Open stope stability assessment through artificial intelligence

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Abstract

Underground mining is a set of methods that allows the extraction of ore in depth, ensuring sustainability and economic viability. One of the problems that arise in underground mine operations is open stope stability. The method for assessing stability of open stopes is the stability graph proposed by Mathews et al. (1981). It is possible to estimate and provide information about this stability and assist in the decision making about its viability. With the data obtained from 35 open stopes from a Zinc mine, the present study aims to use artificial intelligence techniques, specifically artificial neural networks, to process the data and classify the open stopes according to the stability regions of the graph. As a result, the applied methodology presented good assertiveness for the classification of two classes, stable and unstable open stopes, resulting in a global probability success of 82% overall hit probability and 18% apparent error rate. For the classification into three classes, adding the transitional open stopes, the internal validation presented a global probability success of 91% and apparent error rate of 9%. In external validation, the network evaluation measures presented values of global probability success of 42% and apparent error rate of 58%.

Keywords: open stope stability, artificial neural networks, artificial intelligence, sublevel stoping.

1. Introduction

Outcropping mineral deposits or those situated near surface are increasingly scarce. Thus, there is a need for research to be carried out in order to better understand the properties of rock masses and the entire Brazilian underground geological context. In addition, it is extremely important to implement new technologies to ensure the productivity of these structures, reducing problems such as dilution and increasing deposit recovery. The stability of the open stopes permits equipment and people safety, in addition to the operation of the underground mine. The costs of open stop stability in an underground mine are less than those resulting from instability in the rock mass, which provokes equipment damage, loss of life and dilution of reserves.

In this study, the underground mining method applied is Vertical Retreat Mining, which is a form of the sub-level mining method. In this scenario, the ore grade decreases as the depth of the mine increases. Another relevant aspect that must be observed is the presence of ore lenses around the excavations. Due to the small thickness of these lenses, they end up influencing the stability of the excavation, generating areas of weakness where cuttlefish fall. This instability can lead to an increase in the operational dilution, which is a worrying factor in view of the increase in the cost of transportation, in the problems caused in the beneficiation stage, and consequently, in the project's revenue.

The methodology currently used is the stability graph proposed by Mathews *et al.* (1981) for mines 1000 m deep in Canada. However, the results obtained with this methodology have not responded well to the field observations of the mine and, in addition, because it is a methodology empirically proposed, the tendency is that it adapts better to the region where it was proposed. According to Oliveria (2012), it is a constant challenge to estimate this stability in view of anisotropy, heterogeneity, and the presence of discontinuities in rock masses. In relation to the stability graph proposed by Mathews *et al.* (1981), there are contributions made by Potvin (1988), Palkanis (1986) and Mawdesley *et al.* (2001).

In view of these problems, the objective of this study is to propose an alternative methodology to assess the stability of an open stope of an underground mine using artificial intelligence, more specifically, the technique of Artificial Neural Networks (ANNs). This technique capable of receiving an unlimited amount of data and learn its characteristics in order to be able to classify it with the lowest possible error value.

ANN is a computer system structured to receive information, interpret it and make decisions based on training (Nola, 2015). This technique works in a way similar to a neuron, where the system has the ability to "learn" through exposure to a set of input samples combined with the action that would be appropriate for each input (Ferentinou and Fakir, 2017). The application of these techniques has been widely used in rock mechanics and in particular in the prediction of rock properties, such as in the works of Kahraman *et al.* (2010); Rafiai and Jafari (2011); Kumas *et al.* (2011);and Manouchehrian (2012). In addition, other authors were able to predict other geotechnical properties through ANNs, such as in the study by Yang and Rosenbaum (2002), who investigated the availability of estimating the geotechnical properties of a sandstone based on the geological indicators and the study by Celeste and Oliveira (2019), who estimated the resilience module of asphalt pavements.

2. Materials and methods

The original database consists of two variables: number of stability and hydraulic radius, in addition to the stability status, constituting a total of 35 open stopes. Two situations were studied: the classification in two classes, stable and unstable, and the classification into three classes: stable, unstable and transition.

According to Figure 1, the original database was randomly divided into two samples, the training sample for network training and the test sample for network validation, both corresponding to 50% of the original database. Forty networks were trained for each situation; that is, constituting 40 training and test samples selected at random. The network feed was positive, feedforward, and the learning algorithms used were backpropagation (for two classes) and the resilient backpropagation (for three classes).

