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### Probabilistic Analysis of an Open Pit Mine Slope in the Central African Copperbelt with Spatially Variable Strengths

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ABSTRACT: The highly variable nature of weak rock in weathered sedimentary deposits poses significant challenges to open pit and underground mine design. Traditional probabilistic analysis fails to consider all potential mechanisms of instability that may influence slope stability. An approach with spatially variable strengths allows the natural variability of the shear strength properties within the rock mass to be simulated. This paper examines the congruence of geotechnical block modeling and spatial variability analysis to estimate the probability of failure of a highly variable weathered open pit slope in the Central African Copperbelt. The input parameters for the random spatial field simulations are estimated from variography of composited drill hole data and univariate statistics of a 3D block model of rock-mass shear strength. The Rocscience software Slide2 is used to perform the random field simulations and analysis. It is also demonstrated that the total variance can be reduced by the small-scale variability (nugget effect variance) for spatially averaged shear strengths. Typical rock-mass spatial parameters from other projects are summarized.

#### 1 INTRODUCTION

Factor of safety (FOS) is not a consistent measure of the risk of slope failure since it is possible for many levels of risk to exist for the same FOS value. The probability of failure (Pf) is a more explicit measure of risk than FOS, and is estimated by performing a probabilistic analysis considering input parameters as random variables. All geotechnical properties are spatially variable. If spatial variability is not considered in a probabilistic slope analysis, severe over- or under-estimation of the probability of failure can result (Cylwik et al., 2018). In addition to the mean and standard deviation of a parameter, an estimate of the correlation distance is also required to model spatial variability. It is often difficult to obtain the correlation distance of rock-mass strength parameters because they must be estimated with a transformation model and cannot be measured directly (as opposed to fine-grained soil). This publication presents the methodology that has been developed to perform spatially variable probabilistic slope stability analysis within oxide zone deposits in the Central African Copperbelt.

#### 2 CENTRAL AFRICAN COPPERBELT REGIONAL GEOLOGY

The Central African Copperbelt (CACB) is a series of sediment-hosted, stratiform coppercobalt deposits. Most mining is currently focused on the oxide deposits, which typically range in depth from 50 to 300 meters below surface. Ore and waste rocks include dolomites, siltstones, limestones, and sandstones that are variably bedded, brecciated, and altered, as shown



Figure 1. Stratigraphy of Mine Series rocks within the Central African Copperbelt (after Schuh et al., 2012).

in Figure 1. Slope stability is controlled by bedding orientation, faults, rock strength, and groundwater. Most deposits typically consist of a footwall comprised of RGS, and a hanging wall comprised of SDS and CMN rock types, separated by the RAT/RGS contact fault.

#### 3 ROCK-MASS CLASSIFICATION AND STRENGTH ESTIMATION IN WEAK OXIDE ROCKS

A geotechnical rock type (GTR) classification system has been developed specifically for the CACB to provide an index of rock quality using available data. This system focuses on the soft, transition zone rocks that are typically encountered during mining of the oxide portion of the deposits. In comparison,

more commonly used classification systems focus on stronger rocks. A sulphide zone is present below the oxide zone and consists of hard rock. The sulphide zone is not mined in the current open pits, but will be part of future surface and/or underground mining operations. The GTR classification system utilized is based on hardness, talc content, and recovery, and is presented in Table 1. These parameters are interpolated into three-dimensional block models and are used to define geotechnical rock types and domains.

Table 1. OTK classification system				
Geotechnical Rock Type	Talc Index*	Calculated GTR**	Description	
GTR-T	1-3	-1 - 6	High talc content	
GTR0	0,4	$\leq 0.5$	Soil-like material	
GTR1	0,4	≤ 1.5	Friable, weak rock	
GTR2	0,4	≤ 2.5	Transition rock	
GTR3-6***	0,4	≤ 3.5	Hard rock	

Table 1. GTR classification system

\* 0-no talc, 1-massive talc, 2/3-talc along bedding, 4-traces of talc

\*\*  $C_{GTR} = (1 - \% \text{Recovered}) * 0 + (\% \le S6) * -1 + (\% \le R2) * 1 + (\% > R2) * \text{Hardness}$ 

\*\*\* GTR3-GTR6 grouped as one strength for analysis

Different methods of strength estimation are utilized depending upon the character of the material:

- 1. Rock-mass strength using the CNI method (Read & Stacey, 2009) for hard materials (GTR2 to GTR6)
- 2. Joint strength plus 1.5 percent intact strength along bedding for analysis of anisotropic failures in hard rock (GTR2 to GTR6)
- 3. Direct shear strength and intact shear strength for soft rock, talc, RAT/RGS shear, and fault gouge (GTR0, GTR1, GTR-T, faults)

#### 3.1 Block Model

In order to estimate the variability in rock quality for a given deposit, a three-dimensional block model of GTR is created from available drill hole data.

