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Development of Rockburst Prediction Tool using Geotechnical Data: A Case Study of Konkola Mine No.1 Shaft, Zambia

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ABSTRACT

Konkola Mine No.1 Shaft is in the northernmost region of the Zambian Copperbelt mines. It is located south of the Democratic Republic of the Congo border and around 430 km North of Lusaka, the Capital City of Zambia. From 1995 to 2021, the mine recorded at least 40 rockburst events, with local magnitudes ranging from 0.5 to 2.5. Currently, mining activities at Konkola Mine No.1 Shaft have advanced to a depth of 1040m below the surface and 1350 m is the planned maximum depth. Concerns have been raised about the possibility of increased mine-induced seismic activity, particularly rockburst incidents, which could present significant safety and production challenges at deeper levels. This study aimed at developing a tool that could predict the potential for rockburst using geotechnical data. Forty (40) rockburst cases captured by the microseismic monitoring system were compiled. Geotechnical data for each rockburst was collected through rock testing, core logging, and in-situ stress measurements. The data was analysed using statistical tools in Microsoft excel to establish a broad range of values for the significant geotechnical factors including rock quality designation (RQD), maximum tangential stress (MTS), uniaxial compressive strength (UCS), elastic modulus (E_m) linear elastic energy (W_{et}), and principal in-situ stresses (σ_v, σ_H and σ_h). The study developed a rockburst predictive tool (G_RPT) that uses RQD, σ_c, σ_t, σ_Θ, W_{et} and σ_1 as input factors to forecast rockburst potential damage class. Sixteen rockburst cases from the Mufulira Mine were used to validate the G_RPT. The results showed that the proposed G_RPT had an accuracy of 87.5%.

Keywords: Rockburst, geotechnical factors, G_RPT, validation, accuracy

1. Introduction

Rockbursts are dynamic rock mass failures during underground mining under unfavourable stress conditions, causing significant risks to infrastructure, equipment, worker injuries, and fatalities (Wojtecki et al., 2021; Cai and Kaiser, 2018; Zhou and Wang, 2017). As mining depth and construction increases, stress-induced failure processes become more common near excavations and deep inside rock masses (Javed et al., 2019; Kaiser, 1996).

Rockburst damage severity is based on depth of failure and volume of displaced rock. It is classified into minor, moderate, and major or severe levels, based on seismic energy release (Kaiser et al., 1996; Cai and Kaiser, 2018). Damage caused by rock displacement is classified as light, medium, or heavy. The Potvin (2009) rockburst damage scale considers rock mass and support system. Different researchers have come up with other methods to classify rockbursts. For instance, Tan (1992) identified four rockburst grades: weak, moderate, strong, and severe. The classification is based on the extent of damage and mechanical and acoustic characteristics of the rockburst. Russenes (1974) also divided rockbursting activity into four classes from 0 to 3. Class 0 indicates no rockbursting activity, while classes 1, 2 and 3 indicate low, moderate, and high rockbursting activity.

Mining-induced seismicity is primarily due to stress readjustment due to underground stopes and shear stress on fractures (Jaeger et al., 2007; Brady and Brown, 2006). Factors such as depth, production rate, mining geometry, geological discontinuities, and ambient tectonic stress field can significantly contribute to seismicity. Pre-existing cracks can facilitate energy release in rockbursts (Zhou et al., 2011).

Four factors contributing to rockbursts include geotechnical, geology, mining, and seismicity (Li et al., 2017: Kaiser and Cai, 2012). Geotechnical factors include rock strength, rock mass quality, joint fabric, and brittleness. Geology factors include rock type, foliation, and structures. Mining factors involve static stress, local mine stiffness, and excavation sequence. Seismicity factors involve dynamic stresses and ground motions. Keneti and Sainsbury (2018) identified six key factors for rockbursts, including unfavorable stress states, excavation geometry, and advance rate. High stress, brittle rock, and faults increase the risk of rockbursts in mines (Blake and Hedley, 2009).

