A holistic open-pit mine slope stability index using Artificial Neural Networks

Muhammad Fakir [1], Ferentinou Maria [1]

mmuhammadfakir@gmail.com, mferentinou@uj.ac.za

University of Johannesburg, Johannesburg, South Africa

Abstract

The slopes in open-pit mines are typically excavated to the steepest feasible angle to maximize profits. However, there is a greater risk of slope failure associated with steeper slopes. An open-pit slope represents a complex multivariate rock engineering system. Interactions between the factors affecting slope stability in open pit mines are therefore more complex and often difficult to define, impeding the use of conventional methods. To address the problem, the primary role of rock mass structure, in situ stress, water flow, and construction have been extended into 18 key parameters. The stability status of slopes and parameter importance are investigated by means of computational intelligence tools such as Artificial Neural Networks. An optimized Back Propagation network is trained with an extensive database of 141 worldwide case histories of open-pit mines. The inputs refer to the values of extended parameters which include 18 parameters relating to open-pit slope stability. The produced output is an estimated potential for instability. To minimize the subjectivity, the method of partitioning the connection weights is applied in order to rate the significance of the involved parameters. The problem of slope stability is therefore modelled as a function approximation. A new Open-pit Mine Slope Stability Index is thus proposed to assess the potential status regime from a holistic point of view. These values are validated by computing the predicted values against the observed status of stability. The reliability of the predictive capability is computed as the Mean Squared Error, and further validated through a Receiver Operating Characteristic curve. Together with a Mean Squared Error of 0.0001, and Receiver Operating Characteristic curve of 98%, the application illustrates that the prediction of slope stability through Artificial Neural Networks produces fast convergence giving reliable predictions, and thus being a useful tool at the preliminary feasibility stage of study.

INTRODUCTION

In order for a mining company to make full use of its mineral resource, the final slopes are generally as steep as possible (Sjoberg, 1999). A change in slope angle by as little as 2 – 3 ° can be measured in hundreds of millions of dollars in project revenue (Lilly, 2002). However, the risk of steeper slope angles increases the risk of slope failure. Conventional methods of open-pit slope stability design is typically based on the assumed failure mechanism, which include planar, wedge, toppling, and shear failure (Wylie and Mah, 2004). Open-pit mines are therefore associated with large scale rock slopes, which form complex rock engineering systems (Franz, 2009). Slope failure is therefore often a combination of failures along pre-existing geological planes of weakness and failure of intact rock (Sjoberg, 1999). The complexity of the failure results from various factors affecting the stability, which include, amongst others, the geological setting, the geometry of the slopes, the tectonic environment, and/or the short and long term precipitation (Flores & Karzulovic, 2000).

Artificial Neural Networks (ANN) provide a powerful tool to evaluate such complex rock engineering systems. The idea behind the ANN approach stems from the fact that intelligent machines are capable of replicating functions of the human brain such as pattern recognition and modelling of non-linear relationships of multivariate dynamic systems (Haykin, 1994). The Rock Engineering Mechanism Information Technology (REMIT), developed by Hudson (1992), established essential parameters for knowledge infrastructure of rock engineering. This includes a list and description of all the rock properties and their associated descriptions for the rock engineering mechanisms.

Open-pit mines represent a non-linear multivariate dynamic system, where only a broad view of the physical and geometric parameters of the slope can be determined. The study therefore employs the ANN, which is capable of achieving non-one-to–one mapping (Jing and Hudson, 2002), to address slope stability, both as a function approximation problem, and as a classification problem. An ANN is trained using the knowledge extraction algorithm, Back Propagation (Gradient Decent) (BP), based on case histories from an extensive and worldwide database of open-pit rock slope stability, building on Naghadehi (2013). A new Open-pit Mine Slope Stability Index (OMSSI) is proposed which, in addition to general rock mass classifications, takes into account the complex interaction between rock engineering parameters and their influence on stability in a holistic approach.

PREVIOUS STUDIES

There are various geotechnical engineering publications which make use of the ANN modelling approach in rock and soil mechanics. The growing interests in this subject stems from the fact that these systems are efficient for functions such as pattern recognition and the modelling of non-linear relationships of multivariate dynamic systems (Ferentinou & Sakellariou, 2015). Complex engineering mechanisms behaviours are determined by various interactive parameters, which are made up of complex interactions, much of which is not fully understood (Hudson, 1992). Hudson (1992) developed the Rock Engineering Mechanism Information Technologies (REMIT). From this, he produced the fundamental concepts of the infrastructure of rock engineering. These include a comprehensive list of all the rock properties and description of all rock mechanics and rock engineering mechanisms. However, still under research is the individual parameter interaction intensity and parameter dominance for rock engineering systems (Ferentinou & Sakellariou, 2015). Millar and Hudson (1994) applied two ANN's to monitor the performance of rock masses for mining geomechanics. Utilizing parameters from the RMR (Bieniawski 1989) as an example, they concluded that the simulation of ANN processing rules is capable of reproducing fundamental characteristics of rock mass behaviour in a qualitative manner. Neaupane and Achet (2004) presented a case study of landslide monitoring and evaluation at Okharpauwa, Nepal. Slope movements were predicted by means of a BP neural network. Apart from the antecedent rainfall, soil profile, groundwater level and shear strength of soil, an infiltration coefficient was introduced to the network architecture. The produced BP network illustrated slope movement prediction results that were promising and fairly accurate. Wang et al (2004) demonstrated the use of a BP neural network for the case of a landslide in Hubei Province of China. The predicted results indicated the landslide to be in a marginally stable condition. Sakellariou and Ferentinou (2005) presented a study of slope stability prediction using neural networks. Geometrical and geotechnical parameters were utilized as inputs, and the output was the factor of safety. The relative importance of the selected parameters were studied using the method of partitioning the weights and compared to the results obtained with Index Information Theory. Farrokhzad (2008) developed an ANN to predict slope stability at a specified location. The result was compared with older analysis (Bishop's model) methods to assess the validity of the BP network employed. It was concluded that the BP results were considerably close to the conventional analysis results. The prediction of slope stability agreed with values obtained from the Bishop's method.. The application of ANN to slope stability has not being restricted to natural slopes. Lin et al. (2008) aimed at creating an empirical model for assessing failure potential of highway slopes. Special attention was given to the failure characteristics of the highway slope in Alishan, Taiwan, prior to and post, 1999 Chi Chi earthquake. A database of 955 slope records from four highways constituted the basis of the study. The ANN produced was utilised to learn from the database, and thereafter used to study the effects of the earthquake movement on slope stability characteristics. The trained network proved to be effective in classifying slope performance records into groups of stable and failed slopes, using nine influencing variables. Furthermore, the predictive capability of the ANN was high and satisfactory for both training and testing data. Naghadehi (2013) proposed a Mine Slope Instability (MSII) to assess the stability conditions of slopes from 84 case histories worldwide. Eighteen parameters that are obtainable and rated in the field, and that are considered to be most important were used for the MSII definition. Shahin et al. (2001) presents a general overview of some of the applications of ANN in solving some geotechnical problems. The applications include pile capacity prediction (Goh, 1994a, 1995b; Chan et al., 1995; Lee and Lee, 1996; Abu-Kiefa, 1998) settlement foundations, (Goh 1994a, 1995c; Sivakugan, 1998; Shahin et al., 2000) soil properties and behaviour (Goh, 1995; Ellis et al., 1995; Cal 1995; Gribb and Gribb, 1994), liquefaction (Goh, 1994b; Najjar and Ali, 1998; Ural and Saka, 1998) site characterisation, (Zhou and Wu, 1994; Basheer et al., 1996; Rizzo et al., 1996), earth retaining structures (Goh et al., 1995), slopes stability (Ni et al., 1996) and the design of tunnels and underground openings (Shi et al., 1998; Lee and Sterling, 1992). Based Shahin et al. (2001), it was concluded that ANNs perform better than, or as well as, conventional methods.

