Development of a Comprehensive Slope Failure Evaluation Database for Open Pit Mines

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Abstract

Predicting slope behaviour over time is a crucial geotechnical engineering task for open pit mines. Information gathered from monitoring practices is used to anticipate the potential failure of a slope mass, giving mine sites the ability to safely operate with minimal interruption. Correct monitoring procedures and an understanding of failure mechanisms assist with accurately predicting slope failures. This is key to improving the safety of miners, property, and production at a mine site. Current techniques used for prediction, such as statistical learning models, are unable to provide accurate results due to the uncertainties of slope attributes needed. In response, many mines and researchers are gathering and using small, unbalanced data sets that may require complex processing algorithms to try to extract useful information. To address this limitation, researchers at the Spokane Mining Research Division (SMRD) of the U.S. National Institute for Occupational Safety and Health (NIOSH) teamed up with industry partners to investigate the current state of public slope failure databases and outline a proposal for a new comprehensive slope failure evaluation database. The development of a comprehensive database that includes existing data and is continually updated with new entries from mine sites around the globe would help to better understand slope behaviour, determine slope instability alarm settings, and estimate time of failure. This work is a part of NIOSH's Open Pit Highwall Safety project.

1 Introduction

Comprehensive slope performance monitoring is implemented to reduce slope failure to acceptable levels of risk to miners, equipment, and successful mine operation (Williams 2020). The basic requirements of an open pit slope movement monitoring program revolve around the early detection of deformation and displacements, which can be detected through visual observations, ground-based quantitative measurements, and satellite-based surveillance (Eberhardt et al. 2020). Monitoring information is used to anticipate possible acceleration or failure of a moving slope mass (Rose and Hungr 2007), and mining operations can operate safely with minimal interruption if failure mechanisms are understood, and the slopes are properly monitored (Zavodni 2000). Assessing rock slope failure mechanisms requires an understanding of structural geology, groundwater, climate, rock mass strength and deformability, in situ stress conditions, and seismicity (Rose and Hungr 2007).

Recent developments in ground and satellite-based slope monitoring radar have greatly improved the ability to (1) detect and quantify slope movements that can provide early warning of potential slope failures and (2) detect rockfall events. However, early detection of slope instabilities and determination of alarm thresholds is challenging and is currently an evolving topic of research. Several near-miss slope failures have highlighted the need for further research in slope monitoring, slope behaviour prediction, and alarm threshold setting guidelines. In 2019, the NIOSH Mining Program learned of several recent near-miss slope failures that had occurred at surface mines in the western United States, highlighting a gap in slope monitoring practices. This prompted urgency in addressing highwall slope monitoring deficiencies to reduce the risk of injury or death resulting from a slope failure.

Discussions with several highwall engineering and monitoring professionals within the mining industry detailed concerns that guidance is needed on setting trigger alarms and that more research is needed to refine current guidelines. As a result, in October 2021, NIOSH SMRD started the Highwall Safety project, which will run for five years. One of the project's research objectives is to improve slope performance monitoring capabilities at open pit and quarry sites by expanding on slope monitoring radar alarm/notification setting guidelines, working with vendors on improvements to existing monitoring technologies, and improving/expanding the use of monitoring technologies in surface mines and quarries.

The performance monitoring outputs planned for the NIOSH Highwall Safety project will give guidance on setting radar monitoring trigger alarm thresholds, as well as guidance and training on best practices for open pit performance monitoring with ground-based radar interferometry (GBRI), satellite-based interferometric synthetic aperture radar (InSAR), and combined systems. One of the larger tasks associated with these planned outputs involves developing a comprehensive database that includes existing data and is continually updated with new entries from mine sites around the globe to better understand slope behaviour, determine slope instability alarm settings, and estimate time of failure. Therefore, as a starting point for the project, this paper investigates the current state of public slope failure databases and outlines the proposal for a new comprehensive slope failure evaluation database for the benefit of the mining community.

