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Field Investigation of Sandstone Escarpment Stability at East Mountain, Utah, USA

Hamid Maleki[1*], *Chuck* Semborski[2], and *Ken* Fleck[3]

[1]Maleki Technologies, Inc., PO Box 30147, Spokane, WA, USA
[2]Price, UT, USA
[3]Salt Lake City, UT, USA

Abstract. During the last three decades, a significant amount of research has been directed to developing predictive tools for assessing the stability of the Castlegate Sandstone escarpment, travel distances for the debris and the need for any control measures in Central Utah. The cliff-forming Castlegate Sandstone is 60 m thick at the study mine in Utah and lies approximately 250 m above multiple-seam coal reserves. To assess escarpment stability, the authors used multiple regression analysis and extensive data on geology, mining, and escarpment stability collected over many years. The volume of failed rocks was used as the response variable. Mine layout options were developed to minimize cliff instability and frequency of mining-induced surface fractures. Geologic and geometric variables were obtained along 3.7 km of escarpment exposure at 180 study locations. A regression analysis of data from 29 study locations showed that surface topography plays a critical role in influencing escarpment stability. With additional data collected over the next longwall block, important variables were identified including canyon slope, thickness of Castlegate Sandstone and mining influence angle. Finally, the model was used for prediction of escarpment stability in area 3. In remote mining areas of Utah, warning signs were posted at the study areas.

1. Introduction

This paper presents progress being made in developing a predictive statistical model as a tool for assessing the stability of escarpments in the vicinity of Energy West's longwall operations near Huntington, Utah. Such models are ideal for probabilistic risk analysis so that the economic benefits of extracting coal reserves can be compared to the likelihood of escarpment instability. There are two methods routinely used by engineers and researchers to help predict what conditions will be in the future : statistical and computational. Starfield and Cundall [1] identify rock mechanics problems as data-limited, that is, one seldom knows enough about a rock mass to use computational methods unambiguously. These methods, however, are extremely useful for studying failure mechanisms and testing different hypotheses on the cause of the failure. Statistical methods, on the other hand, are uniquely capable of being applied where there are good data, but a limited understanding of certain phenomena, such as the mechanism of escarpment failure (toppling, pure translation, or a combination of these and other mechanisms).

Various investigators from both the U.S. government and universities have used computational techniques for analyzing surface subsidence and escarpment failure mechanisms. The results are in general agreement with studies in the Sydney Basin of Australia [2]. U.S. studies used a combination of two-dimensional, boundary-element [3], finite-element [4], and discrete- element formulations. To overcome the limitations of using small strain, continuum, elastic-plastic code, finite-element deformation was imposed on a detailed discrete-element model of the escarpment and the mudstone foundation and incorporated both horizontal slip planes and vertical joints [5]. The USBM [6] also completed a few preliminary three-dimensional, finite-element modeling studies. While successful in analyzing failure patterns and mechanisms, these studies have clearly identified the limitations of numerical modeling techniques in matching measured surface deformation because of data-limited nature of these modeling efforts among other factors.

*Corresponding author: maleki.tech@yahoo.com

Statistical and semi-analytical techniques have alternatively been used in many rock mechanics problems where there is good data but limited understanding of some natural phenomena such as rock bursts [7], creep [8] and ground support [9], [10]. Other data analyses techniques have also been used by Australian researchers [11] using the results of comprehensive field investigations to identify the influence of individual factors (such as horizontal movements, and cliff heights) on cliff stability. Multivariate statistical evaluation of results is pending additional investigations.

The technical approach for this study consists of a multiphase project in which data collected over many years on geology, mining, and escarpment stability in several mining areas have been digitized for incorporation into a statistical model. This model is has been used by mine personnel for routine assessment of escarpment stability in new mining areas while incorporating new data to enhance model predictions. Model input consists of geologic and mining conditions, including escarpment geometry, orientation of joints with respect to the escarpment, joint density, joint continuity, and mining influence angle.

The authors implemented the first phase of the study during 1997 collecting detailed geologic and mining factors at 29 study locations, each 30-m-wide. In this Corncob Wash study area 1 (primary focus of this paper, figure 1), the 1,000-m-long escarpment exposure provided the opportunity to observe surface effects and evaluate factors that contributed to escarpment instability after mining had been completed followed by study areas 2 and 3. During the second phase of the project, post mining conditions have been characterized along 1,200 m long escarpment exposure (41 study locations, Area 2) in South Newberry study area. Phase 2 results are incorporated in this paper as well. In Rilda Canyon study area 3, premining conditions in the 3,000-m-long study area have been characterized in detail, and postmining conditions surveyed as both the Blind Canyon and the Hiawatha seams were mined in the early 2,000's. This conference has provided the first chance to validate the model by using monitoring data in area 3.