COMPILATION OF WORLDWIDE DATABASE

Influencing Parameters

Hudson (1992) proposed an 'atlas' of categories of factors that affect the stability of generic rock slopes. This is observed as the core list of the research with regards to stability of the slopes. The selection of parameters is based on the recommendations from literature and also builds on the parameters introduced by Naghadehi (2013), which take into account the details of open pit slopes. Eighteen parameters are divided into 9 main groups (Figure 1), which represent those parameters and are regarded to be the key influencing factors with regards to the potential for slope instability in open-pit mines. The parameters descriptions and ratings are defined below. Each parameter corresponds to a rating value with 5 or 6 intervals provided in Table I. Each interval being rated by values ranging from 0.0 to 1.0. The higher the rating, the greater its contribution toward potential slope instability.

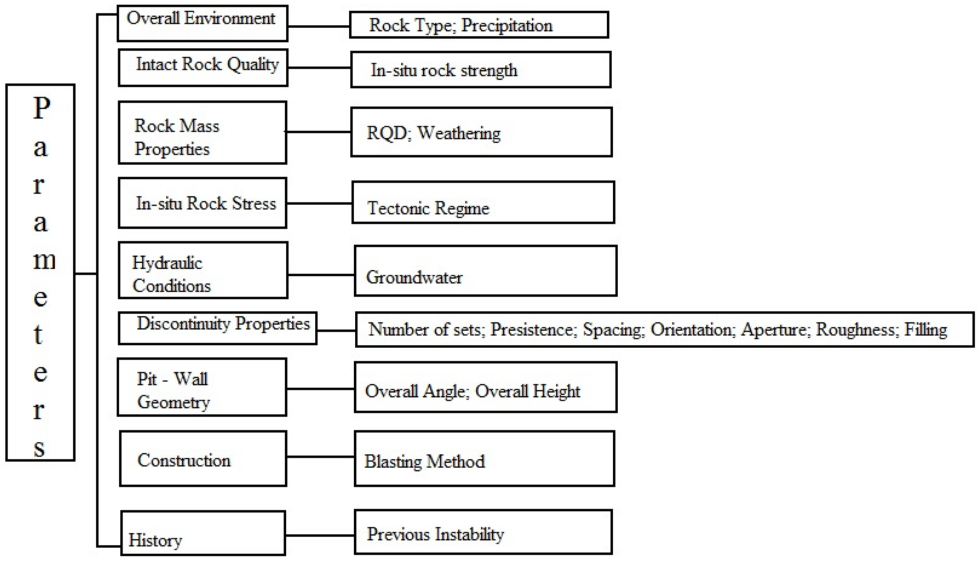

Figure 1: Selected parameters for the system (modified after Naghadehi, 2013)

1. Overall Environment

- Rock type (ROCK): Different lithologies will affect the slope in different ways due to the nature and origin of the rock types. Weaker rocks such as shale can be a major controlling factor concerning slope instability. Whereas in stronger rocks such as granites, the stability may primarily be dictated by the major discontinuities. Furthermore, in rock types such as limestone, solution features (karst features) along discontinuities may trigger failures (Ulusay, 2013). The rock types in this study are classified into six groups depending on their lithological characteristics.

- Precipitation (MAP): Includes both rainfall and snow. Precipitation is highly associated with slope failure and often contributes as a triggering mechanism, often leading to landslides, or reactivation of failures (Naghadehi, 2013). Saturated material is known to be weaker than unsaturated material, and thus, rising of the groundwater table due to periods of heavy rainfall, or continuous periods of rainfall, may in fact provide destabilizing forces, through an increase in the unit weight and the build-up of water pressure in the fractures (Naghadehi, 2013). The mean annual precipitation is classified into five classes ranging from <15 mm/year to >600 mm/year.

2. Intact Rock Quality

- Intact rock strength (UCS): The unconfined compressive strength (UCS) is used to classify the intact rock strength. This parameter is important as it is directly associated with the rock mass rating (RMR), and mining rock mass rating (MRMR) (Bieniawski, 1989). The UCS is divided into six classes ranging from >150 MPa to <25 MPa.

3. Rock Mass Properties

- Rock quality designation (RQD): Fracturing of the rock mass at the slope face is indicated by the RQD (Deere et al., 1967; Deere and Deere, 1988). The RQD values are divided into five classes succeeding the intervals of the RMR produced by Bieniawski (1989)

- Weathering (W): Rocks may undergo degradation when exposed to atmospheric conditions and/or hydrothermal fluids through rock mass (Ulusay, 2013). This degradation exhibits itself in the form of weathering or alteration, depending on the process involved. Weathering degrades the strength of hard rocks by increasing the void ratio and reducing the bonding strength (Ulusay, 2013). Soft rocks may be transformed into residual soils. Weathering also influences the joint spacing and filling of discontinuities (Ulusay, 2013). Therefore, both physical and chemical weathering increase instability of slopes (Giani, 1992; Calcaterra & Parise, 2010). The weathering classification is adapted from the ISRM weathering classification (2007), ranging from 'Fresh (W1)'to 'Completely weathered (W5)'

4. Tectonic conditions and in-situ stress:

- Tectonic regime (TECT): The tectonic history of a rock mass has a major influence on the in-situ stress (Read & Stacey, 2009). Rock masses are subjected to in situ stresses by the weight of the overlying strata as well as the tectonic stress. The World Stress Map demonstrates the earth's tectonic history (WSM, 2008) and shows that the orientation of the maximum horizontal stress is dependent on the location in the tectonic plate (Zoback, 1992, 1997). There is however, a lack of in-situ stress measurements in most open pit mines and thus, the 'tectonic regime' (Rozos et al, 2008) is considered in this study. Naghadehi (2013) states that although the use of tectonic regime introduces uncertainty, it also allows the development of the field estimations more easily. This study furthermore takes into account measurements from the World Stress Map (2008) within the classification of the "tectonic regime". The parameter ratings range from 'Slightly Active' to 'Very Active' based on Rozos et al (2008), the focal measurements of the World Stress Map, as well as relative proximity to and number of plate boundary events (PBE). Where higher focal measurements, close proximity to, and high number of PBE, produces higher ratings.

5. Hydraulic Conditions:

- Groundwater (GRW) percolating through rock reduces the strength. The process therefore reduces the stability of the slope due to a decrease in shear strength as a result of the reduced effective stress (Naghadehi, 2013). The parameter rating is divided following the RMR (Bieniawski, 1989) and SMR (Romana, 1985) classifications.

6. Discontinuity properties

- Number of major discontinuity sets: (DNUM): Discontinuities occur in sets, with some degree of 'clustering' around favoured orientations (Hudson & Harrison, 2001). The number of such discontinuity sets describe the specific rock mass geometry and the block shape and size (Hudson & Harrison, 2001). The block shape and rock mass (an)isotropy are also influenced by the number of discontinuity sets. The parameter is divided into five classes ranging from 0 to more than 3 discontinuity sets.

- Discontinuity persistence (DPER): The discontinuity persistence expresses the range of the discontinuity in the plane (Hudson & Harrison, 2001). The length of the discontinuity impacts the size of blocks that may be formed, and has a major effect on the rock mass strength (Jimenez-Rodriguez & Sitar, 2006). The traditional classes for the parameter are revised to take into account the mutual scales in open pit mine (Naghadehi, 2013).

- Discontinuity Spacing (DSP): Spacing is the distance between contiguous discontinuity intersections (Hudson & Harrison, 2001). Frequency is the reciprocal of spacing, i.e., the mean of the intersection distances (Hudson & Harrison, 2001). The spacing therefore affects the block size within the rock mass and the overall behaviour. For example, many closely spaced joint sets will be likely to to produce isotropic conditions with low cohesion, whereas widely spaced joint sets will produce interlocking conditions (Wylie & Mah, 2004). The classes of this parameter have been altered from the traditional classes of literature to take into account the scale of open-pit mines, with five classes in terms of bench height (Naghadehi, 2013).

