4. RESULTS AND DISCUSSIONS

The data analysis and model generation were done based on the datasets of South Eastern Coalfields Limited (SECL) mines and datasets from past slope failures from the literature. We have collected the data from three mines of SECL and used that data to make our multi-stage model for detecting the onset of acceleration. The data was collected for various slopes in all three mines monitored using the slope stability radar (SSR). It had displacement (enhanced deformation), velocity, and inverse velocity data along with the amplitude, range, and coherence corresponding to the time values. Figure 4.1 below shows the data from the SECL mines. The required data field can be sleceted an exported from SSR Viewer to MS Excel fromat.

Time	Enhanced Deformation(mm)	Inverse Velocity over 60
11-09-2018 14:22	0	
11-09-2018 14:40	1.388351	
11-09-2018 14:57	2.685396	
11-09-2018 15:15	0.9560434	
11-09-2018 15:33	1.282639	0.7796427
11-09-2018 15:51	5.389126	0.2499516
11-09-2018 16:09	8.175602	0.1821425
11-09-2018 16:30	16.13102	0.06589798
11-09-2018 16:48	17.8981	0.06018491
11-09-2018 17:06	17.57043	0.08209304
11-09-2018 17:24	19.52962	0.08807451
11-09-2018 17:42	22.00181	0.1703347
11-09-2018 17:59	20.44722	0.3922925
11-09-2018 18:17	22.45139	0.2048778
11-09-2018 18:35	24.15309	0.2162878
11-09-2018 18:53	23.14034	0.8783235
11-09-2018 19:11	23.70341	0.3071074
11-09-2018 19:29	29.54339	0.1410039
11-09-2018 19:47	31.73848	0.1318324
11-09-2018 20:05	34.56402	0.08753751
11-09-2018 20:23	41.81046	0.05522711

Figure 4. 1: Image of Microsoft Excel Worksheet (.xlsx) file of the data generated by SSR via SSR Viewer of enhanced deformation

The above data is extracted using SSR Viewer graphs. These computers are directly connected to SSR, forming a complete system. The data is exported into excel files by clicking on the graphs, and is the analysed using MATLAB to make this multi-stage model.

4.1 Results of Data Analysis using the Slope Failure Prediction Model for Surface Mines (SFPMSM) Algorithm in MATLAB

Data set to perform this activity may vary. It depends on parameter like sampling frequency, smoothing procedures and filters applied on monitoring data. For better result fitting operation should be performed on a dataset who composed of 10 displacement rate values and analysed on 4 parabolic fitting curves. The first case we ran on the MATLAB using the algorithm was data from Kusmunda Mines. The figure 4.2 shows a part of the dataset. The enhanced deformation values are in mm. For the ease of understanding the enhanced deformation values have also been shown up to two decimal places.

Time	Enhanced Deformation	Enhanced Deformation(upto 2 decimal places)
15-08-2017 14:39	0	0.00
15-08-2017 14:54	-0.01367062	-0.01
15-08-2017 15:08	0.1345652	0.13
15-08-2017 15:22	0.1163002	0.12
15-08-2017 15:36	-0.01766672	-0.02
15-08-2017 15:49	0.4587941	0.46
15-08-2017 16:03	0.683315	0.68
15-08-2017 16:20	0.8484875	0.85
15-08-2017 16:33	0.5231999	0.52
15-08-2017 16:48	0.4118783	0.41
15-08-2017 17:01	0.1849784	0.18

Figure 4. 2 : Kusmunda Dataset (Enhanced Deformation vs Time)

This data was run on MATLAB to find the time of failure of the slope. The steps followed for working on this dataset:

Step 1: Upload the data set of time and cumulative enhanced deformation.

Step 2: Add another column in Excel and named it as change in deformation.

Step 3: Calculate difference in deformation with respect to previous row (taking both value from enhanced deformation column).

Step 4: If change in deformation is negative then remove that row using filters in Excel.

Step 5: Using filtered dataset, find the rate of displacement (velocity) with respect to corresponding time interval.

Step 6: Curve fit the velocity vs time graph in the parabolic or power function.

Step 7: Check for the R^2 value of curve fitting.

Step 8: If R^2 value is <0.8(say) then, it resembles poor curve fitting.

Step 9: Improve the data quality for best curve fitting.

Step 10: After finding the onset of failure time, use IVM.

The output of the codes in shown below in the form of four velocity vs time plots in the figure 4.3(a-d). The graphs below show the variation of deformation rate (velocity) vs time. The time to draw these plots has been indexed in excel, from where the data is input into the MATLAB software. As discussed in the earlier chapter, the graphs show a parabolic trend, allowing us to go further with our methodology for the prediction of the onset of acceleration and the subsequent time of failure.

