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Regular Research Manuscript

Assessing the Importance of Air-Decking Blasting in Controlling BIGV at an Open Pit Gold Mine in Tanzania using ANN Model

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ABSTRACT

Air-decking blasting technique is used to control blast induced ground vibration (BIGV) in several mines including open-pit gold mines located in Tanzania. While the importance of air-deck to control BIGV is practically evident, theoretical models such as BIGV prediction models cannot be used to assess the importance of air-decking. The main objective of this study was to assess the importance of the air-decking blasting technique to control BIGV using the artificial neural network (ANN) Model. To achieve this objective, ANNs were modeled and trained to learn the pattern of data using Multilayer Perception with Back Propagation to predict BIGV. The main results showed that the normalized importance of air-decking in predicting BIGV was 92.4%. Other important parameters were distance from blasting with a normalized importance of 100% and MIC which was relatively low with a normalized importance of about 46.2%. Parameters such as charge length, powder factor, bench height, charge per length, and stemming length were by far less important than air-decking. The ANN model developed in this study appeared to perform well by incorporating air-decking parameters, which traditional BIGV predictors could not. The model also can predict BIGV with an error of about 1.8%. It was recommended that the air-decking technique used at the gold mine should be maintained and practiced to control BIGV for the sustainable development of the mining industry in Tanzania.

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INTRODUCTION

Blast induced ground vibration (BIGV) is one of the main concerns in rock blasting since it is associated with negative environmental effects such as human annoyance and structural damage occurring when blasting is not well-controlled (Kujur, 2010; Taylor, 2010; Kuzu & Hasan, 2005; Oriard, 2002). As rock blasting continues to be the main means of fragmenting hard rock, both ore and waste in underground and surface mines (Lusk and Worsey 2011; Bhandari, 1997; Dick et al., 1983; Suskind et al., 1980), it is evident that techniques to control BIGV is increasingly becoming one of the main interesting topics for research (BGC, 2018; Bansaha et al., 2014; Bender, 2007; Abdel-Rasoul, 2000). Other reasons include the demand for mineral commodities increases, opportunities for the expansion of existing mines, and the establishment of new mines increase. Because of that, the interaction of mining activities and other activities such as the development of human settlements and socio-economic infrastructure increases as well. Furthermore, a rapid increase in the population size, especially in low-income countries such as Tanzania, accelerates the development of socio-economic activities, human settlements, sensitive areas, commercial activities, and infrastructures. Such developments compete with mining and hence reduce the distance between blasting points and nearby communities. For these reasons, new policies and guidelines with more stringent regulations aiming to minimize or protect the health of human beings and safeguard structures have been developed in various countries. For example, in Tanzania, the Environmental Management (Standards for the Control of Noise and Vibration Pollution) GN No. 32, 17 and the Tanzania Bureau of Standards on Vibration put in place a threshold limits of peak particle velocity (PPV) of 5 mm/s. Generation of PPV greater than this limit beyond a boundary of any mine property is considered an excessive vibration and should be minimized using appropriate blast control.

Various blast control techniques were established based on the determinant parameters of BIGV (Mohamed, 2010). Such determinants include burden, explosive amount per delay, stemming, number of holes per detonation, sub-drill length, spacing, number of free faces, delay time and explosive type, separation distance from blasting point to the nearby community, air-decking, bench height, powder factor, charge per length, and charge length (OSMRE, 2017; Elevli and Apaz, 2010; Singh & Singh, 2004). Air-decking technique refers to a technique that allows an air column or air-deck (measured in meters) to be inserted between the explosive charging and stemming in a blast hole. For example, in a blasting that uses Fortis Advantage (FA) - a mixture of 70% Emulsion, 30% Ammonium Nitrate Porous Prills (ANPP), and Gasser/Sensitizer ($NaNO_3$) as an explosive, air deck can be easily and effectively achieved by using airbags. The airbags can be simply inserted at any point down the length of the blast hole or between FA and stemming. The main aim of the air-deck is to reduce blast hole pressure generated by an explosion (Gilmartin, 2020; Rajak et al., 2018).