Rockburst prediction is a crucial task worldwide, preventing and controlling rock failure in underground excavations (Li et al., 2017). Four techniques are used for rockburst prediction: empirical, analytical, numerical modelling, experimental, and intelligent methods (Li et al., 2022; Zhou et al., 2018). The empirical method uses single and multi-indicator indices to assess rock mass quality and evaluate rockburst risk. However, single index criterion has limitations due to complex geological factors. Multi-indicators are used to minimize deviations and improve accuracy. In practical engineering, indicators reflect rock mechanical properties such as uniaxial compressive stress (UCS) or uniaxial tension stress and environment stress conditions such as maximum tangential stress around an underground opening (Lingga and Apel, 2018; Leveille et al., 2017). Factors influencing rockburst include stress level, physical and mechanical properties of rock, structure, excavation mode, temperature, and groundwater (He et al., 2018; Zhang et al., 2017). These factors vary under different geological conditions, making rockburst prediction a complex and indeterminate system question (Zhang et al., 2020).

Several studies have been conducted to predict rockbursts at construction and underground mine sites. These studies have used a combination of models and indicators, including empirical methods and artificial intelligence. For example, Hoek and Brown, (1980) suggested an empirical method to predict rockbursts that relied on unconfined compressive strength, tensile strength, and major principal stress. Pu et al., (2018) used the Decision Tree model to predict rockbursts at the Kimberlite underground mine by considering input parameters such as uniaxial compressive strength, uniaxial tensile strength, tangential stress, and elastic energy index. Ke et al., (2021) used a Naïve Baye model at China's underground projects, considering input parameters such as the maximum tangential stress, elastic energy index, and uniaxial tensile stress. Liu et al., (2021) used a Cloud model to predict rockbursts at the Ashele Copper Mine in China, which considered geological conditions (lithology and geo-stress), mining processes, and microseismic data as input parameters. Farhadian (2021) used the tunnel rockburst classification (TRC) chart, which relied on input parameters such as tangential stress, elastic energy index (W_{et}), and uniaxial compressive strength.

In 1995, Konkola Mine No.1 Shaft experienced a seismic event affecting the southern region, causing significant damage to crosscuts (Mutale, 2004). The mine adopted the Integrated Seismic System (ISS) to monitor microseismic activity, which was replaced by the Institute of Mine Seismology (IMS) system in 2015.

Mining activities at Konkola Mine No.1 Shaft have progressed to a depth of 1040 mL, with plans to reach the maximum depth of 1350 mL. However, there are concerns that mine-induced seismic activity, particularly rockbursts, may become more frequent and pose significant risks to safety and production at greater depths. To address these concerns, a comprehensive study was needed to develop tool that could predict rockburst potential using geotechnical data at Konkola Mine No.1 Shaft.

This paper proposes a Rockburst Predictive Tool (G_RPT) that uses geotechnical data. The G_RPT was tested and validated with 16 datasets from the Mufulira mine, and it could be helpful for other mines facing similar rockburst challenges.

2. Materials and Methods

2.1 Geotechnical data collected

The data was collected from the 40 rockburst sites that were captured by the MS monitoring system at the Konkola Mine No.1 Shaft. The mine is located in the northernmost region of the Zambian Copperbelt, south of the Democratic Republic of the Congo border and approximately 430 km north of Lusaka, the Capital City of Zambia (Figure 1).

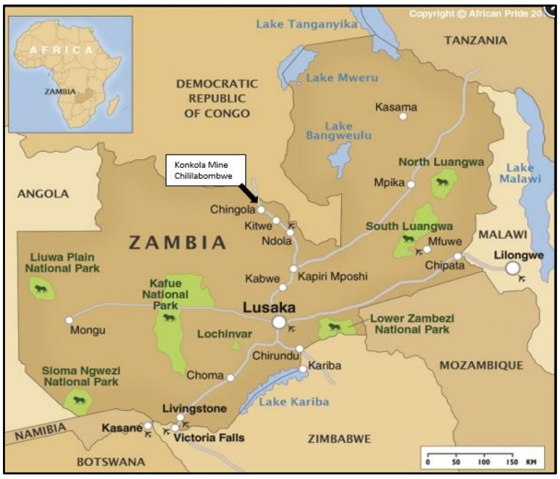

Figure 1: Location map of Konkola Underground Mine (Google Earth, 2021).