- Discontinuity orientation (DOR): The orientation of the discontinuity is defined by the dip direction and dip angle, since the discontinuity is assumed to be planar (Hudson & Harrison, 2001). For the specific slope failure modes, the orientation controls the kinematic admissibility (Jimenez-Rodriguez & Sitar, 1983; Hoek & Bray, 1981). The parameter rating follows Bieniawski (1989) RMR descriptions of 'Very favourable' to 'Very unfavourable'. Building on the recommendations proposed by Romana (1985) SMR, Bieniawski (1989) MRMR and Naghadehi (2013), the specific category is selected according to each case study. The specific rankings are therefore designated according to the relative orientations. This is measured as the differences of the dip direction and dip values of the discontinuities and the excavation surface.

- Discontinuity aperture (DAP): Aperture is defined as the perpendicular distance between the adjacent rock surfaces of the discontinuity (Hudson & Harrison, 2001). An increase in discontinuity aperture promotes further instability by increasing water infiltration, frost wedging, and associated ravelling (Maerz et al., 2005). The classification of the parameter follows Bieniawski (1989) RMR and Romana (1985) SMR.

- Discontinuity roughness (DROUGH): Even though discontinuities are assumed to be planar in terms of orientation and persistence analysis, the surface of the discontinuity may be rough. (Hudson & Harrison, 2001). Discontinuity roughness is directly associated with the shear strength of discontinuities and thus, the stability of slopes and excavations in rock masses (Hoek, 2007; Barton, 1973). Joint roughness may be measured by means of the joint roughness coefficient (JRC). The JRC is the most common index for measuring the roughness. The scale effect on JRC is considered to differentiate between the laboratory and natural conditions (Naghadehi, 2013). The parameter is divided into five classes.

- Discontinuity filling (DF): The type of infilling material plays an important role towards the strength of discontinuities (Hudson & Harrison, 2001). It is therefore important to identify the type of infilling material as well as the strength of the infilling material to be characterised (Naghadehi, 2013). The classification of this parameter follows recommendations by the ISRM (2007) for filling of discontinuities. The parameter rating may range from 'Not filled' to 'Very soft infill'.

7. Pit wall geometry

- Overall slope angle (SL): The slope angle has an important impact on the stability of slopes. The slope angle influences the number of removable blocks that can be formed in a slope in terms of structurally controlled rock masses, (Goodman & Shi, 1985). Furthermore, the steeper the angle, the greater the effect of the driving force on blocks, allowing removable blocks to be prone to failure (Naghadehi, 2013). This parameter is classified following several studies in literature (Naghadehi, 2013; Sjoberg, 1999; Hustruid et al., 2000), from which five classes ranging from '< 30 °' to '> 60 °'.

- Overall slope height (H): The higher the slope, the higher the potential energy for rock blocks. Therefore, the higher the slope, the greater the potential for instability and greater the probability of failure (Kliche, 1999). Furthermore, the stress levels are higher around slopes in deeper pits (Naghadehi, 2013). This parameter is classified into 5 classes ranging from '< 50 m' to '> 300 m'.

8. Construction

- Blasting Method (BL): The type of blasting incorporated in the mine plan is related to the stability of the slope, where damage to the rock face by excessive substantial blasting may cause failure. However light blasting may not be able to excavate at the appropriate rate. The five most common blasting methods in open pit mines according to Hustruid (1999) have been considered to quantify this parameter

9. History

- Previous instability (INST): Evidence of previous instabilities indicate that critical factors may be combining to lead to possible failure. From observation and back-analysis, it is possible to deduce how these factors led to instability and anticipate how they might interact again (Goodman & Shi, 1985). As such, the parameter INST encompasses the time over which the slope is exposed to critical factors combining to produce instability. The parameter has been classified as 'none', 'inactive', 'quiescent', 'relatively active', and 'highly active'.

Database of Case Histories

Geotechnical information with regards to 141 case histories was compiled from 41 open-pit mines from various open pit mines in the world. The data was collected by means of publications and reports from literature, and by direct correspondence with associated mining companies. These cases have been selected according to the available data, as well as being able to provide clear spatial distribution concerning the variability of input parameters. Furthermore, at the time of parameter measurements, each stability status of the slope was also recorded. This allows the categorization of slopes into three main categories according to their status of stability (Kozyrev, 2000; Naghadehi 2013): 'Stable slopes', 'Failure in set of benches (inter-ramp failure)', and 'Overall failure'. In order to quantify the terms for application within the ANN, each term is provided with a rating according to the degree of potential instability. Where Stable = 0, Failure in set of benches = 0.3, and Overall failure = 1.

The ratings have been selected in such a way so as the higher the parameter ratings, the higher the potential for instability. As such, low ratings are associated with stable slopes. Failure in set of benches (inter-ramp failure) is typically associated with structurally controlled failure. There is emphasis based on parameters relating to structurally controlled failure (including discontinuity characteristics), and as such, a rating of 0.3 is provided. Overall failure is given a rating of 1 as the slope is commonly subjected to stress controlled failure. As such, parameter ratings close to 1 are indicative of the potential for overall slope failure.

Table I: Classification parameters of the system

Parameter	Classification categories and ratings					
Rock Type (lithology)	Igneous: Granite, Granodiorite, Diorite and Gabbro; Metamorphic: Gneiss, Quartzite, Amphibolite	Sedimentary: Breccia, Greywacke, Sandstone and Conglomerate; Metamorphic: Hornfels; Igneous: Dolerite, Obsidian, Andesite, Norite and Agglomerate	Sedimentary: Anhydrite and Gypstone; Igneous: Tuff, Basalt, Breccia, Dacite and Rhyolite	Sedimentary: Limestone shale, Dolomite Limestone, Chalk and Siltstone; Metamorphic: Slate, Phyllite	Metamorphic: Schist and Mylonites	Sedimentary: Clay shale Mudstone, Claystone and Marl
	0	0.2	0.4	0.6	0.8	1
Intact rock strength - UCS (MPA)	>150	100-150	75-100	50-75	25-50	<25
	0	0.2	0.4	0.6	0.8	1
RQD %	75-100	50-75	25-50	10--25	<10	
	0	0.3	0.6	0.8	1	
Weathering	W1 Fresh	W2 Slightly weathered	W3 Moderately weathered	W4 Highly weathered	W5 Completely weathered (Decomposed)	
	0	0.3	0.6	0.8	1	
Tectonic regime (Sh= maximum horizontal stress; PBE =Plate boundary events)	Weak (absence of absent meaningful tectonic events), Sh = <15^{o} Minimum PBE ,	Moderate (presence of foliation, schistosity and cleavage), Sh = ±15^{o} Minimum-Moderate PBE	Strong (presence of folds, faults and discontinuities), Sh = 15^{o}-20^{o} Moderate PBE	Very strong (high-fractured zones) Sh = ±20^{o} Frequent PBE	Intense (Imbrications and overthrusts), Sh = 20^{o}-25^{o} Abundance PBE	
	0	0.3	0.6	0.8	1	
Groundwater conditions	Completely dry	Damp	Wet	Dripping	Flowing	
	0	0.3	0.6	0.8	1	
Number of major discontinuity sets	0	1	2	3	>3	
	0	0.3	0.6	0.8	1	
Discontinuity persistence(m)	>5	5-10	10-25	25-40	>40	
	0	0.3	0.6	0.8	1	
Discontinuity spacing(h_b is bench height)	>3h_b	2h_b -3h_b	1h_b-2h_b	1/5h_b-1h_b	<1/5h_b	
	0	0.3	0.6	0.8	1	
Discontinuity orientation (α_d=discontinuity dip direction; α_s=slope dip; βd= discontinuity dip; βs=slope dip)	Very favourable $\beta_d>\beta_s$ and $\alpha_d-\alpha_s>30$	Favourable $\beta_d>\beta_s$ and $\alpha_d-\alpha_s<30$	Fair $0<\beta_d<\beta_s/4$ or $\alpha_d-\alpha_s>30$	Unfavourable $\beta_s/4<\beta_d<\beta_s/2$ and $\alpha_d-\alpha_s<30$	Very unfavourable $\beta_s/2<\beta_d<\beta_s$ and $\alpha_d-\alpha_s<30$	
	0	0.3	0.6	0.8	1	
Discontinuity aperture	No separation	<0.1 mm	0.11 mm	1 - 5 mm	> 5 mm	
	0	0.3	0.6	0.8	1	
Discontinuity roughness (JRC Macro)	Very rough >7	Rough 5-7	Slightly rough 3-5	Smooth 1-3	Slickensided <1	
	0	0.3	0.6	0.8	1	
Discontinuity filling	Not filled	Very hard filling	Hard filling	Soft filling	Very soft filling	
	0	0.3	0.6	0.8	1	
Slope (pit -wall) angle	<30	30-40	41-50	51-60	>60	
	0	0.3	0.6	0.8	1	
Slope (pit-wall) height (m)	<50	50-100	100-200	200-300	>300	
	0	0.3	0.6	0.8	1	
Blasting method	Presplitting	Postsplit	Smoothwall/cushion	Modified production	Regular blasting/mechanical	
	0	0.3	0.6	0.8	1	
Precipitation (annual rainfall and snow)(mm/yr)	<150	150-300	300-450	450-600	>600	
	0	0.3	0.6	0.8	1	
Previous instability	None	Inactive	Quiescent	Relatively active	Highly (obviously) active	
	0	0.3	0.6	0.8	1	