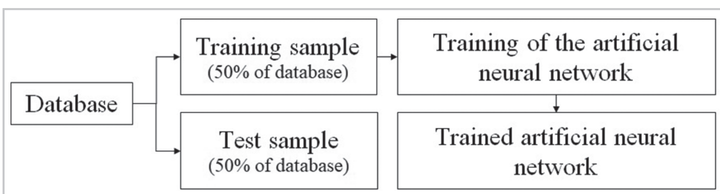

Figure 1 - Flowchart of the applied methodology.ons used in this methodology.

In this study, two forms of validation will be discussed: the internal validation that uses the trained network to predict the classes in the training sample; and external validation that uses the trained network to predict the classes in the test sample. Figure 2 shows the flowchart of validations used in this methodology.

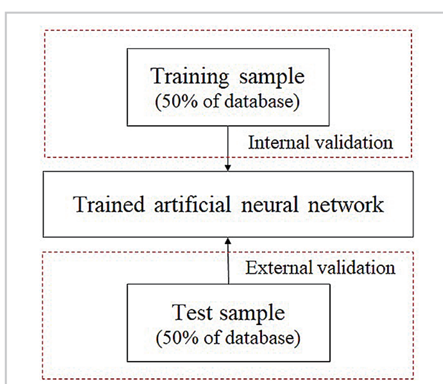

Figure 2 - Flowchart of the validation methodology.

The results of the artificial neural network can be evidenced by confusion matrices shown by Table 1 and Table 2, for the two types of classification studied.

Table 1 - Confusion matrix for the situation with two stability classes.

Confusion matrix 2 classes	Prediction			
	Stable	Unstable	Total	
True	Stable	n_{11}	n_{10}	$n_{11}+n_{10}$
	Unstable	n_{01}	n_{00}	$n_{01}+n_{00}$
	Total	$n_{11}+n_{01}$	$n_{10}+n_{00}$	n_{total}

Table 2 - Confusion matrix for the situation with three stability classes.

Confusion matrix 3		Prediction			
classes		Stable	Unstable	Transition	Total
True	Stable	n_{11}	n_{10}	n_{12}	$n_{11}+n_{10}+n_{12}$
	Unstable	n_{01}	n_{00}	n_{02}	$n_{01}+n_{00}+n_{02}$
	Transition	n_{21}	n_{20}	n_{22}	$n_{21}+n_{20}+n_{22}$
	Total	$n_{11}+n_{01}+n_{21}$	$n_{10}+n_{00}+n_{20}$	$n_{12}+n_{02}+n_{22}$	n_{total}

The values n_{11}, n_{00} and n_{22} are the number of correct predicted in the classification of stable, unstable and transition open stopes, respectively. The values n10 and n_{12} represent the number of stable open stopes that the network has classified as unstable, or transition. The values n_{01} and n_{02} show the number of unstable open stopes classified as stable and in transition. The value n_{21} and n_{20} is the number of transition open stopes classified as stable and unstable, respectively.

The evaluation measures of the trained artificial networks were the global probability of success (GPS) and the apparent error rate (AER). From Equations 1 and 2, we have the calculation of $GPS_{2\ classes}$ and $AER_{2\ classes}$, respectively for classification into two classes. In Equations 3 and 4, $GPS_{3\ classes}$ and $AER_{3\ classes}$ are calculated, respectively, for classification into three classes.

$$GPS_{2\ classes} = \frac{n_{11}+n_{00}}{n_{10}+n_{11}+n_{01}+n_{00}} * 100 \quad (1)$$

$$AER_{2\ classes} = \frac{n_{10}+n_{01}}{n_{10}+n_{11}+n_{01}+n_{00}} * 100 \quad (2)$$

$$GPS_{3\ classes} = \frac{n_{11}+n_{00}+n_{22}}{n_{10}+n_{11}+n_{01}+n_{00}+n_{22}+n_{20}+n_{21}+n_{12}+n_{02}} * 100 \quad (3)$$

$$AER_{3\ classes} = \frac{n_{21}+n_{12}+n_{02}+n_{01}}{n_{10}+n_{11}+n_{01}+n_{00}+n_{22}+n_{20}+n_{21}+n_{12}+n_{02}} * 100 \quad (4)$$

In the classification into two stability classes: stable open stopes and unstable open stopes, the database had a total of 23 highlights. The package used was the neuralnet package, proposed by Fritsch and Günther (2010). The network configuration is in accordance with Haykin (1999). Two neurons were used in the middle layer, with a hyperbolic tangent activation function. Figure 3 illustrates the structure of the network used.