For each rockburst event, laboratory work was conducted to collect data on geotechnical parameters. The rock samples were obtained from the core logs as shown in Figure 2.

Figure 2: Logged borehole for RQD determinations.

2.2 Uniaxial Compressive Strength

The uniaxial compressive strength (UCS) values for the rock samples were determined using the compression and point-loading testing machines (Figure 3). The compression testing machine was used to test the NX 50mm core samples, while the point load testing machine was used for the irregular samples.

(a) (b)

Figure 3: Rock sample testing (a) compression-testing machine and

(b) Point load-testing machine.

The values of the UCS of the rock core samples determined using the point load test machine were calculated using Equation 1:

$UCS = 22 (I_s50)$ (1)

Where;

UCS = Uniaxial compressive strength of the rock in MPa;

22 = Correlated factor, a function of core diameter; and

I_s50 = Corrected point load strength index for the standard core size of 50mm.

2.3 Uniaxial Tensile Strength

The uniaxial tensile strength (UTS) of rock is minimal and is 0.1 times the compressive strength (Bernt and Looyeh, 2019). The UTS values were determined using a relation shown in Equation 2:

$UTS = 0.1\ UCS\ (MPa)$ (2)

Where;

UTS = Unconfined Tensile stress (MPa); and

UCS = Unconfined Compressive Stress (MPa).

2.4 The Rock Quality Designation (RQD)

The Rock Quality Designation Index (RQD) was developed by Deere (Deere et al., 1967) to provide a quantitative estimate of rock mass quality from drill core logs. RQD is defined as the percentage of intact core pieces longer than 100 mm in the total length of the core drilled. The percentages of RQD were obtained using Equation 3 (Deere, 1989).

$$\mathrm{RQD} = \frac{\Sigma \mathrm{Corepieces} > 10\mathrm{cm}}{\mathrm{Total\ length\ of\ core\ run}} \times 100 \qquad (3)$$

Where;

RQD = Rock Quality designation in percentage (%).

RQD values were determined by logging the cores that were obtained from the boreholes. The boreholes were drilled from the surface and intersected the rock units from the hanging wall to the footwall. RQD for the rock samples were obtained using Equation 3.

2.5 Maximum Tangential Stress

Peng et al., (2021), in their field investigation and analysis of rockburst and spalling in a deep hard-rock Mine, found that when the maximum tangential stress (MTS) was between 0.4 - 0.6 times the uniaxial compressive strength of surrounding rock, surrounding rock was prone to local spalling. From this empirical estimation, the author assumed an MTS of 0.5 times the uniaxial compressive strength of rock sample as given by Equation 4:

$$\mathrm{MTS} = 0.5\sigma_c \qquad (4)$$

Where;

MTS = Maximum Tangential Stress (MPa), and

σ_c = unconfined compressive stress (MPa).

MTS values for the 70 rock core samples were calculated using Equation 4.

2.6 Elastic Modulus

For this study, the method developed by Palmström and Singh (2004) was used to determine the Elastic Modulus. The method relates deformation modulus (E_m) with unconfined compressive strength as given by Equation 5:

$$E_m = 0.2\sigma_c \qquad (5)$$

Where;

E_m = Deformation modulus in GPa; and

σ_c = unconfined compressive strength in MPa.

2.7 Linear Elastic Energy

Wang and Park (2001) introduced the linear elastic energy (W_{et}), which is defined as the linear elastic energy stored in the rock specimen before the rock failure point. It is one of the indicators for predicting the rockburst intensity and is expressed as shown in Equation 6:

$$W_{et} = \frac{\sigma 2_c}{2E_m}, \qquad (6)$$

Where;

W_{et} = the linear elastic energy;

σ_c = the UCS of intact rock (MPa); and

E_m = the elastic modulus.

For this study, the W_{et} were calculated using Equation 6 that takes into account the UCS and E_m of the intact rock.

2.8 Principal in situ stress magnitudes

The principal in situ stress magnitudes (σ_v, σ_H and σ_h were calculated based on the in-situ stress measurements conducted at the Konkola Mine No.1 Shaft by Rock Mechanics Technology (RMT) in 2001(Walker, 2001; Carvill, 2001).

