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Sensitivity Analysis on Optimal Combinations of DEM Input Parameters in Granular Flow Simulations

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Recent advancements in numerical analysis have the potential to facilitate the assessment of the runout distances of landslides. However, the computational cost of numerical analysis, such as discrete element method, poses a significant obstacle. In response to this, this study aimed to quantify the importance of four input parameters, namely, friction between elements, friction angle with bottom surface (FABS), the coefficient of restitution (COR), and the spring coefficient, in determining runout distances using XGBoost feature importance considering the particle size distribution. The results indicate that the FABS and COR are the key parameters. The two key parameter spaces were then comprehensively explored using Gaussian process regression response surfaces. The correlation between the FABS and runout distance appeared as a convex function. while the COR exhibited approximately linear correlation throughout the granular flow. The particle size distribution indirectly led to inconsistencies between the bidisperse flow and other flows in the influence mechanisms of FABS and COR. By clarifying this effect, we efficiently identified two optimal parameter sets for landslide risk assessment.

Key Words : *granular flow, DEM, GPR response surface, XGBoost feature importance, particle size distribution*

1. INTRODUCTION

Investigating solid particle flow behavior is essential for understanding mechanism of landslide disasters and hence important for risk assessment. In recent years, numerical analysis techniques have been increasingly applied to the study of granular flow. When studying the properties of granular flow, it is necessary to examine the behavior of granular matter. Based on this concept, the powerful tool for studying particle behavior, Discrete Element Method (DEM)[1], was employed in this study.

In general, multiple simulation runs are conducted to capture the influence of parameters on the characteristics of the granular flow. However, this approach is computationally prohibitive to explore the overall parameter space fully. The emergence of surrogate modeling alleviates this problem. It provides an accurate approximation for the result of numerical simulations in the overall parameter space, and the running time is generally much shorter than that of the original simulation.

The objective of this study is to investigate the influence mechanisms of key parameter sets by considering the particle size distribution. In this study, four parameters(friction angle between elements (FABE), friction angle with bottom surface (FABS), coefficient of restitution (COR), and spring coefficient (SC)) which are important for runout distance in granular flow simulation are considered. Granular flow simulation are conducted by DEM with different parameter sets for 56 cases. XGBoost [2] feature importance is then applied to quantify the importance of each parameter to runout distance of granular flow. Based on the quantification results, the effects of key parameters on the response surfaces were visualized by Gaussian process regression (GPR)[3]. By clarifying these mechanisms, this study identify appropriate parameter sets for landslide risk assessment throughout the entire parameter space.

2. DEM-based granular flow simulation

The polygon particle model is used for DEM simulations shown as Fig. 1. Different particle sizes are realized by resetting the length of the short axis d_i. In this study, four particle size distribution patterns (n = 1, 2, 3, 5) are applied, where n refers to the number of particle sizes. $n = 1$ and 2 are called monodisperse and bidisperse flows, respectively, and the patterns with $n > 2$ are called polydisperse flows. In the case of monodisperse flow, d_i

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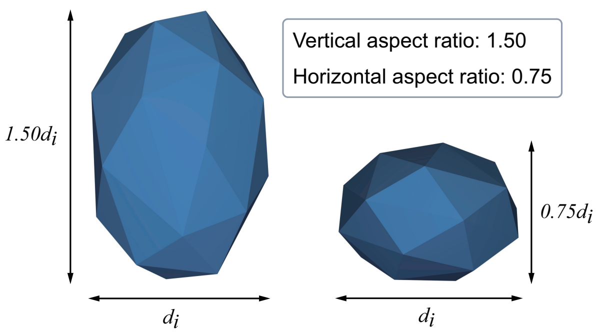
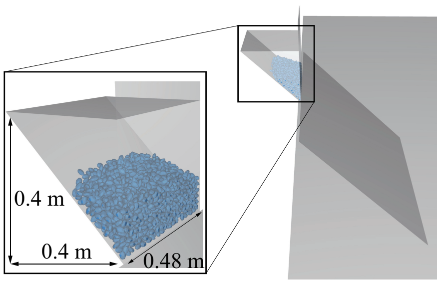
is determined as 2.0 cm, which is the median value of the particle sizes in this study.

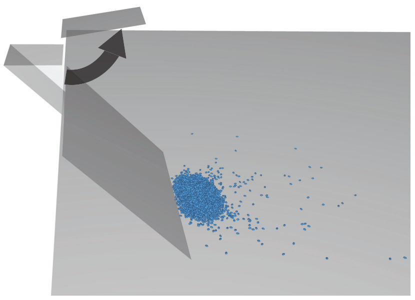


(a) Side view (b) Top view

Fig. 1 Polygon particle model.



(a) Geometory setup



(b) Particle release

Fig. 2 Geometrical conditions for the DEM simulation.

