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Blast Movement Simulation through a Hybrid Approach of Continuum, Discontinuum, and Machine Learning Modeling

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ABSTRACT: Estimating and optimizing rock movement during blasting is important to prevent unnecessary material handling, reduce ore loss and dilution, and minimize environmental footprint. It has been challenging and computationally burdensome to model the whole dynamic process because rock blasting consists of a complex process that generally involves explosive detonation, gas expansion, stress wave propagation, rock fragmentation and throw, and muckpile formation. In this regard, we propose a hybrid approach that captures the first-order impacts on the rock movement due to blasting while achieving accelerated simulation. Specifically, a small-scale continuum model is established to represent an annulus of rock, with explosive in the center and gas pressure resulting from the detonation applied to the borehole surface, which reduces as the borehole deforms. The continuum model simulates the early-stage, near-field rock blasting process and forms a synthetic dataset based on realistic explosive data to train a machine learning model. Key parameters, such as expanded hole diameter, burden velocity, and time-dependent gas pressure, are readily obtained from the constructed machine learning model. Informed by the machine learning model, the subsequent discontinuum model simulates the dynamic rock movement and predicts the muckpile formation in the far field using the rolling resistance contact model. Our results demonstrate the efficacy of the proposed approach to capture the key physics of blast-induced rock movement and realize accelerated blast design optimization aided by machine learning.

1. INTRODUCTION

Rock blasting is a highly effective technique employed for fracturing and moving rock mass with extensive applications in various fields such as mining, quarrying, tunneling, and civil engineering industries. The understanding of rock behaviors during blasting is critical for optimizing blasting design, reducing material loss and/or dilution, as well as minimizing environmental impact and safety hazards. While it is difficult to quantify rock blasting experimentally, numerical simulation approaches have been developed over the years to model the process. However, simulating rock blasting is still a challenging and computationally demanding task. One of the main challenges lies in the complex physical processes that occur during blasting, including non-ideal detonation, near-field rock crushing, fracturing, vibration, ore/waste movement, and muckpile formation. Simulating rock blasting movement is further complicated by the intrinsic heterogeneity of rock materials and variability in blasting conditions, which result in highly nonlinear and discontinuous behaviors. Moreover, the wide range of length and time scales involved in these sub-processes presents a significant computational burden.

Different numerical approaches have been developed to address these challenges. Continuum-based numerical methods, such as the Finite Element Method (FEM) and Finite Volume Method (FVM), primarily concentrate on the damage created by blasting before major fragmentation or the impacts of vibration and stress redistribution after blasting (Lu et al., 2011; Wang et al., 2021). While these mesh-based approaches can handle complex geometries and properties by meshing domains using finer resolution, they assume materials behave in a continuous manner and are not well-suited to directly model crack propagation and rock fragmentation during rock blasting. The large deformation and fragmentation rocks can be better simulated using discontinuum-based methods, such as Discrete Element Method (DEM) and Discontinuous Deformation Analysis (DDA), which can explicitly represent rock fragments and account for the discontinuous nature of rock materials (Furtney & Aglawe, 2021; Potyondy et al., 2020; Potyondy & Cundall, 2004). In recent years, there have been attempts to combine different methods to simulate the blasting process, including the continuum phase focusing on the near-field blasting-induced damage, and the discontinuum phase focusing on the rock fragment displacement and muckpile formation (An et al., 2017; Fakhimi & Lanari, 2014; Onederra et al., 2013).

However, such simulations require intensive computational resources, which can limit the scale and accuracy of the simulations, as well as applicability to practical engineering designs.

To overcome the limitations, a hybrid approach has been proposed that combines simplified numerical models with machine learning techniques. This approach involves using a small-scale *FLAC3D* model (Itasca, 2019) to simulate the early-stage, near-field rock blasting process and generating a synthetic dataset based on realistic explosive data to train a machine learning model. The machine learning model can then predict critical simulation parameters, such as the burden velocity resulting from expansion and pressurization, which are used to inform the subsequent *PFC3D* model (Itasca, 2023). The *PFC3D* model mimics the rock mass with distinct particles governed by the rolling resistance contact model and resolves the dynamic rock movement and muckpile formation in the far field. The hybrid approach offers significant computational savings while retaining the essential physics of blast-induced rock movement.

