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Developing a Model for the Identification of Onset of Failure of Slopes in Surface Mines

Mohd Maneeb Masood[1*], Tarun Verma[1] and Gunda Yuga Raju[2]

[1]Department of Mining Engineering, Indian Institute of Technology (BHU), Varanasi, Uttar Pradesh 221005, India. E-mail: mohdmmasood.rs.min17@itbhu.ac.in*

[2]Department of Mining Engineering, Indian Institute of Technology (BHU), Varanasi, Uttar Pradesh 221005, India.

Abstract

Slope failures in mines pose a serious concern, resulting in fatalities and significant damage to infrastructure and equipment. Despite their complexities, the majority of these slope behaviours are predictable. Mining firms worldwide have long worked on preventing mine slope failures because of the potential for human and material casualties. As a result, various investigations and studies have been done to understand these phenomena and their progression better. In this research, an automated technique is developed to track displacement data and identify the onset of slope failure, which is also the onset of acceleration. A five-step process is employed for a specific dataset. When the analysis produces a positive result for a particular set of slope monitoring data, the slope is accelerating. It helps us to determine the beginning of the slope's acceleration. The generated output may be used as an early warning system that forecasts slope failures to avert potentially catastrophic slope occurrences, boosting overall mining performance and safety standards.

Keywords: *Mine slope, slope monitoring; slope stability radar; onset-of-failure; early warning; prediction.*

1.0 Introduction

Mine slope collapses are intricate and varied. Risk assessment and management are vital to reducing damage to machinery and infrastructure and preventing human fatalities. Remote sensing technologies like the Slope Stability Radar (SSR) and traditional methods may detect pre-failure indicators in unstable locations. The severity of the slope collapse, the timing of the collapse, and the velocity at which it happened are all factors that influence the impact of the slope failure.

Geological risk management has many methods for determining failure time[1], which is a major challenge. Over the years, many researchers have investigated and applied various theories and methods; one of the most popular is the creep theory, which is often used better to explain slope behaviour[2-5]. In particular, Fukuzono's presented the Inverse Velocity Method (IVM) to make failure predictions in the literature[6]. The findings were generally positive[7,8].

This issue of predicting onset of slope failures in mines persists despite decades of research and a number of in-depth investigations. Accurate forecasting requires a deep knowledge of the dataset used to monitor the change in a slope over time. Pinpointing the beginning of the acceleration is critical for effectively using slope behaviour and failure prediction[9]. The determination of the onset of failure is actually the onset of acceleration (OOA). The prediction of onset of failure and the slope behaviour has been usually determined manually[7,10].

There has been extensive usage of these manual approaches, but the lack of automation has hindered real-time evaluation and the development of a system that can predict slope behaviour and failure. In this way, the manual methods provide some results, but they aren't the best choice if you need an immediate alert or response. In order to verify the

*Author for correspondence

behaviour of the raw data, various studies for landslides and structural collapses have also employed a cross over of short-term and long-term moving averages[11]. Notwithstanding these studies of landslides and other natural and man-made structures, there is still no agreed-upon method for determining the beginning of the tertiary creep phase, which is the onset of failure in the majority of the cases of slope failures.

The tertiary creep concept may help slope instability prediction. Forecast accuracy is heavily influenced by the assumption that the data should only include accelerating displacements. Hence, high sample rates and automated collection techniques are required to keep a check on this. Since the sample rate is often too low to accurately capture the acceleration phase, which might last for a number of hours at a time[12], manual data collection is unsuitable when it comes to early warning purposes. Determining the acceleration phase could be simple when done manually by an experienced operator. Still, the issue gets more complicated with near-real-time or real-time acceleration when the software must automatically verify the progress of an accelerating phase and the onset of acceleration. Concerns have also been raised about the rise in automated instrumentation allowing for the simultaneous monitoring of several slopes. Highly complicated models cannot be integrated into the second case because of the astronomical price and processing requirements.

