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Stochastic assessment of pillar stability at Laisvall mine using Artificial Neural Network

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ABSTRACT

Stability analyses of any excavations within the rock mass require reliable geotechnical input parameters such as in situ stress field, rock mass strength and deformation modulus. These parameters are intrinsically uncertain and their precise values are never known, hence, their variability must be properly accounted for in the stability analyses. Traditional deterministic approaches do not quantitatively consider these uncertainties in the input parameters. To incorporate these uncertainties stochastic approaches are generally used. In this study, a stochastic assessment of pillar stability using Artificial Neural Network (ANN) is presented. The uncertainty in the rock mass properties at the Laisvall mine were quantified and the probability density function of the deformation modulus of the rock mass was determined using probabilistic approach. The variability of the in situ stress was also considered. The random values of the deformation modulus and the horizontal in situ stresses were used as input parameters in the FLAC^{3D} numerical simulations to determine the axial strain in the pillar. ANN model was developed to approximate an implicit relationship between the deformation modulus, horizontal in situ stresses and the axial strain occurring in pillar due to mining activities. The closed-form relationship generated from the trained ANN model, together with the maximum strain that the pillar can withstand was used to assess the stability of the pillar in terms of reliability index and probability of failure. The results from this study indicate that, the thickness of the overburden and pillar dimension have a substantial effect on the probability of failure and reliability index. Also shown is the significant influence of coefficient of variation (COV) of the random variables on the pillar stability. The approach presented in this study can be used to determine the optimal pillar dimensions based on the minimum acceptable risk of pillar failure.

1. Introduction

A pillar can be defined as the in-situ rock mass between two or more underground openings. It is the main support in room and pillar mines. The support provided by the pillars controls the rock mass displacement throughout the zone of influence of mining, while the mining proceeds.

The analysis and design of mine pillars generally seek to optimize the size of the pillars so as to maximize the extraction ratio (i.e. amount of ore extracted relative to the total amount of ore available) while maintaining the stability of the mine. Hence the design of pillars has both economic and safety implications. The knowledge of the pillar strength and the determination of the required safety factor for a given loading condition are the most important aspects of pillar design. Conventional pillar design methods comprise the calculation of the mean pillar stress (e.g. the tributary area method and the method by Coates (1981) and the estimation of the pillar strength using empirical formulae (e.g. Obert and Duvall, 1967; Krauland and Söder, 1987; Sjöberg, 1992). Based on the stress and strength of the pillar the factor of safety can be calculated. The factor of safety is the ratio of the pillar strength to the induced stress in the pillar and the pillar fails when the ratio is less than 1.

Though the conventional methods are widely used for pillar design, Alber and Heiland (2001) have expressed some concerns about this conventional approach for pillar design at shallow depth. They observed that the pillar failure at shallow depth could not be properly explained by comparing pillar strength with stresses induced on the pillar by mining activities. They suggested amongst other approaches that pillar failure could be related to strain. Therefore, when considering the strain occurring in the

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pillar the factor of safety can be determined as the ratio of the maximum strain that a pillar can withstand to the strain occurring in the pillar due to mining activities. Nevertheless, either ways of determining the factor of safety are largely deterministic and do not consider the inherent variability of the rock mass properties and that of the in situ stress field. Mean values of these input parameters are generally assumed. The results from the deterministic approach could be misleading depending on the distributive character of the rock property variation (Kim and Gao, 1995). Deng et al. (2003) have reported instances where pillars failed despite the fact that the failed pillars had been considered stable with factor of safety greater than 1.

Therefore, for a reliable design and analysis of construction elements such as mine pillars appropriate methods which incorporate the variability in the rock mass properties must be used. The methods which consider this variability are known as stochastic or probabilistic methods. With a stochastic approach, the stability analysis can be considered as a random system, where the occurrence of a pillar failure is a random event depending on the outcome of the random variables involved.

