A Framework for 4D Quantitative Back-Analysis and Estimation of Geotechnical Hazard Potential in Mines

John McGaughey
Mira Geoscience Ltd, Westmount, Quebec, Canada

ABSTRACT
A framework is presented for quantitative estimation of the probability of geotechnical hazard events in mines. The hazard event may be of any type, such as fault-slip rockburst, strainburst, roof failure, slope failure, or flooding. The method requires models of the mine at points in time when past failures occurred, capturing the state of individual criteria on the rock interface where the geotechnical hazard is experienced. The series of time steps constitutes a 4D mine model to which expert system processes are applied to understand the evolution of hazard in response to the dynamic mine environment. A case study is shown from deep, rockbursting mines that exemplifies the method and demonstrates its practical application and value.

RÉSUMÉ
Un cadre est présenté afin d'estimer quantitativement de la probabilité d'occurrence d'accidents géotechniques dangereux dans les mines. Les dangers peuvent être de toutes sortes tels que les glissements de terrains, les coups ou les ruptures de toit et les inondations. La méthode nécessite des modèles de la mine aux moments précis où de tels accidents se sont produits, captant ainsi l'état de critères particuliers de l'interface rocheux où l'accident géotechnique est survenu. Des systèmes experts sont appliqués au modèle de mine 4D constitué d'une série de représentations temporelles des critères de l'interface rocheux afin de comprendre l'évolution des dangers en fonction de l'environnement dynamique de la mine. Une étude de cas de mines profondes où des coups de toits surviennent illustrent la méthode et démontrent son application pratique et sa valeur.

1 INTRODUCTION

The premise of this work is that zones of elevated groundfall hazard in an operating mine may be identified by quantitative combination of a number of observable or computable input variables. We demonstrate that hazard identification from combining multiple inputs is more effective than interpretation of any single input, and provides a useful result for experienced ground control engineers to interpret within the overall operational mining context. Neither spatial nor temporal prediction of actual groundfalls is presumed to be a reasonable expectation in a dynamic environment where the inputs exhibit both complex inter-relationships and substantial uncertainty. Nevertheless, proactive identification of groundfall hazard zones provides an opportunity for the operation to mitigate both safety risk and production disruption. This approach is similar to that taken in earthquake hazard assessment where the foundation of risk estimation is maps demarcating elevated seismic hazard zones on a relative scale, as opposed to predicting the occurrence of individual earthquakes. Computational assessment of groundfall hazard serves as a quantitative basis for the inclusion of geotechnical hazard estimation in mine planning and design.

Xstrata's Craig Mine near Sudbury, Ontario, experienced substantial production problems due to unexpectedly severe rockbursting conditions. The essence of this case study is to use available data sets describing the mine condition and history of rockbursting to retrospectively determine relative rockburst hazard as a function of multiple measurable criteria. The established hazard function may then be deployed prospectively to evaluate current or future hazard. It demonstrates by example a framework for 4D quantitative "back-analysis" of any type of geotechnical hazard.

2 HAZARD ASSESSMENT STRATEGY

We assume geotechnical hazard to be a computable spatial property that can be portrayed on a 3D model of mine development. Hazard is a property of mine development or other rock interface surfaces (e.g. drift walls, stope backs, shaft walls), not a property of the rock mass volume in which the mining takes place. This is because falls of ground occur at rock interfaces, no matter the underlying cause or the proximity of that cause within the 3D rock mass. A map of relative or absolute probability of ground failure at defined (x, y, z) locations on mine development surfaces we term a *geohazmap,* which may vary in time in response to dynamic mine conditions.

The "hazard equation" for a given hazard type is assumed to be a complex function of many layers of input data, written generally as:

$$\text{hazard}\,(x, y, z, t) = f\,(\text{geology, rock quality, stress, seismicity, development, mining method, other properties}).$$

Establishment of the time-dependent hazard function requires site-specific geotechnical reasoning and experimentation with case study data. Speculative relationships must be tested empirically, so an initial data compilation and analysis must be made. Although the case study described here focuses on a single hazard type, fault-slip induced rockbursting, the methodology presented is applicable to any type of ground failure.