2.0 Methodology

We propose a model for predicting the onset of slope failure by identifying an increasing step in velocity (displacement rate) data. The model is highly advantageous when automated. Stopping the model if one condition is not satisfied speeds up time analysis. This choice has little impact in a single dataset study, but it becomes crucial in several high-sampling rate systems. Multi-step approaches may include conditional tolerance levels and it is possible here in this model. Any hypothetical slope displacement instrument may utilise this technique. The model has five steps, and the onset of acceleration or the onset of failure time is determined once the final step returns positive.

Step 1: Displacement values ($d \geq 0$)

All displacement values should be larger than or equal to zero, since this will guarantee that the data being captured by the monitoring equipment is accurate.

Step 2: Rate of displacement ($v > 0$)

This step checks the rate of displacement.The following tasks can only be completed if four consecutive positive velocities are obtained. To begin this step, we will need a dataset with four values of velocities (i.e., five positive values of d).

Step 3: Velocity increase ($v_i > v_{i-1}$)

Following this, we use data to compare the intervals in measurements to evaluate whether the velocity is increasing. If three of the four velocity values in the dataset satisfy the requirement, it is considered to be met. The main goal of this tolerance level is to prevent errors brought on by outliers in the data used for monitoring. Even if the duration of the negative output at this step may be negligible in comparison with the overall trend of the slope movement, a model trained under the assumption that 100% of the validation conditions of the dataset would provide a positive result may terminate at this step.

Step 4: Analysis of the displacement rate trend

Accelerated velocities should behave non-linearly. Fitting a curve to displacement vs. time data confirms our hypothesis about slope deformation rate behaviour. A power law was used for velocity data to accurately define the creep stages of potentially unstable slopes. Despite being evaluated and calibrated for many data sets using a variety of random dataset windows, the power law function findings did not strongly relate to the raw data. The technique interpolated a general trend, but the power law function only worked for later slope fluctuations. A parabolic function is used to identify upward or downward trends by analysing the velocity vs. time curve's concavity.

The main objective of step 4 is to assess the concavity of the interpolating curve by evaluating the coefficient 'a'in the general equation of the parabola ($y=ax^2+bx+c$). The concavity direction, denoted by the parameter 'a', is calculated by interpolating the velocity data with a parabolic fit. The concavity is shown facing upwards during an acceleration ($a>0$) and facing downwards during a slow-down ($a<0$). The model relies on keeping a check on whether or not a positive 'a' value is present to identify acceleration. Step 4 is completed, and further analysis may proceed if $a>0$ is valid for at least 75% of the data.

Step 5: Concavity check

At this step, the change in the coefficient'a' between two measurements is evaluated for the considerable concavity orientation in the monitoring data curve (i.e., the acceleration decreases or increases if there is a downward or upward orientation). No change in 'a' means the curve is becoming more linear, reducing slope movements. If three of four data points are accurate, Step 5 begins. If this condition holds, an accelerating phase may be begun, and the 'i' value of time indicates the slope's acceleration. The validation of the model is performed by carrying out a parametric analysis on different datasets taken from the field.