2 Literature search

2.1 Past literature associated with slope failure databases

The goal in developing a slope failure database is to gain insight into predicting slope behaviour and time of failure based on several slope attributes, including geologic controls, hydrogeologic conditions, slope geometry, failure mechanism, and displacement rate. BGC Engineering has developed initial empirical tools to help forecast slope failures based on slope failure mode, rock mass quality, and total highwall strain (Brox et al. 2003). Highwall strain is defined as its deformation divided by the total height and is reported as a percent value. Brox et al. (2003) notes that a highwall may begin to form tension cracks around 0.1% strain, reach a stage of progressive movement between 0.6% and 1% strain, and reach a phase of imminent failure at over 1% strain. This collection of case histories is helpful in providing initial information on wedge and planar failure according to rock mass quality and rock mass rating (RMR). The development and utilization of this tool needs to be further investigated with representatives of BGC Engineering.

In Zhou et al. (2019), 221 historical cases of slope conditions between the years 1994 and 2011 were recorded. One hundred six cases were recorded as failures within this database, and the other 115 were recorded as stable. These recorded cases were analysed using the gradient boosting machine (GBM), a supervised machine learning technique, to forecast slope behaviour (i.e., failure vs. stable). The parameters collected in this study for each slope condition include slope height (H), cohesion (C), slope angle (β), unit weight (γ), pore water pressure ratio (r_u), and angle of internal friction (φ). Overall, the GBM model concluded that the slope design parameters significantly influenced slope stability. The study by Zhou et al. was limited in that only the potential for circular failure was analysed with no regard to other types of failure, including plane, toppling, wedge, and buckling. However, this study is beneficial in that it brings forward two main points: (1) the characteristics of 106 past slope failures have been collected through an extensive literature search, which provides a reference point to potentially build upon moving forward, and (2) researchers are already utilizing machine learning techniques to predict slope behaviour based on parameters related to geometry and geotechnical properties.

Additional documentation and web products outside of the mining industry are noted in this study for reference, including studies and monitoring of landslides in the United States (Montgomery et al. 2019, USGS 2022) as well as a Global Landslide Catalog provided by NASA's Open Data Portal (NASA 2022). These existing programs can be instrumental in developing a framework for a comprehensive slope failure evaluation database.

2.2 Bottlenecks of existing slope failure databases

The databases outlined in Section 2.1 provided useful conclusions within their specific applications, particularly in finding trends that designate highwall strain thresholds and utilizing machine learning to characterize the influence of slope design parameters on slope stability. However, steps should be taken to further utilize this information related to slope failure for the benefit of the mining industry as a whole. Unfortunately, the differences in format and inputs for each slope failure between the existing databases can make it difficult to combine effectively. This led NIOSH and mining industry partners to the notion of developing a comprehensive open-pit-mining-focused slope failure database that stores all existing data from the literature search for reference but requires a universal format to be implemented for all entries moving forward.

It's imperative to note that the experience of mine personnel who collected or will collect this information has a significant influence on consistency and validity. The mine personnel may have different levels of training and experience related to specific disciplines such as structural geology, groundwater, climate, rock mass strength and deformability, in situ stress conditions, and seismicity. This variation could lead to inconsistency in the collected data, not only for a particular mine site but also across different mine sites with similar characteristics, making it difficult to confidently reference a database for planning and monitoring purposes. This highlights the importance of continuous training to mine personnel through existing programs at mining universities to help data collectors find common ground and create a network of communication.

3 Proposed comprehensive slope failure evaluation database

3.1 Information the database needs to benefit the mining industry

Specific data and information of each slope failure at a mine site will need to be reported to create a database that acts as a valuable reference to mine personnel worldwide. The Montgomery et al. database referenced in Section 2.1 presents a useful framework of factors that need to be considered in the development of a comprehensive slope failure evaluation database. This framework can be expanded to include pertinent information related to open pit mines, resulting in the model shown in Figure 1, where the input data for each entry would be broken into three categories: slope properties, failure information, and monitoring information.