Several researchers have established various models for predicting BIGV. The most common and widely applied in the mining industry is the Scaled Distance (SD) model, which has been used since 1959 (Duvall & Petkof 1959). In this model, BIGV is measured in Peak Particle Velocity (PPV mm/s) and it is assumed that the PPV is a function of SD. The SD is the ratio of distance to the explosive amount per delay. The general formula for estimating PPV based on the SD model is given in (1).

$$PPV = K[SD]^{-\beta} \qquad (1)$$

where $SD = D/Q^{a}$, K and β are the site constants related to geological structures and rock characteristics.

Several SD models such as Ambraseys and Hendon (1968), Nicholls, et al., (1971), Langefors and Kihlstrom (1976) and Siskind et al., (1980) known as the United States Bureau of Mines Model (USBM) are now used and evaluated in the mining industry (Khandelwal, 2007). However, the USMB model is the most widely used (Parida and Mishra, 2015). The main disadvantage of these models is the consideration and application of a limited number of blasting parameters. In recent years, attention is now given to the models that incorporate more parameters such as linear regression models (Chandra et al., 2017; Mansouri and Farsangi, 2015), Simulation Modeling such as Finite Element Method (FEM) (Jelusi et al., 2021), and Artificial Neural Network (ANN) Model (Lawal et al., 2021; Lawal, 2020; Lawal and Idris, 2019; Saadat et al., 2014; Singh, 2014; Amneih et al., 2013; Mohamed 2011). F

ANN which is a branch of Artificial Intelligence (AI) has been used to determine the influence of various parameters affecting BIGV (Ragam & Davidas, 2018; Tiile, 2016). The main advantage of ANN models lies in their great ability to incorporate many independent variables to predict one or more dependent variables. ANN model can solve more complicated problems involving many variables (A_n) and a non-linear relation between input variables and output variables (Callan, 1999). Like a regression model, the knowledge of relationships between the data is stored in the weights (w_n or coefficients) that exist inside the ANN. The ANN architecture comprises many nodes (perceptrons) in three layers namely input, hidden, and output. The input layer consists of all the inputs that are planned to be used in the data analysis such as all drilling and blasting data in this case. The output layer (in this case PPV) is made of layers of interconnected perceptrons and is used to accumulate the error from all of the nodes to adjust the weights between the nodes for the next trial. Supervised learning tends to determine a set of weights that minimizes an error using backpropagation. The hidden layer is where the work happens and comprises layers of interconnected perceptrons, which use mathematical concepts to determine the turns the data should take. For a prediction model like this, hyperbolic and identity functions may be used in the hidden and output layers, respectively. ANN can perform these calculations in three stages, training, testing, and holdout where the dataset is normally divided into these stages at a ratio of 70: 20: 10 (Picton, 2000; Haykin, 1998; Ripley, 1996; Bishop 1995).

In this study, an open-pit gold mine –North Mara Gold Mine which is located in the North-western part of Tanzania was selected for the assessment of the importance of the air-decking technique. The controlled blast aimed at generating PPV levels less than the threshold value of 5 mm/s at the point of interest in the nearby community. The USBM model was first used to generate more input data for the application of ANN which was then used to assess the importance of air-deck parameters.

METHODS AND MATERIALS

Study Area

North Mara Gold Mine is located in the Northwest of Tanzania. The pit is dominated by two main types of rocks *granodiorite* with a uniaxial compressive strength (UCS) of about 140 MPa and *dolerite* with UCS of 160 MPa. The densities of these rocks vary between 2.7 and 2.85 tonnes/m^3, respectively. The UCS values of the rocks indicate that drilling and blasting operations are required and are the only means of fragmenting rock. The drilling and blasting report indicated that the blast hole diameter was 171 mm while spacing and burden were maintained at 5 m and 4.3 m, respectively (North Mara Gold Mine, 2017). The blasting operations are designed to feed the plant with a daily tonnage of 8,000 tonnes. At the time of data collection, the number of holes per blast varied from 104 to 180. The mineralogical information indicated that gold particles that are disseminated in intensively deformed perversely alternated granitoid intrusive rocks require crushing and grinding in the processing plant to free them (Africa Investment; 2017; North Mara Gold Mine, 2016). The mine is located in proximity to various communities as shown in Figure 1. At the time of data collection, BIGV was considered a great threat to the nearby village in the northeast part of the pit, where blasting operations were taking place. The nearby village was located at a distance of about 500-600 m from blasting operations.