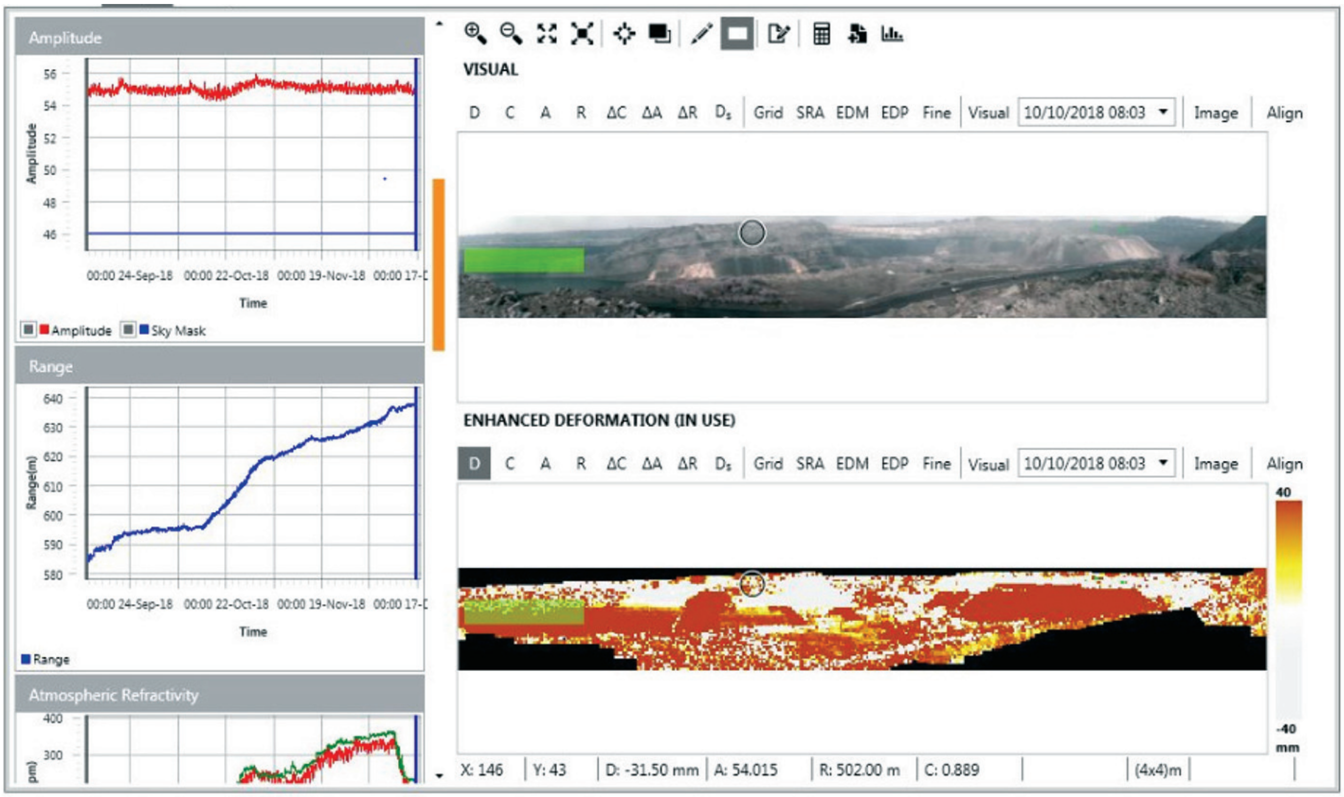

Figure 1: SSR Viewer screen showing the image of the wall/slope, the scanned area, the selection, and the heat map, SECL India

3.0 Case Studies and Validation of the Proposed Approach

Our multi-step model for identifying the onset of failure uses data from South Eastern Coalfields Limited, Bilaspur (SECL) mines. The slope stability radar monitored slopes in all three mines (SSR). It contained displacement, velocity, and inverse velocity data together with the amplitude, range, and coherence related to the time values. Fig.1 displays SSR data collection in the SSR viewer. SSR connects these computers, creating a full monitoring system. MATLAB is used to analyse SSR viewer's data and create the multi-step model.

Using the multi-step approach outlined above, potentially dangerous acceleration patterns may be extracted from displacement data for real-time monitoring. The method simulates a real-time capture even though all the monitoring data shown here comes from the past.

Case Study 1

The case study is from an undisclosed SECL mine. Fig.2 shows the pictorial view of the slope face being monitored.

SSR displacement data showed constant acceleration, suggesting the creep had entered the third phase of development. The onset of failure of a slope may be calculated from the date of the first acceleration leading to slope collapse. In spite of many preliminary activations, the model was able to identify the beginning of acceleration or failure correctly. In addition, the tolerance levels used in the model were functioning correctly.

A slope failure happened on August 16, 2017, at a SECL mine. The collapse may have been induced by nearby excavation activity or by the heavy rain that has been falling. This was the face where the SSR was moved days before it failed to detect movement on the ostensibly unstable slope.