The detailed geometrical conditions for DEM simulations are shown in Fig. 2. The ranges of parameters are determined with reference to the authors' experience and values employed in related studies [4,5]. The target output is the maximum runout distance for each mass ratio, with one indicator set for each 10th percentile of the runout distance from 10% to 100% for 10 indicators. For example, the 80^{th} percentile runout distance (l_{80} in Fig. 3) is the maximum runout distance of 80% of the particles. This indicates that 10 surrogate models were constructed with 10 runout distance indicators as the output. Latin hypercube sampling (LHS) is adopted to sample 56 simulation cases with various parameter sets that produce the training data for the response surfaces constructed in this study.

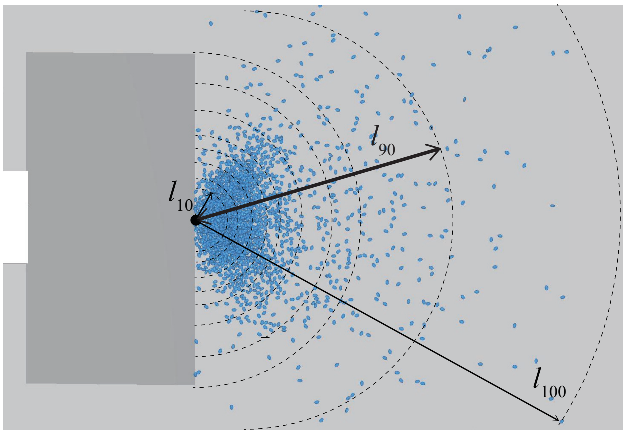


Fig. 3 Image of outputs (100%-100% runout distance).

3. Sensitivity analysis

(1) XGBoost parameter importance

The effect of each parameter is quantified by XGBoost feature importance to identify key parameters and compress the input dimension for response surfaces. FABE, FABS, COR, SC are taken as input data for the XGBoost to calculate the feature importance with outputs, which represent 10%-100% runout distances in terms of particle mass. Fig. 4 illustrate the feature importance of the four parameters in all runout distance scenarios and particle size distribution patterns. In all the particle size distribution patterns, the importance of the FABE and SC was relatively low, whereas the FABS and COR were the key parameters; moreover, the effect of the COR increased significantly at a runout distance of approximately 80% runout distance. This indicates that, for the top 20% of the particles, the COR is the key parameter controlling the runout distance. This is because the main energy loss originates from friction between the particles and the bottom surface; the effect of the COR is evident in the 80%-100% runout distance, where the interactions between the particles are inconspicuous and the movement of individual particles is dominant.

(2) GPR response surface

In the previous section, the importance of the four parameters was quantified using XGBoost, with the FABS and COR identified as the key parameters. Based on the GPR surrogate models, the three-dimensional response surfaces of the FABS and COR can be visualized with respect to the runout distance. Fig. 5 shows the GPR surface of the FABS and COR at a runout distance of 90%. The two horizontal axes denote the FABS and COR, and the vertical axis represents the 90% runout distance. The color of the response surface indicates the magnitude of the runout distance, and the red points represent the DEM simulation cases used as the training data. The predicted standard deviation reflects the confidence interval of the GPR surrogate models, and the two gray translucent surfaces represent intervals with 90% confidence. The GPR

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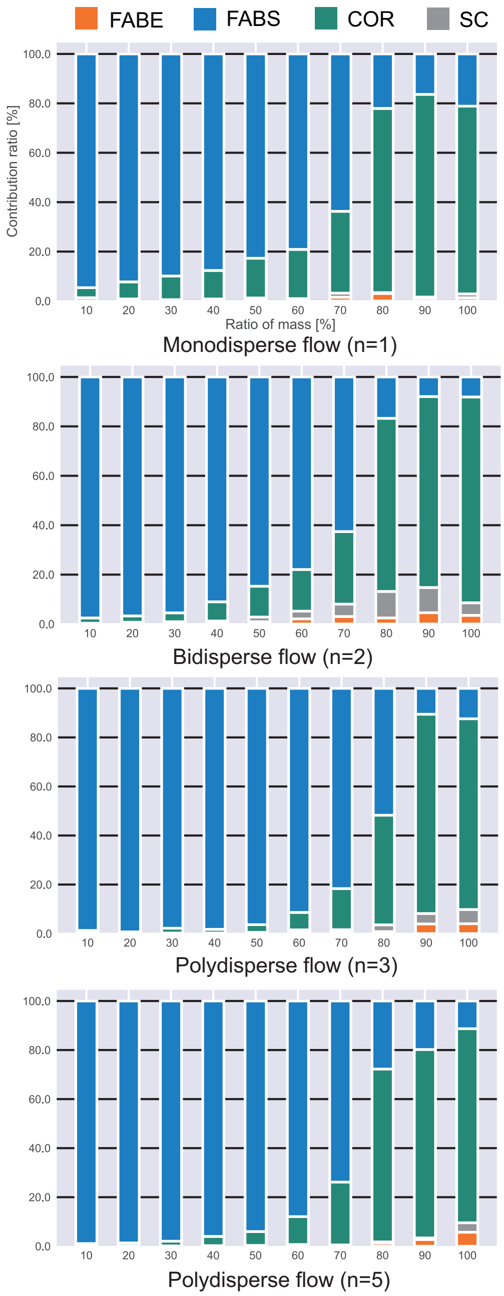

Fig. 4 XGBoost feature importance.

