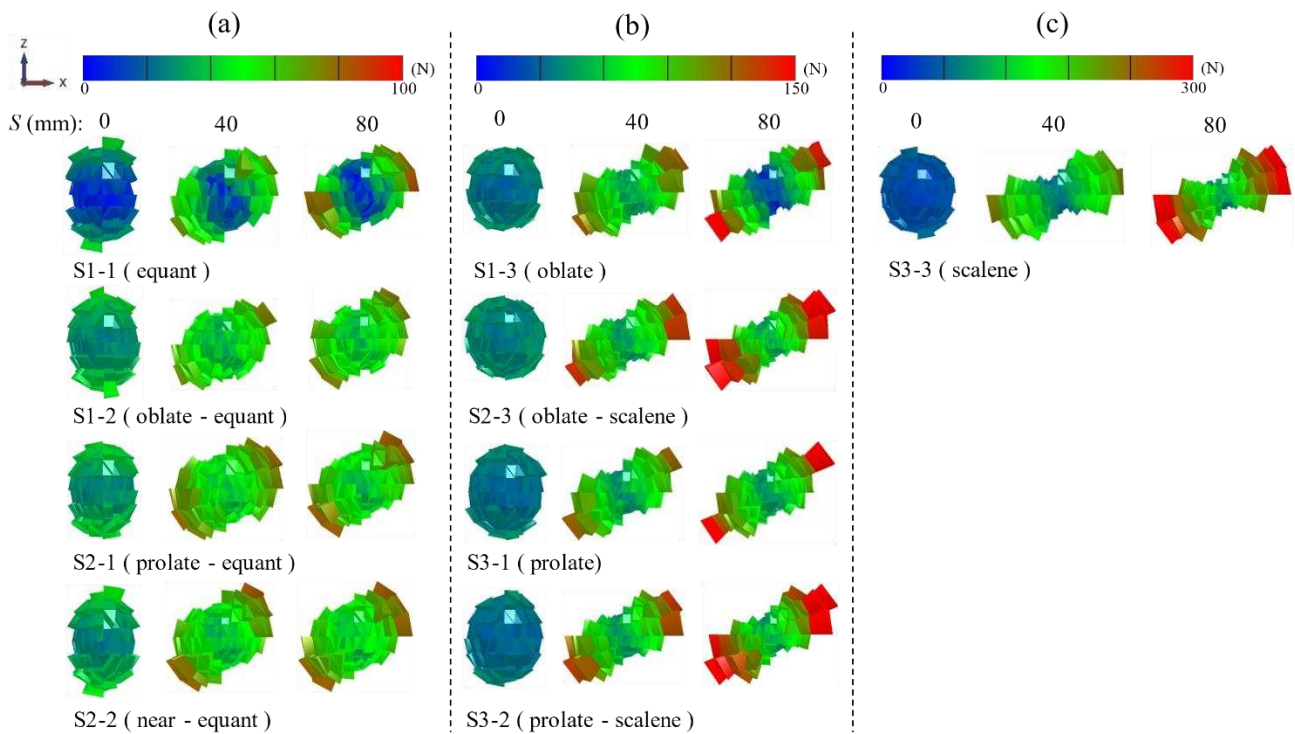
451 characteristics.

452

453   Fig. 15. Histogram of normal contact force distribution for coarse aggregates of various shapes: (a) the

454   specimens when EI and $FI \geq 0.75$; (b) the specimens When $EI \leq 0.55$ or $FI \leq 0.55$; (c) the

455   specimens when EI and $FI \leq 0.55$.

456   **6.3 Fabric tensor**

457   Fabric anisotropy is an important characteristic of granular materials. Therefore, the concept of a

458   fabric tensor (Oda, 1982; Satake, 1978) is now studied to investigate the internal structure of

459   aggregates. According to (Oda, 1982; Ouadfel and Rothenburg, 2001), the probability density function

460    $E_{(c)}$ of contact normals (the unit normal vector between contact particles) at a spherical unit surface

461   is:

462
$$\int_0^{2\pi} \int_0^{\pi} E_{(c)} \sin(\beta) \, d\alpha d\beta = 1 \tag{15}$$

463   where the ranges of α and β are $0 \leq \alpha < 2\pi$ and $0 \leq \beta < \pi$, respectively. Hence, the fabric

464   tensor of a contact normal can be expressed as:

465
$$\Phi_{ij} = \int_0^{2\pi} \int_0^{\pi} E_{(c)} \, n_i \, n_j \sin(\beta) \, d\alpha d\beta \tag{16}$$

466   where n_i is the unit vector of a contact normal, given as a column vector

467    $(\sin(\beta)\cos(\alpha), \sin(\beta)\sin(\alpha), \cos(\beta))$; n_j is the transpose matrix of n_i, which can also be written

