An investigation of the effect of rock brittleness on rockburst prediction in seismically active mines

Alexey Sharipov
School of Mining and Geosciences, Nazarbayev University, Astana, Kazakhstan

Amoussou Coffi Adoko
School of Mining and Geosciences, Nazarbayev University, Astana, Kazakhstan

ABSTRACT The aim of this paper is to investigate the effect of the brittleness indices (B1 and B2) on the rockburst damage potential classification performance using Artificial Neural Network classifiers. Rockburst incident cases from seismically active mines are used to implement the proposed ANN models. Several scenarios were considered. The performance of the models was evaluated and the results indicated that the brittleness index has a great influence on the predictive performance of the models, especially for severe rockburst cases. The classification rates vary between 60-88% depending on the scenarios. Overall, B_2 showed a slight higher impact on the model accuracies compared to B_1. The classification results showed some superiority over existing studies. It is concluded the results of the present study can be useful in managing ground prone to rockburst.

Keywords: Rockburst potential damage, rock brittleness, ANN classifiers, rockburst intensity, mine seismicity.

1 INTRODUCTION

The increasing demands for minerals today have compelled many mining operations to go deeper. Some mines have been operating at more than 3 km depth already (Blake & Hedley 2003; Hasegawa et al. 1989); Nussbaumer (2000). Nevertheless, one of the major challenges with deep mines is the likelihood of seismic events occurrence due to the mining activities (Nussbaumer 2000). Rockburst is defined as a sudden release of energy stored in a surrounding rock mass under high-stress conditions (Kaiser & Cai 2013). This results in excavation damages that could present serious threats to the safety of mine workers, equipment and mine profitability. Based on these considerations, rockburst is one of the fundamental challenges confronting mining engineers that calls for intensive research aimed at investigating the rockburst mechanism, prediction of rockburst intensity, and control measures (He et al. 2012).

Despite the extensive research on the rockburst phenomenon, accidents and fatalities associated with rockburst still occur, especially in seismically active mines, threatening the profitability of underground mining operations. Pan et al. (2018) noted that current theoretical knowledge about the rockburst is a typical black box. Existing methods of predicting rockburst intensity suffer from the lack of fundamental understanding of factors triggering the rockburst which eventually leads to the poor reliability of the many existing rockburst intensity prediction models. Over the past few decades, various researchers and practitioners have intensively studied rockburst mechanisms and investigated ways to predict its damage potential necessary for an adequate management of rockbursts (He et al. 2012). The concept of Rockburst Damage Potential (RDP) was proposed by Heal et al. (2006) to quantify the vulnerability rockburst during excavation as input parameters obtained from monitoring data such as stress conditions, ground support, span and seismic activities. Furthermore, several techniques have been employed for estimating and predicting rockburst intensity, these include stress criteria classification, in situ testing, empirical charts and a wide range of predictive models based on microseismicity data (Heal 2010; N. Li et al. 2020; X. Li et al. 2021; Maxutov & Adoko 2021; Zhou et al. 2012; Zhou et al. 2016). Nevertheless, one of the drawbacks of these models is that the rock mass brittleness index which is the critical parameter linked with rockburst, is not properly accounted for. Further studies are needed in this regard. Therefore, this paper aims to investigate the effect of the rock brittleness on the rockburst damage potential.

2 ROCKBURST DATA DESCRIPTION

In this paper, cases of rockburst incidents were compiled from 13 Australian and Canadian mines and consist of 254 cases of reported rockbursts (Heal, 2010). The selected rockburst parameters are: stress conditions (E_1), ground support system capacity (E_2), excavation span (E_3), effect of geological structure (E_4), peak particle velocity (PPV). In addition to these, the tensile strength σt and the compressive strength σc of the rock mass were determined on the basis of the available filed reports, to allow calculating the brittleness indices B_1 and B_2 defined as: $B_1 = \sigma_c/\sigma_t$; $B_2 = (\sigma_c - \sigma_t)/(\sigma_c + \sigma_t)$.