3. Data analysis

The collected data included unconfined compressive strength (UCS), unconfined tensile strength (UTS), Rock quality designation (RQD), maximum tangential stress calculated based on the UCS values, elastic modulus, elastic strain energy (W_{et}) and the principal in situ stresses (σ_v /MPa, σ_H /MPa, σ_h /MPa). Microsoft Excel was used to analyse the data and established the ranges of values for each parameter as shown in Table 1.

Table 1: Geotechnical factors contributing to rockburst at Konkola Mine No.1 Shaft.

Factor	**Range**	**Most frequent range**	**No. of samples**
RQD /%	60 - 88	60 - 69	80
σ_c /MPa	74 - 330	160 - 244	60
σ_t /MPa	6.5 - 30.5	6.5 - 14.5	80
σ_θ /MPa	37 - 165	80 - 122.3	70
σ_v /MPa	19.5 - 32.1	28 - 32.1	40
σ_H /MPa	16.7 – 27.5	28 – 32.1	40
σ_h /MPa	11.8 – 19.4	24 -27.5	40
E_m/GPa	36.8 -75	36.8 - 49.5	76
Log (W_{et} /Jm^{-3})	5.1 - 6.4	5.6 - 6.0	80

3.1 Development of rockburst prediction tool

The G_RPT program calculates ratings based on six parameters: unconfined compressive strength, rock quality designation, unconfined tensile strength, tangential stress, principal in-situ stress, and linear elastic energy. It integrates C++ logic into a C# Windows Forms application, creating a graphical user-friendly interface.

3.2 Validation of the rockburst prediction tools

The G_RPT was validated using 16 datasets from Mufulira Mine, a nearby mine with a history of rockbursts, and tested on six factors included compressive strength (σ_c), rock quality designation (RQD), unconfined tensile strength (σ_t), maximum tangential strength (σ_θ), Major principal in-situ stress (σ_1) and linear elastic energy (W_{et}). The authors selected accuracy as the metric evaluation index to verify the performance of the G_ RPT. The accuracy was calculated by dividing the total number of true predictions by the total number of actual classes of the rockbursts.

4. Development of the Geotechnical – Based Rockburst Predictive Tool

Six geotechnical factors were established as contributing factors to rockburst. The factors were as highlighted in Section 3.1. The geotechnical factors were categorised into four groups with assigned ratings as presented in Tables 2 to 7.

Table 2: Rating (R1) for Compressive Stress, σ_c (MPa).

σ_c (MPa)	**R1**
$\sigma_c < 74$	1
$74 \leq \sigma_c < 202$	2
$2002 \leq \sigma_c < 330$	3
$\sigma_c \geq 330$	4

Table 3: Rating (R2) for Rock quality designation, RQD (%).

RQD (%)	**R2**
RQD < 60	1
60 ≤ RQD < 74	2
74 ≤ RQD < 88	3
88 ≤ RQD ≤ 100	4

Table 4: Rating (R3) for Tensile strength, σ_t (MPa).

σ_t (MPa)	**R3**
$\sigma_t < 6.5$	1
$6.5 \leq \sigma_t < 18.5$	2
$18.5 \leq \sigma_t < 30.5$	3
$\sigma_t \geq 30.5$	4

Table 5: Rating (R4) for Tangential stress, σ_θ (MPa).

σ_θ (MPa)	**R4**
$\sigma_\theta < 37$	1
$37 \leq \sigma_\theta < 101$	2
$101 \leq \sigma_\theta < 165$	3
$\sigma_\theta \geq 165$	4

Table 6: Rating (R5) for Principal in – situ Stress, σ_1 (MPa).

σ_1 (MPa)	**R5**
$\sigma_1 < 19$	1
$19 \leq \sigma_1 < 26$	2
$26 \leq \sigma_1 < 32$	3
$\sigma_1 \geq 32$	4

Table 7: Rating (R6) for Linear Elastic Energy, W_{et} (J/m^3).