468   as n_i^T. The corresponding fabric tensor can be readily obtained from DEM results as:

469
$$\Phi_{ij} = \frac{1}{N_c} \sum_{k=1}^{N_c} n_i n_j \tag{17}$$

470   where N_c denotes the total number of contacts in the granular assembly, and $i, j = x, y, z$ in the

471   Cartesian coordinate system.

472   The fabric tensor in Eq. (17) has three eigenvalues, Φ_1, Φ_2, Φ_3 ($\Phi_1 \geq \Phi_2 \geq \Phi_3$) and three

473   corresponding eigenvectors. The eigenvectors and eigenvalues determine the direction and size of

474   fabric anisotropy respectively. A deviatoric eigenvalue (Barreto et al., 2009) was proposed to determine

475   the anisotropy under the influence of three eigenvalues of the fabric tensor. Note that fabric tensors

476   exhibit greater anisotropy with increasing deviatoric eigenvalues. Deviatoric eigenvalues indicate the

477   concentration of embedded forces that resist shear deformation. The concentration of embedded forces

478   increase the contact forces on the particles in the shear region, resulting in particle fragmentation.

479   Following the concept above, Φ_d reflected the anisotropy of the fabric tensor (deviatoric fabric

480   tensor), expressed by:

481
$$\Phi_d = \frac{1}{\sqrt{2}}\sqrt{(\Phi_1 - \Phi_2)^2 + (\Phi_1 - \Phi_3)^2 + (\Phi_2 - \Phi_3)^2} \tag{18}$$

482   Figure 16 shows the variation of Φ_d with S for different specimens at σ_n=100 kPa. Φ_d

483   increased with increasing S for all specimens, and the trend in Φ_d differed from specimen to specimen.

484   Given $\sigma_n = 100$ kPa and $S = 80$ mm, a quadratic function was used to establish the

485   relationship between EI, FI and Φ_d, as shown in Figure17a and Eq. (19). $\Phi_{d\,min}$=0.026 when

486     $EI = 0.856$ and $FI = 0.849$.

487
$$\Phi_d(EI, FI) = 0.84 - 1.00EI - 0.91FI + 0.48EI^2 + 0.43FI^2 + 0.21EIFI \tag{19}$$
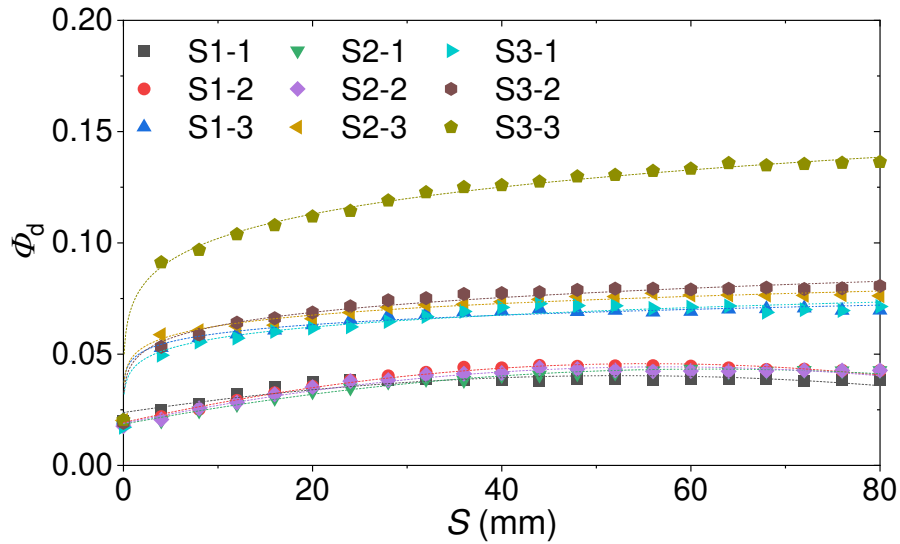
488
489   Fig. 16. Variation in Φ_d with S at $\sigma_n = 100$ kPa.

490   Figure 17b demonstrates that EI and FI had approximately equal influences on Φ_d for coarse

491   aggregates. For instance, Φ_d was 0.032 for oblate-equant specimens and 0.033 for prolate-equant

492   specimens, a difference of 3.13%. Φ_d was 0.063 for oblate specimens and 0.069 for prolate

493   specimens, a difference of 9.60%. Φ_d was 0.076 for oblate-scalene specimens, and 0.081 for prolate-

494 scalene specimen, a difference of 6.56%. All the above cases show that the influence of EI and FI

495 on Φ_d for coarse aggregates was similar. The intermediate axis P_2 of particles could be ignored due

496 to its limited influence.