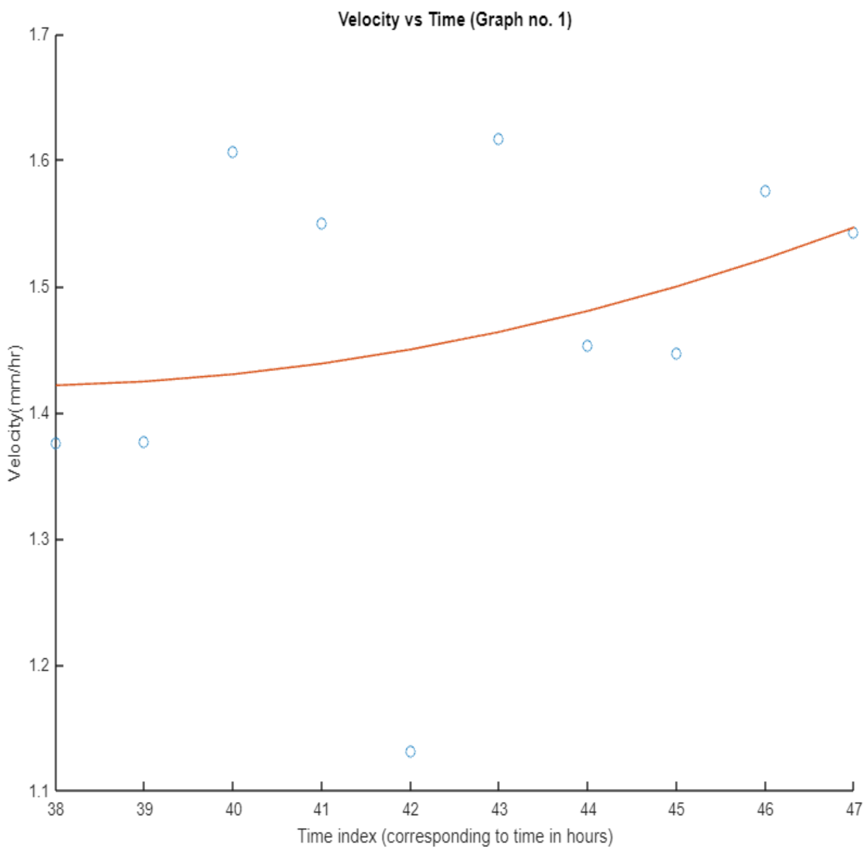

Figure 4. 3(a) : Kusmunda Dataset (Velocity vs Time index)

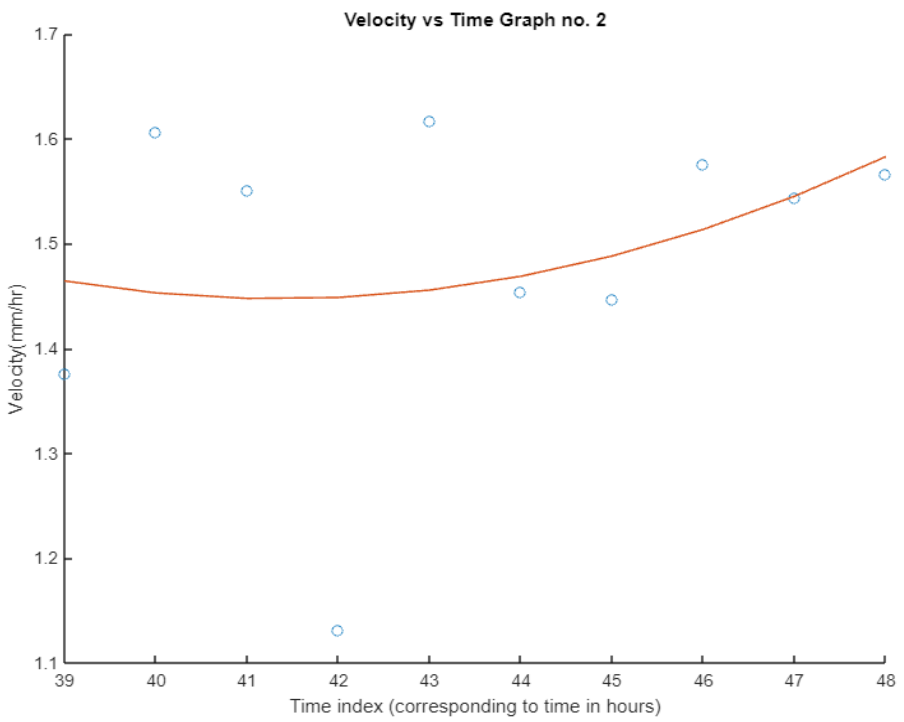

Figure 4. 3(b) : Kusmunda Dataset (Velocity vs Time index)