#### 3.1.1 Domains

Prior to estimation of GTR, the model area is divided into geotechnical domains based on rock type and depth from surface. Rock types are categorized into the following groups:

- SDS Group: SDB, SDS, and CMN formations
- RSC Group: RSF and RSC formations
- RGS Group: RAT and RGS formations

Rock quality generally improves with depth. Rock groups are further divided into zones of similar geotechnical characteristics based on depth from surface.

- Weathered zone (1) well-developed saprolitic horizon consisting primarily of GTR00 material. The weathered zone typically extends between 5 and 60 meters below the surface.
- Intermediate zone (2) variably weathered rocks that range in strength from soft, soillike material (GTR00 to GTR01) to harder, more competent rock (GTR02 to GTR03). This zone comprises the majority of the oxide pit slopes.
- Competent, lower zone (3) predominantly hard rock (GTR03). The contact between this and the overlying intermediate zone is typically located at or just below the toe of the oxide pit slopes.

Additional domain boundaries are defined as needed based on field observations and/or analysis of drill hole data (e.g., around fault zones).

#### 3.1.2 Estimation of GTR

Drill hole data are composited on fixed 1.5-meter intervals honoring logged or modeled rock type boundaries. Variograms of composited GTR data are generated for each domain to determine input parameters for ordinary kriging. Model values for the sample area are estimated using ordinary kriging with domain-appropriate (isotropic or bedding parallel) search criteria.

#### 3.1.3 Conversion of GTR to Shear Strength

Cohesion and friction angle vales are estimated for each individual drill composite. This is accomplished by creating continuous functions that estimate shear strength in between the integer values of GTR, as shown in Figure 2.



Figure 2. Example continuous functions to convert GTR to cohesion and friction angle.

#### 4 PROBABILISTIC ANALYSIS WITH SPATIAL VARIABILITY

#### 4.1 Example Cross Section – FZ\_2

The example deposit trends roughly southwest to northeast and is geologically and structurally complex. The sedimentary sequence is repeated several times due to folding and thrusting along the RGS bounding thrust fault system.

Section FZ\_2 in contains two fault blocks with near-vertical stratigraphy separated by the RGS bounding thrust fault, as shown at the bottom of the cross section in section 4.3. In the upper benches, the RGS bounding fault puts the Mines Series uncomformably against the CMN formation. Another Mines Series sequence is at the toe of the pit slope and is in fault contact with the RGS Breccia on the south wall.

#### 4.2 Input Parameters

Cohesion and friction angle are assumed to be spatially variable for this analysis. Unit weight is assumed to be constant. The following procedures are used to estimate the input properties:

- The mean value ( $\mu$ ) is estimated from the model blocks of cohesion and friction within each geotechnical domain, limited to within 25 meters in front of and 75 meters behind (into the wall) the pit slope design. The block model is the best mean estimator of the values of cohesion and friction angle within the potential zone of instability. The median value of the blocks is utilized due to the long tail in the distribution of strength values (Fig. 3).
- The distribution type is estimated from the distribution shape of the drill hole composites of cohesion and friction angle. An example distribution of the SDB/SDS/CMN Rock type for weathered zone 2 is shown in Figure 3.
- The correlation coefficient between cohesion and friction angle is estimated form the cohesion and friction angle values of the drill hole composites.
- The long-scale variance  $(\sigma_V^2)$  is used as the input variance for the spatial analysis, and is estimated by fitting a variogram model to the experimental variogram of drill composites of cohesion and friction. Example variogram models are shown in Figure 3.
- The correlation distance ( $\theta$ ) is estimated by fitting a variogram model to the variogram of drill composites of cohesion and friction.
- The minimum strength considered in the simulations is that of GTR0 material, or cohesion of 48.2 kPa and friction angle of 24.3 degrees.