The dependent parameter in this study is the rockburst damage scale (RDS) which is being classified. The RDS is defined as R1, R2, R3, R4, and R5; R5 being the most severe. The distribution of the data is shown in Table 1. As it can be seen the RDS is unevenly distributed (imbalanced) with more non-severe rockburst cases, 63 % of R2 and R3 combined together and 37% of severe rockburst cases (R4 and R5). A linear regression showed that the variables have a very poor linear correlation with the RDS. In order to reduce the dimensionality of the data for better efficiency, the damage initiation factor (DIF) and depth of failure factor (DFF) defined as the ratio of E_1/E_2 and the ratio of E_3/E_4, respectively, are also used as input parameters. A sample of the data is provided in Table 1. The rockburst catalog can be found in Heal (2010). The rockburst scales were merged to reduce the unbalance. In this study, 5 scenarios were investigated in order to highlight how the number of rockburst scales impacts the results as follows; 1st scenario: (R2, R3, R4, R5); 2nd scenario: (R2+R3, R4, R5); 3rd scenario: (R2, R3+R4, R5); 4th scenario: (R2, R3, R4+R5); and 5th scenario: (R2+R3, R4+R5).

Table 1. Data sample.

E_1/E_2	E_3/E_4	PPV	B_1	B_1	Actual	Target Vectors
12.00	8.40	0.50	61.64	0.97	R4	(0, 0, 1, 0)
7.50	8.40	0.40	61.64	0.97	R2	(1, 0, 0, 0)
10.00	12.00	1.11	58.21	0.97	R4	(0, 0, 1, 0)
9.38	3.80	1.76	50.80	0.96	R3	(0, 1, 0, 0)
6.00	21.00	1.77	50.80	0.96	R2	(1, 0, 0, 0)
4.50	18.20	2.22	53.90	0.96	R5	(0, 0, 0, 1)
4.50	18.20	2.22	53.90	0.96	R4	(0, 0, 1, 0)
7.41	8.00	3.52	56.06	0.97	R5	(0, 0, 0, 1)

7.41	5.40	1.17	48.92	0.96	R3	(0, 1, 0, 0)
7.41	10.00	1.76	48.92	0.96	R2	(1, 0, 0, 0)
11.00	8.00	2.50	29.68	0.94	R5	(0, 0, 0, 1)

3 RESULTS AND DISCUSSIONS

3.1 Model configurations and training

The RDP model was developed using an artificial neural network (ANN) on MATLAB software. The *Patternnet* function was used to generate the network. The data were randomly divided into three: 70%, 15%, and 15%, as training, validation, and testing datasets, respectively as suggested by other researchers. It is worth mentioning that the main objective behind using both validation and testing is to avoid overfitting. The input data for the modeling included the parameters described in the previous section. The targets were the RDS values which have been assigned as orthogonal vectors (with 1 and 0 as components) because of the classification task. The number of neurons varies from 2 to 200 and hidden layers from 1 to 3. A trial-and-error method was implemented with different configurations till the optimal model was found. Using fewer nodes than possible was necessary in order to avoid overfitting. Logistic sigmoid (Logsig) and softmax transfer functions were applied to the hidden and output layers, respectively. Usually, the softmax function is used by neural networks for multi-classification problems, which returns output between 0 and 1.

A screenshot of the model structure is shown in Figure 1. It can be seen that the model structure in Figure 10 consists of 3 nodes for input variables, 2 hidden layers with 20 nodes in each for training, and 3 output nodes corresponding to the 2nd scenario without brittleness. Figure 2 shows an example of the model validation. It can be seen that the best validation performance corresponding to a loss of 0.19 at epoch 22.