BACK-PROPAGATION METHODOLOGY

Rosenblatt (1958) first introduced the perceptron model which was based on the brain model. The most commonly used multilayer perceptron is the back-propagation (BP) algorithm which is an extension of the least mean squares (LMS) (Haykin, 1994). Back-propagation describes the manner in which the gradient of the squared error function is computed for non-linear multilayer networks. Each unit in the hidden layer is interconnected with units of the output layer. However, units within the same layer are not interconnected (Figure 2).

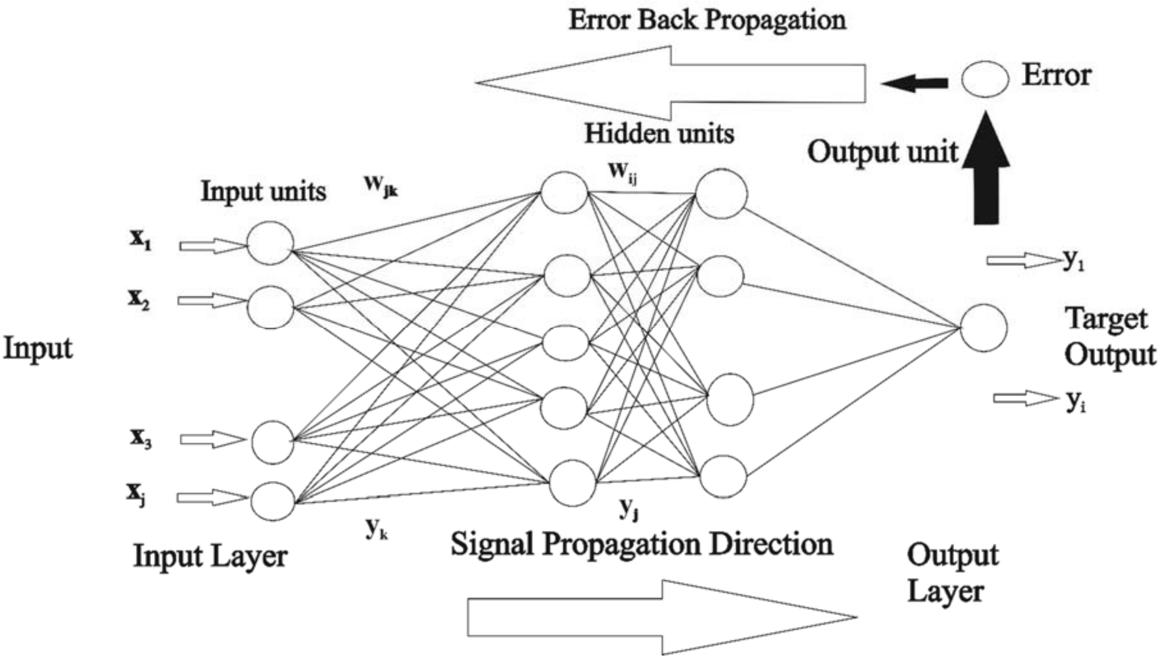

Figure 2: Typical Back-propagation network.

The basic mathematical concept of the BP is provided in literature (Hush and Horne 1999). An elementary mathematical description of the BP is given below. The BP algorithm employed in the current study uses the sigmoid function. Sigmoid functions are continuous differentials that consists of the hard limit transfer, the linear, and the log-sigmoid transfer functions. These functions are also known as the squashing functions since their output is limited to a limited range of values:

$$f(x) = \frac{1}{1+e^{(-ax)}} \quad [1]$$

Where a is a slope parameter.

In the forward pass, the given input vector $y_k^{(p)}$ for each node j in the hidden layer receives a net input:

$$x_j^{(p)} = \sum_k w_{jk} y_k^{(p)} \quad [2]$$

w_{jk} is the weight between hidden node j and input node k. Each node j produces an output:

$$y_j^{(p)} = f\left(x_j^{(p)}\right) = f(\sum_k w_{jk} y_k^{(p)}) \quad [3]$$

As a result, each output node i receives:

$$x_i^{(p)} = \sum_j w_{ij} y_j^{(p)} = \sum_j w_{ij} f((\sum_k w_{jk} y_k^{(p)}) \quad [4]$$

w_{ij} represent the weight between output node I and hidden node j. Therefore, the final output is:

$$y_i = f\left(x_i^{(p)}\right) = f(\sum_j \boldsymbol{w_{ij}} \boldsymbol{y_j^{(p)}}) = \boldsymbol{f}(\sum_j \boldsymbol{w_{ij}} \boldsymbol{f}(\sum_k \boldsymbol{w_{jk}} \boldsymbol{y_k^{(p)}})) \quad [5]$$

Once all the input data is presented to the network during the backward pass, the error is calculated as the mean squared error (MSE) over all the output units. To improve the prediction and minimize the error, a method of updating the weights is critical for the network development. The learning process is centred on correcting the weights, after each iteration. The error is defined by the following function:

$$E = \frac{1}{2}\sum_i (y_i - d_i) \quad [6]$$

d_i represents the desired output of each node i in the output layer. Function E is the continuous differentiable function of all the weights and therefore the method of gradient descent can be applied as:

$$\Delta w_{ij} = -n\frac{\partial E}{\partial w_{ij}} \quad [7]$$

n represents a constant that determines the learning rate. Applying the chain rule the learning algorithm quantifies the derivative term $\partial E/\partial w_{ij}$. The complete derivation of the learning algorithm will not be presented as it lies outside the scope of this paper (Hush and Horne, 1999).

Once training is complete and the neural network has 'learnt' with the provided training samples, the influence of the input values on the output can be determined. Remembering that the information provided by the database observations is contained within the weights (W) of the ANN, which is fixed once learning has been completed, it is then possible to compute the influence of the input on the output using these calculated weights (Yang and Zhang, 1998). The BP has generated criticism with its ability to converge. However, if it is properly trained it tends to produce results that are reasonably accurate when new data set inputs are introduced (Naghadehi, 2013).