2.1 Methodology

We have adapted our hazard estimation procedure from experience in mineral exploration targeting, which is a conceptually similar process in a different application. In both cases the general principle is to combine multiple data streams to determine spatial zones with desired statistical characteristics. The objective is to find (*x, y,* z) locations, otherwise difficult to discern, where certain special combinations of conditions exist. We use GOCAD™ 3D earth modelling software with a plug-in module called *Targeting Workflow* to guide the user through the required series of pre-processing, statistical analysis, and computational targeting steps. In the remainder of this paper we use the words “targets” or “targeting” to refer generically to the process of identifying zones within an earth model that satisfy certain criteria (such as enhanced groundfall hazard).

A multi-disciplinary GOCAD “common earth model” (McGaughey, 2006) is created as the fundamental data support for the various types of data that are to serve as the hazard criteria. The hazard criteria data are modelled as continuous or classified variables on a triangulated “hazard surface” which, in this case, is specified to be the entire set of Craig Mine “Zones 10 and 11” development surfaces, including drifts, ramps, and stopes. Hazard criteria used here were a mixture of interpreted rock properties such as lithology, rock quality, and disking, along with other potential hazard indicators such as depth, stress, seismicity, and proximity to faults. “Target” hazard locations are identified, ranked, and classified by computing and analyzing a score at each location (vertex) on the surface. A quantitative, probabilistic approach is taken by the workflows to computation of the score function by allowing the user to select amongst: a) a knowledge-driven framework in which expert knowledge is used to manually classify, score, and weight individual criteria; b) a data-driven framework in which training data of known valid targets in the model are used to classify and weight the input criteria; and c) classifications and scores from other models of similar settings which may be imported for application to a new model area.

The methods described here are inspired by a history of successful application in 2D GIS systems in mineral exploration going back to the 1980’s and 1990’s (see for example Bonham-Carter, 1994 and 1997), and more recent experimentation in 3D for exploration applications (Apel and Böhme, 2006; Caumon et al., 2006). The Bayesian weights-of-evidence algorithm deployed at the core of data-driven applications of Targeting Workflow is based on the work of Apel and Böhme (2006) and their “Predict” software.

The *Targeting Workflow* software takes the user through a sequence of pre-processing, prediction modelling, and post-processing steps. It provides a number of statistical investigations of input data and target validation procedures, offering both knowledge-driven and data-driven frameworks. Knowledge-driven expert-system approaches rely on expert users to convert opinions on the relevance of input data to the hazard estimation, based on experience, into numerical scores used in the combination of multiple data streams. Knowledge-driven systems do not require historical groundfall events for users to set weighting systems for the input data streams. Data-driven systems use statistical methods to set weights for individual data streams depending on their correlation with historical groundfalls. They are thus “unbiased” but require construction of the site history. (Bias can still affect the process in a number of ways from selection and modelling of hazard criteria to interpretation of several statistical tests carried out by the workflow.) There are many algorithms within each of the knowledge-driven and data-driven approaches, of which only a few have been currently implemented in Targeting Workflow. At the highest level the workflow steps consist of:

1. Select modelling approach: a) Boolean Overlay, b) Weighted Boolean Overlay, c) Multi-class Index Overlay, d) Weights-of-evidence;
2. Define model space and select hazard criteria properties;
3. Select training data (known occurrences of groundfall);
4. Re-classify, remove or combine individual hazard criteria properties if appropriate;
5. Define individual criteria weights based on expert opinion (knowledge-driven) or training data (data-driven);
6. Generate prediction model;
7. Analysis and validation of prediction model;
8. Hazard zone generation, classification, and ranking.

The Targeting Workflow was deployed in this case study using a data-driven approach since a reasonably rich data set of historical groundfall was available. The data-driven approach used is “Weights-of-Evidence”, a well-established statistical method in 2D spatial targeting applications such as mineral exploration, environmental, and geotechnical. Other well-established data-driven approaches are logistic regression and probabilistic neural networks, which may be considered alternatives to the weights-of-evidence approach adopted here.

3 CRAIG MINE CASE STUDY

We applied a 4D weights-of-evidence back-analysis procedure to rockburst-induced fall of ground (FOG) hazard estimation at Craig Mine Zones 10 and 11. Weights-of-evidence provides a statistical assessment of the correlation between known occurrences of some condition (rockburst-induced falls of ground in this case) and multiple sets of measurable data.

Geotechnical hazard analysis using 4D weights-of-evidence was performed on two separate model areas at Craig mine: the ore zone and the footwall. They were treated separately because of a belief that the conceptual models for ore zone FOGs and footwall FOGs may differ. Locations of known groundfalls, used as training data, were divided into two subsets based on whether they were within the ore zone or footwall. The footwall model contained 8 known FOGs and the ore model contained 11 known FOGs as listed in Table 1. The location of each FOG was represented as a vertex on the 3D mine model wireframe used for computing the hazard forecast. Because of location uncertainty, vertices within a 10 m buffer of the FOGs were also included as FOG locations.