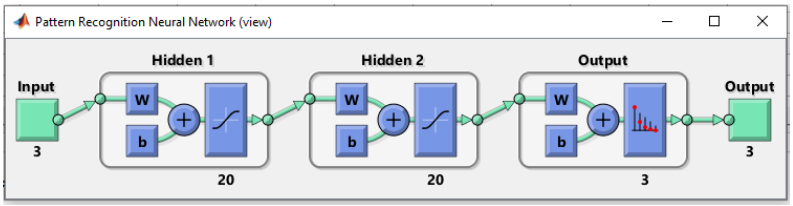

Figure 1. The architecture of the ANN model.

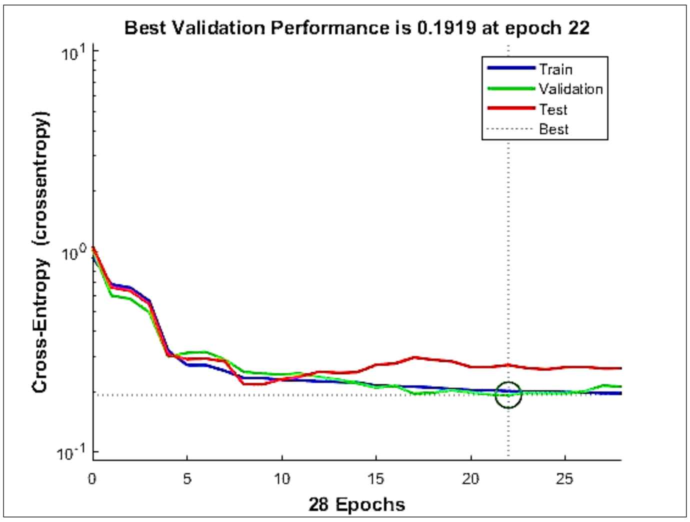

Figure 2. Example of validation performance of the model.

3.2 Classifications

Table 2 shows a sample of the classification corresponding to 1st scenario. As it can be seen, the models failed to correctly classify the R_3 cases. Overall, despite the accuracy of prediction being between 50 and 60%, most of the R_3 cases were misclassified as R_2 class. So, for example, when B1 is considered in the model, only 13 R_3 cases out of 48 cases were properly classified. Such misclassification may occur due to the imbalanced dataset. R_2 rockburst cases account for about half of the observations, therefore the trained model tends to be biased toward predicting correctly R_2 class.

Table 2. Sample of the confusion matrix illustrating the misclassification patterns.

		Target classes (without brittleness)					Target classes (with B_1)				
		R_2	R_3	R_4	R_5	Total	R_2	R_3	R_4	R_5	Total
Predicted as	R_2	103	32	23	4	63.6%	99	25	16	2	69.7%
	R_3	2	9	2	2	60.0%	11	13	14	8	28.3%
	R_4	7	3	33	7	66.0%	5	9	29	6	59.2%
	R_5	4	4	5	14	51.9%	1	1	4	11	64.7%
	Total	88.8%	18.8%	52.4%	51.9%	62.6%	85.3%	27.1%	46.0%	40.7%	59.8%

3.3 Performance evaluation

In addition to the misclassification rate, the performance indictors used to evaluate the models included, precision, recall and F_{1score} as defined in Equations 1-3. In these equations TP, FP and FN stand for: true positive, false positive and false negative, respectively.

$$p(precision) = \frac{TP}{TP + FP} \tag{1}$$

$$r(recall) = \frac{TP}{TP + FN} \tag{2}$$

$$F_{1score} == 2\frac{pr}{r + p} \tag{3}$$

The TP, FP and FN values obtained from the confion matrices were used to calculate these performance indicators. The results for the 1st and 5th scenarios, are provided in Tables 2 and 3, respectively. In the 1st scenario, R_3 class has been poorly classified regardless of the brittleness. In the 5th scenario, the effect of the brittleness is clear with an increase of 4-6% of the F_{score}.

Table 2. Performance evaluation for the 1st scenario.

