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Rock Mass Excavatability Estimation Using Artificial Neural Network

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Abstract: One important decision in design of surface mine is the selection of mine equipment and plant. Demand for mechanical excavation is growing in mining industry because of its high productivity and excavation in large scale with lower costs. Several models have been developed over the years to evaluate the ease of excavation and machine performance against rock mass properties. Due to complexity of excavation process and large number of effective parameters, approaches made for this purpose are essentially empirical. There are many uncertainties in results of these models. An attempt is made in this paper to revise the exisiting models. Neural network models for estimation of rock mass excavatability and production rate of VASM-2D excavating machine at Limestone quarry in Retznei, Austria, is presented. Input parameters of this model are Uniaxial compressive strength, tensile strength and discontinuities spacing of rocks. Output is the specific excavation rate per power consumption (bcm/Kwh) as the productivity indicator. Average of deviation between actual data and results estimated by neural network model was only 15% which is in an acceptable range.

Keywords: Rock mass excavatability, Artificial neural network, Retznei, Austria.

INTRODUCTION

There are several methods for doing excavation. Mechanical excavation has had many advantages over the conventional drilling and blasting technique including high productivity, improved safety, minimal ground disturbance, elimination of blasting vibration and the uniform muck size which allows for the conveyor belt to maximize the benefits of the mechanical excavators (i.e. high production and lower costs, automation etc) for all applications performance of machine under specific conditions must be understood. Several models have been developed over the years to evaluate the ease of excavation, machine performance and production rate of different mechanical excavators against rock mass properties. Due to complexity of the excavation process and large number of parameters involved, approaches made for this purpose are essentially empirical (Copur et al. 1997).

The influencing parameters of the performance of mechanical excavation can be divided into six groups; intact rock properties, rock mass properties, cutter type, cutting geometry, machine specifications and operational parameters. In this paper the effect of intact rock and rock mass properties on excavatability has been considered. It is evident that each of these properties must be measured in accordance with the special procedures and standards (Franklin et al. 1971). It is well known and established that prediction of mechanical excavators performance relying only on a single parameter, may provide widely inaccurate results. So, in the recent years, various multi parameter indexes or empirical classification systems have been derived for the general assessment of rock mass excavatability.

A graphical method which allows assessment of excavation method by using only two geotechnical parameters, namely; discontinuity spacing and rock strength, was published by Franklin et al. (1971). The graph, subdivided into areas of digging, ripping and blasting, was later revised by other authors based on data obtained from further case studies. Goktan and Eskikaya (1991) developed a “Rock Mass Rippability Index” applicable to sedimentary rocks of surface lignite mines. The index, which is a combination of rock uniaxial compressive strength and coefficient of relative rock mass weakness, was found to correlate well with the rates at which the rock can be ripped and dozed for loading. A “Rippability Index” carrying the concepts of the physics of self-ordered criticality was developed, and compared to available ripping forces for various bulldozers (Caterpillar Tractor Company, 1980). MacGregor et al. (1994) have used a database of detailed ripping and geological data from highways and mine sites and have developed a method to estimate ripper productivity for identifying difficult ripping conditions. The method is based on the multiple variable regression analysis of the database. The dominant factors affecting productivity are including uniaxial compressive strength of the rock, seismic wave velocity, joint roughness and strength, weathering, discontinuities and bulldozer mass.

In the recent years, various empirical classification systems have been developed for the general assessment of rock excavatability or for specific applications such as rock rippability. Classification systems are based on gathered geotechnical data and observations made in the field for a variety of excavation processes. The adopted procedure in most of these classification systems is the quantification of geotechnical parameters that are related to machine performance, leading to a single rating or index. The ratings obtained by this way are then related to the ease of rock excavation classes and machine types to be used.

Weaver (1975) proposed a "rippability rating chart" that is very similar to Bieniawski's Geomechanics Classification System. The rippability of the material is based on an assessment of seismic velocity, rock strength, joint spacing, joint gauge, joint continuity, joint strike and dip orientation, and weathering. In his system, the weighted numerical values determined for each input factors are summed to arrive to a total rating which is then used to assess excavation class and bulldozer size.