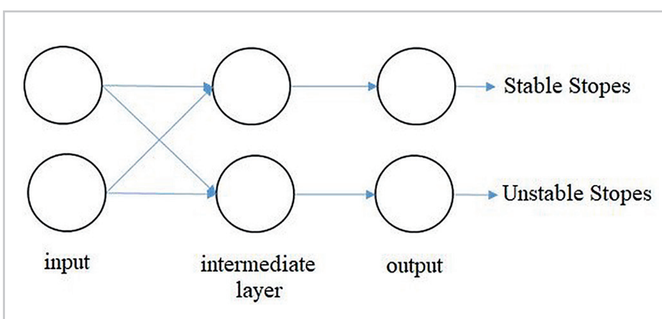

Figure 3 - Structure of the artificial neural network used for classification into two stability classes.

The network errors in this situation were calculated and classified as type 1 and type 2, considering only the network errors as a universe. These errors were identified as error 1 where the unstable open stopes are classified as stable (Equation 5); and error 2 where stable open stopes are classified as unstable (Equation 6).

$$Error\ 1 = \frac{n_{01}}{n_{10}+n_{01}} * 100 \quad (5)$$

$$Error\ 2 = \frac{n_{10}}{n_{10}+n_{01}} * 100 \quad (6)$$

In the case of three stability classes: stable open stope, transition open stope and unstable open stope, the database had a total of 35 open stopes. The package used was the neuralnet package, proposed by Fritsch and Günther (2010). In this problem, two intermediate layers were used with four neurons in each layer, with a hyperbolic tangent activation function. The network learning algorithm was the resilient backpropagation. Figure 4 illustrates the structure of the network used.

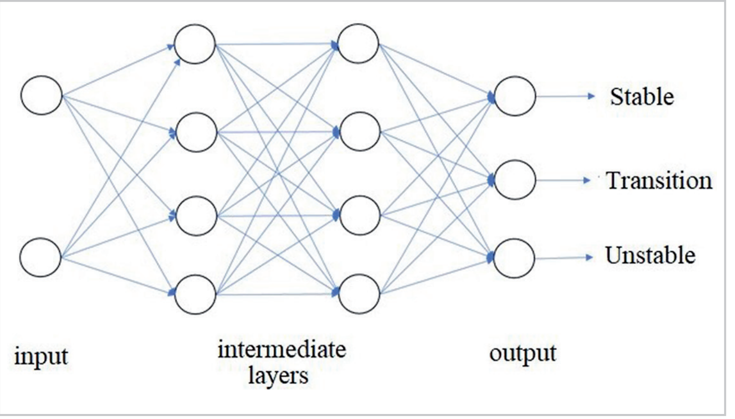

Figure 4 - Structure of the neural network used for classification into three stability classes.

3. Results and discussions

Figure 5 shows the scatterplot graphs for the hydraulic radius of variables and stability number for the open stopes in the two classification situations under study, being the condition for two classes and the condition for three classes. It is observed that the distribution of the open stopes in transition makes it difficult to separate into areas, such as in the stability graphs of Mathews *et al*. (1981) and Potvin (1988).

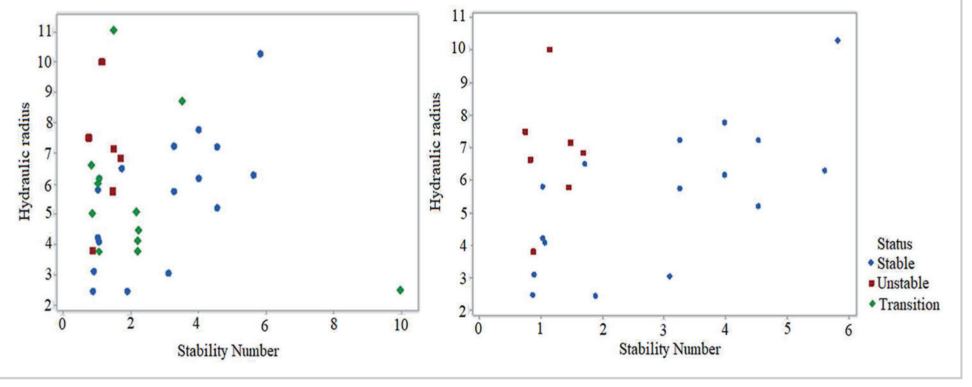

Figure 5 – Dispersion graphs for three-class and two-class stability.

First, for the classification problem in two classes: stable open stope and unstable open stope, Figures 6 and 7 show the behavior of the $GPS_{2\ classes}$ and $AER_{2\ classes}$ of the network trained in internal and external validation for the 40 iterations performed, respectively. In Figures 6 and 7, notice that in the internal validation, the network presents a stable result, without representative peaks.