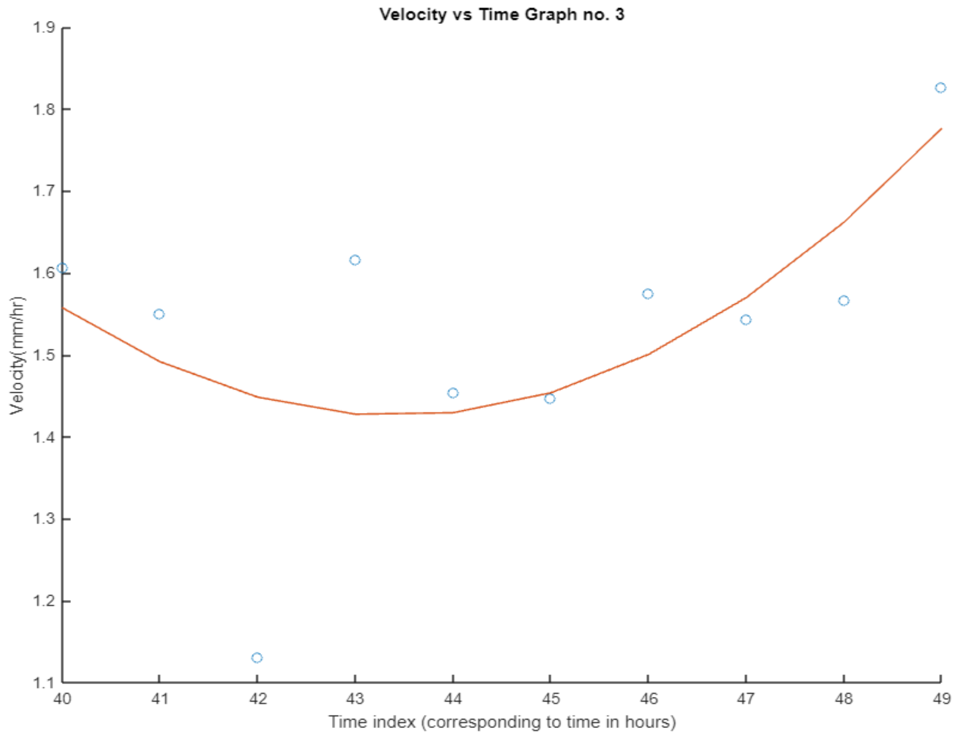

Figure 4. 3(c) : Kusmunda Dataset (Velocity vs Time index)

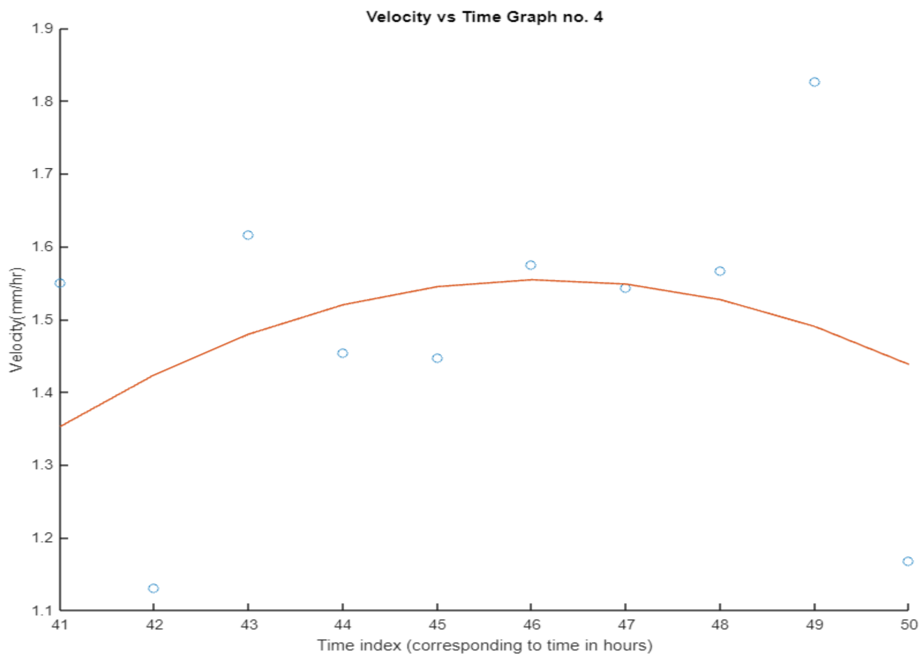

Figure 4. 3(d) : Kusmunda Dataset (Velocity vs Time index)

The codes for finding the onset of acceleration were written, mentioned in Appendix B.

Acceleration phase (OOA/OOF) reached at velocity index 36 and deformation index 37.

Therefore, the time (Date-time) is 15/08/2017 23:04:06.

Applying Inverse Velocity method on the data, considering this time as 0, the time of failure was 16/08/2017 10:53 am, which was very close to the actual failure occurrence at 11:03am.

Next, we ran the algorithm using MATLAB on a digitized dataset. One of the digitized datasets from Australia's Tuckabianna West is shown in the table 4.1 from excel. Australia's Tuckabianna West open pit mine saw a rock slope failure. Ten days before the main failure, several pre-collapse rockfall incidents were in the vicinity. These events occurred before tertiary creep began, lasting around six days (Moretto et al., 2017). A stress fracture was discovered on the upper slope, and a series of surface scans were ordered to keep an eye on the situation. It was stated that mining persisted during acceleration (Glastonbury & Fell, 2002).