Weaver's system was then modified by Minty and Kearns (1983). They included new parameters such as the groundwater conditions and surface roughness of discontinuities. Another modification of Weaver's rating system was proposed by Smith (1986). His primary change was the omission of seismic wave velocity. The "Excavatability Index" developed by Kirsten (1983) is based on Norwegian Geotechnical Institute's "Q" system that was specially developed for tunneling. The input parameters of the system are: uniaxial compressive strength, number of joint sets, RQD, joint roughness, joint alteration, joint orientation, and joint spacing.

Boundary values for various excavation classes' intervals is given by an index which is produced by product of the input parameters values. The "Diggability Index" rating method devised by Scoble and Muftuoglu (1984) defines five rock classes based on four geotechnical parameters: uniaxial compressive strength, bedding spacing, joint spacing and weathering. The index is derived by summation of the rated values of these input parameters. The index considers both geotechnical factors and excavating equipment capabilities. On the other hand Singh et al (1986) suggested a "rippability rating chart" which classifies rock mass according to the selected geotechnical parameters. In this method, a numerical rating is given for each of the parameters including rock tensile strength, abrasiveness, seismic velocity, weathering and discontinuity spacing. The last rating is used for the selection of ripper types. An empirical ground classification system based on rock strength, block size, weathering and relative ground structure was developed by Hadjigeorgiou and Scoble (1988). The selected geotechnical parameters are rated and combined together to suggest an "Excavation Index" which is related to excavation effort and excavation classes. Karpuz (1990) proposed an excavation rating system that utilize five rock mass and rock material properties related to excavation method and excavator performance, including uniaxial compressive strength, rock hardness, discontinuity spacing, degree of weathering and seismic wave velocity.

The proposed rating system helps in the selection of excavation equipment as well as drilling and blasting requirements. More recently, Basarir and Karpuz (2004) have devised a rippability classification system for marls in lignite mines. Rock parameters included in the system are: uniaxial compressive strength, seismic wave velocity; discontinuity spacing and Schmidt hammer hardness. Each of these input parameters are rated separately. Rippability classes of rocks are determined according to the final rating. Accordingly, appropriate dozer types and their expected production rates are specified.

These models have been used to either direct or indirect selection of appropriate excavation systems or equipment that will be used in mining and civil works. Some of these criteria and their input parameters listed in Table 1. Number of stars in table shows the relative importance of parameters in each assessment method.

The existing conventional methods used for excavatability estimation have some deficiencies that can be as following; (1) use of linguistic terms as input value of some parameters, (2) predetermined and sharp class boundaries in classification systems whereas the rock mass quality is gradational in nature and (3) prescribed rating scales representing contribution of each criterion to the overall quality. In conclusion some uncertainties are encountered when these systems are employed for the determination of excavatability.

As the artificial neural network (ANN) models can cope with the complexity of complicated and ill-defined systems in a flexible and consistent way. In the last few years use of artificial neural network has increased in many areas of engineering. In particular, ANN has been applied to many geotechnical engineering problems and has demonstrated some degree of success. A review of the literature reveals that ANN has been used successfully in pile capacity prediction, modeling soil behavior, site characterization,

Table1. Geotechnical parameters considered in various excavatability assessment systems

Assessment method	Relative importance of each parameter									
	SV	*σc*	*PLI*	*Hd*	*Ab*	*Wea*	*Jsw*	*Jp*	*Jsp*	*Jor*
Frankline et al (1970)			****				****		*	***
Weaver (1975)		****		**			****	*	*	*
Kirsten (1982)		****					****			**
Minty and Kearns (1983)	****		**			**	***	*	*	
Scoble and Muftuglu (1984)		**				**	****			**
Smith (1986)		**				**	****	*	*	
Karpuz (1990)	****	***		**		**	****			
Hadjigeorgiou and Scoble (1990)			***			**	****			*
Pettifer and Fookes (1994)			****			*	****			**

Where the individual characteristics are:
SV: Seismic Velocity; *Hd*: Rock Hardness; *Jsw*: Joint spacing; *Jor*: Joint Orientation
σc:UCS; *Ab*: Abrasivity; *Jp*: Joint persistence; *Jsp*: Joint separation
PLI: Point Load Index; *Wea*: Weathering

earth retaining structures, settlement of structures, slope stability, design of tunnels and underground openings, liquefaction, soil permeability and hydraulic conductivity, soil compaction, soil swelling and classification of soils.