2. MODEL OVERVIEW

The hybrid approach to simulating rock blasting involves the integration of three components:

- A 1D FVM model (*FLAC3D*), which represents the detonation along with the elastic and plastic deformation occurring in the rock near the explosive. The model resolves the equilibrium pressure and the size of the hole when the pressure of the reaction products is balanced by the deformation in the rock near the hole.
- A machine learning model, which is trained on a synthetic dataset generated by *FLAC3D* simulations and an analytical model to estimate the burden movement velocity, taking into account factors such as gas pressurization and venting during burden acceleration.
- A 3D DEM model (*PFC3D*), which simulates the rock mass using particles with rolling resistance and resolves rock movement and final muckpile shape, with the burden velocity initialized based on the machine learning model.

3. CONTINUUM MODELING

FLAC3D utilizes an explicit finite volume formulation that captures the complex behaviors of a continuous three-dimensional medium as it reaches equilibrium or steady plastic flow. Here, small-scale 1D axisymmetric *FLAC3D* models are built in dynamic mode with a Mohr-Coulomb constitutive model to describe the near-field rock response during blasting. The rock is represented as a cylindrical annulus that is 11 m in diameter with the explosive in the center. An example of the small-scale model is presented in Fig. 1. An axisymmetric geometry is created by applying roller boundary conditions to the top and bottom surfaces of a 2D wedge, which represents $1/32^{nd}$ of a circle. To predict the product equation of state (EoS), velocity of detonation (VoD), and heat of reaction for common explosive products like ANFO and emulsion, a non-ideal detonation program (Braithwaite & Sharpe, 2009) and realistic explosive data are utilized. In the *FLAC3D* model, the borehole is pressurized at a rate determined by the VoD, and the borehole gas pressure is applied to the inside surface of the borehole. As the borehole undergoes radial deformation, the applied gas pressure is reduced based on the EoS. A more detailed description is given in Furtney et al. (2013). This model accounts for both elastic and plastic deformation in the rock and assumes the gas products expand isentropically.