Table 4. 1: Digitized dataset of Tuckabianna West open pit mine rockslide

Time	Deformation(mm)
2.508931	0.982519997
3.225705	0.979887218
3.987351	1.307668132
4.726598	1.635531319
5.421121	2.294137296
6.22764	2.952331901
6.94471	4.272012084
7.706356	4.599792998
8.445641	5.092945306
9.185073	6.247254094
9.924394	6.905695522
10.66386	8.225293431
11.3809	9.379684494
12.12033	10.53399328
12.85961	11.02714559
13.62144	12.18137211

14.33844	13.17047405
15.0778	13.9942046
15.81727	15.31380251
16.5343	16.46819357
17.29613	17.62242008
18.03556	18.77672887
18.75256	19.76583081
19.44738	21.74674975
20.16445	23.06642994
20.90385	24.0554496
21.64331	25.37504751
22.40511	26.36398491
23.12236	28.51011069
23.83951	30.16036912
24.53418	31.48013157
25.25132	33.13039
25.96847	34.78064842
26.70801	36.43082457
27.42504	37.58521563
28.11979	39.23555633
28.83693	40.88581475
29.5988	42.20533039
30.31587	43.52501057
31.01062	45.17535127
31.75005	46.32966006
32.46716	47.81462936
33.1843	49.46488779
33.87905	51.11522848
34.61851	52.43482639
35.31333	54.41574533
35.96361	57.55385266
36.56906	60.52683542
37.10749	64.3265106
37.6236	68.45684629
37.96066	73.24899666
38.27539	78.37180755
38.50061	83.82552577
38.70339	89.11403715
38.90616	94.40254853
39.04182	100.021885
39.043	105.3111368
39.11138	110.6001418
39.22464	116.2195606
39.29313	122.0044329
39.38391	127.2933557
39.43001	133.0783103

39.52079	138.3672331
39.52201	143.8217741
39.6129	149.6065642
39.68125	154.7302801

This case study's acceleration reference value was derived by analysing how the phenomena have progressed and studying the work of the authors aforementioned. It is possible to pinpoint the commencement of the acceleration phase between 4-5th March based on trends in displacement data. The digitized dataset is represented by graphs below as Fig 4.4. and Fig 4.5. In both the cases, the 0 on the Time axis corresponds to 30th January. A linear displacement trend was seen during the period of constant velocity. An acceleration phase was observed, which finally led to slope collapse. Data collected on 4th March met all conditions for Stage 5, but data obtained on 5th March only met Stage 3 requirements, according to software results. Since 7th March, the displacement trend showed accelerated behaviour, and all monitoring measures have passed Stage 5.

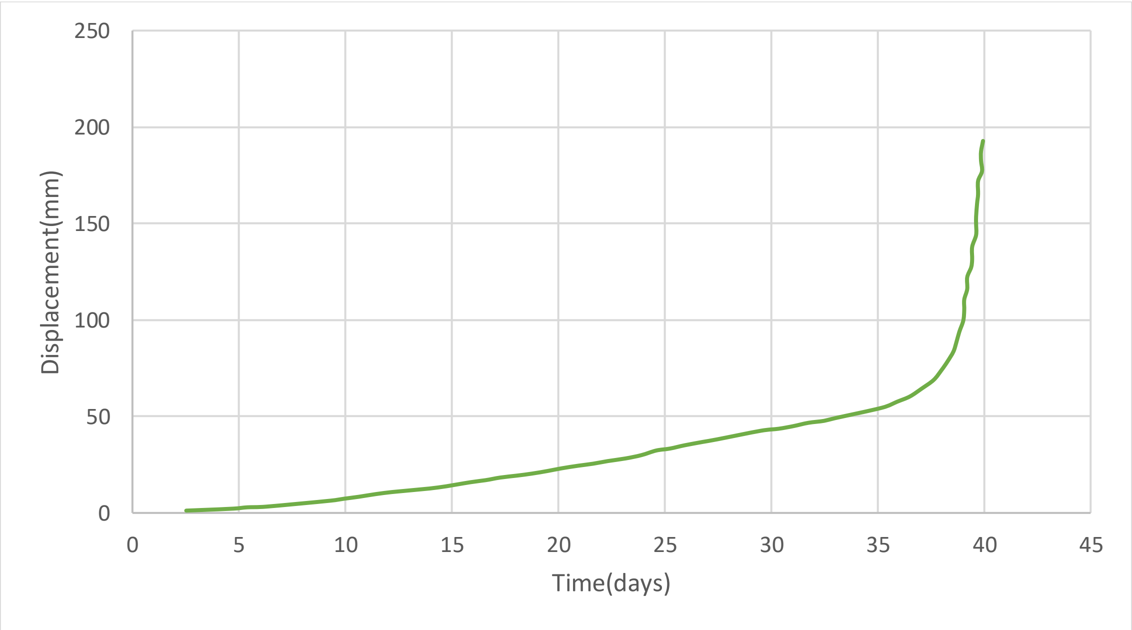

Figure 4. 4: Displacement vs. Time plot for Tuckabianna West open pit mine (digitised data) (Moretto et al., 2017).