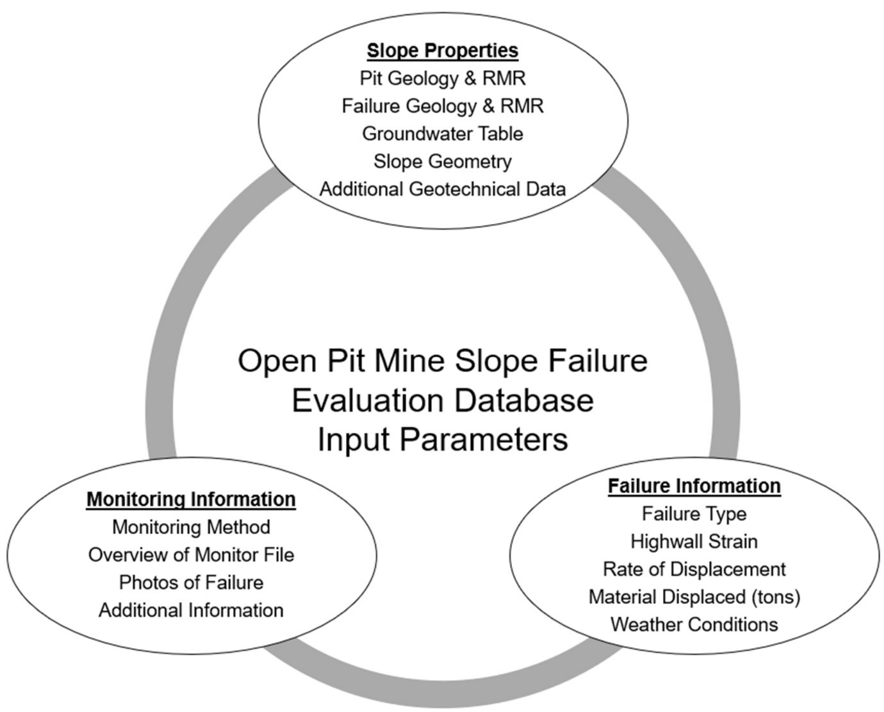

Figure 1. A proposed data model for comprehensive slope failure evaluation database

3.2 Potential benefits associated with the proposed database

3.2.1 Progressing the development of trigger action response plans

There are numerous case studies within the mining industry where previous knowledge of failures at a mine site helped mitigate and prevent failures moving forward. For example, the 2013 slope failure at Bingham Canyon represents a successful application of slope monitoring technology, in that world-class expertise in monitoring and predicting highwall failures did prevent what could have been multiple fatalities and infrastructure damage (Ross 2017). However, recent instances where mine site geotechnical engineers failed to adequately understand a slope instability and predict the time of failure resulted in several near-miss slope failures in the United States that could have been "mine disasters" in fatality count.

Near real-time monitoring can provide advanced warning by means of automated alarms that typically trigger when a predetermined alarm threshold is exceeded (Graaf et al. 2020). The effectiveness of monitoring systems, and monitoring programs in general, hinge on the appropriateness of mine-specific alarm thresholds that are selected by mine personnel (Audige et al. 2020). While slope displacement and velocity thresholds are the most commonly used parameters, there are no hard-and-fast rules in setting alarm thresholds; sound engineering judgement based on relevant experience is required (Graaf et al. 2020, Armstrong et al. 2020). The selection of alarm threshold settings is important, and the selection of inappropriate alarm thresholds can lead to a false sense of security and potentially dangerous conditions. A discussion of current guidelines for setting alarm thresholds and predicting time of failure is provided in Sharon and Eberhardt (2020). If a public slope failure database was available to geotechnical engineers worldwide, mine sites with similar geometry and geotechnical properties learn from one another, helping lead to the development of more refined trigger action response plans (TARP) with appropriate alarm thresholds.