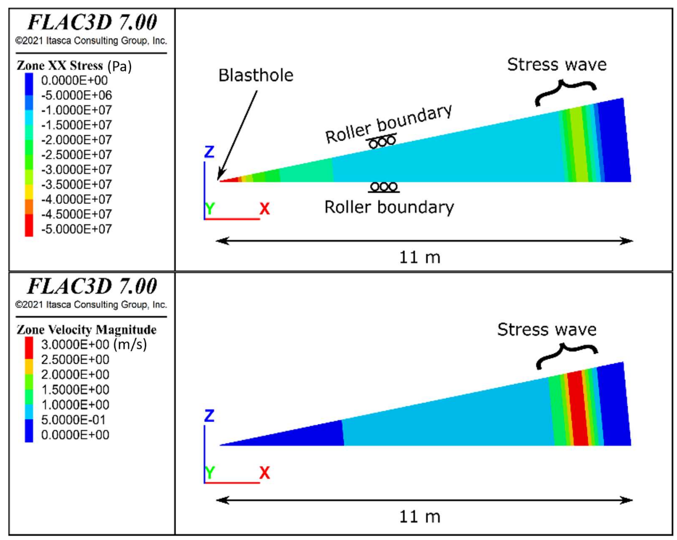


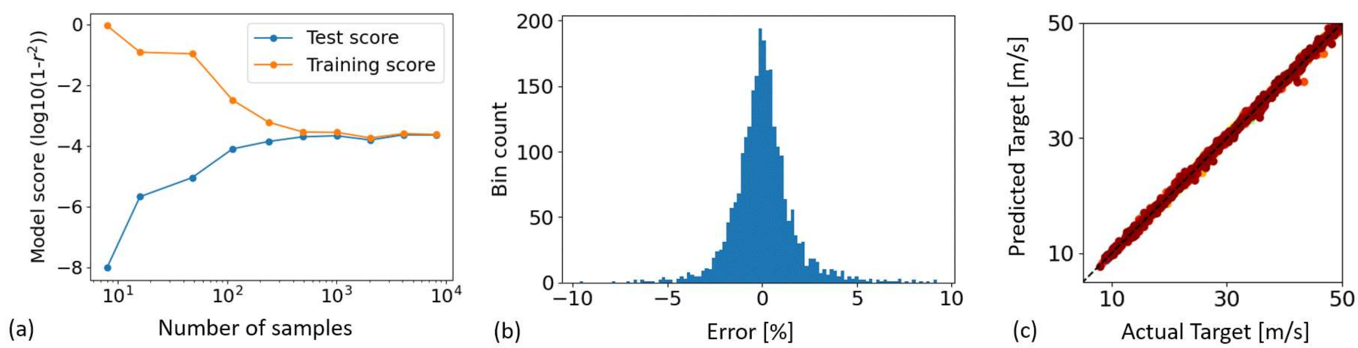
Fig. 1. 1D axisymmetric *FLAC3D* model. The plots show color contours of radial stress (top) and velocity magnitude (bottom) in the rock during blasting, the blast induced stress wave can be seen near the right boundary (updated after Furtney et al., 2022).

As the rock is loaded by the explosive gas, the nearest rock to the borehole experiences compressive hoop stresses and undergoes plastic failure. The model is executed for a duration equivalent to 90% of the time taken by a p-wave to travel from the blast hole to the external boundary of the model. Over this time interval, the gas pressure and local rock stress reach a quasi-steady state before significant radial tensile fracturing or radial gas flow takes place. The pressure at this state is defined as the equilibrium pressure, which serves as the initial state for predicting burden movement using machine learning in the next phase. This model is intended to only represent processes between detonation and the equilibrium pressure state. It is worth noting that the time-dependent fracturing process occurs between the equilibrium state and the beginning of burden movement, which is deliberately not considered in this modeling to maintain model simplicity to generate a large synthetic dataset.

4. MACHINE LEARNING MODEL

The application of machine learning in rock mechanics simulations has become increasingly popular due to its potential to improve the efficiency of numerical simulations and recognize patterns of nonlinear behaviors of rocks when trained on large datasets. Typically, in the geomechanics field, we face a scarcity of data, which limits our ability to develop accurate models. To overcome this limitation, surrogate models trained on synthetic data generated by numerical models have proven to be an effective solution. These surrogate models can predict the outputs of complex models for a wide range of input parameters with high computational efficiency (Furtney et al., 2022).

With the equilibrium pressure and final borehole diameter results from the near-field *FLAC3D* models, the burden velocity can be estimated through an analytical model established for burden movement calculation. The analytical model considers the expansion work done by gas products and gas venting through blast-induced fractures and the stemming pore space. The results of the *FLAC3D* model and the analytical model are then used to train a surrogate model to predict the burden movement velocity (Furtney et al., 2013). A neural network with three hidden layers, each comprising seven nodes, was trained using an extensive dataset of 10,000 *FLAC3D* model runs. The open source scikit-learn multi-level perceptron regressor model was used. All the nodes have hyperbolic tangent activation and the network is fully connected. The L-BFGS solver is used for the standard back propagation training. No hyperparameter tuning was done in this case, experience with similar work informed the choices for layer sizes and activation functions. The training dataset includes a range of critical features, including explosive type, modulus, UCS, hole radius, bench height, burden, and explosive charge length, while the regression targets are equilibrium pressure, burden velocity, and crushed zone radius. The resulting neural network can predict the burden velocity required for the subsequent DEM simulations within a fraction of a second to good accuracy. The burden velocity prediction has an r^2 value of 0.9997. The predictions for burden velocity are within 2.5% of the true value 95% of the time. Fig. 2 shows the model learning curve, model error histogram, and predicted vs actual plots. The final image in Fig. 2 shows a web application developed to perform the machine learning predictions. The application can be accessed here: https://jkfurtney.github.io/ml_blasting/