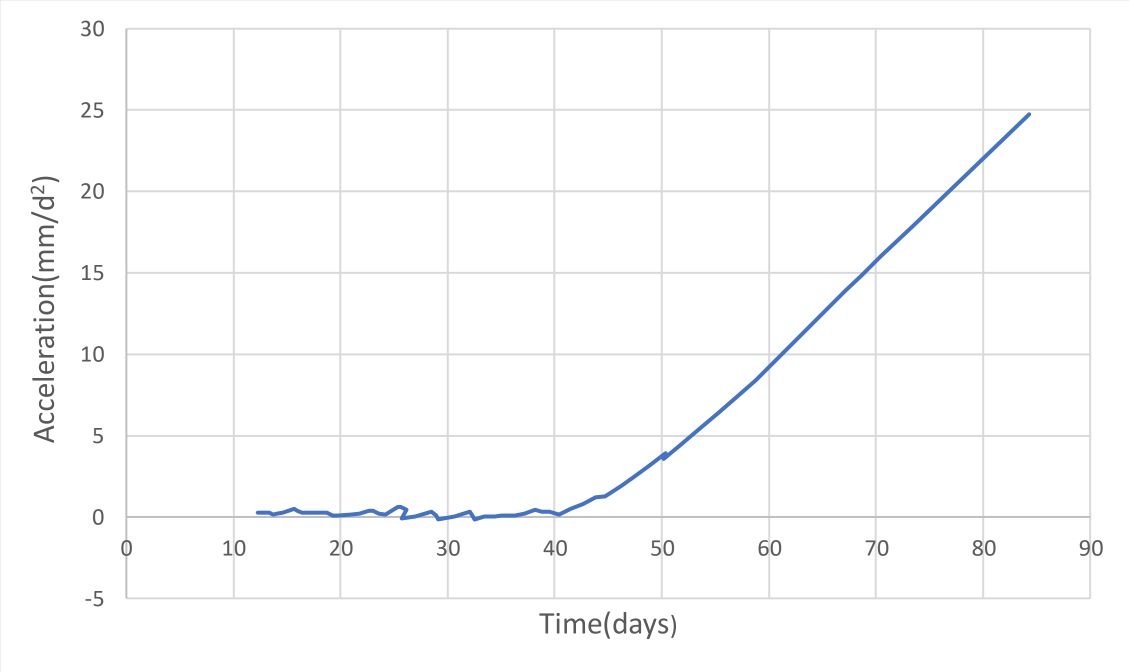

Figure 4. 5 : Acceleration vs. Time plot for Tuckabianna West open pit mine (digitised data (Moretto et al., 2017))

These findings indicate that this case study's OOA date likely falls between 4-5th March, which was in line with the literature reference value. The table 4.2 shows the results of the OOA values predicted by the model for four slope failures cases.

Table 4. 2 : Results for Validation of the model comparing the Predicted and Actual Values for (a) Onset of acceleration (b) Date of Failure.

Data Set	Predicted Onset-of-acceleration	Actual Onset-of-acceleration
Dataset 1	15th August	15th August
Dataset 2	29th July	29th July
Dataset 3	20th November	20th November
Dataset 4	4th March	4th March

Data Set	Predicted Date of Failure	Actual Failure
Dataset 1	16th August	16th August
Dataset 2	9th August	10th August
Dataset 3	1st December	2nd December
Dataset 4	10th March	11th March

Corresponding to these OOA values, the time of failure were predicted which lied within the range of 1 day. Explanation related to the failure datasets used above is done in the following paragraphs;

Dataset 1 deals with the data of a slope failure provided by Kusmunda mines, SECL. The slope being monitored, started showing movements. The SSR was shifted to monitor the slope. The data collected lead to the prediction of OOA. The OOA predicted was 15th of August and the predicted slope failure was on 16th August. The slope failed on 16th August, 11:03am.

Dataset 2 deals with a case study from Nara Prefecture, Japan, on August 10, 2004 (Suwa, Mizuno, and Ishii 2010). The problem began being noticed in January 2004, when cracks showed up near the slope. Various monitoring tools were set up, like extensometers to watch the unstable slope's movement. The system could even send an automatic message if certain limits were crossed. At 5.10 AM on August 8 the velocity reached 4 mm over 2 hours. The slope failure occurred 43 hours later, luckily without any casualties (Suwa, Mizuno, and Ishii 2010). The data obtained from this monitoring was used in this study to test if the proposed method can correctly identify the tertiary phase of the slope failure. The displacement data from the extensometers showed a constant creep until July 31st when an acceleration was observed, signifying the shift from a secondary to a tertiary phase of creep (Suwa, Mizuno, and Ishii 2010). Based on this observation, July 31st can be seen as the reference point for the slope’s acceleration onset, marking the start of the phase that eventually led to the slope collapsing. Even though some early activations were detected, the algorithm accurately pinpointed the acceleration phase. Specifically, the first data point that met all the algorithm's conditions was recorded on August 1st. From this point onward, the algorithm consistently identified the acceleration phase for all subsequent data points. Hence, it is concluded that the point of acceleration onset corresponds to the displacement measured on July 29th, aligning well with the defined OOA in the literature for this failure. Additionally, a closer examination of each condition reveals that the monitoring value on July 29th only satisfied Stage 2 but was included in the accelerating dataset due to the tolerance factor in the algorithm. From July 30th onward, each data point met all conditions in the proposed method. Thus, July 30th can be considered a more reliable OOA point, aligning closely with Suwa, Mizuno, and Ishii's (2010) findings.