Timestamp	Date of FOG	Footwall	Ore
T1	Nov 6, 2003		✓
T2	March 4, 2004	✓	
T3	June 3, 2004	✓	
T4	August 19, 2004		✓
T4	August 29, 2004		✓
T5	Nov 30, 2004		✓
T6	July 7, 2005		✓
T6	July 24, 2005	✓	
T7	Aug16, 2005	✓	
T8	Oct 27, 2005	✓	
T8	Oct 31, 2005	✓	
T9	Apr 3, 2006		✓
T10	May 21, 2006		✓
T11	Sep 11, 2006		✓
T12	Jun 22, 2007		✓
T13	Dec 1, 2007		✓
T14	Mar 4, 2008	✓	
T15	Apr 19, 2008		✓
T16	Dec 24, 2008	✓	

Table 1. List of groundfall dates used as training data in the Craig mine hazard forecast, subdivided into footwall groundfalls and ore zone groundfalls. Each individual timestamp required a separate mine model to be constructed. Rockbursts occurring within the same month used the same mine model, under the assumption that dynamic modelled variables changed minimally.

In order to carry out the weights-of-evidence statistical analysis, individually modelled hazard criteria were assigned to each vertex of the mine development wireframes, for each modelled snapshot in time. The time snapshots were chosen to correspond to the time of rockburst occurrences. If the location of a specific vertex (x, y, z, t) corresponded to the location of a rockburst, within the chosen 10 m buffer, that vertex would be flagged as a "training" point. The weights-of-evidence process then uses this data to build a statistical model that enables computation of the probability that any point in space and time on the mine infrastructure will experience a rockburst.

Hazard criteria are defined as geotechnical factors that may be related to groundfall in the Craig Mine. Hazard criteria are represented in the GOCAD model as continuous or discrete variables on the mine development (Table 2). Some of these variables are static, for example rock code, disking and proximity to the orebody. Other variables are dynamic and therefore vary over time as new groundfalls are occurring, for example age of mine development, stress and microseismic event density. The list of variables used as hazard criteria was created initially through brainstorming with site personnel, and then refined in the modelling process. The mine infrastructure was modelled for dynamic variables at each of 16 different timestamps. Because separate models were constructed for the ore zone and footwall, a total of 19 individual mine models were made.

Static Properties:	rock type
	core breaks
	core disking
	proximity to drift intersections
	proximity to fault terminations
	proximity to faults
	proximity to footwall contact
	proximity to hanging wall contact
	proximity to ore contact
	RQD
	infrastructure orientation (azimuth)
	proximity to high fault-slip tendency
	proximity to faults intersections
	ground support type
	mining method
Dynamic Properties:	microseismic event density
	average shear/compressional energy
	average seismic moment
	average static stress drop
	average local magnitude
	average apparent stress
	age of mine development

Table 2. List of static and dynamic variables available as hazard criteria for the Weights-of-Evidence model.

Conversion of raw geotechnical data to GOCAD hazard criteria is an important interpretational step. How raw data is ultimately represented in the model as hazard criteria must be defined by geotechnical experts. The process should be performed in such a way as to maximize the spatial correlation between patterns of the hazard criteria properties and locations of known groundfalls. This requires knowledge of the specific mine site as well as an understanding of how the data are captured and processed. For example, disking measurements from drillhole points in this study were run through a 3D geostatistical simulation to produce a continuous property on the hazard surface, microseismic point data were grouped into six month time windows upon which cluster density was computed, and fault slip tendency on fault segments were classified and represented as proximity properties.