W_{et} (J/m^3)	**R6**
$\text{Log}(W_{et}) < 5.1$	1
$5.1 \leq \text{Log}(W_{et}) < 5.9$	2
$5.9 \leq \text{Log}(W_{et}) < 6.4$	3
$\text{Log}(W_{et}) \geq 6.4$	4

The total ratings (TR) were calculated based on the ratings assigned to each factor with the minimum TR of 6. The rockburst classification based on TR is shown in Table 8.

Table 8: Rockburst class prediction based on total rating (TR).

TR	**Rockburst Classification**
TR = 6	No damage
$6 \leq TR < 15$	Minor
$15 \leq TR \leq 20$	Moderate
$20 \leq TR < 24$	Strong
$TR \geq 24$	Extra strong

Each rockburst event was described using the categories of no damage, minor, moderate, and strong. The rockburst damage classes are presented in Table 9.

Table 9: Rockburst Damage Classification (Potvin, 2009; Kaiser et al., 1996).

Rockburst class	**Failure characteristics**
Minor	Support system is loaded, loose in mesh, plate deformed, shotcrete cracked Rock spitting, spalling or shallow slabbing, a shallow skin of fractured or loose rock, generally less than 0.25 thick, Moderate new mesh bagging with a few broken wires. Minor mesh bagging for a standard support system. If rock ejection is the mechanism involved, Minor falls of ground may occur, although the thickness (weight) of rock would be small enough that a standard support system should be capable of retaining this material in place. The weight of the rock in the failing ground is less than m^2.
Moderate	Some broken bolts, mesh bulged, shotcrete heavily fractured. The rock is heavily fractured and may have displaced violently. Mesh will be bagged at its capacity and is often torn or pulled over rock bolt plates. Many holding elements will have failed but the volume of broken rock is limited such that drifts are still accessible. Generally characterized by fractured or loosened rock of 0.25 m to 0.75 m in thickness
Strong/Major	Major damage to support system, retention capacity severely compromised. Wide scale Fall of ground that may render it impassable due to substantial amounts of displaced rock. Most ground support components would be broken or damaged and shotcrete or other retaining elements would have lost their functionality, permitting unraveling of broken rock between holding elements. deep fracturing or the presence of damaged rock to a depth of more than 0.75 m around the opening
Extra strong/ Severe	Complete failure of support and almost complete closure of the all drift or drive, Seismic energy release in excess of 10^9 Joules, Local magnitude of greater than 2.5

4.1 Developing a Geotechnical Based Rockburst Prediction Tool (G_RPT)

The G_RPT is a software application developed to predict the potential occurrence of rockburst events based on assigned ratings to geotechnical parameters. The application combines C++ logic for rating calculations with a C# Windows Forms graphical user interface to provide an intuitive and user-friendly experience. The development of a G_RPT followed the steps as outlined in the flowchart shown in Figure 4:

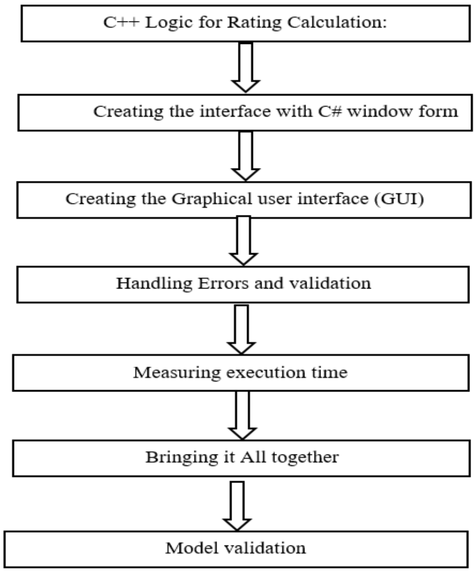

Figure 4: Developing a G_RPT.

4.2 C++ Logic for Rating Calculation

The first step was writing the code rating calculation logic in C++ (Figure 6). The logic considers six geotechnical parameters: Rock Quality Designation (RQD), unconfined compressive strength (UCS), unconfined tensile strength (UTS), maximum tangential stress (MTS), log of linear elastic energy (W_{et}), and in-situ maximum principal stress. Each parameter is assigned a rating based on predefined ranges. The program calculates total ratings to make predictions about the class of rockburst events.