ARTIFICIAL NEURAL NETWORK

Artificial neural network, ANN, as they are known today, originate from the work of McCulloch and Pitts (1943), who demonstrated the ability of interconnected "neurons" to calculate some logical functions. Later, Rosenblatt (1958) presented the first operational model of a neural network named 'Perceptron'. The perceptron, built as an analogy to the visual system, was able to learn some logical functions by modifying the synoptic connections.

ANN has massively parallel, distributed and adaptive systems, modeled on the general features of biological network with the potential for ever improving performance through a dynamical learning process. Neural network is made up of a great number of individual processing elements, the neurons, which perform simple tasks. A neuron, schematically represented in Fig.1, is the basic building block of neural network technology. It performs a nonlinear transformation of the weighted sum of the entering inputs to produce the output of the neuron. The input to a neuron can come from other neurons or from outside the network. The nonlinear transfer function can be a threshold, a sigmoid, a sine or a hyperbolic tangent function (Hagan et al. 2002).

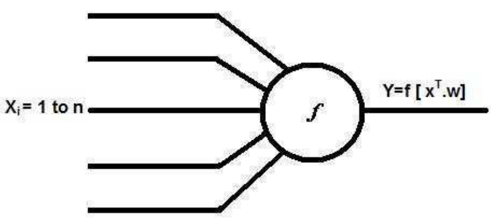

Fig.1. A simple processing neuron.

Neural network is comprised of a great number of interconnected neurons. There exists a wide range of network architectures. The choice of the architecture depends upon the task to be performed. For modeling of physical systems, a feed forward layered is usually used. It consists of a layer of input neurons, a layer of output neurons and one or more hidden layers. In present work, a three-layer feed forward network is used.

In the neural network, the knowledge causes in the interconnection weights between neuron and topology of the network. Therefore, one important aspect of a neural network is the learning process whereby representative examples of the knowledge to be acquired are represented to the network. Then, it can integrate this knowledge within its structure. Learning implies that the processing element somehow changes its input/output behavior in response to the environment. The learning process thereby consists in determining the weight matrices. It produces the best fit of the predicted outputs over the entire test data set. The basic procedure is, set the weights between adjacent layers to random values. An input vector is then impressed on the input layer. Then, it is propagated through the network to the output layer. The difference between the computed output vector of the network and the target output vector is then adapted to the weight matrices using an iterative optimization technique to progressively minimize the sum of squares of the errors. The most versatile learning algorithm for the feed forward layered network is back-propagation. The back-propagation learning law is a supervised error-correction rule. Here, the output error, that is, the difference between the desired and the actual output, is propagated back to the hidden layers. Now, if the error at the output of each layer can be determined, it is possible to apply any method which minimizes the performance index to each layer sequentially.

Back-propagation Algorithm with Levenberg-Marquardt Algorithm

Multi-Layer Perceptron (MLP) is perhaps the best-known type of feed forward network. MLP has generally three layers: an input layer, an output layer and an intermediate or hidden layer. Neurons in the input layer only act as buffers for distributing the input signal *xi* to neurons in the hidden layer. Each neuron j in the hidden layer sums up its input signals xi after weighting them with the strengths of the respective connections w_{ji} from the input layer and computes its outputs *yj* as a function *f* of the sum, viz.

$$y_j = f(\sum w_{ji} x_i) \tag{1}$$

Where, *f* can be a simple threshold function or a sigmoid, hyperbolic tangent or radial basis function.