Figure 2: Image of the face/wall/slope being monitored, SECL India

Case Study 2

SSR monitoring of one location in a SECL mine revealed consistent activity. After noise removal, displacement data revealed a constant rise. The displacement and other relevant data were recorded to see whether the site would exhibit slope failure. MATLAB was used to analyse the data once it was exported to an Excel file. The data met the requirements in the early stages of the model, but subsequent phases failed.

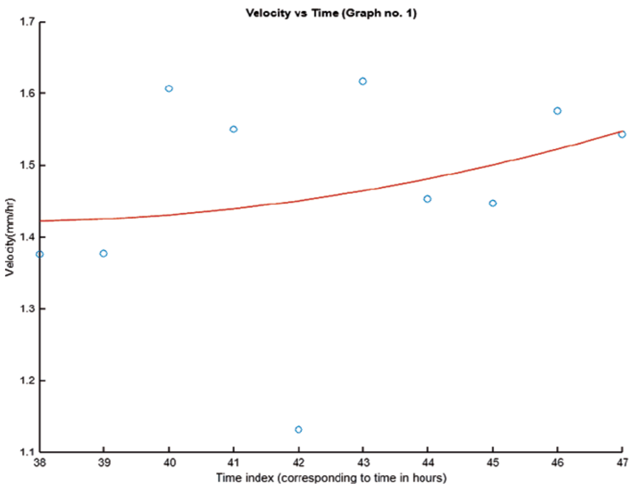

Figure 3: Trend analysis using MATLAB, Case Study 1.