Figure 3. Section FZ\_2, intermediate zone 2, SDS rock type, cohesion A) Variograms of drill hole composites, B) Histograms of drill hole composites, and C) Histograms of model blocks.

## - Important Considerations for Spatial Variability Input Parameters

- Note that the variance and correlation distance of a parameter should not be estimated from interpolated data such as a block model, since block interpolation methods do not retain the variance of the raw data (they are typically best mean estimators).

Only the long-scale variance of the data set must be considered for slope stability analysis with spatial variability. The nugget variance  $(\sigma_N^2)$ , or "nugget effect," which is due to short-scale variation, measurement error, positional error, and/or inherent randomness, does not need to be considered. An example validating this concept is shown in Figure 4. Calculation of a variance reduction function (Cylwik et al. 2018, Vanmarcke 2010) shows that the nugget effect variance does not contribute to the variance of a spatial average. Slope stability is controlled by the spatial average strength along the slip surface, not by the strength at any one point along it, and therefore the nugget variance is not required.

- It is also important to ensure that the covariance functions used by the variogram fitting software and by the slope stability random field generator are equivalent. For this analysis, Hexagon MineSight software was used to perform the variography. For the exponential/Markovian covariance function, MineSight uses " $-3\tau/\theta$ " as the exponent whereas Slide2 uses " $-2\tau/\theta$ ", and therefore correlation distances exported from Mine-Sight must be multiplied by two-thirds before being input into Slide2.



Figure 4. Comparison of two data fields to demonstrate that the nugget effect does not alter the spatial average of a data field.

#### 4.3 Results

Figure 5 presents the results of the spatially variable probabilistic analysis for cross section  $FZ_2$  with 1000 spatial simulations. Each of the 1000 simulations optimizes a global minimum critical slip surface that tends to pass through the weakest materials for that particular simulation. The deterministic global minimum FOS value is 1.404 (shown in red), the mean probabilistic FOS value is 1.119, and the  $P_f$  is 8.1 percent. The geology model is shown at the bottom of the section for reference and the slope is underlain by one of the 1000 spatial simulations. The 1000 optimized slip surfaces are colored by FOS value, and the distribution of FOS values is shown in the upper left. Many potential critical failure mechanisms are identified by the analysis. The majority of critical surfaces with low FOS values are located in the lower slope (indicating that this mechanism has the greatest  $P_f$ ) and represent a failure mechanism different from the deterministic minimum surface.

#### 4.4 Typical Spatial Variability Parameters for Rock

Correlation length and long-scale variance parameters for rock properties are often difficult to estimate due to lack of available data and also because of a scarcity of published values. Typical observations from the variograms of published data (Cylwik et al. 2018, Exadaktylos et al. 2008, Hsu and Nelson 2006) include:

- Parameters that measure rock-mass fracturing (e.g., RQD, GSI structure rating) typically have a very large correlation length, whereas fracture strength and intact strength typically have very small correlation lengths. RQD data correlation lengths can be as

Table 2. Typical correlation length and
nugget effect ranges for rock properties

Rock	Correlation	Nugget
Property	Length	Effect
RQD, RMR	20-80 m	20-50 %
UCS, σ <sub>Tensile</sub>	< 10 m	50-100%

small as 15 meters or as large as 200 meters (with typical values being 20 to 80 meters).

- All variograms of rock-mass strength properties typically show a nugget effect. This may occur in rock and not as often in soil because of the discontinuous nature of rock.

- Typical ranges for spatial parameters of rock properties observed across many mine sites are provided in Table 2.



Figure 5. Results of spatially variable slope analysis of section FZ\_2.

#### 5 CONCLUSIONS

Probabilistic slope analysis allows for the risk between various mine plans to be directly and quantitatively compared. Spatial variability modeling in Slide2 allows for many random field simulations to be run to identify potential failure mechanisms that otherwise may not be considered in traditional analysis. It is often difficult to estimate spatial parameters of rock-mass strength properties, since rock-mass strength cannot be measured directly. In this paper, it was demonstrated that rock-mass strength can be estimated and assigned directly to the drill hole composites and spatial parameters may be estimated from them. A block model is used to obtain mean estimates of strength for each domain. All sources of potential uncertainty deserve consideration in a probabilistic analysis, including uncertainty of the statistical mean, transformation model, lithological boundaries, pore water pressure, etc. Potential failure mechanisms that involve structural components must also be considered and incorporated into rock slope analysis.

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