Field Data

Field data were collected from five consecutive blast shots carried out in February 2019. Thus, daily blast reports and visual examination constituted the main sources of blast data. For the BIGV data, the seismograph equipment was set out at one point in the village area where PPV and the distance from blasting points were measured. The set-up of equipment and measurement of PPV was performed according to the national guidelines of TBS (2011) and NEMC (2015). The field data are presented in Table 1.

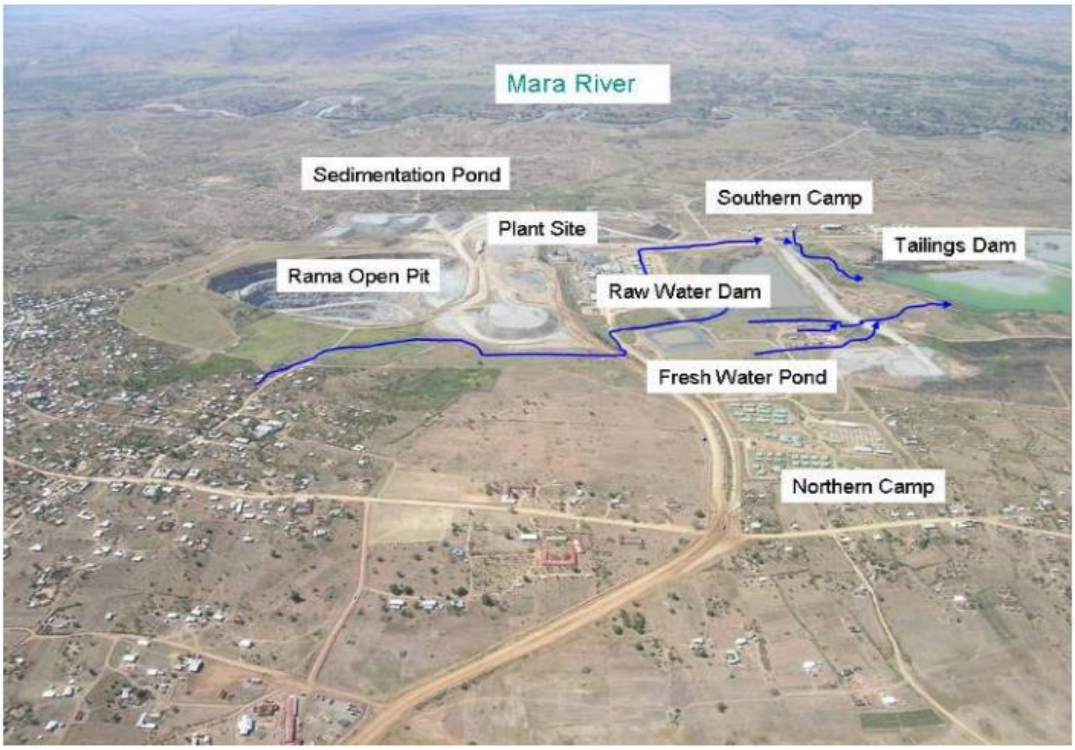

Figure 1: Pit Location and nearby community at North Mara Gold Mine, (Shelp *et al*., 2009)

Table 1: Drilling and blasting parameters used in the ANN model, (Field data, 2019)

Parameter	Blast 1	Blast 2	Blast 3	Blast 4	Blast 5
Stemming height (m)	3.50	3.50	3.50	3.50	3.00
Air-decking (m)	2.20	2.10	2.30	2.20	1.40
Bench height (m)	10.50	11.30	11.00	10.50	7.00
Powder factor (kg/m^3)	0.77	0.78	0.74	0.72	0.52
Charge per length, (kg/m)	28.71	28.71	28.71	28.71	26.64
Charge length (m)	4.80	5.70	5.20	4.80	2.60
Distance from blasting (m)	611.00	630.00	320.00	579.00	670.00
MIC (kg)	212.00	399.0	790.00	1483.00	4561.00
Observed PPV (mm/s)	12.60	6.70	1.20	2.00	10.10
Predicted PPV (mm/s)	12.72	6.54	1.27	2.00	10.21

The field data enabled the author to validate the USBM Model (1) where the coefficients of the model were obtained. The validated model is shown in (2)

$$PPV = 500\,x \left(\frac{D}{\sqrt{Q}}\right)^{-1.66} \qquad (2)$$

The model was used to predict PPV at the observation points and the data were also entered in Table 1 for comparison purposes.