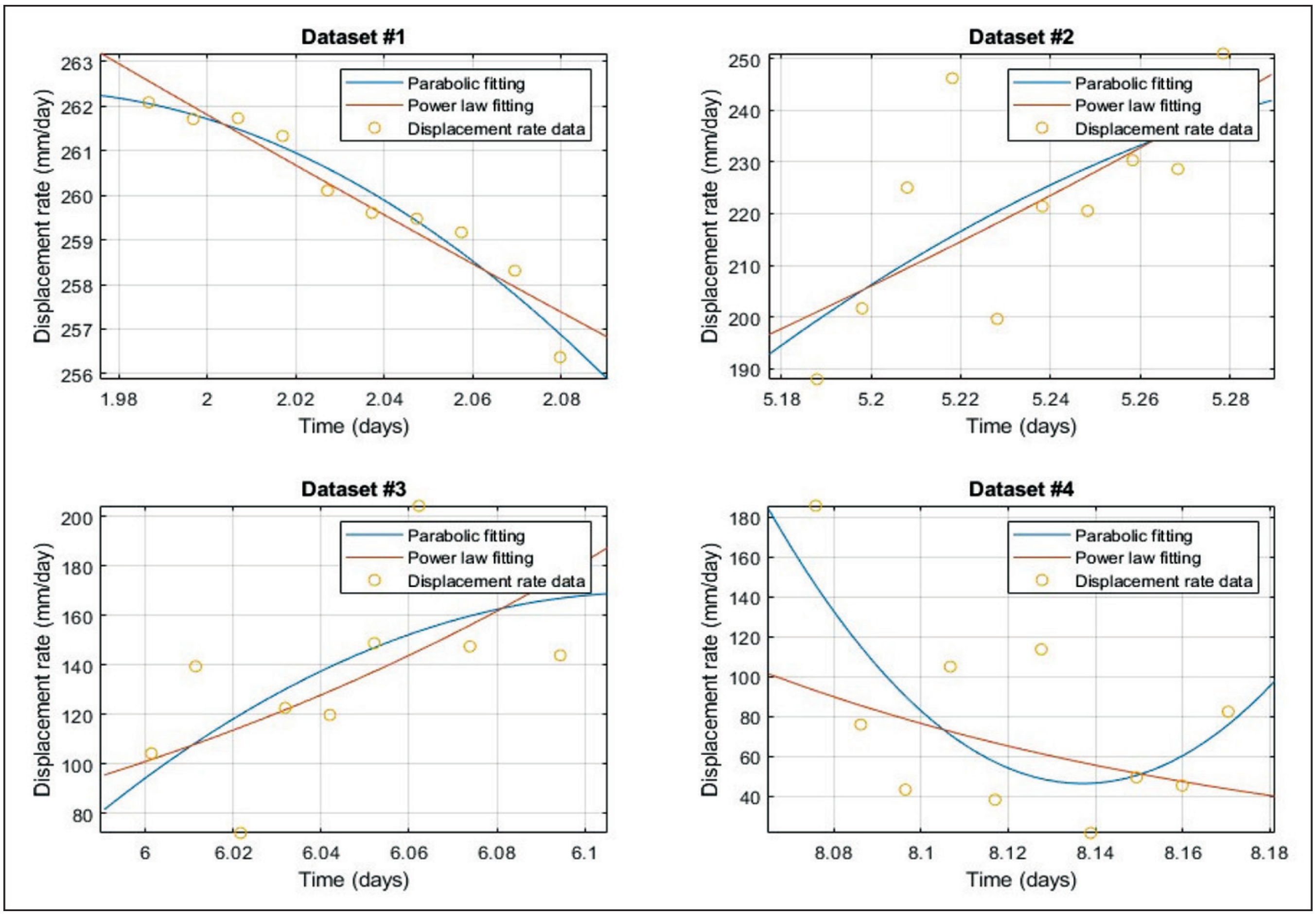

Fig. 4. Trend analysis using MATLAB, Case Study 2

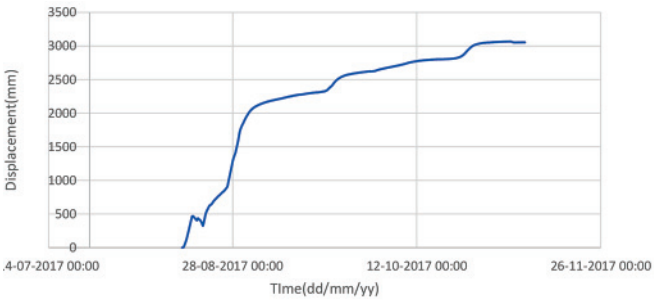

Fig 5. Displacement vs. Time plot for a SECL mine slope, Case Study 2

There have been no indications of collapse on the slope, and it seems to be maintaining its stability at present. Also, we utilised Microsoft Excel to determine the acceleration phases and the concavity of the velocity curve, both of which served as checks on our model. Excel and MATLAB produced similar findings.

It is possible that improved data analysis might be achieved in all cases/datasets by filtering and smoothing the raw monitoring data. Also, better outcomes might be achieved by including additional data analysis methods in the proposed strategy. However, it should be emphasised that false alarms may in many cases be simple to identify when future datasets do not satisfy one of the model step requirements, even with the tolerance levels.

4.0 Conclusion

Improved efficiency, dependability, and precision in slope monitoring equipment have emerged in recent years. An early warning system might benefit significantly from automated data gathering, signal processing, and dissemination. There may be benefits to risk management and prevention from a strategy that emphasises the detection of important events, such as an increase in velocities. While there has been a lot of research on failure-predicting models, there haven't been many that look for acceleration or failure from the start. Predictions end up being off because a critical event in slope failure is being overlooked.

Our ultimate goal is to provide a multi-step system that can spot rising trends in displacement monitoring data on its own. Distinct behaviours of slopes are also uncovered in this manner. Thus, this work addresses a critical research need in mining engineering by enabling more accurate forecasts of slope collapse and allowing for a deeper understanding of slope behaviour.

In addition, the model's key parameters were calibrated using a series of parametric assessments. The study presents example studies that successfully replicate a real-time collection during a collapse, proving the validity of the methods presented. Based on analyses of displacement data, it was determined that the mine slope went through two distinct stages of development. The model also allows for a direct comparison of the predicted date of acceleration's beginning to the observed acceleration profiles.

Data collected from several locations and time periods is being used to analyse our multi-step technique. We're working to build a system that uses the developed model to track and record the movement of slopes over time. Additionally, we want to utilise this model to establish a state-of-the-art, user-friendly early warning system for mines that can accurately anticipate slope failures and alert mining staff to imminent collapses.

5.0 Acknowledgements

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