3.2.2 Machine learning (ML) applications

Many non-ML techniques for slope stability assessment have been developed, including limit equilibrium methods (LEM) or random finite element methods (RFEM) (Griffiths and Fenton 2004). There are some notable drawbacks to these methods, such as the difficulty of determining the mechanical parameters for a failure, which make them challenging to model. Another important disadvantage of traditional slope stability assessment techniques is the time and cost constraints for implementing such models. This disadvantage is something machine learning is uniquely capable of overcoming. Recently, machine learning methods have been successfully applied to a wide range of predictive modelling and classification tasks in the geospatial sciences, which we believe is at least partially attributed to their ability to model complex patterns and relationships from a variety of input data without assumptions.

For example, Lu and Rosenbaum (2003) used artificial neural networks (ANN) to evaluate slope stability based on geotechnical properties and historical behaviours of the collected slope cases. They developed the ANN using a data set of 97 slope cases. Hoang and Pham (2016) introduced metaheuristic-optimized least squares support vector classification for slope assessment with 168 cases. In practice, there are several empirical or semi-empirical approaches that are implemented with local monitoring data and therefore prone to overfitting because they are based on a small amount of collected data (Basahel and Mitri, 2017). Artificial intelligence studies provide new alternatives to empirical methods and some other conventional statistical techniques. However, these methods usually require a large amount of data, and they are mostly computationally expensive. Recent developments of deep learning methods and convolutional neural networks show continued and accelerated adaption in the geological sciences, changing our ability to map and model slope failure features.

Table 1 shows just some of the work being done in next generation slope analysis and prediction. As our understanding of slope failures grows and new advances in artificial intelligence are developed, we can clearly see that the need for data, both for training and testing, grows as well.

Table 1. Past machine learning approaches used for slope analysis and prediction

Work Referenced	Parameters Used	Machine Learning Approach	Number of failure events in data set
Zhao, (2008)	γ, Φ, c	Support Vector Machine (SVM)	10
Das et al., (2011)	r_u, H, α, γ, Φ, c	Artificial Neural Networks (ANN)	46
Verma et al., (2016)	c, α, Φ	Artificial Neural Networks (ANN)	100
Feng et al., (2018)	r_u, H, α, γ, Φ, c	Naive Bayes Classifier (NBC)	82
Zhou et al., (2019)	r_u, H, α, γ, Φ, c	Gradient Boosting Machines (GBM)	221

r_u: Pore pressure ratio, c: Cohesion, Φ: Friction angle, γ: Unit weight, H: Height, α: Slope angle

4 Potential challenges

4.1 Data storage

Storing and maintaining large sets of data over time at a high growth rate can be challenging. Factors such as capacity, throughput, scalability, and cost are involved in any ideal storage solution. The ability of the storage device to scale its access time, data transfer rate, and cost-effectiveness can be critical in the continued use of a large data environment like the one proposed here.

4.1.1 Proposed Solution

For the initial database creation, we recommend against starting with full radar data file, which may be unreasonably large to store in a small database, some InSAR files average 5 gigabytes (GB) per frame. In the future, some monitoring files may grow even larger, with NASA's prototype NASA-ISRO SAR (NISAR) data averaging 25 GB per frame. Instead, we propose starting with a screenshot of the failure from the mine’s monitoring software with the end goal of storing the full radar data in a secure and trusted source. One such source that we recommend in this outline is the Geotechnical Center of Excellence (GCE), part of the Lowell Institute for Mineral Resources in Arizona.

4.2 Data labelling

Many labelled slopes are needed for training neural networks, which requires a significant amount of site-specific information and labelling of the radar/InSAR profiles. This makes it difficult for any single group of researchers or individual companies to achieve large, high-quality training sets, especially and especially so for new training sets.

4.2.1 Proposed Solution

The workload can be lowered by either providing a tool that enables faster labelling or by sharing training data with other researchers. We aim to achieve both by embedding an online labelling tool to our proposed failure database. This proposed tool will provide an intuitive user interface for labelling images, verifying annotations, and managing radar/InSAR data sets. The labels will be saved internally in a standard format to ensure compatibility. However, they will be exported in user-defined formats so that no changes in the existing training processes of the contributors will be needed. We hope to partner with local university programs to have graduate students label each data file as either noise or failure (small scale, large scale, wedge, associated strain, etc.), with NIOSH researchers periodically ensuring accuracy while providing guidance on slope failure identification to improve the quality of labels going forward.