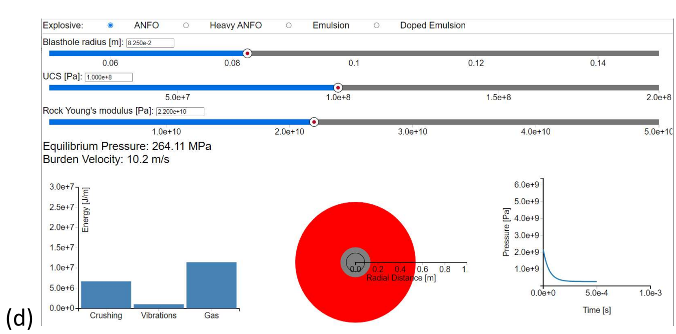


Fig. 2. a) Learning curve, b) error histogram, c) predicted vs actual velocity plots, and d) web application.

5. DISCONTINUUM MODELING

The *PFC* program provides a general purpose, distinct-element modeling framework that can simulate the movement and interaction of finite-sized particles (e.g., disk with unit thickness in 2D, sphere in 3D). The particles are rigid bodies with finite mass that move independently of one another. These particles interact with one another through pairwise contacts that generate internal forces and moments. Synthetic material can thus be formed by an assembly of rigid grains that interact at contacts. In the context of rock blasting, the angular shape of fragmented rock prevents the fragments from rotating easily, leading to interlocking behavior within the rock mass, while discrete element models like *PFC3D* use spherical elements that rotate readily. Instead, to simulate rock movement during blasting, a rolling resistance linear model was implemented in *PFC3D* to account for the energy dissipation that occurs due to rolling resistance at the contacts between particles representing the fragments. The rolling resistance contact model incorporates a torque acting on the contacting pieces to counteract the rolling motion (Ai et al., 2011; Wensrich & Katterfeld, 2012). The behavior of the rolling resistance linear contact model is similar to the linear model, except that the internal moment is incremented linearly with the accumulated relative rotation of the contacting pieces at the contact point. The contact model was implemented at both ball-ball contacts and ball-wall contacts.

PFC3D models were constructed to simulate rock casting and muck pile formation, with the initial velocity of rock fragmentation obtained from the machine learning prediction. Table 1 shows a few key parameters that define the contact model. A comprehensive description of all parameters of the rolling resistance linear contact model is available in the *PFC* documentation (Itasca, 2021). Note that the Young's modulus is set to a value that is smaller than normal to optimize the simulation timestep. This value is sufficient to ensure that the system remains within the rigid grain limit (i.e., further increasing the modulus/contact stiffness would not significantly affect the results). The relatively high friction coefficient and rolling friction coefficient were used to enhance particle friction and interlocking, which can be verified by comparing with field measurements and laboratory experiments.

6. MODELING RESULTS

A *PFC3D* model was developed to simulate the rock movement and muckpile formation in a bench blasting scenario using an echelon pattern for inter-hole and inter-row delay. The bench was created using *PFC* balls with a mean diameter of 0.2 m and a relative deviation of 0.5 to account for rock fragmentation with varying sizes. The rolling resistance model was applied to both ball-ball contacts and ball-wall contacts. The model consisted of ~400,000 balls with a density of 2600 kg/m^3 (as shown in Fig. 3).

The focus of the DEM model is to simulate the rock movement and muckpile formation. Rock fragmentation is assumed to be completed and the initial velocity of the balls is obtained from the machine learning model. The bench has dimensions of 84 m × 24 m × 12.5 m, and the regions to be blasted are indicated by colored blocks in plan view in Fig. 4. The bench is placed on a flat surface and faces a simplified 30-degree slope, which is simulated using a *PFC* wall and represents the slope of an existing pile. It is worth noting that the bench geometry and slope angle are designed to be representative of a typical bench blasting scenario and can be readily modified to suit different blasting conditions.

