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Using machine learning, experimental observations, and numerical modeling to better understand the crushed zone in rock blasting

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1 INTRODUCTION

Explosives are a cost-effective means to break and move rock. Near the blasthole, the explosive induces compressive stresses that are well beyond the strength of the rock leading to the development of a crushed zone. The stresses near the hole are typically compressive for around 500 microseconds. Further from the hole and at later times, the blast induced stresses become tensile leading to fragmentation by mode I fracture propagation.

It is important to understand the size of the crushed zone and the amount of the explosive energy that is dissipated in crushing for two reasons: first, because, depending on the extraction technique, the presence of fines may influence positively or negatively the downstream mineral recovery; and second, because crushing consumes explosive energy that would otherwise do useful work fracturing and moving the rock.

This paper describes a numerical model that predicts crushed zone size. Numerical predictions of crushed zone size are compared with the experimental data and dimensional analysis given in (Esen et al. 2003). Finally, a machine learning based surrogate model for crushed zone size is described and used to investigate a discrete element model contact model for the crushed zone.

2 NUMERICAL MODEL

A small-scale 1-D axisymmetric *FLAC3D* (Itasca 2017) model represents an annulus of rock 4 m (12 ft) in diameter with the explosive in the center. Figure 1 shows a schematic of this small-scale model. The simple elasto-plastic Mohr-Coulomb constitutive model is used to describe the rock. Vixen2009, a non-ideal detonation program, and realistic explosive data are used to describe the explosive (Braithwaite & Sharpe 2009). Vixen2009 predicts the product equation of state (EoS), the velocity of detonation (VoD), and the heat of reaction. The gas pressure resulting from the detonation is applied to the borehole surface. The modeling starts at the borehole pressure of the explosive (also known as the explosion pressure) which is the pressure when the products have returned to the original density by expanding axially along the hole. As the borehole deforms radially, the applied gas pressure is reduced according to the gas equation of state. This model accounts for both elastic and plastic deformation in the rock and tracks the energy quantities associated with stress wave propagation. Before the stress waves reach the outer boundary of the model, the calculation is stopped. At around 500 microseconds, the gas pressure and local rock stress reach a quasi-steady balance, which is termed the equilibrium state or equilibrium pressure. This state is reached before significant radial tensile fracturing or radial gas flow has occurred. This model is described in more detail in (Furtney et al. 2012).

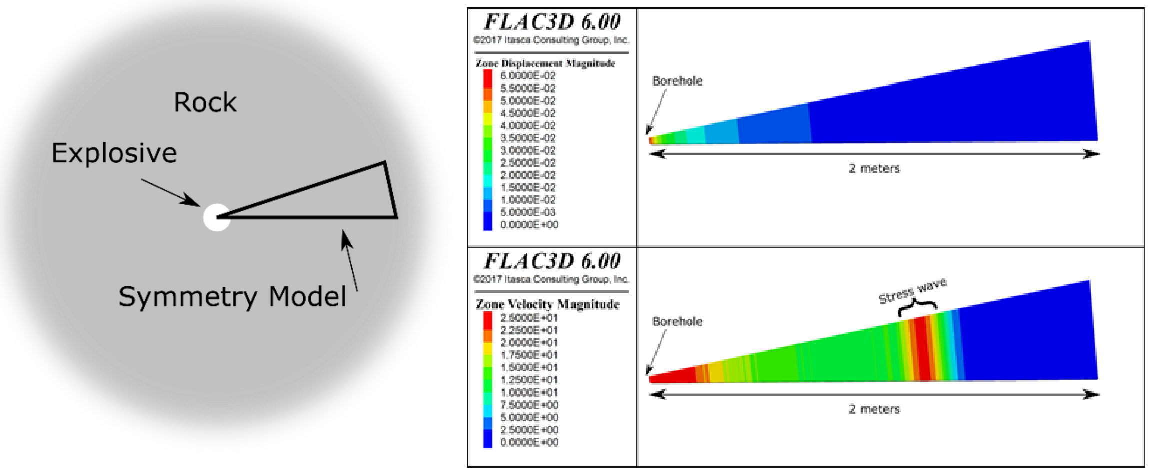

Figure 1. Small-scale model schematic and results.