3.1 Modelling Results

Continuous and discrete hazard criteria are converted to binary properties for our current implementation of the Weights-of-Evidence technique (there are alternative formulations that use multi-class or “fuzzy” class-membership properties). Each geotechnical criteria is divided into two classes based upon a threshold or cut-off value that best separates regions of the hazard surface containing a large proportion of training data (i.e. have a history of groundfall) from those regions containing few or no training data (no groundfalls). The effectiveness of this binary classification in separating regions of hazard from non-hazard, per variable, is the essence of the statistical correlation test between the groundfall training data and the input hazard criteria. Positive and negative “weights” are computed for each criteria as a measure of the degree of correlation with the training data. Weights and contrast are determined by assessing the spatial correlation between training data (groundfalls) and the binary classes. The optimum cut-off or range for the binary property is determined by computing weights and contrast values for multiple binary representations of the same variable. Contrast is defined by the difference between the W+ and W- values. It is plotted as a function of binary cut-off in order to assess the cut-off level that maximizes the contrast (maximizing the spatial association between the hazard variable and the known groundfalls). If a peak or isolated anomalous value on a contrast curve plot is not obvious it indicates that there is little or no correlation between the location of known groundfalls and the anomalous pattern on the hazard criterion. If this occurs the variable is not used in the combination algorithm, as was the case for several properties in both the ore and footwall models at Craig Mine. Examples of contrast curves, binary properties showing favourable and unfavourable zones for a given criteria, and an output table of contrast weights for given criteria are shown in Figures 1-2 and Table 3.

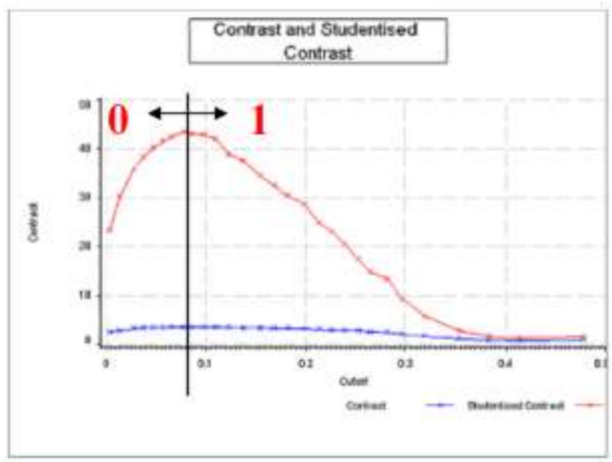

Figure 1. Example contrast curve plot for microseismic density with binary property cut-off value on the x-axis and contrast value for that cut-off on the y-axis. The peak of the Studentized contrast curve (red) indicates on the x-axis the value at which microseismic event density evaluated on the mine development (approximately 0.07), the value above which rockbursts become relatively favourable. The microseismic event density scale is relative.

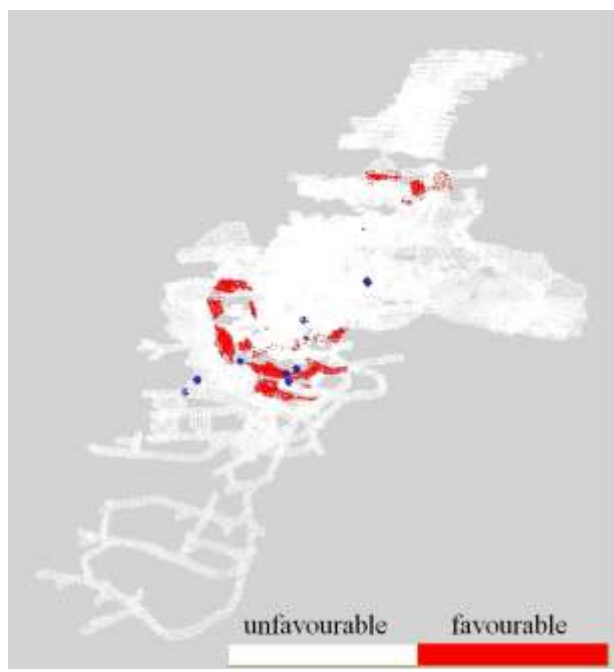

Figure 2. Binary microseismic density property displayed on model area as points with a cut-off at 0.07. The parts of the mine infrastructure wireframe in red correspond to places (for this snapshot in time) where the relatively high microseismic event density (greater than 0.07) indicates elevated rockburst hazard. The microseismic event density map changes continuously in time as activity occurs. Blue diamonds show locations of ore zone FOGs.

Hazard Criteria	Weight
proximity to ore contact	28.1
disking	25.5
core breaks	24.1
RQD	20.2
microseismic event density	17.2
average seismic moment	15.5
proximity to high fault slip	11.3
drift orientation	9.5
age of development	5.4
proximity to fault intersections	5.4
proximity to drift intersections	2.1

Table 3. List of hazard criteria, for the footwall model, ordered by degree of correlation to the history of rockbursting. The “Weight” column is the Studentized contrast (difference between positive and negative weights normalized by standard deviation), a conventional measure of degree of correlation between the modelled criteria and the phenomenon, in this case the record of fault-slip induced rockbursts. Note that in this case, seismic event density, typically the variable most used to assess rockburst potential, is weighted as the fifth most important modelled criteria.