Simulated Data

Model (2) was used to simulate PPV data at a distance varying from 100 to 2000 m. The simulated PPV data for Blast 1 up to 5 were presented in Table 2.

Table 2: Simulated PPV data used in the ANN model

Distance (m)	PPV (mm/s)				
	Blast 1	Blast 2	Blast 3	Blast 4	Blast 5
100	266.84	108.64	22.95	38.04	65.66
200	88.03	35.84	7.57	12.55	21.66
300	46.01	18.73	3.96	6.56	11.32
400	29.04	11.82	2.50	4.14	7.14
500	20.32	8.27	1.75	2.90	4.99
600	15.18	6.18	1.31	2.16	3.73
700	11.86	4.83	1.02	1.69	2.92
800	9.58	3.90	0.82	1.37	2.36
900	7.93	3.23	0.68	1.13	1.95
1000	6.70	2.73	0.58	0.96	1.65
1500	3.50	1.43	0.30	0.50	0.86
2000	2.21	0.90	0.19	0.32	0.54

Data Analysis

The data were scrutinized for outliers, missing, and collinearity and thereafter were loaded in the SPSS for analysis. In the IBM SPSS package, drilling and blasting parameters distance, MIC, stemming, air-decking, bench height, powder factor, charge per length, and charge length were selected as input data while PPV was selected as output data for analysis. The neural network was designed to learn what pattern exists in the data that helps to predict the results most accurately. Multilayer Perception (MLP) with Back Propagation (BP) was selected because of its great ability to work with prediction problems. It was targeted to partition the datasets into the ratio of 70%: 20%: 10% for training, testing, and holdout. However, SPSS automatically provided 70.8% of the datasets to train the tool to learn the pattern. The other 15.4% of the datasets was used to check the learning and 13.8% was used to check the accuracy of the overall learning (Table 3).

Table 3: Case Processing Summary for Prediction of BIGV

Sample	Number	Percent
Training	46	70.8%
Testing	10	15.4%
Holdout	9	13.8%
Valid	65	100.0%

The details about input and output parameters are shown in Box 1. As could be seen, three layers of input, hidden, and output were obtained from SPSS. The input layer consists of 8 units or neurons: air-decking, distance, MIC, stemming, bench height, powder factor, charge per length, and charge length. These were treated as covariates or independent variables in the model. For the hidden layer automatic architecture selection choose 3 nodes. The output layer which, was used for the dependent variable PPV, indicated 1 unit or neuron. The rescaling method for both covariates and scale dependents was standardized. For the hidden layer, the activation function used was hyperbolic tangent while the activation function for the output layer was identity.

The corresponding network diagram that SPSS used to predict PPV is shown in Figure 2. The dark lines between one node and another represent weights less than 0 (take away from the model) and the blue ones represent weights greater than 0 (add to the effect).

Box 1: Determinant parameters of PPV in the SPSS model

Input Layer	Covariates	1	Distance
		2	MIC
		3	Stemming
		4	Air-deck
		5	Bench height
		6	Powder factor
		7	Charge per length
		8	Charge length
	Number of Units		8
	Rescaling Method for Covariates		Standardized
Hidden Layer(s)	Number of Hidden Layers		1
	Number of Units in Hidden Layer 1[a]		3
	Activation Function		Hyperbolic tangent
Output Layer	Dependent Variables	1	PPV
	Number of Units		1
	Rescaling Method for Scale Dependents		Standardized
	Activation Function		Identity
	Error Function		Sum of Squares