3 COMPARISON WITH EXPERIMENTAL DATA

A collection of 92 crushed zone measurements for different types of rock and explosive is given in Esen et al. 2003. The work discusses the mechanism leading to the crushed zone and provides a dimensional analysis which relates explosive and rock properties to the crushed zone size. The ratio of original hole radius, r_0, to the radius of the crushed zone, r_c, is given as,

$$\frac{r_0}{r_c} = 1.231(CZI)^{-0.219}$$

$$CZI = \frac{P_b^3}{K\sigma_c^2}$$

where, *CZI* is the crushed zone index, P_b is the explosive borehole pressure, K is the dynamic rock stiffness, and σ_c is the rock uniaxial compressive strength (UCS). In order to compare the numerical model results to this data, a parameter study is run with the numerical model over a range of *CZI* values. The numerical model varies the explosive type, the UCS, rock modulus and hole diameter independently. Latin hypercube sampling is used to choose the set of input parameters. Figure 2 shows the comparison in linear and log space. The black points and trendline are the experimental data and the color points are the numerical model predictions. The following observations are made:

- In linear space (left), there are two distinct regimes in the data, the near vertical region corresponds to decoupled charges where there is little to no compressive failure in the rock and the near horizontal region corresponds to fully coupled charges where crushing occurs.
- The numerical parameter study did not include any decoupled charges.
- The crushed zone is defined in the numerical model as the radius at which 90% of the plastic energy deformation has occurred. This is an arbitrary cutoff, choosing a smaller cutoff would move the numerical predictions closer to the trend line.
- In log-log space (right), the range in scatter is similar between the experimental data and numerical predictions.

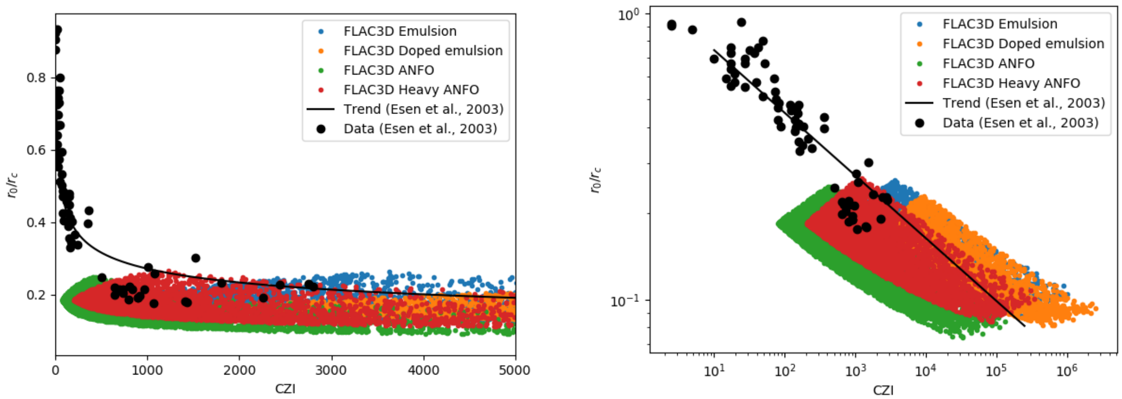

Figure 2. Comparison between numerical models and experimental data in linear and log space.

4 MACHINE LEARNING

The parameter study described in the previous section is used to train a machine learning model to predict crushed zone size. Machine learning is the art and science of enabling computers to make predictions of complex phenomena without explicit programming. In contrast, *FLAC3D* is explicitly programmed to solve the equations describing the deformation of a continuum. Machine learning has seen rapid growth in the last 10 years with the advent of large data sets and powerful new techniques. In earth resource engineering, we are typically in the data-limited regime where this magnitude of data is unavailable. Using synthetic data generated by validated numerical models is one way to apply machine learning techniques in this data-limited regime.