The output of neurons in the output layer is computed similarly. The back-propagation algorithm, a gradient descent algorithm, is the most commonly adopted MLP test algorithm. It gives the change Δw_{ji} in the weight of a connection between neurons *j* and *i* as follows.

$$\Delta w_{ji} = \eta \delta_j x_i \tag{2}$$

Where η is a learning rate factor and δj is a parameter depending on whether neuron *j* is an output neuron or a hidden neuron. For output neurons,

$$\delta_j = \left(\frac{\partial \mathrm{f}}{\partial \mathrm{net}_{\mathrm{j}}}\right)\left(y_j^{(t)} - y_j\right) \tag{3}$$

And for hidden neurons,

$$\delta_j = \left(\frac{\partial \mathrm{f}}{\partial \mathrm{net}_{\mathrm{j}}}\right)\sum_q (w_{qj}\delta_q) \tag{4}$$

In equation (3), net_j is the total weighted sum of input signals to neuron *j* and $y_j^{(t)}$ is the target output of neuron *j*. As there are no target outputs for hidden neurons, in equation (4), the difference between the target and actual output of a hidden neuron *j* is replaced by the weighted sum of the δq terms already obtained from neurons *q* connected to the output of *j*. Thus, iteratively, beginning with the output layer, the çä term is computed for neurons in all layers and weight updates determined for all connections (Stefen et al. 1997).

Back-propagation searches on the error surface by means of the gradient descent technique in order to minimize the error. It is very likely to get stuck in local minima. Various other modifications to back-propagation to overcome this aspect have been proposed and the Levenberg-Marquardt modification has been found to be a very efficient algorithm in comparison with the others like Conjugate gradient algorithm or variable learning rate algorithm (Hagan et al. 2002).

Levenberg-Marquardt works by making the assumption that the underlying function being modeled by the neural network is linear. Based on this calculation, the minimum can be determined exactly in a single step. The calculated minimum is tested, and if the error and there is still other lower point, the algorithm moves the weights to the new point. This process is repeated iteratively on each generation. Since the linear assumption is ill-founded, it can easily lead Levenberg-Marquardt to test a point that is inferior (perhaps even wildly inferior) to the current one. The clever viewpoint of Levenberg-Marquardt is that the determination of the new point is actually a compromise between a step in the direction of steepest descent and the above-mentioned leap. Successful steps are accepted and lead to a strengthening of the linearity assumption (which is approximately true near to a minimum). Unsuccessful steps are rejected and lead to a more cautious downhill step. Thus, Levenberg-Marquardt continuously switches its approach and can make very rapid progress.

The equations for changing the weights during test in Levenberg-Marquardt method are given as follows:

$$Modifying \Rightarrow \Delta\vec{W} = (J^T J + \mu I)^{-1} J^T \vec{e} \tag{5}$$

Where J is the Jacobian matrix of the derivative of each error to each weight, μ is a scalar and e is an error vector. The Levenberg-Marquardt algorithm performs very well and its efficiency is found to be of several orders above the conventional back propagation with learning rate and momentum factor.

Design of the Optimum Artificial Neural Network

Generally, there is no direction and precise method for determining the most appropriate number of neurons to include in each hidden layer in the neural network. This problem becomes more complicated as the number of hidden layers in the network increases. To establish an optimal network, one needs to begin with train and test the artificial neural network using a subset of all data sets. This process is referred to a pilot experiment. This experiment is based on a certain number of samples; a sample being a set of input data and observed/measured information. In the pilot experiment data set, the samples are divided into a test set and a validation set. Network with different numbers of hidden nodes will be trained for convergence of the test samples, measuring their performance with the validation set, and choosing the network that yields the best performance of the validation set. Finally, this selected network model will be used for the whole data set (Stefen et al. 1997).

Then the model is tested with the validation set. Input parameters of this validation set are fed to the model via input nodes and weighted layer-by-layer from the hidden layer(s) to the output layer. In this research all data were grouped in two parts, named train and test data. We ignored validation data because we did not have enough data, that did not interfere our modeling. Outputs, "predicted Specific Excavation values (bcm/Kw.h)" from the network, are then used to compare with the desired outputs (measured Specific Excavation values). If the network outputs of the pilot experiment are in agreement with the measured data as indicated by small differences between output and desired/ target data, the network is useable for the application. Performance of the developed network was tested with the help of:

1 drawing a scatter diagram of estimated versus target values

2 Computing mean absolute error (MAE) using:

$$MAE = \frac{1}{Q}\sum_{1}^{Q}|y-x| \tag{6}$$

Where x is target; y is network output; Q is number of test patterns.