4.3 Visibility and hesitancy in reporting failure to a shared database

A significant question associated with this type of work involves understanding who has access to the slope failure information and whether this type of information could be used against the company that submits to the database. This can lead to hesitancy from mining companies to get involved with such a project.

4.3.1 Proposed Solution

Researchers at NIOSH want to help create a product that users feel comfortable with. With that comes the need for collaboration and transparency. Ideally, the database would be available to the public through the Open Pit Highwall Safety NIOSH webpage (NIOSH 2022); however, there may be information that mine sites do not want to disclose. Therefore, the development of the database could include the creation of an integrated user and permission management system that will allow contributing mines to decide which of their input data to be set as public or private. Additionally, it has been suggested that there be a lag time between when the event occurred and when the failure data is publicly shared on the database.

5 Conclusions

The proposals in this paper represent a first step in identifying the needed information, benefits, and current challenges associated with the development of a collaborative slope failure database. Moving forward, NIOSH engineers on the Highwall Safety project would like to compile a list of mining companies and representatives who would be interested in submitting slope failure information, as detailed in this paper, to help initiate the development of the database. Additionally, increased collaboration is needed to further discuss the ideas presented here to develop a beneficial product for all users. Overall, the goals and activities associated with this study and the NIOSH Highwall Safety project are designed for the betterment and improved safety of open pit mining projects worldwide.

6 Disclaimers

The findings and conclusions in this report are those of the author(s) and do not necessarily represent the official position of the National Institute for Occupational Safety and Health, Centers for Disease Control and Prevention. Mention of any company or product does not constitute endorsement by NIOSH, CDC.

7 References

Armstrong, J., Audige, E., Coli, N., Eberhardt, E., Fagen, C., Farina, P., Jung, J., Katsaga, T., Leoni, L., Ness, M., Nuewirt, A., Preston, C., Ruest, M., Schwarz, E., Sharon, R., Stacey, P. (2020). Data analysis and utilization, Ch. 7, In Sharon R, Eberhardt E (eds.), *Guidelines for slope performance monitoring*. Clayton, Australia: CSIRO, pp. 187–217.

Audige, C., Bals, A., Beale, G., Coetsee, S., Coli, N., Colombo, D., Creighton, A., DeBeer, J., de Graaf, P., Dight, P., Eberhardt, E., Fagen, C., Falorni, G., Hamman, E., Haugen, B., Hawley, M., Hunter, G., Leighton, J., Leoni, L., Mphathiwa, N., Nel, L., Noon, D., Pere, V., Pienaar, A., Preston, C., Randall, O., Rose, N., Rutledge, D., Saunders, P., Swartz, E., Sharon, R., Stacey, P., Wessels, F. (2020). Monitoring requirements, limitations and applications, In Sharon R, Eberhardt E (eds.), *Guidelines for slope performance monitoring*. Clayton, Australia: CSIRO.

Basahel, H., Mitri, H.S. (2016) Validation of empirical rock mass classification systems for rock slopes. Presented at the 3rd Intern. Symp. On Mine Safety, Science and Engineering (ISMS), Marina Bay Sands, Singapore, Aug. 2016, pp. 127–132.

Brox, D., Newcomen, W., MacDonald, H. (2003). Utilizing Strain Criteria to Predict Highwall Stability Performance. ISRM 2003-Technology roadmap for rock mechanics. South African Institute of Mining and Metallurgy.

Das, S.K., Biswal, R.K., Sivakugan, N., Das, B. (2011). Classifcation of slopes and prediction of factor of safety using diferential evolution neural networks. *Environ Earth Sci* 64(1):201–210. https://doi.org/10.1007/S12665-010-0839-1

Eberhardt, E., Ness, M., Noon, D., Schwarz, E., Stacey, P. (2020). Overview of slope monitoring, In Sharon R, Eberhardt E (eds.), *Guidelines for slope performance monitoring*. Clayton, Australia: CSIRO.

