Petrophysical Characterization of Comminution Behavior

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Statement of Originality

This thesis contains no material that has been accepted for a degree or diploma by the University of Tasmania or any other institution, except by way of background information which is duly acknowledged in the thesis, and to the best of the candidate’s knowledge and belief, contains no material previously published or written by another person, except where due acknowledgement is made in the text of the thesis.

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Statement of Co-authorship

This research was conducted as a component of the major AMIRA P843 project on Geometallurgical Mapping and Mine Modeling. The author contributed to this research program as part of a large team of researchers but had primary responsibility for the conduct of the petrophysical research program within P843.

Several conference papers have been published by the candidate and his supervisors in the course of this research. Chapter 3 has been partly published as a scientific manuscript in co-authorship with supervisors Dr. Peter Fullagar and Dr. Michael Roach. Some sections of Chapters 2 and 6 have also been published in co-authorship with Dr. Peter Fullagar. Chapter 5 has been partly published in co-authorship with Dr. Peter Fullagar, Prof. Steve Walters and Dr. Toni Kojovic.

Dr. Peter Fullagar has developed the linear programming algorithm as used and clearly referenced in Chapter 7. The candidate had the main responsibility for data collection, analysis, interpretation, modeling, documentation and presentation. Comminution data were provided by Dr. Simon Michaux and Dr. Toni Kojovic. The supervisors contributed to data analysis and interpretation of result. A series of programs developed by Dr. Peter Fullagar was used during data processing.

The candidate planned the thesis outline and was responsible for writing the full thesis. Dr. Peter Fullagar, Dr. Michael Roach and Prof. Steve Walters provided editorial assistance on all chapters.
Abstract

Comminution or feed size reduction is typically the first stage of ore processing at mines. Comminution tests are commonly conducted to assess the processing behavior of ore and to aid in process design and equipment selection. Testing for Bond mill work index (BMWi), a measure of the ore grindability, and A*b, a measure of the ore crushability, is common in this regard. These destructive tests are expensive and time consuming and, hence, are conducted on a limited number of large volume samples which in most cases are not representative of the entire orebody. Therefore alternative means are desirable for efficiently characterizing comminution behavior.

Petrophysical properties have the potential for effective characterization of ore comminution behavior for a truly representative suite of samples. Petrophysical measurements are quick, non-destructive, and relatively cheap. Petrophysical data can be recorded either downhole or on core. If calibrated against measures of ore crushability and grindability, petrophysically-based models could provide virtually continuous downhole prediction of comminution attributes in intervals of drill holes where these parameters are not available. This thesis presents a new approach for characterization of ore comminution behavior based on petrophysical measurements.

As an alternative to downhole geophysical logging, a Geotek multi-sensor core logger (MSCL) was evaluated. Density, P-wave velocity, P-wave amplitude and magnetic susceptibility, as well as core imagery, were measured on drill cores from two Australian copper-gold deposits, namely Cadia-East, NSW, and Ernest Henry, QLD. The Geotek system had never previously been used at metalliferous mines. It provides data with acceptable accuracy if carefully and systematically calibrated but the data quality is adversely affected by the small size and condition of the core. The accuracy achieved in production logging was approximately ±1.35% for density, ±6.5% for P-wave velocity, and ±1% for magnetic susceptibility.

The relationships between petrophysical properties and comminution attributes (A*b and BMWi) was directly investigated, since small-scale comminution tests had been performed on selected 2m intervals of the same drill core. At Cadia East, the ore is hard in terms of both crushing and grinding. At Ernest Henry the ore is more variable but generally softer.
In most cases the relationship between petrophysical properties and comminution parameters is dependent on ore type. Hence class-based approaches for comminution modeling were devised and implemented. Crushability (A*b) can be related to petrophysical properties more reliably than grindability (BMWi). This is consistent with the fact that petrophysical properties and crushability are measured on whole rock while BMWi is measured on crushed composite samples. Prediction of high BMWi materials (>10 kWh/t) proved difficult, perhaps because particles are more competent at crushed size.

An important outcome is that magnetic susceptibility is a good indicator of A*b at both sites and can be used to define different comminution domains. At Ernest Henry, as susceptibility increases A*b increases (samples are easier to crush) because magnetite acts as crack initiator. At Cadia East, ore becomes harder to crush as susceptibility increases; the association of feldspar with magnetite was most probably the reason for the low values of A*b in this case.

At Ernest Henry, models were developed for prediction of A*b and BMWi values in depth intervals where petrophysical measurements are available but comminution test data are not. Four petrophysical classes were defined based on P-wave velocity, P-wave amplitude, density and susceptibility using cluster analysis. Regression models were developed for A*b and BMWi using petrophysical properties for each class. The overall root mean square (RMS) error of prediction for BMWi and A*b are 1.39 kWh/t and 27.3 respectively.

Comminution modeling at Cadia East was difficult due to the limited variability of comminution parameters. Four classes were defined based on variability of A*b and BMWi around their respective mean values. A*b and BMWi were then linked to petrophysical properties and assays using a neural network approach. The performance of neural networks for prediction of comminution classes was tested by successively treating each hole as an independent hole. The prediction accuracy ranged from 51% to 77%.

A novel approach for prediction of petrophysical properties and comminution attributes from core images was also investigated at Ernest Henry. Estimates of mineral abundance from classified core images were first adjusted to achieve compatibility with assay data. Bulk density was then predicted from mineral volumes and densities with a relative error of prediction of 3.5%. Regression coefficients for A*b and BMWi were estimated for each mineral phase via least squares optimization. This method provides a means for
prediction of $A^*$ and BMWi in depth intervals where classified imagery is available but
comminution test data are not. The RMS errors of prediction for $A^*$ and BMWi are 33.3
and 1.68 kWh/t respectively.

The two case studies from different geological environments show that petrophysical data
can provide useful information for characterization of comminution behavior and hence
prediction of mill throughput. Petrophysics-based comminution models have limitations
but they are adequate for use during process planning. The accuracy of such models can
be improved by reducing uncertainties in petrophysical and comminution measurements,
refining data classification techniques, by increasing the number of petrophysical
properties recorded, and by incorporating other data including assays in the analysis.
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