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Contribution of DEM parameters in granular flow simulations

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Abstract: This study aims to quantify the contribution of input parameters to the results of granular flow simulations using the DEM. A series of granular flow simulations is performed using the DEM with different combinations of input parameters, such as the spring coefficient, damping coefficient, restitution coefficient, and friction coefficient. Indexes of run-out distance and deposition length are defined, and surrogate models of the indexes are obtained from the results of the DEM simulations via radial basis function interpolation. A Monte Carlo simulation (MCS) is then carried out with quantified density distributions of the input parameters. Because the surrogate models can be obtained as simple mathematical functions, it is possible to perform a sufficient number of calculation cases with different combinations of input parameters. By using this framework, the distribution of the two indexes can be represented while considering the uncertainties in the input parameters with a low calculation cost. Then, based on the results obtained from the MCS, the contribution rate of each parameter is quantified. According to the obtained results, it is confirmed that the basal friction angle is the parameter that most influences the deposition length, while the coefficient of restitution also has a dominant effect on the run-out distance.

Keywords: discrete element method, granular flow, contribution rate.

1. Introduction

Numerical methods based on continuum modeling have been proposed to predict flow behaviors and traveling distances of flow-like landslides (e.g., Ssasa, 1987, Savage & Hutter, 1989, Iverson & Denlinger, 2001, Moriguchi et al., 2009, McDougall et al., 2014). These methods are regarded as powerful tools for risk assessment of slope disasters. Discrete modeling is another approach applicable to studying flow-like landslides. Well-known examples of discrete approaches are the discrete element method (DEM) (Cundall, 1971) and discontinuous deformation analysis (Shi, 1988). In particular, DEM has become an important tool in the risk evaluation of slope disasters owing to the rapid development of computer power in recent years. However, parameter setting is still an issue in DEM simulation. Although some studies related to the parameter setting in the DEM (e.g., Zhou, 2018, Roessler et al., 2019, Grobbel et al., 2014) have been reported, it is still difficult to determine the DEM parameters in a universal way. To establish an efficient method for parameter setting, it is also important to know the contribution rates of the parameters on the simulation results. Information on these contribution rate enables us to know how which parameters require more time and effort to determine. For this purpose, this study aims to quantify the contribution of input parameters to the results of granular flow simulations using DEM. A series of granular flow simulations is performed using the DEM under different combinations of input parameters. The obtained results are then statistically analyzed, and the contribution rate of each parameter is quantified.

2. Numerical method

This study employs commercial DEM software (ROCKYDEM, 2015) to simulate glandular flows. Polygonal elements can be used in the software. Figures 1 and 2 show schematics of the contact detection process. As shown in Fig. 1, neighboring elements are listed with the help of a circumscribed sphere. Contact between elements is then detected based on the common plane (CP) method (Cundall, 1988). The CP is defined as a rigid plane dissecting the space between the elements. Because contact between elements can be detected by checking the distance between the CP and the nearest vertex of the element, the contact algorithm can be effectively simplified. Figure 3 shows an image of the interparticle model used in this study.

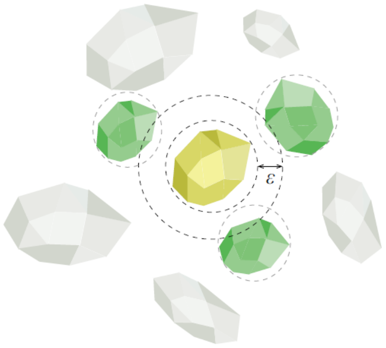


Figure 1. Searching neighboring elements.

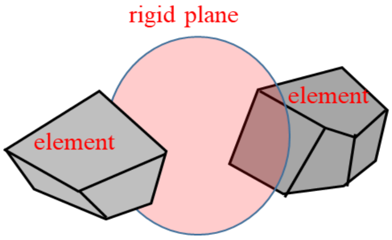


Figure 2. Common plane method.

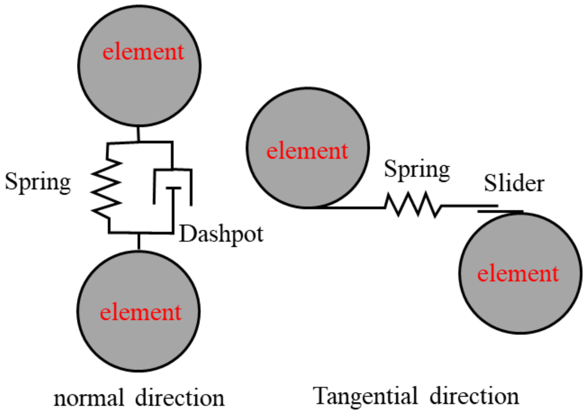


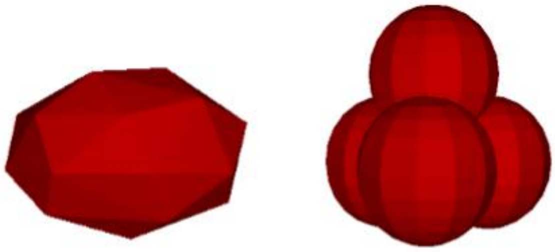
Figure 3. Interparticle force model.