For each time stamp of the mine model the relative hazard may be computed by combining computed weights for a list of criteria interpreted to be most relevant (Figure 3).

4 CONCLUSIONS

This project is the first we are aware of that formally combined a time history of mining and groundfall into a single computational 4D statistical analysis. Much of the project effort was dedicated to formulating a practical methodology to achieve this, and to the computer modelling required to implement it.

The key conclusion is that the quantitative, statistical approach employed in this project for forecasting groundfall hazard related to fault-slip rockbursting was effective at Craig Mine Zones 10 and 11. The results are promising for the prospect of deploying an effective method of computing and displaying zones of elevated groundfall hazard within the project area studied. To the extent that other areas, whether at Craig Mine or elsewhere, experience groundfall hazard in an environment where the same conceptual model holds and the geotechnical environment is similar, the same type of groundfall hazard may be similarly assessed, using weights computed here. The hazard assessment strategy may also be used as a design tool for mine planning, so that geotechnical risk could be quantitatively included alongside other mine design criteria.

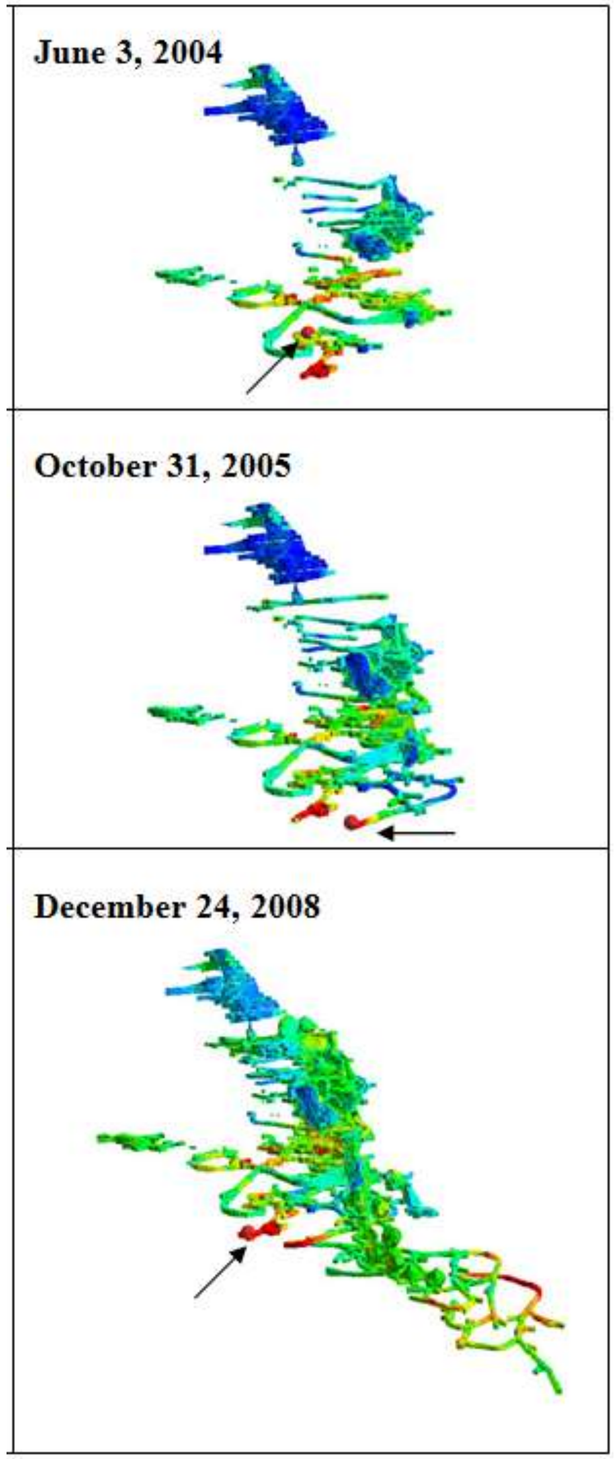

Figure 3. Hazard forecast result mapped computed on the mine development surface at various time stamps for the footwall model. Actual rockburst locations are displayed as red spheres and indicated by arrows.

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