The dataset 3 is from a digitized dataset of a case study about a slope collapse that occurred in December, around 5 km northwest of Fukui City, Japan (Saito 1979). The collapse was likely triggered by excavation activities in a borrow-pit at the slope's base. Signs of instability were first noticed on October 4th, with a long crack appearing on a hillside at Agoyama. Measuring instruments were promptly set up to monitor the slope's displacement, and a failure forecasting analysis was conducted. Despite some challenges due to irregular movements and partial failures, the collapse was predicted slightly before it occurred on December 2nd at 1:30 AM (Saito 1979). The displacement recorded by on-site instruments started at 10 mm per day in the initial monitoring phase, increased to 20 mm/d by the end of October, and escalated to 100 mm/day after November 20th (Saito 1979). Given this data, the OOA date for comparison with the algorithm application for this case study could be placed when displacement significantly increased, which was November 20th. The results demonstrated the effectiveness of the proposed methodology, correctly identifying the acceleration trend from the displacement measured on November 23rd. Accordingly, the OOA for this case study can be placed on November 20th, aligning with the previously defined reference value. Another interpretation considers the displacement on November 21st, which doesn't meet Stage 5 but is part of the accelerating trend along with previous data classified as an accelerating point. This interpretation would set the onset of acceleration on November 18th, a few days before the previous estimation. Despite being slightly earlier than the OOA reference value, this prediction is still valuable in defining the accelerating trend.

The dataset 4, is digitized from a case study of a rockslide in Tuckabianna West open pit mine, Australia, likely triggered by excavation works (Glastonbury & Fell 2002), earlier being discussed. The onset of acceleration was identified between March 4th and 5th. The analysis, like in previous case studies, showed a clear transition from constant velocity to accelerating phase, leading to slope collapse. The OOA date was approximately on March 4th, aligning with the literature's reference value.

All case studies showed a consistent pattern: a linear trend followed by an accelerating stage. However, some false positives were observed due to local fluctuations in the dataset and dataset digitization quality. Implementing filters and smoothing procedures could mitigate these inaccuracies. False alarms typically lasted no more than two consecutive measures and were easily distinguishable when subsequent datasets did not meet one of the algorithm sub-criteria.

4.2 Parametric Analysis Results and Discussions:

The analysis focuses on developing a predictive model for mine slope failure based on the onset of acceleration (OOA) phase. The study considers the influence of the number of monitoring data and rate limit values on the accuracy of the predictive model. The analysis is performed using MATLAB, as a tool for numerical analysis and data visualization.

In the first part of the analysis, the study considers different configurations of the number of monitoring data and rate limit values. The study uses the parabolic model fitting to estimate the onset of failure or onset of acceleration phase. The parabolic model fitting is a widely used method for assessing the acceleration phase of slope movement. The parabolic model fitting estimates the velocity of slope movement by fitting a parabolic curve to the displacement-time data. The acceleration phase is identified by assessing the second derivative of the displacement-time curve.

To evaluate the influence of the number of monitoring data (d) and rate limit values, the study compares a reference dataset with a four-point dataset with a 75% rate limit to a five-point dataset with different rate limit values (60% and 80%) and a six-point dataset with rate limit values of 67% and 83%. The study considers 10 monitoring data for the parabolic model fitting. The study finds that all configurations provided the same Onset of failure/Onset of Acceleration (OOF/OOA) estimation, except for the d=6, 4/6 (number of monitoring data=6, rate limit= 67%) model which placed the OOF/OOA one day earlier. This can be seen in the figures 4.6 and 4.7. The study also finds that an increase in the number of monitoring data results in a delayed fulfilment of stage 5 conditions of the Slope Failure Prediction Model for Surface Mines (SFPMSM), ultimately leading to a postponed identification of the onset of failure time. This delay is a drawback in a methodology that aims to provide timely evaluations for early warning purposes. Moreover, the study finds that a percentage limit higher than the reference value does not significantly improve the identification of false positives, except for the 83% rate in the d=6 configuration, which provides a significantly delayed OOF/OOA estimation.

To further evaluate the influence of the number of monitoring data on the occurrence of false positives, the study considers two datasets. The study finds that datasets with a higher number of data points generate more false positives before the actual onset of acceleration, while datasets with fewer data points display a lower reliability in the assessment of the critical acceleration phase. The study shows that the analysis performed with datasets ranging from 10 to 12 points consistently fulfilled the stage 5 of the SFPMSM conditions after the OOF/OOA identification. However, datasets with fewer monitoring data points, such as n=8 and n=9, were unable to provide a reliable assessment of the onset of acceleration, leading to an inaccurate OOF/OOA identification. One of the examples can be seen in the figure 4.8.