3. DEM simulation

As mentioned above, a series of granular flow simulations is performed using DEM. Two types of elements, polygonal elements and clump elements, as shown in Fig. 4, are used in this study to investigate the effect of element shape on the contribution rate. A uniform particle size is considered; hence, the effect of particle size distribution is excluded. Figure 5 shows the model slope used in this study. Figure 6 represents an example of the results of the granular flow simulation.

Two indexes, namely, the deposition length and run-out distance, are defined to quantify the depositional behavior. The two indexes are illustrated in Fig. 7. The position of the leftmost particle is defined as the origin of the deposition length and run-out distance and is defined based on the concept of the quartile. The deposition length is described as the length between the origin and the third quartile. The run-out distance is expressed using the midpoint between the third quartile and the maximum traveling distance. We assume that the deposition length and run-out distance can represent the characteristics of the main part of the particle mass and traveling distance, respectively.

Table 1 shows the ranges of input parameters considered in this study. We perform the simulation with different combinations of DEM input parameters, such as the spring coefficient, friction angle between elements, basal friction angle, and coefficient of restitution. We perform 40 calculation cases with parameter sets obtained by the Latin hypercube method (McKay et al., 1979). In addition, 16 kinds of parameter sets are also tested in consideration of the minimum and maximum values of each parameter range. The total number of calculation cases is hence 56.



Polygonal element Clump element

Figure 4. DEM elements.

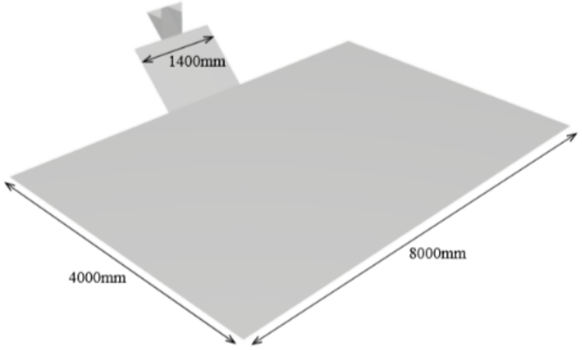


Figure 5. Slope model.

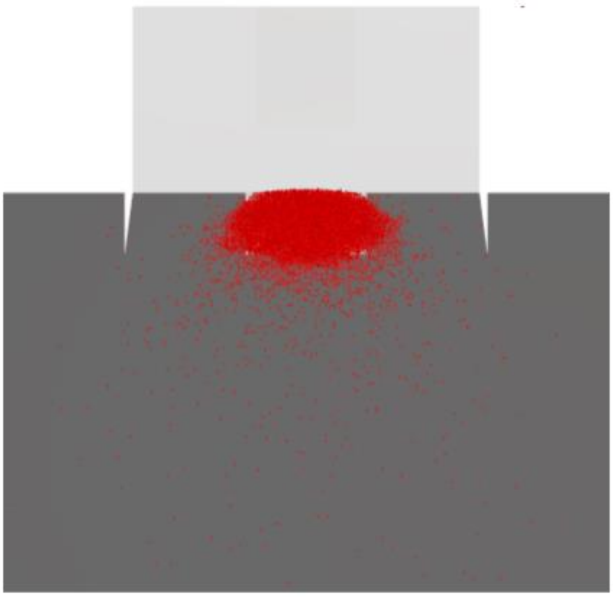


Figure 6. An example of simulated results.

Table 1. Parameter range

Parameters	Min	Max
Spring coefficient (N/m)	20	20
Friction angle between elements (deg.)	20	20
Basal friction angle (deg.)	0.3	0.3
Coefficient of Restitution	1.0×10^5	1.0×10^7

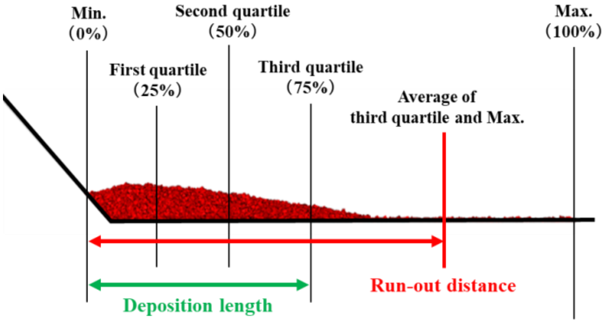


Figure 7. An image of indexes.