2. Characterization of geologic, mining and response variables

The first step in developing predictive statistical models was to create suitable numerical values that express geologic and mining conditions in the study area (figure 1). The second step was to reduce the number of independent variables by combining some existing variables into new categories and identify highly correlated independent variables. Reducing the number of variables is needed when there are too many variables to relate to the number of data points. The presence of highly correlatable variables influences what procedures are selected for multiple regression analyses. The third step was to develop a multivariate regression model and identify significant factors that contribute to escarpment stability.

The study areas were partitioned into cells approximately 30 m wide. This resulted in 29 cells for the Corncob Wash study area, 41 cells in the South Newberry area, and 110 cells in the Rilda area. The authors estimated geologic, mining, and response variables for individual cells based on field mapping, examination of borehole logs, and aerial photographs obtained before and after mining. Data statistics are excluded from this paper due to limitation of space.

Most variables are self explanatory. Below is a brief description of some of the variables (identified in italics).

- *Joint sets 1 and 2* are the primary and secondary persistent joint sets mapped in each area.
- The *angle between joint sets and an escarpment* can possibly influence escarpment stability, a hypothesis based on observations of subsidence-related fracturing in the western United States [12]. Using this hypothesis, an escarpment may have a higher probability of failure where the angle between joints and the escarpment (or mining boundaries) is small (0 to 30 degrees).
- The *excavation width-to-depth ratio* is similar to a subsidence engineering term (NCB[13]) that relates the total width of an excavation to the average depth of cover over the panel of interest. This ratio measures changes in subsidence mode as excavations are widened during mining of successive panels. As the ratio approaches 1.4, a supercritical subsidence stage is reached.
- Based on a review of mining maps and experience in Newberry Canyon [4-5]), *escarpment shape* (convex or concave) appears to influence escarpment stability and thus is included as a geologic variable. Observations in the Newberry Canyon by researchers from the University of Utah indicate that virtually all of the failures occurred in a concave portion of the escarpment. A hypothesis was that natural erosion of the escarpment took place at a faster rate at these locations as a result of higher premining structural density [5].
- The *influence angle* is defined as the angle from a horizontal plane and a line from the mining limit to the base of the Castlegate escarpment (figure 2). This angle is 90

degree where the escarpment is directly above the mining limit and over 90 degree in areas outside the mining limit.

Several indexes were created to combine joint data from various data sets into a single variable ;

- The *joint set i and escarpment* index (or INJSiE) took values 0 to 4 depending on the amount of deviation between a joint set and the escarpment (figure 3).
- The *joint set i and face* index (or INJSiF) took values 0 to 4 depending on the amount of deviation between a joint set and longwall face.
- The *joint set i* index is a cumulative measure of joint orientation and block size, as follows.

INJSiE + INJSiF + horizontal continuity * vertical continuity / spacing
where INJSiE = the joint set i and escarpment index and INJSiF = the joint set i and face index

- The *erosion under escarpment* index equals values of 1 and 0, depending whether the area under the escarpment at the particular cell is eroded or not.
- The *escarpment shape* index equals values of 1 and 0 for concave and convex escarpment geometries.
- The *failure* index equals values of 0, 1, and 2, depending on the estimated volume of failed material within the cell of interest. The failure index was selected from among other response variables, including tensile cracking and vertical and horizontal movement on the surface, because it best describes the stability of the escarpment and can be estimated for each cell. The failure index is used as a dependent variable in regression analyses.

3. Results

Because there are many variables that could influence the stability of the escarpment, it is important to study trends in the data and use prudent statistical procedures that take into account the interrelationships among independent variables. To study these relationships, a bivariate correlation matrix was constructed to measure the linear correlation among geologic, mining, and response variables. The correlation matrix includes correlation coefficient, number of data points, and two-tailed significance tests. The correlation coefficient (r) indicates the strength of linear relationships between any pair of variables.

Based on a review of the correlation matrix, the authors found fair correlation between the failure index variable and several independent variables, as well as among some independent variables. For example, the correlation coefficients between the failure index variable and the escarpment shape and influence angle variable are 0.58 and -0.48, respectively. However, escarpment shape and influence angle happen to have fair correlation as well (correlation coefficient equals -0.48). Thus, there is an interrelationship among the independent variables that can be taken into account using step-wise inclusion of these independent variables while conducting multiple regression analyses [7].

To identify important factors that contribute to escarpment stability, a multiple regression analysis was used. Escarpment stability was estimated using the failure index as the dependent variable. The multilinear regression procedure consisted of entering independent variables one at a time into the equation using a forward selection method (SPSS [14]). In this method, a variable is entered into the equation using the largest correlation with the dependant variable. If a variable fails to meet entry requirements, it is not included in the equation. If the first variable meets the criteria, the second variable with the highest partial correlation is then selected and tested for entering into the equation. This procedure is very good when there are hidden relationships among the variables. The multiple correlation coefficient, R, which is a measure of goodness-of-fit, for the last step is 0.68.

Based on an examination of standardized regression coefficients for the first 29 cells (which were fully undermined in 1997, Figure 1) it was shown that surface topography plays a critical role in influencing escarpment stability. With additional data collected over the next longwall block (40 more cells), important variables were identified including canyon slope, thickness of Castlegate Sandstone and mining influence angle.