Appendix 2A: C++ code for G_RPT

```
#include <iostream>
using namespace std;
//Welcome to Geotechnical Based Rockburst Prediction Tool(G_RPT)
//This program predicts damage class based on the total ratings assigned to Geotechnical
Parameters
//VARIABLE DECLARATION
double TensileStrength, TangentialStress, ElasticEnergy, PrincipalStress, quality, stress,
prediction;
double RatingTensileStrength, RatingTangentialStrength, RatingElasticEnergy;
double RatingQuality, RatingStress, RatingPrincipalStress, Ratingprediction;
//MAIN PROGRAM
int main(){
    cout<< "Enter "<< endl;
   cin>> quality;
   cout<< "Enter Compressive Stress"<< endl;
   cin>> stress;
   cout<< "Enter Tensile Strength"<< endl;
```

Figure 5: Screenshot of C++ code for G_RPT.

4.3 Developing the Graphical Interface with C# Window

The C++ logic was integrated with a C# Windows Forms application to develop a user-friendly graphical interface. Visual Studio was utilised to design the interface, which includes various elements such as labels, text boxes, and buttons. Visual Studio's designer was used to create a user-friendly interface.

Labels guided users and text boxes allowed input. A "Run" button initiated the prediction process, and an additional label displayed the execution time of the prediction. The C++ logic code was integrated into a C# Windows Forms application using Visual Studio's design tools, resulting in a user-friendly GUI (Figure 6) with labels, text boxes, buttons, and an execution time display (Figure 7).

Appendix 2B: GUI Code for G_RPT

```
using System;
using System.Diagnostics;
using System.Windows.Forms;
namespace GeotechnicalRockburstPredictionApp12
{
  public partial class Form1 : Form
  {
    public Form1()
    {
      InitializeComponent();
    }
    private double CalculateRating(double value, double range1, double range2, double
range3, double range4)
    {
      if (value < range1)
      {
        return 1;
      }
      else if (value >= range1 && value < range2)
      {
        return 2;
      }
      else if (value >= range2 && value < range3)
      {
        return 3;
      }
      else if (value >= range3 && value <= range4)
      {
        return 4;
```

Figure 6: Screenshot of GUI code for G_GRPT

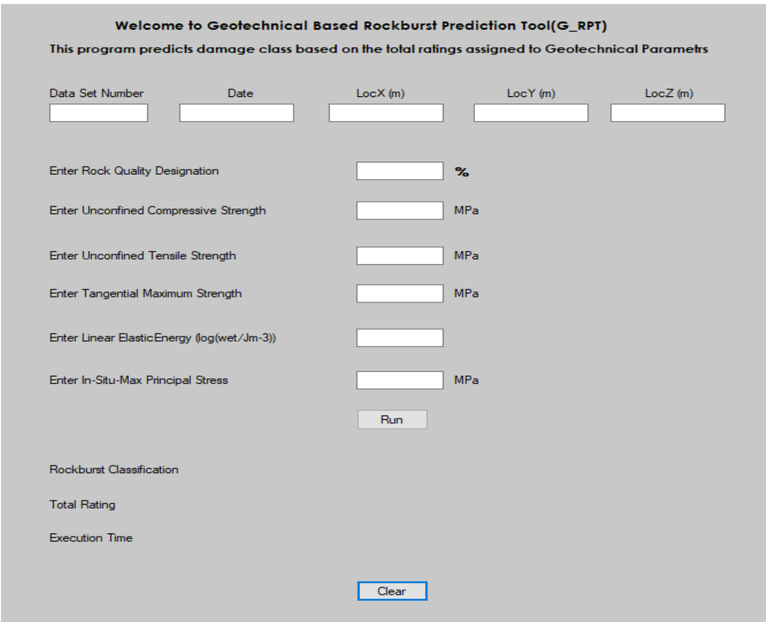

Figure 7: GUI for the G_RPT.

The user inputs the details of a rockburst event that include dataset number, date and location. The user then inputs the six geotechnical parameters for the event 1: rock quality designation (RQD) =80%, unconfined compressive strength (UCS) = 270 MPa, unconfined tensile strength (UTS) = 26 MPa, maximum tangential stress = 162 MPa, log (elastic linear energy) = 6.4 and principal in-situ maximum stress = 38 MPa. After inputting, the user can start the prediction process by clicking the "Run" button and the prediction results are presented in the GUI (Figure 8). A "Clear" button resets the input fields so the user can input another dataset.