4. Surrogate model

Based on the results of the 56 cases explained in the previous chapter, surrogate models of the deposition length and run-out distance can be created. In other words, a simple mathematical equation can be defined by analyzing the results obtained in the numerical simulation. In this study, radial basis function (RBF) interpolation (Buhmann, 1990) is used to create the surrogate model. It should be noted that the L2 regularization term is introduced to avoid overlearning. Once the surrogate models are created, the results can be obtained with an arbitrary combination of input parameters. Furthermore, the computational cost of this approach is extremely low compared to that of a numerical analysis. Therefore, the surrogate model plays an important role when a number of trials is required, as in this study.

5. Quantification of contribution rate

After the surrogate models of the deposition length and run-out distance are obtained based on the simulated results, a Monte Carlo simulation (MCS) is then carried out to quantify the contribution rates of the input parameters. For the inputs of the MCS, normal distributions with mean that are the median values of the range of each input parameter are assumed. It is also assumed that the range of each parameter is three times the corresponding standard deviation. The deposition length and run-out distance are calculated with 10000 trials of the MCS. The contribution rate of each input parameter is calculated based on the variance of the obtained density distribution of the two indexes. Specifically, the contribution rate of the parameter is calculated by the following equation.

$$\lambda_i = \sigma_i^2 / \sigma_{all}^2 \tag{1}$$

where σ_{all}^2 is the variance of the distribution obtained when all the parameters are changed. On the other hand, σ_i^2 is the variance when only the ith parameter is changed and all other parameters are fixed at the mean value. Because the total contribution rate may not be 100%, the contribution rate obtained in the above equation is normalized as follows.

$$\widehat{\lambda_i} = \lambda_i / \sum_{k=1}^{n} \lambda_k \tag{2}$$

where n is the total number of parameters. Table 2 and Table 3 show the obtained contribution rates for both the deposition length and run-out distance. Although there are some differences due to the particle shape, the same tendency can be seen in the results. The results indicate that the basal friction angle and coefficient of restitution are the main factors controlling the deposition length and run-out distance, respectively. This is because the energy loss due to bottom friction dominates the behavior when the granular materials behave as a group, and the coefficient of restitution has a strong effect on the behavior at the tip of the particle mass where the particles individually move. It should also be noted that the spring coefficient and the friction angle between elements have almost no effect on the results. It is important to identify input parameters that have high contribution rates, but as shown here, information on parameters that have low contribution rates is also important. In particular, the spring coefficient is strongly related to the stability of the calculation, and the calculation time becomes long when a high spring coefficient is used. Because the contribution rate of the spring coefficient is not very high, we do not have to determine the parameter so strictly.

This fact is extremely important in considering the practical use of DEMs. Additionally, although it is often difficult to set the value of the friction angle between elements, the contribution degree determined in this study suggests that this parameter does not have to be so strict.

Table 2. Contribution rate for the run-out distance

Parameters	Contribution rate (%)	
	(Polygon)	(Clump)
Spring coefficient (N/m)	0.1	0.1
Friction angle between elements (deg.)	3.1	6.5
Basal friction angle (deg.)	26.5	29.9
Coefficient of Restitution	70.3	63.6

Table 3. Contribution rate for the deposition length

Parameters	Contribution rate (%)	
	(Polygon)	(Clump)
Spring coefficient (N/m)	0.4	0.1
Friction angle between elements (deg.)	0.6	1.2
Basal friction angle (deg.)	93.6	95.9
Coefficient of Restitution	5.4	2.7

5. Conclusions

The contribution rates of DEM parameters in granular flow were numerically examined based on the results of a series of granular flow simulations. Surrogate models of the deposition length and run-out distance were used to obtain a sufficient number of calculation cases. According to the quantified contribution rates, the basal friction angle mainly affects the deposition length, and other parameters have low contribution rates. Regarding the run-out distance, the basal friction angle and the coefficient of restitution are dominant parameters. It should also be mentioned that the spring coefficient and the friction angle between elements have low contribution rates. This finding indicates that we do not have to spend considerable amounts of time and effort determining these two parameters. However, the conclusion summarized here is based on the simulated results obtained in this study only. Thus, a more detailed investigation is needed to generalize the knowledge of the contribution rates of DEM parameters.

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