The concept of a surrogate model is a powerful link between the traditional paradigm of numerical modeling and the new paradigm of machine learning. A surrogate model is a machine learning model trained with synthetic data generated by a numerical model. Surrogate models are fast and can accurately predict the outputs of a complex model for a range of input parameters. A drawback of advanced numerical modeling is the complexity in setting up, running, and interpreting a model. Surrogate models have none of these disadvantages.

A neural network with three hidden layers of 15 nodes each was trained with data from 20,000 *FLAC3D* model runs. The training data features are: explosive type, modulus, UCS and hole radius and the regression targets are the crushed zone size, the equilibrium pressure and the partition of the explosive's total energy into percentages of crushing, vibrations and gas. The Python based scikit-learn MLPRegressor model is used (Pedregosa et al. 2011). The resulting neural network can predict the crushed zone radius, equilibrium pressure and explosive energy partitions, in a fraction of a second, to within 0.1%. The model is presented as a single-page web application in which gives instant results updates as input sliders are moved. This type of fast running surrogate model is useful for training, application by field practitioners, and can be used for probabilistic analysis. The model is published here: https://jkfurtney.github.io/ml_blasting/

5 SUMMARY AND FUTURE WORK

A zone of crushed rock develops around a blasthole when blast induced compressive stresses exceed rock strength. Understanding this crushing process is important in choosing the best explosive for a given rock and for optimizing blasting outcomes. This abstract describes a numerical model for the crushed zone, compares with experimental data and uses synthetic data from the numerical model to train a machine learning model. This process of investigation lead to the following conclusions:

- The relative size of the crushed zone is mostly independent of the starting hole diameter.
- Increasing the rock UCS or modulus decreases the crushed zone size and increases the equilibrium pressure.

- In general, emulsion type explosives do more work at higher pressures and result in lower equilibrium pressures. In contrast, ANFO explosives do less work at higher pressures and have higher equilibrium pressures.
- The crushed zone size alone is not the only relevant explosive-rock characterization. In most cases, the ANFO gives a larger crushed zone than an emulsion, but around 40% less energy is dissipated in plastic flow compared to an emulsion.
- This model does not include volumetric collapse which may be relevant in some rock types.
- The numerical parameter study in this work focuses on fully coupled charges, there is another regime involving decoupled charges that should be investigated further.

Despite the complexity of rock blasting, numerical modeling has demonstrated value in understanding, designing, and analyzing rock blasting outcomes. Analysis of rock blasting involves solving inter-related sub problems, including: non-ideal detonation, explosive-rock interaction, crushing, fracturing, gas flow, fragmentation, vibrations, and muck pile movement. From 2001 to 2012, Itasca in collaboration with the University of Queensland was part of the Hybrid Stress Blast Model (HSBM) project which developed and validated a discrete element based numerical model of the complete blasting process called Blo-Up (Ruest et al. 2006, Furtney et al. 2009, Onederra et al. 2013). The discrete element method is a natural fit to model blasting because the method is dynamic and can explicitly represent fracturing and fragmentation. But, the direct application of explosive gas pressure to a blasthole in a bonded discrete element model results in an over-prediction of the crushed zone size, an under-prediction of the equilibrium pressure and an inaccurate partition of the explosive energy. To overcome this limitation, Blo-Up version 1 used a custom DEM contact model that allowed for yielding in compression and Blo-Up version 2 replaced this with a continuum model to describe the crushed zone. It is desirable to have a fully discrete model for blasting so there is renewed interest in the idea of a contact model with yielding in compression. Ongoing work involves using the machine learning model predictions of crushed zone size and equilibrium pressure to parameterize a new *PFC3D* v6 (Itasca 2018) contact model that will give a more accurate crushed zone behavior.

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