a. Excluding the bias unit

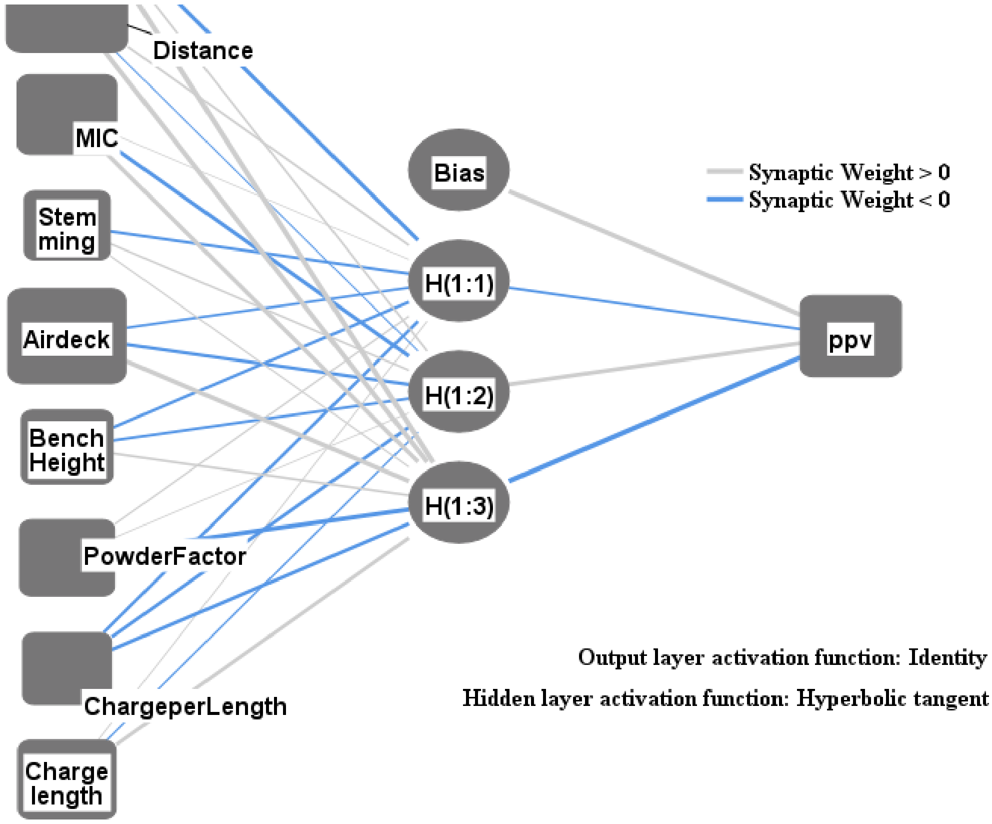

Figure 2: Network Diagram for Predicting BIGV

RESULTS AND DISCUSSIONS

The main results of the ANN model are the parameter estimates (assigned weight of each parameter in the model), errors that the model tries to minimize during training, testing, and holdout, and lastly the importance of each predictor.

Weights of Parameters in the Model

The estimated synaptic weight of each predicting parameter including air-deck as predicted in the SPSS is given in Table 4.

Errors in the BIGV Model

The errors in the training, testing, and holdout samples for the model as obtained from SPSS were presented in Table 5. As could be seen in the table, the sum-of-squares error was displayed because the output layer was a scaled dependent variable. Also, the type of error function that the network tried to minimize during training, testing, and holdout was a relative error. The relative error for the training was the lowest among the three errors, which was 0.018 compared to relative errors for testing and holdout which, were 0.214 and 0.271, respectively. The stopping rule used was one consecutive step with no decrease in error. The errors can be visualized in two ways: *first* scatter plot of observed vs. predicted PPVs and *second* residual vs. predicted value of PPV generated by the SPSS. The scatter plot of observed and predicted PPVs is shown in Figure 3.

Table 4: Weight of Air-deck parameter in the BIGV Model

Predictor		Predicted			
		Hidden Layer 1			Output Layer PPV
		H(1:1)	H(1:2)	H(1:3)	
Input Layer	(Bias)	-0.721	0.244	4.945	
	Distance	0.248	-0.092	3.991	
	MIC	0.019	-0.642	0.804	
	Stemming	-0.419	0.227	0.131	
	Air-deck	-0.358	-0.445	1.427	
	Bench Height	-0.422	-0.377	0.318	
	Powder Factor	0.145	0.028	-1.200	
	Charge per Length	-0.442	-0.446	-0.454	
	Charge length	0.060	-0.211	0.586	
Hidden Layer 1	(Bias)				3.353
	H(1:1)				-0.359
	H(1:2)				0.738
	H(1:3)				-4.044

Table 5: Summary of the accuracies of the model to predict PPV

Stages	Parameter	Value
Training	The sum of Squares Error	0.396
	Relative Error	0.018
	Training Time	0:00:00.02
Testing	The sum of Squares Error	12.579
	Relative Error	0.214
Holdout	Relative Error	0.271

Dependent Variable: BIGV

a. Error computations are based on the testing sample.