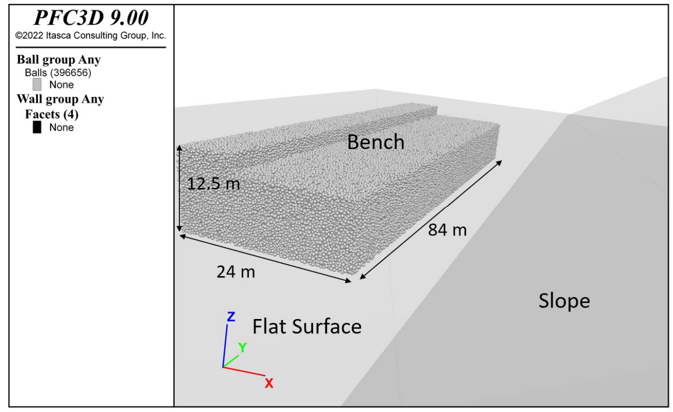


Fig. 3. *PFC* model showing the bench to be blasted.

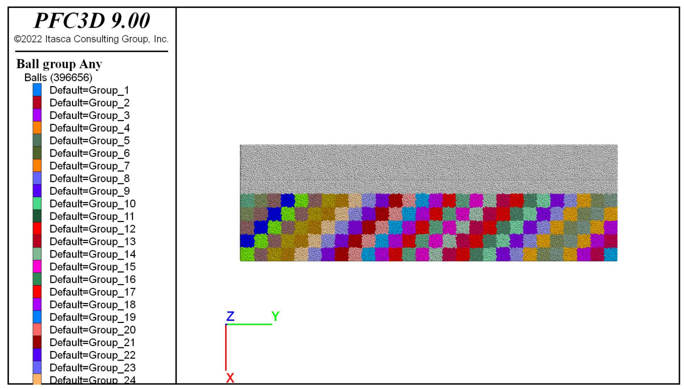


Fig. 4. Echelon pattern implementation in the *PFC* model, plan view.

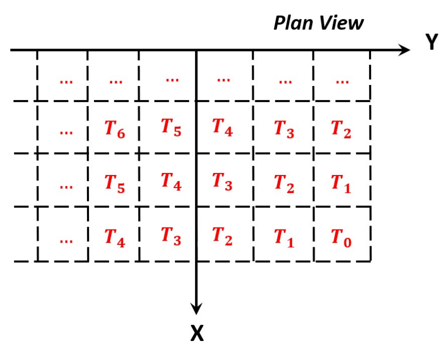


Fig. 5. Echelon pattern, numbers indicate firing sequence.

Table 1. Key parameters of the contact model

Parameters	Unit	Value
Nominal Young's modulus	Pa	1e7
Normal-to-shear stiffness ratio	-	2
Friction coefficient	-	0.5
Rolling friction coefficient	-	0.5

The blast volume in the simulation was divided into smaller groups with a burden and spacing of 3 m. An echelon pattern was used with a delay time of 30 milliseconds assumed for neighboring blocks (see Fig. 5).

The velocity was applied to the groups during the simulation at time $T_i = T_0 + i * \Delta T$, where T_0 is the time the first group of fragmented rocks is cast due to blasting and ΔT is the time delay. The initial velocity of rock fragmentation for the simulated case was obtained from the machine learning model prediction, which considered input parameters such as explosive type, modulus, UCS, hole radius, bench height, burden, and spacing. The velocity was found to be 12.7 m/s.

The simulation result at the end of cast blasting is shown in Fig. 6. Fig. 7 shows the cross-sectional view of the muckpile shape. The simulation indicated that the rock piles were generally evenly spread along the length of the bench. The cross-sectional view showed that the cast blasting movement had different behaviors, and the final location of the rock blocks being casted depended on their proximity to the free surface, with rocks near the surface more likely to spread. Fig. 8. shows the muckpile formation of another simulation case with the same settings but the slope facing the bench removed. The simulated muckpile shape agreed with the muckpile formation commonly observed in the field for cast blasting operations (Taherkhani & Doostmohammadi, 2015). By adjusting the blasting design parameters, the muckpile shape could also be further optimized using the proposed approach in order to improve equipment access and minimize the environmental footprint.