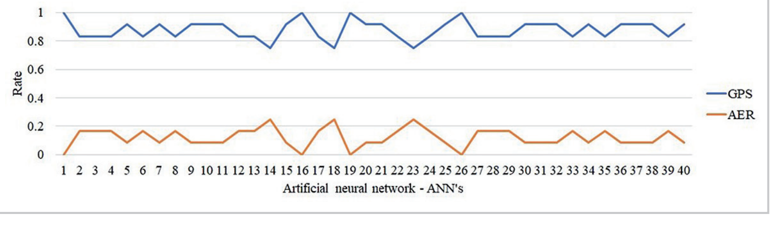

Figure 6 - Result of the internal validation for two stability classes.

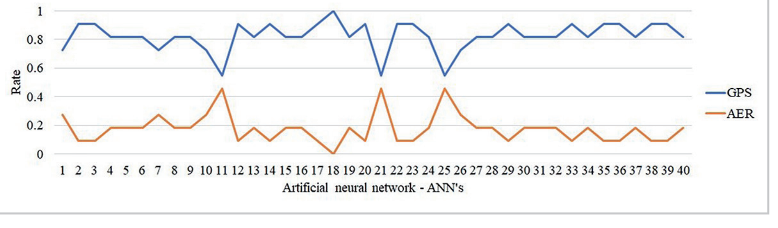

Figure 7 - Result of external validation for two stability classes.

In external validation, it is possible to observe three peaks of increase in $AER_{2\ classes}$, but if compared to the number of iterations performed, these isolated peaks do not compromise the stability of the network. In addition, it is possible to observe points where the network correctly classifies all highlights. Table 3 shows the statistical summary of the results of the network.

Table 3 - Statistical summary of the classification results for two stability classes.

Validation	Variablel	Average	Minimum	Maximum
Internal	$GPS_{2\ classes}$	0.88	0.75	1.00
Internal	$AER_{2\ classes}$	0.12	0.00	0.25
External	$GPS_{2\ classes}$	0.83	0.55	1.00
External	$AER_{2\ classes}$	0.17	0.00	0.45
Internal	Error 1	0.61	0.00	1.00
Internal	Error 2	0.29	0.00	1.00
External	Error 1	0.43	0.00	1.00
External	Error 2	0.55	0.00	1.00

In validations, the network presented an average $GPS_{2\ classes}$ of 88% and 83%, with a minimum value of 75%. This is a remarkable result since the network presents high values of global probability of correctness in the great majority of the iterations it performs. In relation to $AER_{2\ classes}$, when stratifying the two types of errors that the network can make, Error 1 appears with greater recurrence, representing on average 61% of the total errors of each generated network, as shown in Table 3. Error 2 represents on average 29% of the total errors of each generated network. This can interpret as a non-conservative trend in the network, since Error 1, whose unstable open stopes were classified as stable, occurred more frequently. Figure 8 shows what one of the networks obtained for this classification condition.

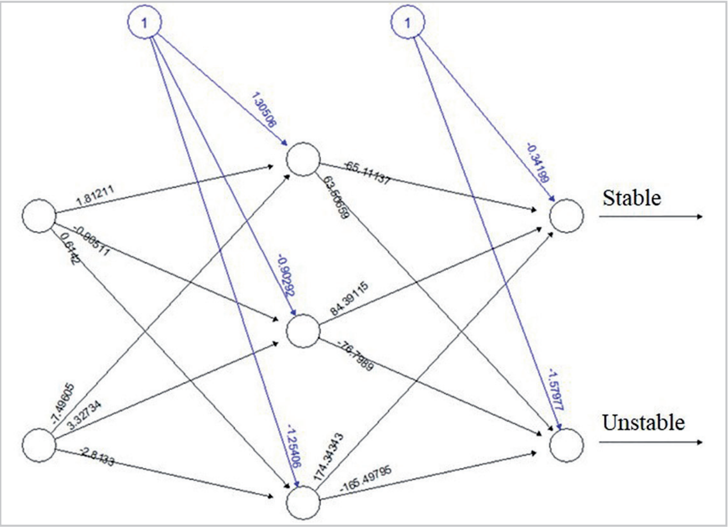

Figure 8 - Result of the artificial neural network, in the classification in two classes.

Regarding the results for the classification problem into three classes: stable, unstable and transition enhancements, Figures 9 and 10 show the results obtained regarding $GPS_{3\ classes}$ and $AER_{3\ classes}$, in the internal and external validations, respectively. Table 4 shows the statistical summary for the neural network assessment measures.