RESULTS

Artificial Neural Network

The database of 141 case histories was constructed using the 18 classification parameters and the coding values mentioned above. The neural network developed for training has an architecture in the form of 18-18-1-1, which consists of an input layer (18 neurons), two hidden layers (18 neurons and 1 neuron respectively), and an output layer (1 neuron). Training, validation, and testing of the network was conducted in Matlab v. 9.0 (2016a). The BP algorithm in this study is used to directly calculate the first partial derivative of each input for variations in each output. Thus, once training is completed, the learning process stops, and the network is not allowed to adapt. The weights and thresholds are assumed to be constant for all connections. Furthermore, the input and output values are normalised into a range of 0 – 1 via linear normalization for cases that do not obey this range.

Training was conducted on 90 % of data that is randomly selected. The mean squared error (MSE) for the training was calculated to be 0.0001 at 256 iterations. The convergence of input data to target data (Figure 3) shows that training of the ANN results in very good predictive capabilities. It can be seen that slopes with a ratings close to 0 are stable, whereas those close 0.3 and 1 are those which are predicted to be subjected to failure in set of benches and overall failure respectively.

The network is then validated by simulating with 5 % of data, and then tested with the remaining 5 %. Training data is that which is presented to the network during training, and the network adjusts according to its error. Validation on the other hand is used to measure the networks generalization, and halts the training process when generalization stops improving. The testing process employs data not used for training and validation. As such, these have no effect on training and provide an independent measure of the networks performance during and after training.

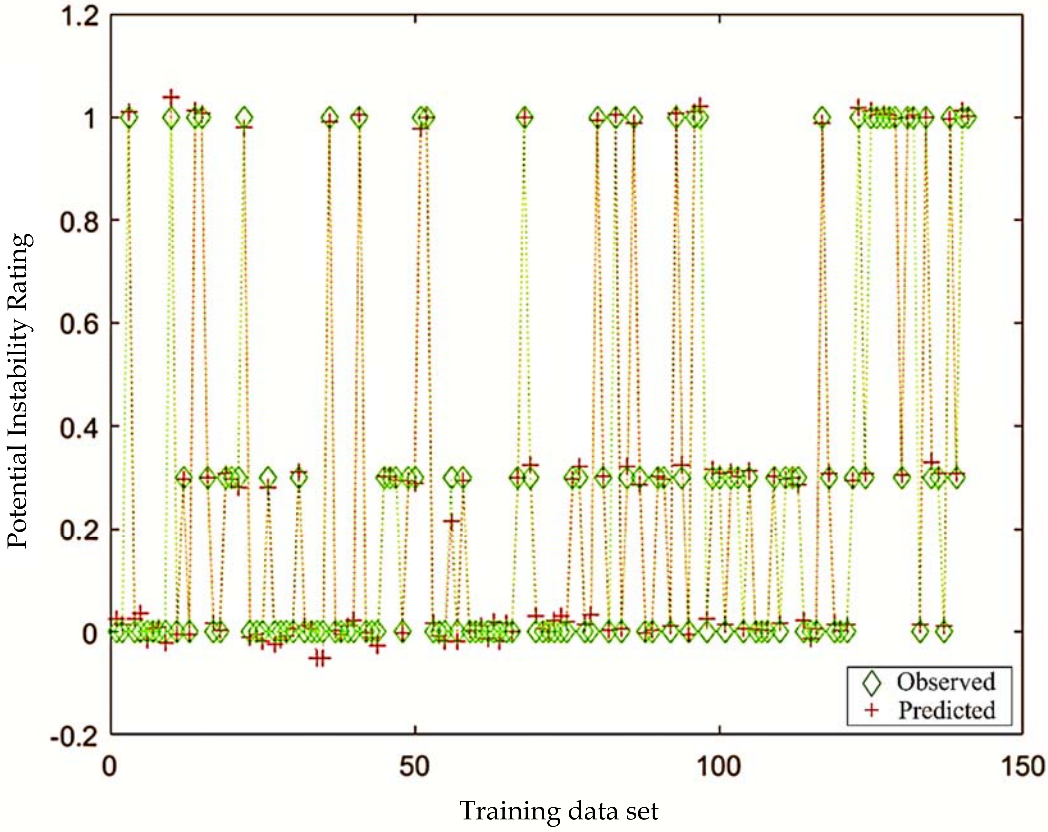

Figure 3: Convergence plot for training data set.

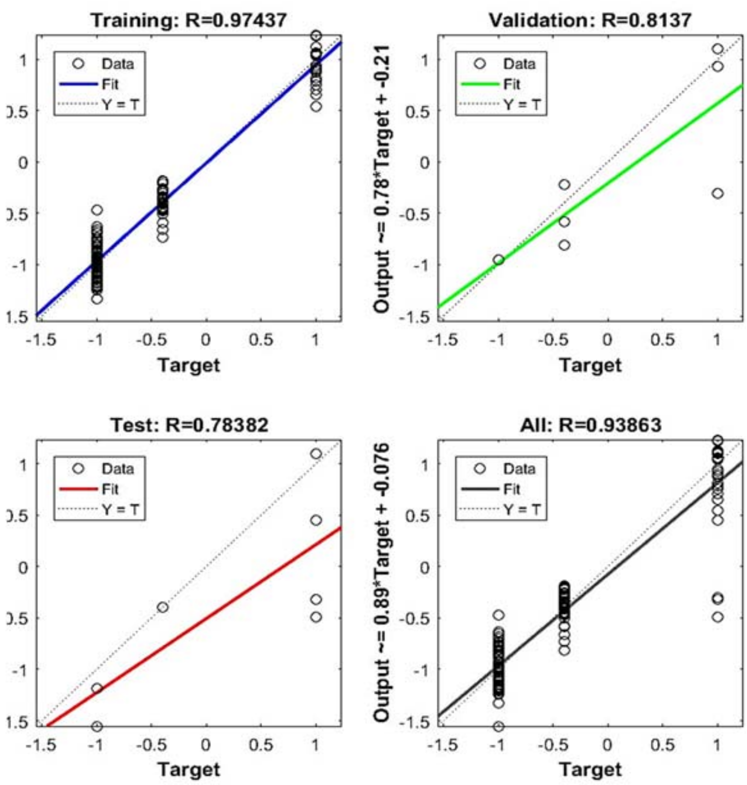

Figure 4: Regression analysis for training, validation and testing data.

The regression fit (Figure 4) is presented for all data sets, with an overall R value of 0.93. To obtain additional verification of the network performance, the error histogram (Figure 5a) is plotted. The bars represent the training data, validation data and test data. The errors are small for the training, validation and test sets, however there are samples which represent outliers. These outliers are valid data points, and may be the result of the network inferring for these points. The performance plot (Figure 5b) is a plot of the errors for all three sets.

As mentioned, validation is used to measure the networks generalization, and to stop training when generalization stops improving. As such, training was stopped at 256 iterations, with the best validation performance of 0.001. The results are reasonably good as the mean squared error is very small, and the test set error and the validation set error have similar characteristics. Overfitting is a training problem that occurs, where the error for the training set is driven to be very small, but when new data is presented to the network, the error is large. As such the network duplicates or memorizes the training examples, but has not learned to generalize to new situations. For the current network, no significant overfitting has occurred when the best validation performance occurs.