497

498
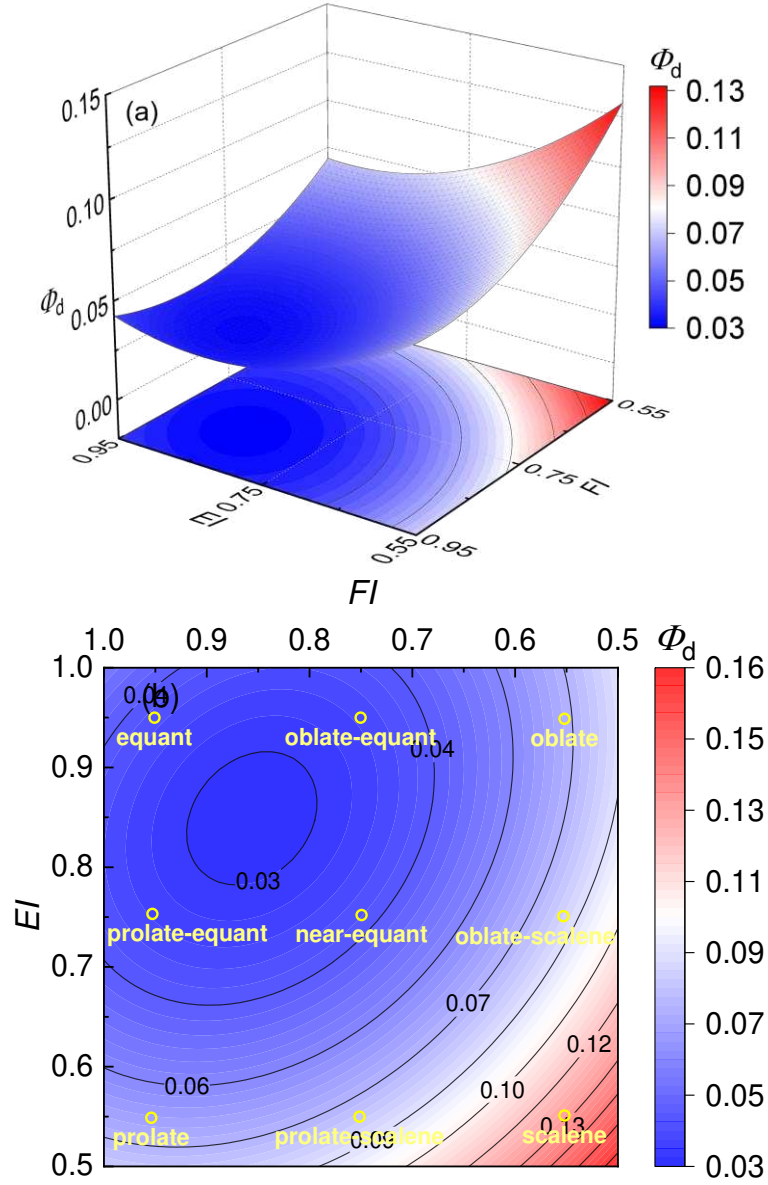
499 Fig. 17. Φ_d as a function of EI and FI at $\sigma_n = 100$ kPa and $S = 20\%$: (a) fitted quadratic

500 surface; (b) contour.

501   It should be emphasized that the preceding analysis assumed that particles were not subject to

502 fragmentation. The results show that as particle irregularity becomes more significant, shear strength

503 of the assemblies increases, which contradicts certain experimental findings (Jing et al., 2020). Indeed,

504 more irregular particle shapes can lead to increased bending moments and a higher likelihood of

505   fragmentation (Afshar et al., 2017; Fang et al., 2022; Zou, 2018). The utilization of non-crushable

506   particles in DEM simulations has inherent limitations since it may diverge from actual scenarios once

507   particle breakage ensues. Nevertheless, the use of rigid blocks presents an advantageous technique for

508   scrutinizing inter-particle contact conditions, independent of the particle strength. Consequently, it is

509   possible to identify aspect ratio thresholds as a benchmark for selecting suitable particle shapes that

510   mitigate grain crushing while providing adequate strength for the fabrication of aggregate supporting

511   layers in transportation infrastructure.

512   Similar to the analysis approach in Section 5.2, the influence of FEI on Φ_d was analyzed. Based

513   on the grain irregularity, the relative deviatoric fabric tensor Φ_r is defined as:

$$\Phi_r = \frac{\Phi_{d\,max} - \Phi_d}{\Phi_{d\,max} - \Phi_{d\,min}} \tag{20}$$

515   where $\Phi_{d\,min}$ is the minimum value calculated by Eq. (19) and $\Phi_{d\,max}$ occurs when the specimen

516   is scalene.