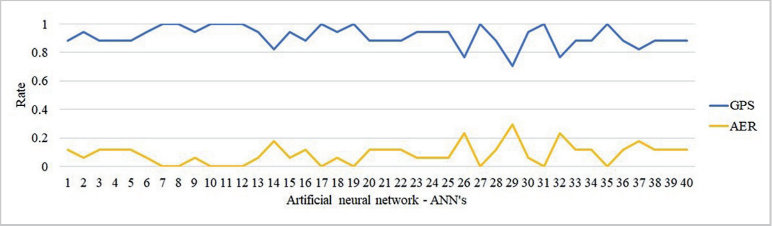

Figure 9 - Result of internal validation for three stability classes.

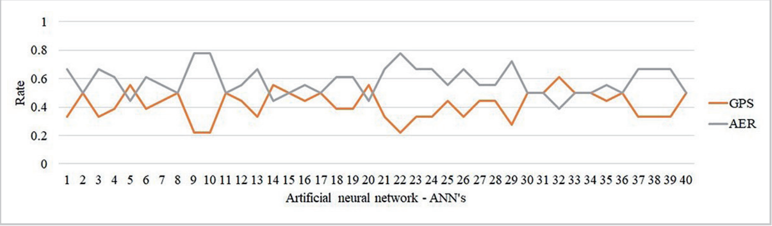

Figure 10 - Result of internal validation for three stability classes.

Table 4 - Statistical summary of the classification results for three stability classes.

Validation	Variable	Average	Minimum	Maximum
Internal	$GPS_{3\ classes}$	0.91	0.71	1.00
Internal	$AER_{3\ classes}$	0.09	0.00	0.29
External	$GPS_{3\ classes}$	0.42	0.22	0.61
External	$AER_{3\ classes}$	0.58	0.39	0.77

In the internal validation the $GPS_{3\ classes}$ was, on average, equal to 91%, with maximum values of 100% in some iterations, and the $AER_{3\ classes}$ equal to 9% on average, and these are very relevant results due to the complexity of the problem. Regarding external validation, the results oscillated in average values of 42% and 58%, for GPS3 $_{classes}$ and $AER_{3\ classes}$, which are considered low values. The low number of enhancement data and the complexity of the classification in three overlying classes culminated in these results. Figure 11 shows one of the networks obtained for the condition of classification into three classes: stable, unstable and transition highlights.

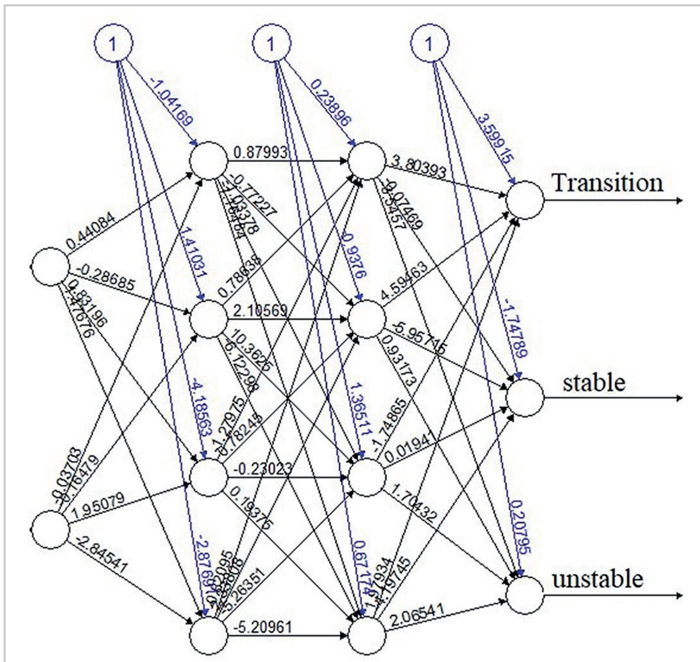

Figure 11 - Result of the artificial neural network, in the classification in three classes.

4. Conclusions

The proposed methodology proved to be capable of being used to assess the open stope stability. The networks were able to identify patterns and satisfactorily classify the studied open stopes. Two situations were presented: two stability classes and three stability classes. The results for the first situation proved to be more effective.

In the first situation addressed, for internal validation, on average the $GPS_{2\ classes}$ was 88% and $AER_{2\ classes}$ was 12% and for external validation, on average the rates were 83% and 17%. In the classification for three classes, the most complex situation studied in herein, the results for internal validation were 91% for $GPS_{3\ classes}$ and 9% for $AER_{3\ classes}$. However, for external validation the results were not satisfactory, with the $GPS_{3\ classes}$ found equal to 42% and the $AER_{3\ classes}$ equal to 58% and this may be due to the small number of data available for the study.

This research is innovative and the results obtained can be an alternative methodology to the Stability Graph, mainly considering the results of the situation for two classes.

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