The model was recently verified using monitoring results in area 3 (figure 4). Model predictions are in fair-good agreement with the actual experience after the extraction of both seams. Predicted unstable areas, shown in magenta, correspond mostly with oberved failure zones shown in red. Additional analysis is planned to improve on predictive capabilities of the model.

Measurement of debris travel distances are in agreement with initial projections using the Colorado Rock Fall Simulation Program (330-m). In remote mining areas of Utah, warning signs were posted at the study areas. At other locations in Colorado, trap systems (trenches and berms) are reported to be effective for control of large blocks/debris [15]. Some spalling blocks are in the range of 10 to 800 tons.

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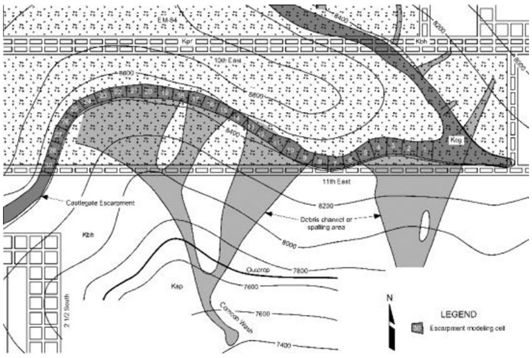

Fig. 1. Mining and escarpment geometry, Study area 1.

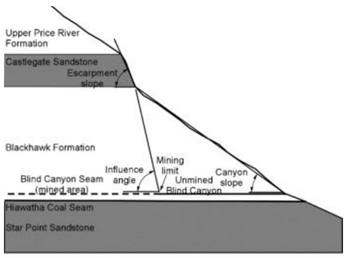

Fig. 2. Escarpment and mining geometry.

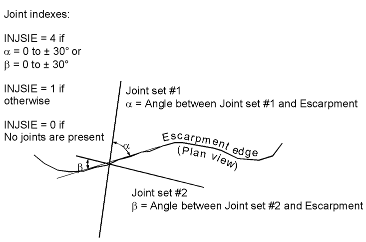

Fig. 3. Escarpment geometry and geological discontinuities.

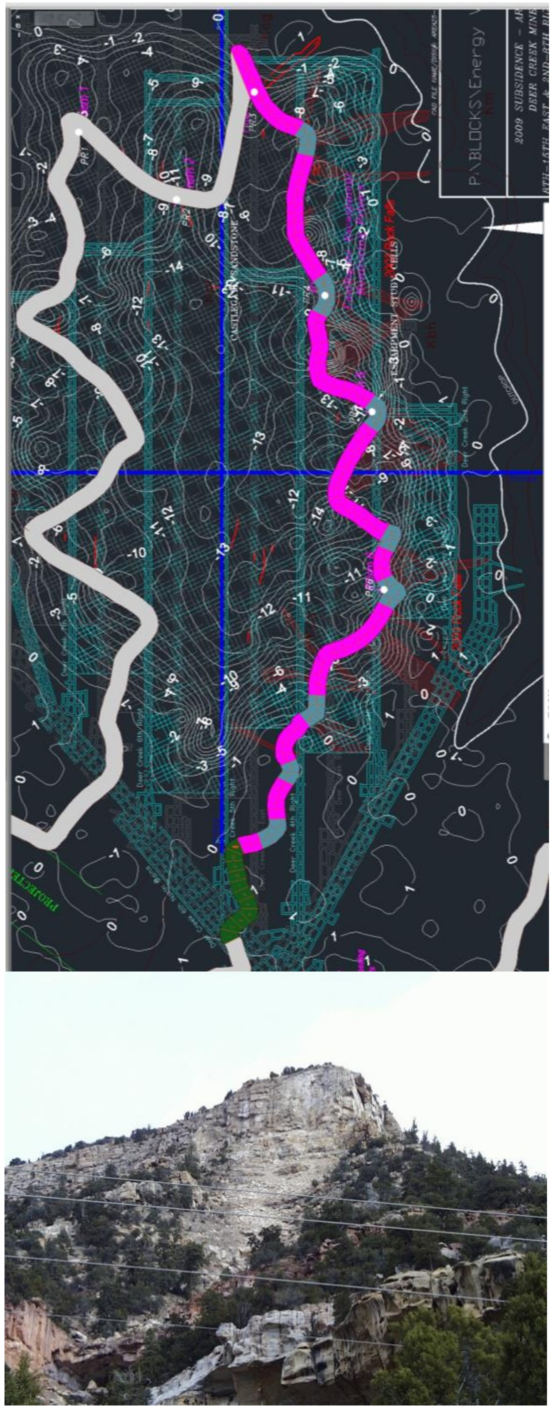

Fig. 4. Study area 3, subsidence contours, cell locations and escarpment failure zones shown in red (top), observed failure pattern (bottom).

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