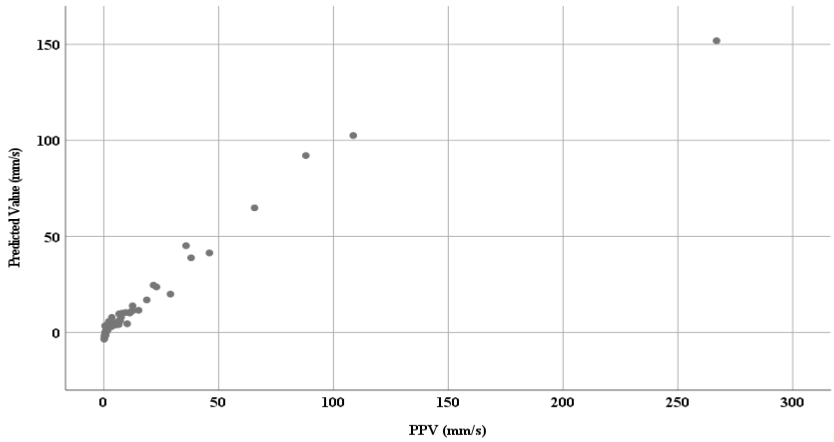

Figure 3: Predicted PPV vs. observed PPV for BIGV model

The figure shows a near-straight line of approximately 45^0 which, indicates that the model is doing fine such that linear regression between observed and predicted values could be formulated as shown in (3).

$$P = a + b V + e \qquad (3)$$

where P is the predicted PPV; V is the observed PPV; a and b are the model coefficients and e is the model error.

The scatter plot for the residual vs. predicted value of PPV is shown in Figure 4. The figure shows a broad band of the predicted PPV against residual where the residual versus predicted appeared to be like a horizontal band centered on the X-axis. This implies that there are no obvious omissions.

Estimation of the Importance of Air-Deck in Controlling BIGV

Estimation of the importance of air-deck in predicting BIGV was obtained as a result of the impact or sensitivity analysis of the independent variables. This was requested in the SPSS and the results are presented in Figure 5. The importance is a measure of how much the network's model-predicted value changes for different values of the air-deck. As could be seen in Figure 5, both the importance and normalized importance were provided. The normalized importance of air-deck in predicting BIGV was 92.4%. The other important parameters worth mentioning were the distance from blasting and MIC. The normalized importance of these parameters was 100% and 46.2%, respectively.