. Figure 4. 9 shows acceleration phases to help in predicting time of failure.

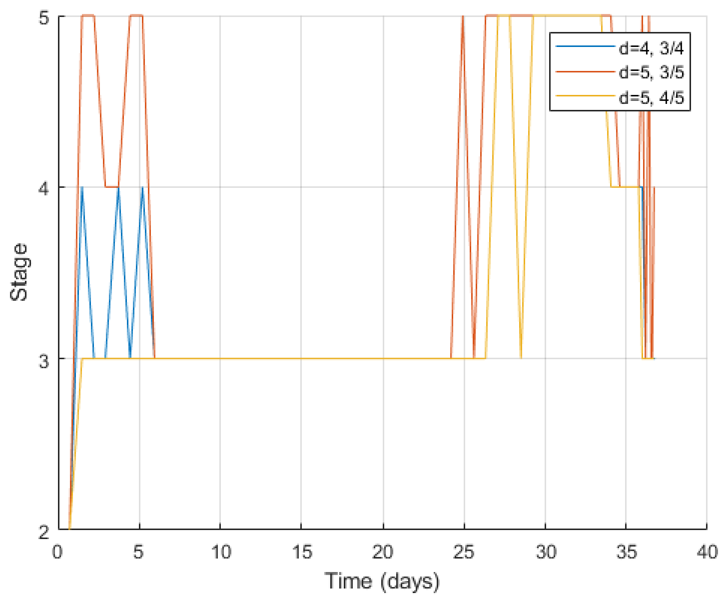

Figure 4. 6: Output of Parametric analysis for values of d and percentage limit using MATLAB

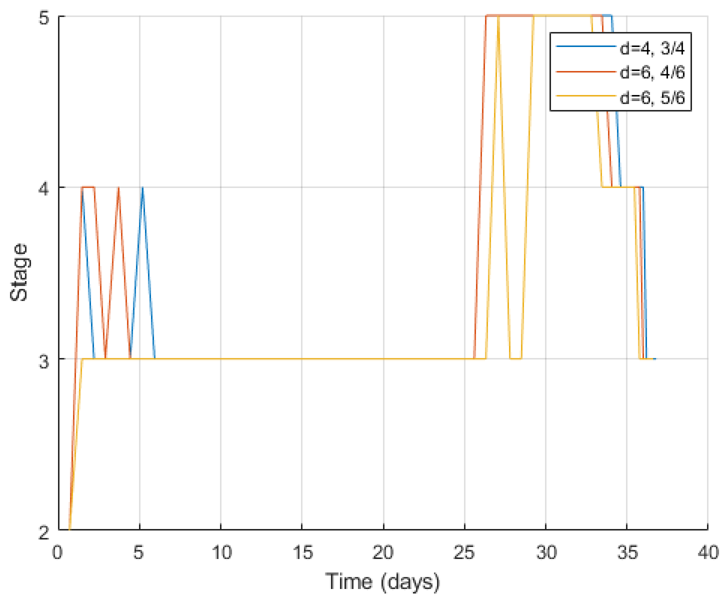

Figure 4.7: Output of Parametric analysis for values of d and percentage limit using MATLAB