A number of stochastic approaches have been applied to various geotechnical problems, including underground excavation problems (e.g. Chen et al., 1997; Lilly and Li, 2000; Cai, 2011; Idris et al., 2011; Dohyun et al., 2012), tunnel support (e.g. Schweiger et al., 2001; Li and Low, 2010; Oreste, 2005), subsidence (e.g. Torano et al., 2000) and pillar stability (e.g., Pine, 1992; Joughin et al., 2000; Griffiths et al., 2002; Deng et al., 2003; Cauvin et al., 2009; Najafi et al., 2011; Recio-Gordo and Jimenez, 2012; Wattimena et al., 2013). Pine (1992) presented a probabilistic approach for pillar design whereby normal probabilistic distributions were assumed for the random variables and the safety margin. Joughin et al. (2000) employed the point estimate method (Rosenblueth, 1981) to account for rock strength variability in the probabilistic method they presented for the design of chromite pillars in South Africa. Griffiths et al. (2002) analysed the stability of underground pillar by using random field theory with elasto-plastic finite element algorithm in a Monte Carlo framework. Deng et al. (2003) presented a probabilistic mine design method which combines the finite element methods, neural network and reliability analysis. Cauvin et al. (2009) used probabilistic approach to assess the effect of uncertainty in mining pillar stability analysis. Najafi et al. (2011) utilized First Order Second Moment (FORM) and Advanced Second Moment (ASM) for the probabilistic stability analysis of chain pillar in a coal mine in Iran. A probabilistic model based on linear classifier theory to predict the behaviour of pillar in longwall and retreat room and pillar mining was presented by Recio-Gordo and Jimenez (2012). Wattimena et al. (2013) employed logistic regression to predict the probability of coal pillar stability for given pillar geometry and stress condition.

In general, stochastic assessment of pillar stability is performed by two procedures: the first step is to quantify the uncertainty in the rock mass properties in order to determine the basic statistical parameters (i.e. mean and variance) and probability density functions (PDFs) of the strength and deformation modulus of the rock mass using the Monte Carlo method. The Monte Carlo (MC) simulation technique is often adopted in the geotechnical stochastic analyses with implicit or explicit solutions but when the analysis is associated with numerical modelling then the MC simulation technique becomes time consuming and less appealing.

In the second step, the probability of failure is determined with respect to a specific failure criterion, which can either be the induced pillar stress exceeding the pillar strength or the strain occurring in the pillar exceeding the defined threshold strain value for the pillar. The onset of failure in the context of this study is defined as the limit state when the peak strength of the pillar is exceeded or the strain occurring in the pillar exceeds the peak strain for the pillar. For underground excavations this limit state is not known explicitly, instead numerical analysis using the finite difference method (FDM) or the finite element methods (FEM) can be combined with function approximation tools to construct a closed-form expression for the limit state surface. Recently, many function approximation tools have been proposed such as the response surface method (RSM), the point estimate method (PEM), and the Artificial Neural Network (ANN) to model the relationship. ANN, due to its high performance, has been one of the tools used in geotechnical engineering to model the relationship between non-linear multivariate variables (Sonmez et al., 2006).

In this study, a stochastic approach was used to analyse the pillar stability at the Laisvall mine in Sweden while considering the variability in the rock mass properties and in the in-situ stresses. The uncertainty in the rock mass properties at the Laisvall mine were quantified and the probability density function of the deformation modulus of the rock mass was determined. Also the variability of the horizontal in situ stresses was considered. The random values of these parameters (i.e. deformation modulus and horizontal in situ stresses) were used as input parameters for the FLAC^{3D} (Itasca, 2012) analyses to determine the axial strain in the pillar. The ANN model was developed to approximate an implicit relationship between the deformation modulus, horizontal stresses and the pillar axial strain within the range of possible values of the random input parameters. The closed-form relationship generated from the trained ANN model together with critical axial strain, which the pillar can withstand, was used to define a pillar performance function. The performance function was used to assess the stability of the pillar in terms of probability of failure and reliability index.

1.1. Artificial Neural Network (ANN)

The ANN, also referred to as neural network, is an information system that imitates the behaviour of the human brain by emulating the operation and connectivity of the brain to generate a general solution to a problem. ANN can be used to extract patterns and detect trends from problems where the relationship between the inputs and outputs are not sufficiently known. In recent years, ANN has been frequently used for functions approximation in different fields of science, including geotechnical engineering (Sahin et al., 2001). Basically, ANN consists of simple interconnected nodes or neurons as shown in Fig. 1 where p is the input, w is the weight, b is the bias, f is the transfer function and a is the output.

If the neuron has N number of inputs then the output a can be calculated as:

$$a = f(\sum_{i=1}^{N} w_i p_i + b) \tag{1}$$

There are different types of transfer functions that can be used in ANN such as hard limit transfer function, linear transfer function, log-sigmoid transfer (Beale et al., 2012). The choice of the transfer function depends on the specification of a problem that the neuron is attempting to solve (Beale et al., 2012).

The architecture of ANN consists of the number of layers, the number of neurons in each layer and the neuron transfer functions. Two or more neurons can be combined in a layer and a network

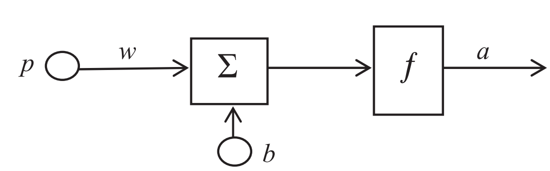

Fig. 1. Simple structure of ANN model.