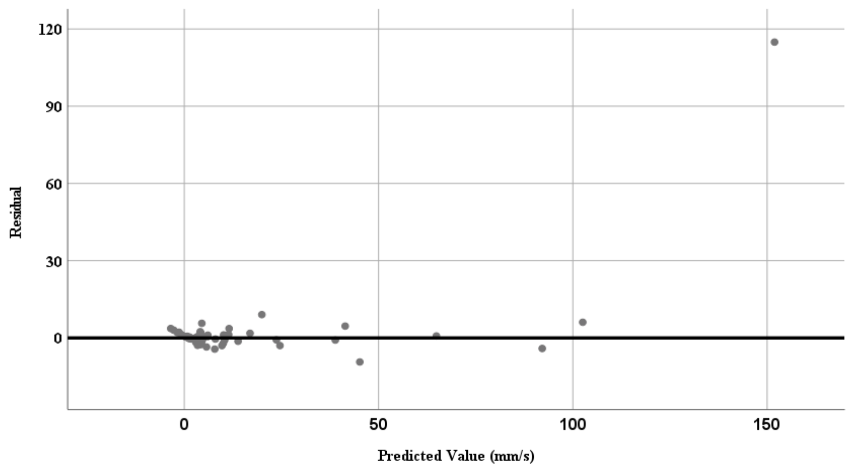

Figure 4: Predicted value of PPV vs residual

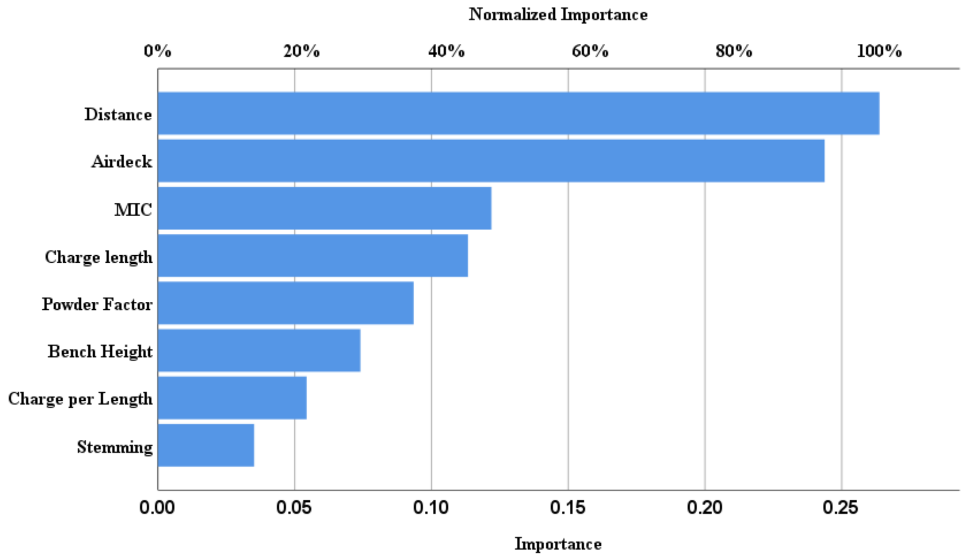

Figure 5: Importance of Air-deck in the prediction model of BIGV

CONCLUSION

ANN models were established using Multilayer Perception with Back Propagation for the assessment of the importance of air-decking blasting in controlling BIGV at an open pit gold mine located in North-west Tanzania. The main results showed that air-deck was one of the main determinant parameters of BIGV with a normalized importance of 92.4%. The other important parameters were the distance from blasting with a normalized importance of 100% and MIC which was relatively low with a normalized importance of about 46.2%. The other parameters such as charge length, powder factor, bench height, charge per length, and stemming were by far less important than air-deck. The ANN model developed in this study appeared to perform well by incorporating air-deck parameters which traditional models such as the USBM model could not. The model also can predict PPV with an error of about 1.8%. The results imply that the mine should continue using the air-decking blasting technique for sustainable development of the mine. It is, however, recommended that future research should focus on the collection and application of more datasets to improve the results.

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REFERENCES

Abdel-Rasoul, E. (2000). “Measurement and Analysis of the Effect of Ground Vibrations Induced by Blasting at the Limestone Quarries of the Egyptian Cement Company”, *Cairo University*, ICEHM 2000, 54-71.

Africa Investment (2017). “Acacia Mining Tanzania Gold Production Up 13% in 2016”. http://www.tanzaniainvest.com/mining/gold-production-2016-acacia Accessed on 9th September 2024.

Ambraseys, N. and Hendron, A. (1968). “Dynamic behavior of rock masses”. In: *Rock Mechanics in Engineering practices.* London: Jons Wiley & Sons, 203-207

Amneih, B. H., Mohammadi, A. and Mozdianfard, A. (2013). “Predicting Peak Particle Velocity by Artificial Neural Networks and Multivariate Regression Analysis”. *Journal of Mining and Environment*, 125-132.

Bansah, K.J., Assan, E and Galecki, G. (2014). "Predicting the Impact of Rock Blasting on Building Structures at Awunakrom in the Ahanta West District of Ghana". *Research Journal of Environmental and Earth Science*, **6**(7): 358-363.

Bender, W. L. (2007). "Understanding Blast Vibration and Airblast, their Causes, and their Damage Potential". Cleaveland, Society of Explosives Engineers, 1-38.

BGC (Australia) Pty, Ltd. (2018) "BGC Voyager II Quarry Blast and Vibration Management Plan", Environmental Management Plan, the Lakes, Shire of Northam.

Bhandari, S. (1997). "Engineering Rock Blasting Operations". Brookfield A. A. Balkema Publishers.

Bishop, C. (1995). "Neural Networks for Pattern Recognition", 3rd ed. Oxford University Press, Oxford.