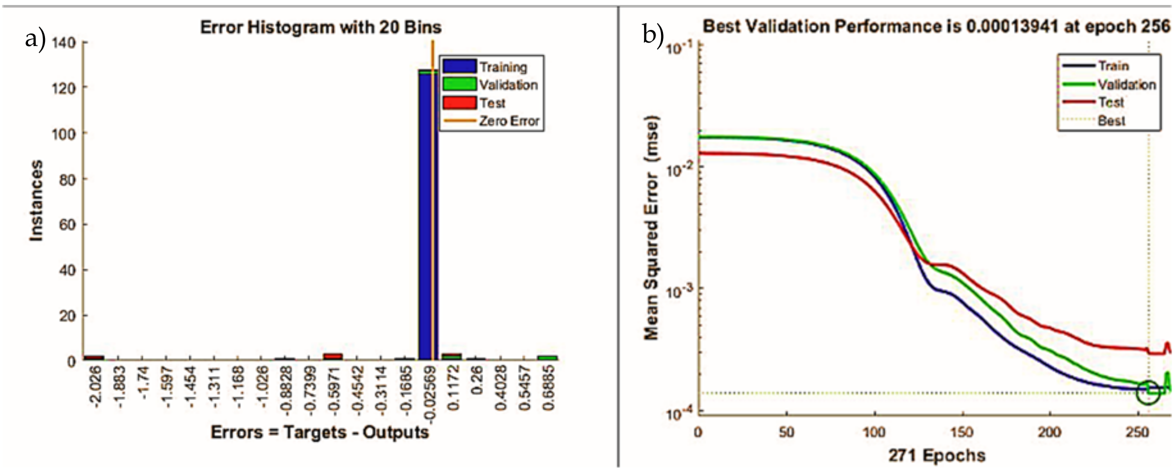

Figure 5: a) Error histogram; b) MSE performance.

Parametric Study

Considering the theoretical importance of rating geometrical and physical parameters that are used to describe geomtechnical engineering problems, the study aimed to define the parameters controlling slope stability in open-pit mines. Towards this goal, the method of partitioning of the connection weights and information theory algorithms are applied in order to rate the significance of the involved parameters. The interaction matrix is then applied to assess the dominance and interaction intensity for the same parameters.

In order to code the generic interaction matrix from Back Propagation network training, the connection weights, from 1st to second layer and second to 3rd layer are converted to rating values through the use of partitioning of connection weights introduced by Garson (1991) and applied by Goh et al. (1995) and Sakellariou & Ferentinou (2005) amongst others. This method involves partitioning the hidden output connection weights into components associated with each input node.

The output of the parametric study is presented in Figure 6. The most dominant parameters are discontinuity characteristics such as aperture, persistence, number of major discontinuity sets, as well as orientation. Some of these parameters may be difficult to be measured. As such, their relative significance can be linked to the large variability and uncertainty about these parameter. However, the results indicate that small changes in these parameter values may drastically affect the stability status of the open-pit slope. For example, weathering has the lowest dominance, with a percentage dominance of 3.7 %. In parallel, the highest rated parameter is discontinuity aperture with 7.3 %. It should be of note that the inherent variability of each parameter in the database plays a vital role to the computation of the OMSSI. Therefore, even though the parametric study provides valuable information concerning the most dominant parameters, it is clear that all the selected input parameters are very important according to the ANN, and all 18 parameters have to be considered in the computation of the OMSSI.

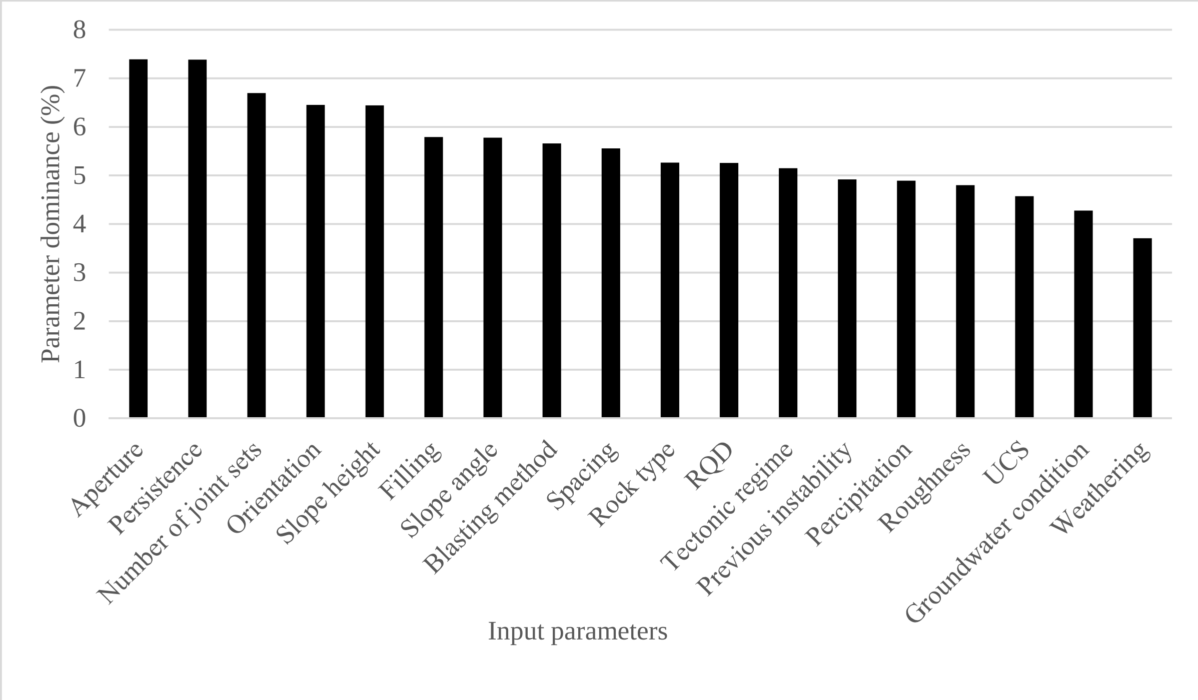

Figure 6: Parameter dominance within the rock engineering system.

Open-pit Mine Slope Stability Index (OMSSI)

The values of each parameter are scaled in such a way that, when all the ratings are equal to the maximum value of 1, the maximum possible OMSSI value is 100. The OMSSI indicates the level of potential instability. Three zones of the stability status can be observed from Figure 7. A ‘safe zone’ for cases with values OMSSI ≤ 50 represent stable conditions; a zone with cases of higher possibility of failure in set of benches represent those of limited-scaled failure with values corresponding to 51 ≤ OMSSI ≤ 62; and a zone with cases of large scale or overall failures, corresponding to values of OMSSI ≥ 62, representing unstable conditions.

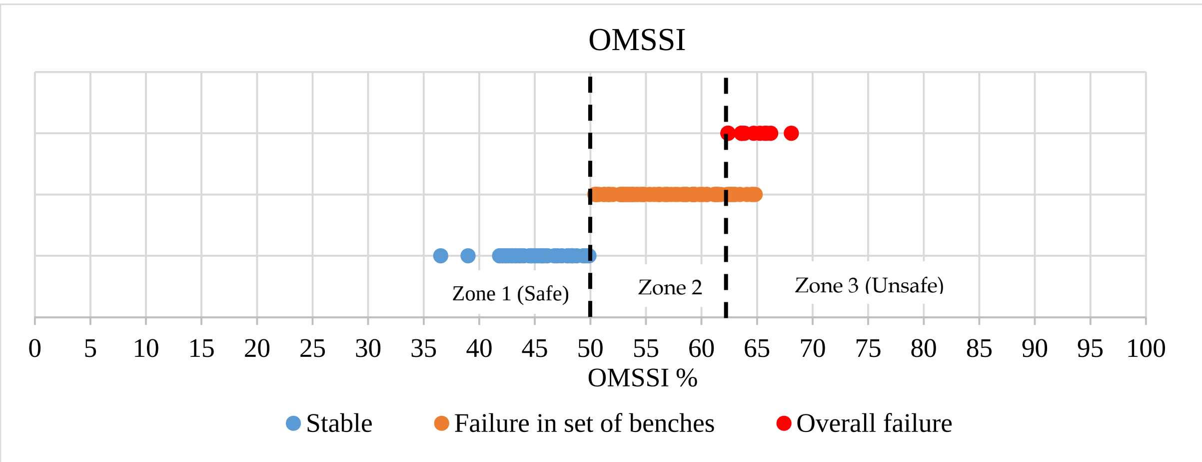

Figure 7: OMSSI zones of stability and values calculated for 126 cases of the database.