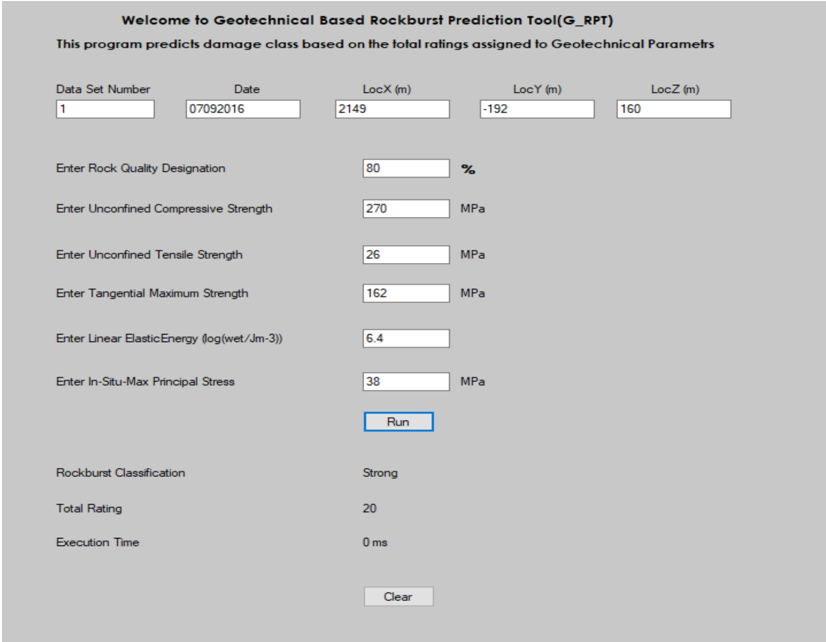

Figure 8: Rockburst damage classification results predicted using G_RPT.

4.4 Error Handling and Validation

The user inputs were validated to ensure that only valid numeric values were entered. If invalid input was detected, a message box was displayed, indicating the error.

4.5 Execution Time Measurement

The Stopwatch class from the System Diagnostics namespace was used to measure the execution time of the prediction process. The execution time was then displayed in milliseconds on the interface.

4.6 Final Integration and Testing

The C++ rating calculation logic was integrated into the C# program by creating methods to calculate ratings for each parameter. The ratings were then summed up to determine the total rating. Predictions were made based on the total rating, and the result was displayed on the GUI.

4.7 Addition of a Clear Button

As an enhancement to the user experience, a "Clear" button was implemented. This button, when clicked, resets all input text boxes to an empty state, allowing users to input the next set of entries without manual deletion.

4.8 Validation of the Geotechnical based Predictive Rockburst Tool

To validate G_RPT, 16 sets of geotechnical data from rockburst events at Mufulira Mine were used due to its proximity and similar geotechnical and geological characteristics to the Konkola Mine No.1 Shaft. The details of the rockburst events included Event No., Event Date, Event Time, LocX (m), LocY (m), and LocZ (m) as shown in Table 10.

Table 10: Details of rockburst events used for validation of the G_RPT.

Event No.	Event Date	Event Time	LocX (m)	LocY (m)	LocZ (m)
1	7-Oct-16	0:34	2149	-192	160
2	7-Oct-16	1:05	2200	-245	144
3	30-Aug-16	14:06	2269	-348	164
4	10-Sep-16	16:54	3050	-654	-49
5	10-Sep-16	16:54	3050	-654	-49
6	19-Sep-16	6:48	3378	-464	-51
7	19-Sep-16	10:53	3063	-569	4
8	13-Nov-16	19:33	3112	-418	-31
9	14-Nov-16	19:19	3104	-581	-36
10	28-Jan-17	3:50	2761	-676	-595
11	12-Jul-17	8:43	1496	-243	98
12	16-Jan-18	17:07	3270	-903	-715

13	25-Oct-19	5:20	2661	-312	-532
14	27-Oct-20	4:54	3085	-539	-279
15	21-Nov-22	0:51	3129	-511	-379
16	21-Nov-22	1:01	3051	-514	-169

The rockburst classes predicted were compared to the actual classes determined by geotechnical engineers at the Mufulira Mine. The predicted and actual rockburst classes for the 16-rockburst events are shown in Table 11.