517   As shown in Fig.18 and Eq. (21), there is an exponential relationship between FEI and Φ_r. The

518   fitted data were obtained from simulations based on the particle samples in Section 5.2. As FEI

519   increased, Φ_r first increased rapidly and then slowly. The maximum curvature of this function was

520   taken as the threshold for the variation in Φ_r with FEI. The maximum value of curvature existed

521   when $FEI = 0.47$.

$$\Phi_r = 0.88 - 19.71e^{-10FEI} \tag{21}$$

523   Thus, when there is an axial particle size difference, for example if the aggregates have prolate,

524   oblate, or scalene shapes, the anisotropy of the fabric tensor increases dramatically. It is possible to

525   minimise the potential for particle breakage by maintaining FEI greater than the threshold (0.47).

526   Accordingly, the ratio of the maximum and minimum axial dimensions, can be considered to be
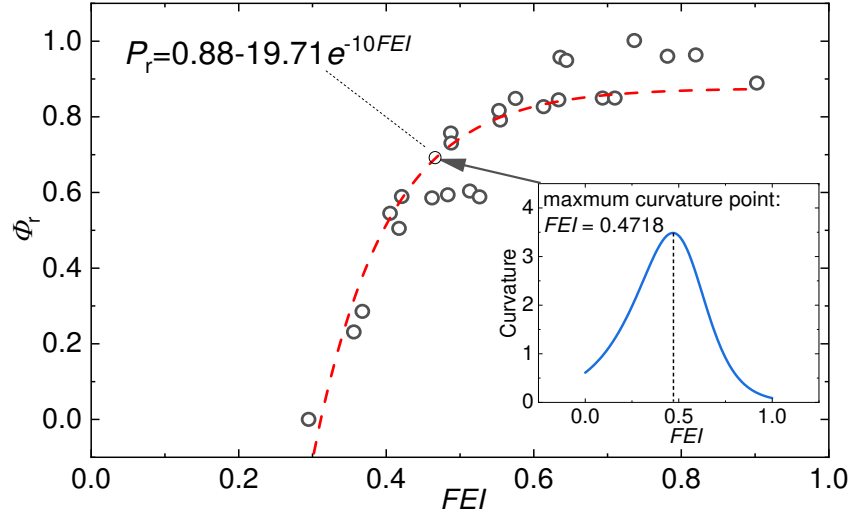
527   approximately 2:1.

$$P_r = 0.88 - 19.71e^{-10FEI}$$

maxmum curvature point:
$FEI = 0.4718$

528

529　Fig. 18. Variation in Φ_r with *FEI* and the corresponding curvature distribution ($\sigma_n = 100$ kPa,

530　$S = 80$ mm).

7 Conclusions

531

532　　A quantitative investigation was carried out to examine the impact of particle aspect ratio on the

533　compaction characteristics and shear behavior of coarse aggregates. The study employed laser

534　scanning technology to obtain 3D surface profiles of 700 coarse aggregate particles, from which three

535　orthogonal axial dimensions (P_1, P_2, P_3), *EI*, *FI*, and *FEI* indexes were selected to characterize particle

536　shapes. To simulate the compaction and direct shear tests on nine typical coarse aggregates with

537　representative shapes, DEM simulations were employed. Mathematical functions were developed from

538　macro- and meso-scale perspectives to relate shape indexes to porosity, shear strength, and the fabric

539　tensor. The major conclusions are:

540　　a) Regarding the *EI* and *FI* indexes, statistical indicators such as the fitting parameters of Weibull

541　distribution, mean, coefficient of variation, skewness, and kurtosis show no significant difference

542　between the real particles and the reproduced Rblocks. It is evident that Rblocks are capable of

543　effectively depicting the actual shape of coarse aggregates in discrete element simulations.

544　　b) In regards to compaction, an exponential function characterizes the correlation between the

545　inter-particle friction and porosity, whereas the regression parameter ζ can be defined as a quadratic

546　function of *EI* and *FI*. The impact of *EI* and *FI* on particle porosity is analogous. A threshold of *FEI* ≈

547 0.5 can regulate the packing density of coarse aggregates.

548 c) The relationship between the peak shear strength and vertical stress with the same initial

549 porosity can be described by a power function. The regression parameter η can be expressed as a

550 quadratic function of *EI* and *FI*. The effect of *EI* and *FI* on the peak shear strength of the assemblies

551 is similar.

552 d) Distinct aggregate shapes result in varying distributions of normal contact forces. Prolate or

553 oblate particles, in particular, exhibit a noteworthy increase in the inhomogeneity of the normal contact

554 force distribution. The anisotropy of the fabric tensor is influenced similarly by both *EI* and *FI*. The

555 relative anisotropy of the fabric tensor can be utilized as a guide to choose appropriate aspect ratios

556 while maintaining control over particle fragmentation.

557 The novel equations that were developed can aptly represent the correlation between the aspect

558 ratios and the compaction/shear properties. By using the proposed *FEI* threshold, which is based on

559 the relative porosity and the relative anisotropy of the fabric tensor, suitable coarse aggregates can be

560 selected for use as fill material.

Acknowledgements

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