3 Computing mean square error (MSE) using:

$$MSE = \frac{1}{Q}\sum_{1}^{Q}(y-x)^2 \tag{7}$$

Where x is target; y is network output; Q is number of test patterns [18].

SPECIFIC EXCAVATION INDEX PREDICTION BY ANN

The main aim of this research is to investigate the influence of rock mass and intact rock properties on the excavatability of rock and examine the effectiveness new developed technique to predicate the excavatability of rock and machine performance at the design stage. The research work was carried out within the following constraints:

- In this study the excavatability index is defined as a volumetric extracted rock (in cubic meter) per unit of power (in Kilo Watt Hour)
- The work was based on assessing the machine performance of one type continuous mechanical excavators, the VASM-2D.
- The monitoring of machine performance consists of recording the power required for different levels of production.
- The assessment of rock mass properties was mainly based on recording the presence and frequency of occurrence of discontinuities.
- Intact rock properties have been assessed by laboratory tests and involved Unconfined Compressive Strength (UCS) and Brazilian Tensile Strength (BTS). Other indexes such as Toughness and Brittleness also can be used, but they are defined as relations of UCS with BTS. From where ANN can cover these relations, then in this research it is preferred to not consider them.
- The data are used, collected from ten zones of two separated part in Limestone quarry in Retznei, Austria (Suseno, 1996).

When studying effects of UCS, BTS, discontinuities spacing are related to specific excavation index as the machine productivity indicator (as shown in Figs. 2, 3 and 4) and one can draw the surprisingly consistent conclusion if all data series are considered together, there are no strong trends in the relationship between any one of the parameters and the specific excavation index. This indicates that more than one parameter influences the magnitude of specific excavation index. While if a series of single harvest for a particular zone to be considered, it will be seen that by increasing in compressive strength, specific excavation index is reduced. In other words it means that for power consumption per a unit, smaller volume of stones may be extracted .This situation is also true for tensile strength of stone. In Figs.2 and 3, data series for every special zone are detectable.

Moreover, an approach based on artificial neural network (ANN) was used to develop predictive relations. Since ANN enable one to map all influencing parameters for specific excavation.

An artificial neural network was employed to analyze 51 sets of available data to develop the model. 36 data sets were used for train stage and 15 sets were left for test stage.

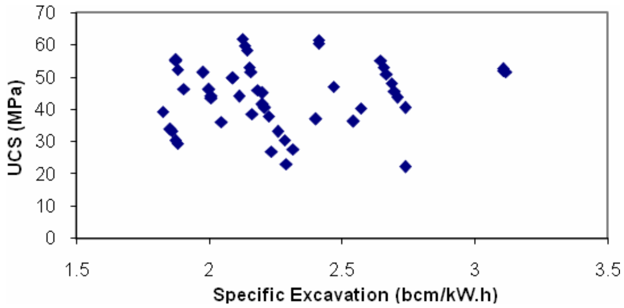

Fig.2. Relation of UCS with specific excavation

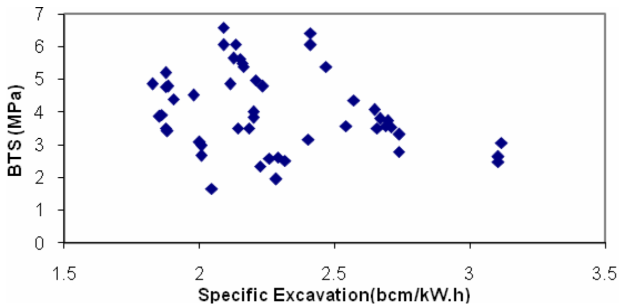

Fig.3. Relation of BTS with specific Excavation

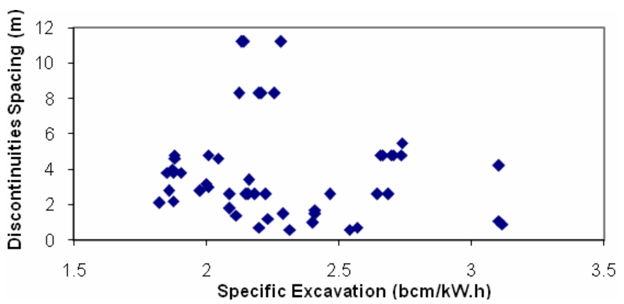

Fig.4. Relation of discontinuity spacing with specific excavation

The Neural Network toolbox of MATLB software was utilized for network development.