The results indicate three regions of pertaining to potential slope instability. There is an observed overlap between the status of stability for the whole dataset. This is expected since the OMSSI represents an empirical method. Despite the large number of factors that are considered, it cannot entirely replicate the complex reality of large scale rock engineering environments such as that of open-pit mines (Naghadehi, 2013). The limits between zones have therefore been selected conservatively. For example, there are slopes which are within Zone 1 predicted as "failure in set of benches", or even predicted as "overall failure" when they fall within Zone 2. These are regarded as conservative errors as they predict the worst case scenario. Table II shows that while the majority of cases are successfully predicted, there are however cases that differ. The overall accuracy of the simulated results is shown by the ROC curve (Figure 8), with an area under the cure of 98 %.

Table II: Predicted cases

Mine	Observed behaviour	OMSSI	Status of Prediction
Orapa	Stable	46.77	Successful
Tati	Failure in set of benches	61.28	Successful
Jwaneng	Stable	51.24	Successful
Marathon	Failure in set of benches	57.86	Successful
Chandmari	Stable	60.48	Unsuccessful
Miduk	Overall failure	73.72	Successful
Mkuushi	Stable	45.28	Successful
Chadormalou	Stable	42.92	Successful
Choghart	Failure in set of benches	60.14	Successful
Sungun	Overall failure	62.69	Successful
Venetia	Stable	52.78	Unsuccessful
Chuquicamata	Failure in set of benches	56.7	Successful
Sandsloot	Stable	46.09	Successful
Aitik	Failure in set of benches	54.79	Successful
La Yesa	Failure in set of benches	59.2	Successful

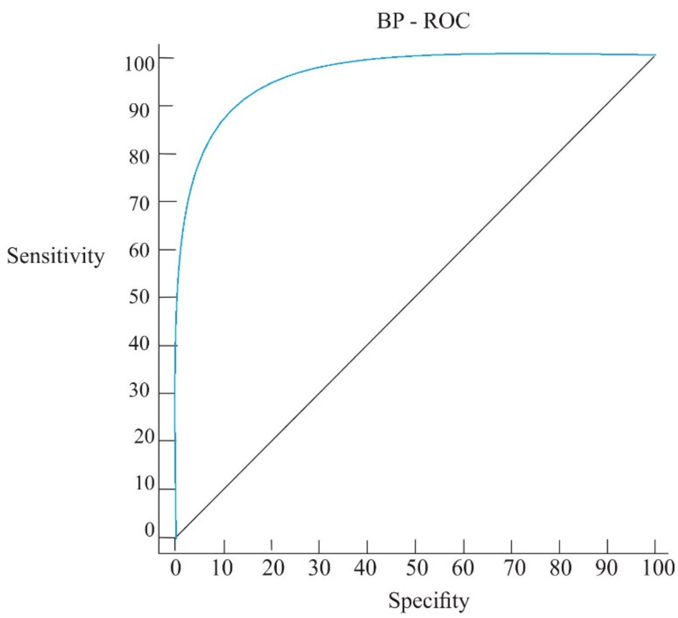

Figure 8: ROC curve

CONCLUSION

The OMSSI is presented to assess the stability status of slopes in open-pit mines and is intended to be a rock mass rating system. The method employs ANN to account for the complex interactions that exist between parameters affecting slope stability in a holistic approach and provide reliable predictions for the status of stability. It is based on a worldwide database of case histories of open pit mines and therefore accounts for project specific characteristics of slope failure. The 18 parameters employed are those, which are considered the key parameters affecting the design of open pit slopes, and which are easily obtainable.

The BP methodology provides an objective rating of the importance of the parameters involved. Through partitioning of the weight matrix, analysis of the parameters dominance can be studied. It provides valuable insight into the parameters which control the stability status of open-pit slopes. Thus, allowing the identification of the most dominant parameters and identifying which parameters need to be controlled within the rock engineering environment. It is observed that even though discontinuity characteristics appear to be the most dominant parameters, all 18 parameters are significant for the construction of the OMSSI. As such, in the test of significance, the inherent variability of each parameter in the database plays a vital role.

The OMSSI is validated by an additional number of case histories that are not utilized for training and of which differ concerning the conditions of stability. The results indicate that ANN is an ideal area for the application of open-pit mine slope stability analysis of real projects, where often the problem is dictated by non-linear equations, conveying to the use of intelligence tools. However, the method is empirical and therefore further reliability can be improved as professionals become more acquainted with its use and the database is extended. Therefore, the OMSSI does not aim to replace conventional approaches to slope stability analysis. It does however provide a useful tool to provide accurate approximations to reality utilizing the available data.

REFERENCES

Abu-Kiefa, M.A. (1998). General regression neural networks for driven piles in cohesionless soils. J. Geotech. & Geoenv. Engrg., ASCE, 124(12), 1177-1185.

Barton, N. (1973). Review of a new shear strength criterion for rock joints. Eng Geol, 7, 287-322.

Basheer, I. A., Reddi, L. N., and Najjar, Y. M. (1996). Site characterisation by neuronets: An application to the landfill siting problem. Ground Water, 34, 610-617.

Bieniawski, Z.T. (1989). Engineering rock mass classifications. New York: Wiley; 251p.

Cal, Y. (1995). Soil classification by neural-network. Advances in Engineering Software, 22(2), 95-97.

Calcaterra, D., Parise, M. (2010). Weathering as a predisposing factor to slope movements. The Geological Society, London. 248 p.

Chan, W. T., Chow, y. K., and Liu, L. F. (1995). Neural network: An alternative to pile driving formulas. J. Computers and Geotechnics, 17, 135-156.

Deere, D. U., Hendron, A. J., Patton, F. D., Cording, E. J. (1967). Design of surface and near surface construction in rock. In: Fairhurst C., editor. Proceedings of the 8th US symposium on rock mechanics, failure and breakage of rock. New York: c Soc Min Engrs Am Inst Min Metall Pet Engrs. p. 237–302.

Deere, D. U., Deere, D. W. (1988). The rock quality designation (RQD) index in practice. In: Kirkaldie L, editor. Rock classification systems for engineering purposes, 984. Philadelphia: ASTM Special Publication. p. 91–101.

Ellis, G. W., Yao, C., Zhao, R., and Penumadu, D. (1995). Stress-strain modelling of sands using artificial neural networks. J. Geotech. Engrg., ASCE, 121(5), 429-435.

Farrokhzad, F., Jan Ali Zadeh, A., Barari, A. (2008). Prediction of Slope Stability Using Artificial Neural Network (Case Study: Noabad, Mazandaran, Iran). Sixth International Conference on Case Histories in Geotechnical Engineering. Missouri University of Science and Technology, Scholar's Mine.

Ferentinou, M.D., Sakellariou, M.G. (2015). Introduction of an objective matrix coding method for rock engineering systems through self-organising maps. 13th ISRM International Congress of Rock Mechanics, 10-13 May, Montreal, Canada.

Flores, G., Karzulovic, A. (2000). The Role of the Geotechnical Group in an Open Pit: Chuquicamata Mine, Chile, in Slope Stability in Surface Mining, W. Hustraid 2001, 141-152.

Franz J. (1992). An investigation of combined failure mechanisms in large scale open pit slopes. PhD thesis, School of Mining Engineering, The University of New South Wales, Sydney, Australia; 2009, 387 p.

Garson G. D. (1991). Interpreting neural-networks connection weights. AI Expert 1991; 6:47–51.

Giani, G. P. (1992). Rock slope stability analysis. Rotterdam: Balkema.

Goh, A.T.C. (1994a). Nonlinear modelling in geotechnical engineering using neural networks. Australian Civil Engineering Transactions, CE36(4), 293-297.

Goh, A. T. C. (1994b). Seismic liquefaction potential assessed by neural network. J. Geotech. & Geoenv. Engrg., ASCE, 120(9), 1467-1480.

Goh, A.T.C. (1995a). Back-propagation neural networks for modeling complex systems. Artificial Intelligence in Engineering, 9, 143-151.