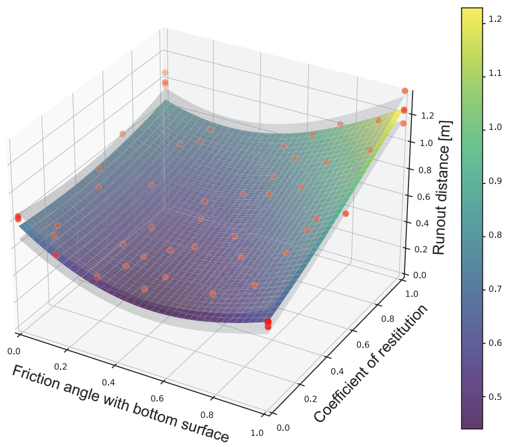

Fig. 5 Response surface for 90% runout distance in monodisperse flow.

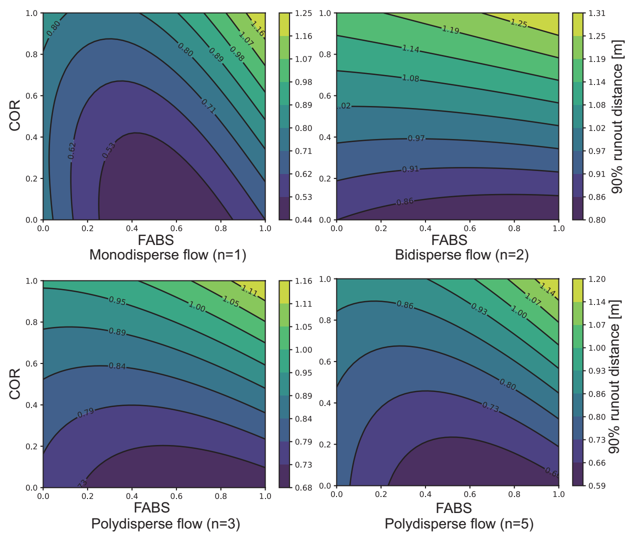

Fig. 6 GPR response surfaces of 4 particle size distribution patterns.

response surface intuitively reveals the influence mechanisms of the COR and FABS. For the 90% runout distance, COR and runout distance have a nearly linear relationship, while FABS shows a convex function. Note that each input parameter was normalized to the range [0, 1] at the stage of constructing the GPR surrogate models. Therefore, FABS = 0 represents the FABS taking the minimum of the initial range.

To provide an examination on the particle size distribution patterns, the contour plots (plan view of the surface response in Fig. 5) of the 90% runout distance is depicted in Fig. 6. In polydisperse flow, particularly in the $n = 5$ pattern, the influence mechanism of FABS is consistent with the trends observed in monodisperse flow. As the number of particle sizes increases, the influence of COR becomes more pronounced. Regarding the bidisperse flow pattern, the convex function of the FABS with respect to the runout distance is not manifested compared with other patterns. It should note that in the particle size distribution considered in this study, the maximum and minimum particle sizes are fixed. An increase in the number of sizes implies a decrease in the gap between each size. This implies that in bidisperse flow, the difference in sizes between the two types of particles is quite pronounced. Hence, this result can be attributed from that the aggregation of massive particles in the front part of the bidisperse flow. It strengthens the positive correlation between the COR and the runout distance, and weakens the convex function correlation of the runout distance with the FABS.

Although the trend in bidisperse flow differs to some extent from the other three patterns, the parameter sets that give the highest risk remain the same position as in the other three. By exploring the influence mechanisms of key parameters via response surfaces, the most valuable ex-

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ploratory parameter sets were (CORmax, FABSmax and CORmax, FABSmin) identified.

4. Conclusion

According to the result of XGBoost, it is demonstrated that FABS and COR are the influential parameters in evaluating the runout distance. The impact mechanism of FABS is more complicated, with an approximately negative correlation in the middle and rear and an evident convex function in the front part of monodisperse flow. COR shows a nearly linear relationship with runout distance throughout the granular flow. The value of this study is that it determines engineering priorities by quantifying the importance of various input parameters for DEM simulations. In addition, a comprehensive exploration of the impact mechanisms of key parameters leads to recommendations for appropriate parameter combinations for risk assessment.

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