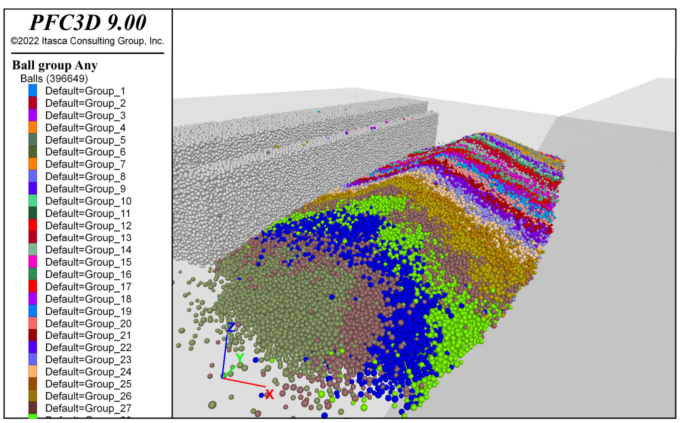


Fig. 6. Muckpile formation in the *PFC* model.

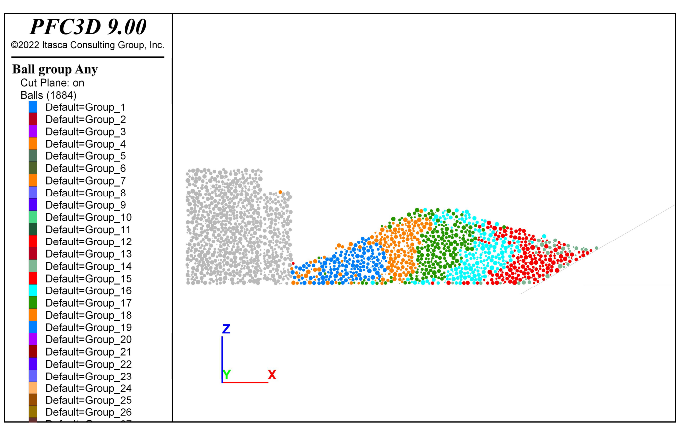


Fig. 7. Muckpile formation in the *PFC* model, cross-section view.

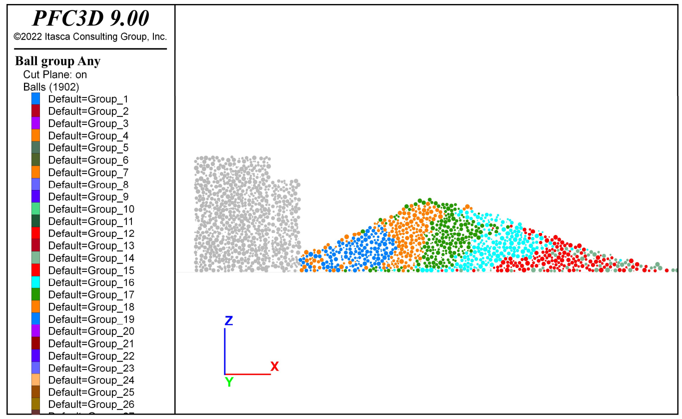


Fig. 8. Muckpile formation in the *PFC* model without the slope, cross-section view.

7. CONCLUSIONS

The study proposes a hybrid approach that combines a small-scale continuum model, a machine learning model, and a 3D discontinuum model to capture the key physics of blast-induced rock movement and predict muckpile formation. The continuum model simulates the early-stage, near-field rock blasting process and forms a synthetic dataset based on realistic explosive data to train a surrogate model using an artificial neural network. The surrogate model is capable of achieving rapid prediction of the burden movement velocity, taking into account factors such as gas pressurization and venting during burden acceleration. With the burden velocity and geometric parameters obtained from the machine learning model, the 3D discontinuum model only needs to focus on resolving the phase of rock movement and muckpile formation using discrete particles with rolling resistance, thus achieving faster simulations.

The proposed approach aims to provide a simplified but effective prediction of blast-induced rock movement by utilizing different numerical methods to capture the essential physics during the blasting process. Therefore, some physical effects, such as fracture propagation after reaching the equilibrium pressure and before the burden movement, are not considered in the approach. Additionally, the size distribution of the generated balls in the DEM simulations can be further improved by incorporating empirical fragmentation models to predict the expected size distribution based on rock/explosive properties and design variables (Cunningham, 2005). Despite these limitations, the hybrid approach provides a promising solution to the computational challenges of modeling the complex processes in large-scale rock blasting and can contribute to more efficient and cost-effective blasting designs and operations.

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