The most influencing parameters are: Unconfined Compressive Strength (UCS), Brazilian Tensile Strength (BTS) and discontinuous spacing. Artificial neural network model structure is schematically represented in Fig.5.

The data are fed into the ANN, where the input layer consists of 3 input nodes that represent all influencing factors. The process attempts to establish the optimal neural network model and an appropriate number of train epochs for the problem. The variables used in this trial and error process are: (1) the architecture of the neural network, which is composed of a number of hidden layers and a number of

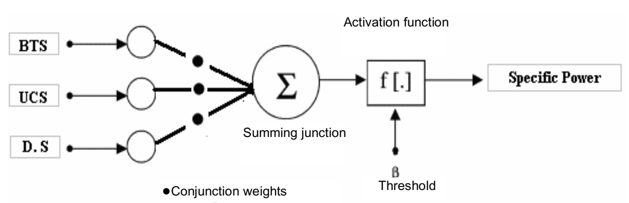

Fig.5. Artificial neural network structure.

Table2. Details of optimized neural network model

Characteristics of ANN model	Value/Description
No. Train Data	36
No. Test Data	15
No. Optimum Neuron in Hidden Layer	15
Global Error Function	MSE
Activation Function Hidden layer	Tan-Sig
Activation Function Output layer	Liner
Optimization Algorithm	Levenberg_ Marquardt
No. Optimum Epochs	20
MAE Train	0.13
MAE Test	0.15
MSE Train	0.033
MSE Test	0.047

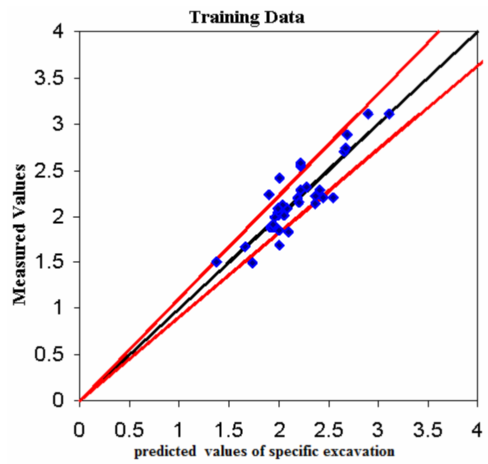

Fig.6. Cross - correlation between predicted and measured values of specific excavation by ANN for train data.

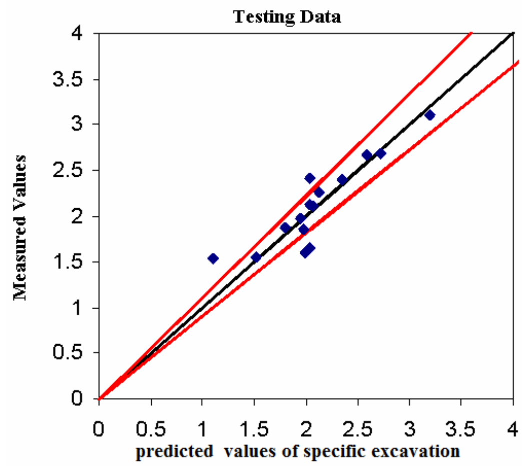

Fig.7. Cross - correlation between predicted and measured values of specific excavation by ANN for test data.

hidden nodes in each hidden layer; and (2) the number of epochs. Therefore, based on all performances of the network models in the test set, the optimal network gives the lowest MSE that is shown in Table 2.

Figure 6 shows the predicted specific excavation versus the actual values for train data. Results of model for test data are showed in Fig.7. The results depicts that the model has a very good ability to predict specific excavation of machine in excavating per unit of energy (Kw.h) as the productivity. The MAE of the model is 0.13 and 0.15 for train data and test data respectively.