Feng, X., Li, S., Yuan, C., Zeng, P., Sun, Y. (2018). Prediction of slope stability using Naive Bayes Classifer. *KSCE J Civ Eng* 22:941–950. https://doi.org/10.1007/s12205-018-1337-3

de Graaf, P., Jenks, P., Mattern, J., Ness, M., Pienaar, A., Rose, N., Schwarz, E., Sharon, R., Turner, R., Wessels, F. (2020). Data utilisation and communications, Ch. 8, In Sharon R, Eberhardt E (eds.), *Guidelines for slope performance monitoring.* Clayton, Australia: CSIRO.

Griffiths, D.V., & Fenton, G.A. (2004). Probabilistic slope stability analysis by finite elements. *Journal of Geotechnical and Geoenvironmental Engineering* 130: 507–518.

Hoang, N., & Pham, A. (2016). Hybrid artificial intelligence approach based on metaheuristic and machine learning for slope stability assessment: A multinational data analysis. *Expert Syst Appl* 46: 60–68.

Lu, P., & Rosenbaum, M.S. (2003). Artificial Neural Networks and Grey Systems for the Prediction of Slope Stability. *Natural Hazards* 30: 383–398.

Montgomery, J., Knights, M., Xuan, M., Carcamo, P. (2019). Evaluation of Landslides Along Alabama Highways. Highway Research Center, Auburn University Samuel Ginn College of Engineering.

NASA (2022). Global Landslide Catalog (GLC). National Aeronautics and Space Administration. https://data.nasa.gov/Earth-Science/Global-Landslide-Catalog/h9d8-neg4.

NASA (2017). Getting Ready for NISAR - and for Managing Big Data using the Commercial Cloud https://earthdata.nasa.gov/learn/articles/tools-and-technology-articles/getting-ready-for-nisar

NIOSH (2022). Mining Project: Open Pit Highwall Safety. Centers for Disease Control and Prevention. https://www.cdc.gov/niosh/mining/researchprogram/projects/project_openpitsafety.html.

Rose, N., Hungr, O. (2007). Forecasting potential rock slope failure in open pit mines using the inverse-velocity method. *Int J Rock Mech Min Sci* 44(2): 308–320.

Ross, B. (2017). Rise to the occasion: lessons learned from the Bingham Canyon Manefay Slide. Littleton, CO: Society for Mining, Metallurgy, and Exploration.

Sharon, R., Eberhardt, E., eds. (2020). *Guidelines for slope performance monitoring*. Clayton, Australia: CSIRO.

USGS Landslide Hazard Program (2022). U.S. Landslide Inventory Web Application. United States Geological Survey. https://usgs.maps.arcgis.com/apps/webappviewer/index.html?id=ae120962f459434b8c904b456c82669d.

Verma, A., Singh, T., Chauhan, N.K., Sarkar, K. (2016). A hybrid FEM–ANN approach for slope instability prediction. *J Instit Engs India Ser A* 97(3): 171–180. https://doi.org/10.1007/s40030-016-0168-9

Williams, C. (2020). Radar course introduction. Geotechnical Radar Monitoring 2020 Virtual Course. Geotechnical Center of Excellence, The University of Arizona.

Zavodni, Z. (2000). Time-dependent movements in open-pit-slopes, In Hustrulid W et al. (eds.) *Slope stability in surface mining*. Littleton, Colorado: Society for mining, metallurgy and exploration.

Zhao, H.B. (2008). Slope reliability analysis using a support vector machine. *Comput Geotech* 35(3): 459–467. https://doi.org/10.1016/j.compgeo.2007.08.002

Zhou, J., Li, E., Yang, S., Wang, M., Shi, X., Yao, S., Mitri, H.S. (2019). Slope stability prediction for circular mode failure using gradient boosting machine approach based on an updated database of case histories. *Safety Science* 118: 505–518, https://doi.org/10.1016/j.ssci.2019.05.046.

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