RDS	No Brittleness			$\boldsymbol{B_1}$			$\boldsymbol{B_2}$		
	Precision	Recall	$\boldsymbol{F_{1score}}$	Precision	Recall	$\boldsymbol{F_{1score}}$	Precision	Recall	$\boldsymbol{F_{1score}}$
R_2	63.6%	88.8%	74.1%	69.7%	85.3%	76.7%	66.0%	90.5%	76.4%
R_3	60.0%	18.8%	28.6%	28.3%	27.1%	27.7%	61.5%	16.7%	26.2%
R_4	66.0%	52.4%	58.4%	59.2%	46.0%	51.8%	54.8%	54.0%	54.4%
R_5	51.9%	51.9%	51.9%	64.7%	40.7%	50.0%	65.0%	48.1%	55.3%
Average	60.4%	53.0%	53.3%	55.5%	49.8%	51.6%	61.8%	52.3%	53.1%

Table 3. Performance evaluation for the 5th scenario.

RDS	No Brittleness			$\boldsymbol{B_1}$			$\boldsymbol{B_2}$		
	Precision	Recall	$\boldsymbol{F_{1score}}$	Precision	Recall	$\boldsymbol{F_{1score}}$	Precision	Recall	$\boldsymbol{F_{1score}}$
$R_2 + R_3$	82.4%	93.9%	87.7%	86.8%	92.1%	89.3%	87.6%	95.1%	91.2%
$R_4 + R_5$	85.1%	63.3%	72.6%	83.8%	74.4%	78.8%	89.5%	75.6%	81.9%
Average	83.8%	78.6%	80.2%	85.3%	83.3%	84.1%	88.6%	85.4%	86.6%

3.4 Discussions

Overall, all models indicate an increase in the classification rate with the decrease in RDS classes. There were 3 scenarios with 3 RDS classes. The F_{1score} of R_3 class is very low for scenarios 1 and 3, where the R_3 the class was not combined with other classes. However, combining the R_2 and R_3 classes significantly improved the accuracy of the models. On the other hand, the results were also affected by the amount of data (unbalanced data). The maximum accuracy level achieved with scenario 5 was 88.2 % and the F_{1score} was 86.6 %. These results showed superiority over existing works in which the same data were used (Zhou et al. 2016).

It can be also observed that by incorporating the brittleness indices, the model performance has improved. Particularly, the models have shown increased accuracy and precision for higher rockburst damage scales, indicating that the rock brittleness is an important contributor to the rockburst intensity. Thus, for non-severe rockburst (R_2 and its combinations) the increase in F_{1score} ranged from 1.4 % to 13.3 %, whereas the increase in F_{1score} for severe rockburst cases (R_5 and its combinations) was about 3.5-27.9 %. On the other hand, there were also cases when the prediction accuracy was lower for the models considering the brittleness indices, therefore the statement above might not work for all cases but represent the overall picture. In addition to this, the influences of brittleness indices were also compared. In most cases, B_2 has a tendency to show better results compared to B_1.

4 CONCLUSIONS

The aim of this paper was to investigate the effect of the brittleness indices (B1 and B2) on the rockburst damage potential classification performance. ANN classifier models were implemented. The performances of the model were evaluated via the classification rate, precision, recall and F_{1score}.

It was found that ANN classifiers are useful tools to study the RDP. The optimal network structure was found to be two hidden layers with 20 neurons in each layer. Overall accuracy (i.e. success rate) varies between 60-88% depending on the scenarios. These results show superiority over existing studies. The confusion matrices showed that R_3 is the most misclassified RDP class. Most R_3 cases were recognized as R_2. Nevertheless, it was not due to data size; it seemed to have derived from the definition of the R_3 scale. On the other hand, R_2, R_4 and R_5 are the least misclassified in that order.

In general, the model performances increased with the decrease in the number of classes of RDP. This result is in agreement with expectations because the ANN found it easier to recognize fewer labels. However, it is worth mentioning that the data size of each class also impacts the results. The results indicated a variable effect of the brittleness on the accuracy of the results depending on the scenarios and the brittleness indices. Therefore, it is suggested the incorporation of the brittleness indices in the establishment of RDP tools.

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