The lines on two sides of central line in Figs. 6 and 7 shows error, that is around 10 percent. In addition, for some train and test data, quantities for estimating the network, the error is less than 10 percent.

CONCLUSION

Neural network is well developed to use in applications with availability of enough and suitable data and high complexity where the estimation is concerned. Comparison between real and resulted estimation from neural network shows very low discrepancy. Operation of neural network in this paper states the higher ability of neural network in identifying system (knowing the effecting parameters in utility power and omitting same factors with low influences) and making connection between efficient parameters, with balance of utility power. Having enough databases (data with good tolerance, and enough quantity), one can model neural network more developed and complete following the mentioned procedure.

References

Basarir, H. and Karpuz, C. (2004) A rippability classification system for marls in lignite mines. Engg. Geol., v.74, pp.303-318.

Caterpillar Tractor Company (1980) Caterpillar performance handbook, Edition 11.

Copur, H., Rostami, J., Ozdemir, L. and Bilgin, N. (1997) Studies on Performance Prediction of Roadheaders Based on Field Data in Mining and Tunneling Project. Int. 4th Mine Mechanization and Automation Symp., Brisbane, Australia, 4A1-4A7.

Franklin, J.A., Broch, E. and Walton, G. (1971) Logging the mechanical character of rock. Inst. Min. Metall., pp.A1-A51.

Goktan, R.M. and Eskikaya, S. (1991) Prediction of ripping machine performance in terms of rock mass properties. Civil Engg S. Africa, v.31(1), pp.13-24.

Hadjigeorgiou, J. and Scoble, M.J. (1998) Prediction of digging performance in mining. Internat. Jour. Surface Min., pp.237-244.

Hagan, M.T., Demuth, H.B. and Jesus, O.D. (2002) An Introduction to the Use of Neural Networks in control Systems. Internat. Jour. obust and Nonlinear Control, v.12, pp.959-985.

Karpuz, C., Pasamehmetoglu, A.G., Bozdag, T. and Muftuoglu, Y.V. (1990) Rippability assessment in surface coal mining. *In:* Proceedings of the fourth international symposium on mine planning and equipment selection, Calgary. Rotterdam, Balkema, pp.315-322.

Kirsten, H.A.D. (1983) Efficient use on construction of tractor mounted rippers. Civil Engg. S Africa, pp.247-264.

MacGregor, F., Fell, R., Mostyn, G.R., Hocking, G. and Nally, G. (1994) The estimation of rock rippability. Quart. Jour. Engg. Geol., v.27, pp.123-144.

McCulloch, W.S. and Pitts, W. (1943) A Logical Calculus in the Ideas Immanent in Nervous Activity. Bull. Math. Biophys., pp.115-133.

Minty, E.J. and Kearns, G.K. (1983) Rock mass workability. Hydrogeology and Environmental Geology Spec. Publ., v.11.

Rosenblatt, F. (1958) The Perceptron: A Probabilistic Model for Information Storage and Organization in the Brain. Psychol. Rev., v.68, pp.386-408.

Scoble, M.J. and Muftuoglu, Y.V. (1984) Derivation of a diggability indexfor surface mine equipment selection. Min. Sci. Tech., v.1, pp.305-322.

Singh, R.N., Denby, B., Egretli, I. and Pahtan, A.G. (1986) Assessment of ground rippability in opencast mining operations. Min. Mag., Univ. Nottingham, v. 38, pp.21-34.

Smith, H.J. (1986) Estimating rippability by rock mass classification. *In:* Proc. 27th US symposium on rock mechanics, University of Alabama; pp.443-448.

Stefen, M. et al. (1997). Well_log correlation using a back propagation neural network. Mathematical Geol., v.29(3), pp.413-425.

Suseno, K. (1996) The influence of rock mass and intact rock properties on the design of surface mines with particular reference to the excavatability of rock. PhD thesis, University of Curtin.

Weaver, J.M. (1975) Geological factors significant in the assessment of rippability. Civil Engg. South Africa, v.17(12), pp.313-316.

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