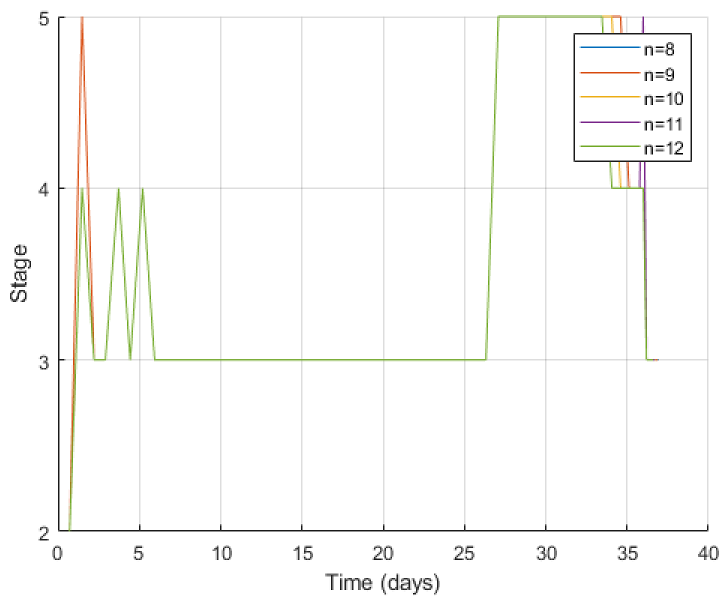

Figure 4. 8 : Output of Parametric analysis for values of n using MATLAB

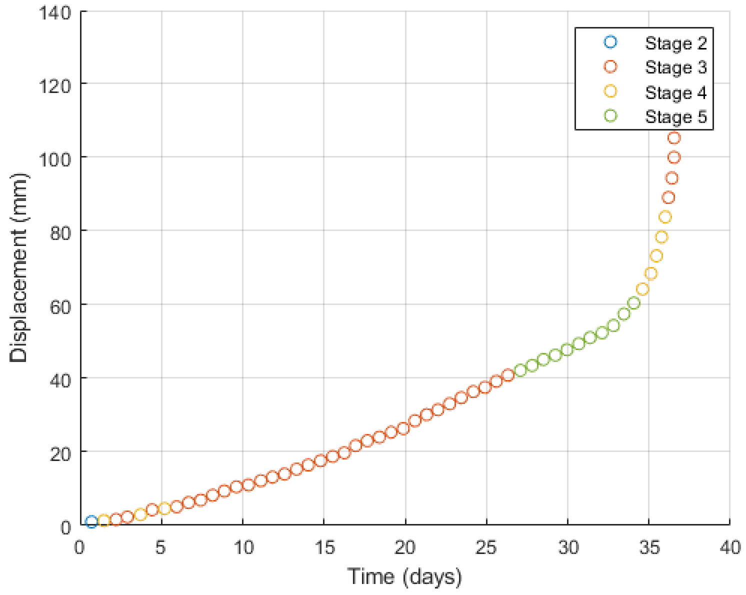

Figure 4. 9 : Plot of displacement vs time for onset of failure prediction using the proposed model

The analysis highlighted the importance of carefully selecting the appropriate parameters for a predictive model for slope failure based on the onset of acceleration phase. The study shows that the number of monitoring data and rate limit values significantly influence the performance of the predictive model. The study recommends selecting an appropriate number of monitoring data points and rate limit values to obtain reliable and timely assessments of the critical acceleration phase for early warning purposes. The values of n (moving dataset window has ten elements), d and percentage limit are very critical for every analysis of slope behaviour and prediction of failure. The SFPMSM always follows the algorithm at every stage.

The slope failure prediction model proposed is designed for real-time monitoring scenarios, aimed at identifying potentially critical acceleration trends based on displacement data. To demonstrate the application of the proposed algorithm, scenarios are presented with all the details of the algorithm and the importance of the values of n, d and the percentage limits that were set for the algorithm. Although the monitoring data used in this study are historical, the proposed procedure is intended to simulate real-time acquisition since the algorithm generates a new result each time a sampled value is processed by the automatic software. The following considerations are important to note regarding the algorithm's application to these case studies: Displacement rate datasets were collected from the field and also digitized from scientific literature.

To perform the stage 4 of the model, a dataset consisting of 10 displacement rate or velocity values (n=10) was selected for all case studies. This means that at least 12 displacement values are required to perform the complete analysis since the first velocity can be evaluated starting from the second reading, and stage 5 requires two nonlinear interpolations to check the concavity behaviour. Based on the results obtained in the parametric analyses, a 4-point dataset and a percentage limit of 75% were used for these elaborations. In summary, the algorithm's application to real case scenarios demonstrated its effectiveness in identifying potentially critical acceleration trends based on displacement data. The minimum number of displacement values required to perform the complete analysis is 12. The algorithm's parameters, such as the 4-point dataset and the percentage limit of 75%, were determined based on the results in the parametric analyses.

4.3 Limitations of the study

A thorough examination of the SSR's data yielded the results needed for this study. However, there were certain limitations to the research. Acknowledging these limitations provides a comprehensive view of the model's capabilities and constraints, enabling researchers and practitioners to identify areas for refinement and future research. We have tried to mention the limitations related to our work in the following paragraphs;

1. The model's accuracy heavily relies on comprehensive data. Incomplete or sparse data might not capture the full range of factors influencing slope stability, potentially

leading to inaccurate predictions. When it came to analysing deformation behaviour, only a small number of case studies were used to validate the SFPMSM. Because slope radar monitoring is relatively a new technique, there is not much of a database to draw on for study. This is particularly true in India. The database of radar-monitored recordings of slope collapse has also not been made public by mining corporations to a great extent and in some cases the companies are not willing to share it with researchers outside their contracts. The research utilised just SSR data and some digitized data from literature review. Consequently, there is some limitation to the dataset type. More slope monitoring data, in conjunction with displacement data from the mining slopes with different constraints, would have provided additional information.

2. Assumptions made to simplify the model (e.g., not including geological properties of the slope) may not accurately reflect the complex, heterogeneous nature of real-world slopes in some cases. Assuming linear relationships may oversimplify the complex, non-linear behaviour of slopes of some slopes, limiting the model's accuracy in capturing the true underlying dynamics, especially in the conditions of heavy rainfall.
3. Human interventions like extreme vehicle movement or disturbances to the SSR are factors that can alter slope monitoring data that is being captured using the SSR, and failing to consider these changes can affect the model's predictions.

4. The scope of the research does not involve a detailed examination of radar mathematics. The research has studied the methods of radar monitoring and the process but does not take into account the complete mathematics and electronics of RADAR technology.