Table 11: Validation and testing results FOR the G_RPT

Event	**RQD (%)**	**σ_c (MPa)**	**σ_t (MPa)**	**σ_Θ (MPa)**	**W_{et} (J/m^3)**	**σ_1(MPa)**	**Predicted class**	**Actual class**
1	80	270	26	162	6.4	38.0	Strong	Moderate
2	80	250	24	150	6.3	38.4	Moderate	Moderate
3	80	250	23	150	6.3	32.6	Moderate	Moderate
4	80	283	24	170	6.4	38.4	Strong	Moderate
5	80	247	24	148	6.3	38.4	Moderate	Moderate
6	80	267	25	160	6.3	38.4	Moderate	Moderate
7	80	247	24	148	6.3	38.4	Moderate	Moderate
8	80	263	25	158	6.3	38.9	Moderate	Moderate
9	80	252	24	151	6.3	38.4	Moderate	Moderate
10	80	255	25	153	6.3	38.9	Moderate	Moderate
11	80	260	25	156	6.3	38.9	Moderate	Moderate
12	80	256	24	154	6.3	38.9	Moderate	Moderate
13	80	247	23	148	6.3	39.3	Moderate	Moderate
14	80	268	24	161	6.3	39.8	Moderate	Moderate
15	80	267	25	160	6.3	40.2	Moderate	Moderate
16	80	251	25	151	6.3	40.2	Moderate	Moderate

Table 11 shows that the G_RPT predicted fourteen (14) true classes of rockburst and two (2) false classes. The 14 true predicted classes moderate while the two false predicted were classified as strong.

Given the predictions of the rockburst classes, the usefulness of the tool was verified using the prediction accuracy as an evaluation index. The accuracy was computed using Equation 7:

Accuracy (%) = 1 - $Error\ Rate$ (7)

Where;

$$\text{Error Rate} = \left|\frac{Total\ number\ of\ \ True\ predictions - Total\ number\ of\ actual}{Total\ Number\ of\ actuals}\right|$$

The G_RPT correctly predicted 14 out of 16 actual rockburst events, resulting in 87.5% accuracy computed using Equation 7.

4. Results and Discussions

4.1 Development and Validation of Rockburst Predictive Tool

The predictive tool for rockburst (G_RPT) was developed based on the geotechnical factors. The factors were unconfined compressive strength (σ_c), rock quality designation (RQD), unconfined tensile strength (σ_t), tangential stress ($\sigma_{o)}$, principal in-situ stress (σ_1) and linear elastic energy (W_{et}).

The RPT was evaluated on 16 cases from each dataset, and the study found that the G_RPT had a prediction accuracy of 87.5%. The G_RPT can accurately predict rockbursts and can be applied during the stages of feasibility study, design, and operation**.**

The establishment of a standardised classification system for rockbursts is of utmost importance due to the likelihood of varying methods of assessment employed by different researchers. The categories utilised in G_RPT may diverge among mines, potentially affecting the efficiency and reliability of the G_RPT. Thus, it is imperative that researchers reach a consensus on a universal classification system.

The graphical user interface (GUI) had some limitations of not able to import all the parameters at once. Hence, each set of parameters was computed per run. However, the computing time or speed was found to be fast with the results being obtained in milliseconds

5. Conclusion

The predictive tool for rockburst (G_RPT) was developed, based on the geotechnical factors. The factors were unconfined compressive strength (σ_c), rock quality designation (RQD), unconfined tensile strength (σ_t), tangential stress ($\sigma_{o)}$, principal in-situ stress (σ_1) and linear elastic energy (W_{et}). The

G_RPT were evaluated on 16 rockburst events from Mufulira Mine. The study found that the RPT had a prediction accuracy of 97%. The G_RPT can accurately predict rockbursts and could be applied during the stages of feasibility study, design, and operation**.**

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