Goh, A.T.C. (1995b). Empirical design in geotechnics using neural networks. Geotechnique, 45(4), 709-714.

Goh, A.T.C. (1995c). Modeling soil correlations using neural networks. J. Computing in Civil Engrg., ASCE, 9(4), 275-278.

Goodman, R. E., & Shi, G. (1985). Block theory and its application to rock engineering. Englewood Cliffs, N J: Prentice-Hall.

Gribb, M.M., Gribb, G.W. (1994). Use of neural networks for hydraulic conductivity determination in unsaturated soil. Proc., 2nd Int. Conf. Ground Water Ecology, J. A. Stanford and H. M. Valett, eds., Bethesda MD: Amer, Water Resources Assoc., 155-163.

Haykin, S. (1994). Neural Networks: A comprehensive foundation. New York: Macmillan College Publishing Company.

Hoek, E. (2007). Practical rock engineering. Course notes, Hoek's Corner. Retrieved from Rocscience: https://www.rocscience.com/

Hoek, E., Bray, J. W. (1981). Rock slope engineering. 3rd edition London: The Institution of Mining and Metallurgy; 358 p.

Hudson, J.A. (1992). Rock engineering systems, theory and practice. Chichester: Ellis Horwood.

Hudson, J.A. (1992a). Atlas of rock engineering mechanisms. Part2-Slopes, Int. J. Rock Mech. Mining Sci., 29, 157–159.

Hudson, J. A., & Harrison, J. P. (2001). Engineering Rock Mechanics: An introduction to the principles. London: Elsevier, 2001.

Hush, D.R., Horne, B.G. (1999). What's new since Lippman? IEEE Signal Process. Magazine, 9–39.

Hustruid, W. A. (1999). Blasting principles for open-pit mining. Vol. 2 Theoretical Foundations. Rotterdam: Balkema.

Jimenez-Rodriguez, R., & Sitar, N. (1983). Influence of stochastic discontinuity network parameters on the formation of removable blocks in rock slope stability. Int J Rock Mech Sci Geomech Abstr, 20, 227-36.

Jing, L. and Hudson J.A. (2002). Numerical methods in rock mechanics, Int. J. Rock Mech. Mining Sci., 39, 409–427

Kliche, C. (1999). Rock slope stability. Society for Mining, Metallurgy, and Exploration (SME).

Kozyrev, A.A., Reshetnyak, S.P., Maltsev, V.A., Rybin, V.V. (2000). Analysis of stability loss in open-pit slopes and assessment principles for hard, tectonically stressed rock masses. In: Hustrulid WA, McCarter MJ, Van Zyl DJA, editors. Slope stability in surface mining. Littleton: Society of Mining, Metallurgy and Exploration Inc. p 251–6.

Lee, C., and Sterling, R. (1992). Identifying probable failure modes for underground openings using a neural network. Int. J. Rock Mechanics and Mining Science & Geomechanics Abstracts, 29(1), 49-67.

Lee, I.M., and Lee, J. H. (1996). Prediction of pile bearing capacity using artificial neural networks. Computers and Geotechnics, 18(3), 189-200.

Lilly, P.A. (2002). Open pit mine slope engineering: a 2002 perspective. In: 150 years of mining, Proceedings of the AusIMM Annual Conference, Auckland, New Zealand.

Lin, H.M., Chang, S.K., Wu, J.H., Juang, C.H. (2008). Neural network-based model for assessing failure potential of highway slopes in the Alishan, Taiwan Area: Pre- and post-earthquake investigation. Engineering Geology 104 (2009) 280–289

Maerz, N. H., Youssef, A., Fennessey, T. W. (2005). New risk-consequence rockfall hazard rating system for Missouri highways using digital image analysis. Environ Eng Geosci; 11: 229–49.

Millar, D.L., Hudson, J.A. (2004). Performance monitoring of rock engineering systems utilising neural networks, Trans. Inst. Mining Metall. Section A – Mining Ind., 103, (1994), A13– A16.

Najjar, Y.M., and Ali, H. E. (1998). CPT-based liquefaction potential assessment: A neuronet approach. Geotechnical Special Publication, ASCE, 1, 542-553.

Neaupanea, K.M., Achetb, S.H. (2004). Use of backpropagation neural network for landslide monitoring: a case study in the higher Himalaya. Engineering Geology 74 (2004) 213–226

Ni, S.H., Lu, P.C., Juang, C.H. (1996). A fuzzy neural network approach to evaluation of slope failure potential. J. Microcomputers in Civil Engineering, 11, 59-66.

Read, J., & Stacey, P. (2009). Guidelines for open pit slope design /editors, John Read, Peter Stacey. Melbourne: CSIRO Publishing.

Rizzo, D.M., Lillys, T.P., and Dougherty, D.E. (1996). Comparisons of site characterization methods using mixed data. Geotechnical Special Publication, ASCE, 58(1), 157-179.

Romana, M. (1985). New adjustment ratings for application of Bieniawski classification to slopes. Proceedings of the international symposium on role of rock mechanicss, (pp. 49-53). Zacatecas, Mexico.

Rosenblatt, F. (1958). The perceptron: A probabilistic model for information storage and organisation in the brain, Psychol. Rev., 65, 386–408.

Rozos, D., Pyrgiotis, L., Skias, S., Tsagaratos, P. (2008). An implementation of rock engineering system for ranking the instability potential of natural slopes in Greek territory: an application in Karditsa County. Landslides; 5(3): 261–70.

Sakellariou, M., Ferentinou, M. (2005). A study of slope stability prediction using neural networks. Geotechnical and Geological Engineering 23: 419-445. DOI 10.1007/s10706-004-8680-5

Shahin, M.A., Jaksa, M.B., Maier, H.R. (2001). Artificial Neural Network Application in Geotechnical Engineering. Australian Geomechanics. p 49-62.

Shi, J., Ortigao, J.A.R., Bai, J. (1998). Modular neural networks for predicting settlement during tunneling. J. Geotech. & Geoenv. Engrg., ASCE, 124(5), 389-395.

Sivakugan, N., Eckersley, J.D., and Li, H. (1998). Settlement predictions using neural networks. Australian Civil Engineering Transactions, CE40, 49-52.

Sjöberg, J. (1999). Large scale slope stability in open pit mining- a review. Ph.D. Thesis, Lulea University of Technology, 790 p.

Ulusay, R. (2013). Harmonizing engineering geology with rock engineering on stability of rock slopes. Rock Characterisation, Modelling and Engineering Design Methods – Feng, Hudson & Tan, 11-22.

Ural, D.N., and Saka, H. (1998). Liquefaction assessment by neural networks. Electronic Journal of Geotechnical Engrg., http://geotech.civen.okstate.edu/ejge/ppr9803/index.html.

Wang, H.B., Xu, W.Y., Xu, R.C. (2004). Slope stability evaluation using Back Propagation Neural Networks. Engineering Geology 80 (2005) 302– 315

Wyllie, D.C., Mah, C. W. (2004). Rock slope engineering, civil and mining. 4th ed. London: Spon Press; 431p.

Yang, Y., Zhang, Q. (1998). A new method for the application of artificial neural networks to rock engineering system (RES). International Journal of Rock Mechanics and Mining Sciences 35 (6), pp. 727-745.

Zare Naghadehi, M., Jimenez, R., KhaloKakaie, R., Jalali, S.M.E. (2013). A New Open-Pit Mine Slope Instability Index Defined Using the Improved Rock Engineering Systems Approach. International Journal of Rock Mechanics and Mining Sciences 61, pp. 1-14.

Zhou, Y., and Wu, X. (1994). Use of neural networks in the analysis and interpretation of site investigation data. Computer and Geotechnics, 16, 105-122.

Zoback, M. (1992, 97). First - and second - order patterns of stress in the lithosphere: the World Stress Map Project. J Geophys Res, (B8), 11761-82.