Callan, R. (1999). "The Essence of Neural Networks". Prentice Hall, UK

Chandra, K. R., Sastry, V. R., Hegde, C. and Shreedharan, S. (2017). "Prediction of Peak Particle Velocity using Multi-Regression Analysis: case studies", Geomechanics and Geoengineering, **12**(3): 207-214, DOI: 10.1080/17486025.2016.1184763

Dick, R. A., Fletcher, L. R. and D'adrea, D. A. (1983). "Explosive and Blasting Procedures Manual". Bureau of Mines, Washington, D.C.

Duvall, W. I. and Petkof, B. (1959). "Spherical Propagation of Explosion Generated Strain Pulses in Rock", Washington: US. Department of the Interior, Bureau of Mines

Elevli, B. and Arpaz, E. (2010). "Evaluation of Parameters Affected on the Blast Induced Ground Vibration (BIGV) by using Relation Diagram Method (RDM), Acta Montanistica Slovaca, **15**: 261-268

Gilmartin, S. (2020). "How Air-decking can Reduce CO_2 Emissions and Provide Other Benefits in Quarry Blasting, Air-decking and the Environment in Quarry Management Issue of April 2020.

Haykin, S. (1998). "Neural Networks: A Comprehensive Foundation", 2nd ed. Prentice Hall, UK

Jeluši, P., Ivaniˇ, A., Lubej, S. (2021). "Prediction of Blast-Induced Ground Vibration Using an Adaptive Network-Based Fuzzy Inference System". Applied Science. **11**(1): 203. 10.3390/app11010203

Khandelwal, M. S. T. N. (2007). "Evaluation of Blast-Induced Ground Vibration Predictors", Mumbai: Department of Earth Science, Indian Institute of Technology.

Kujur, B. K. (2010). "Blast Vibration Studies in Surface Mine", Rourkela: National Institute of Technology.

Kuzu, C. and Hasan, E. (2005). "An Assessment of Environmental Impacts of Quarry-blasting Operation: a Case Study in Istanbul, Turkey". Environmental Geology, **48**(2): 211-217. DOI:10.1007/s00254-005-1291-5

Langefors, U. and Kihlstrom, B. (1976). "The Modern Technique of Rock Blasting". John Wiley & Sons.

Lusk, B. and Worsey, P. (2011). "Explosives and Blasting". In: *Mining engineering handbook*. USA: Society for Mining, Metallurgy, and Exploration, Inc., pp. 443-460

Lawal, A. I. (2020). "An Artificial Neural Network-based Mathematical Model for the Prediction of Blast-induced Ground Vibration in Granite Quarries in Ibadan", Oyo State, Nigeria, Scientific Africa 10.1016/j.sciaf.2020.00413

Lawal, A.I. and Idris, M. A. (2019). "An Artificial Neural Network-based Mathematical Model for the Prediction of Blast-induced Ground Vibration, International *Journal of Environmental Studies*, **77**(2): 1-17, 10.1080/00207233.1662186

Lawal, A.I., Kwon, S. and Kim, G.Y. (2021). "Prediction of the Blast-induced Ground Vibration in Tunnel Blasting using ANN, Moth-flame Optimized ANN, and Gene Expression Programming". *Acta Geophysics*, **69**: 161–174, 10.1007/s11600-020-00532-y

Mansouri H and Farsangi, E. (2015). "Blast Vibration Modeling using Linear Superposition Method", Journal of Mining & Environment, **6**(2): 125-140

Mohamed M. T. (2011). "Performance of Fuzzy Logical and Artificial Neural Network in the Prediction of Ground and Air Vibrations", *Journal of Engineering Sciences*, Assiut University, **39**(2): 425-440. 10.21608/jesaun.211.127550

Mohamed, M. T. (2010). "Vibration Control" DOI: 10.5772/intechopen.83953 in Lallart, M. (2010) Vibration Control, Lyon, France. DOI: 10. 5772/250

Nicholls, H. R., Johnson, C. F. and Duvall, W. I. (1971). "Blasting Vibrations and Their Effect on Structures", Pittsburgh: United States Bureau of Mines

North Mara Gold Mine. (2016). "Nyabirama Geology". Tarime, Mara: NMGM on Notes Board.

North Mara Gold Mine. (2017). "Daily Production Report" (01-08 January 2017). Tarime: Unpublished.

Office of Surface Mining, U.S. Department of Interior. (2017) "Surface-Blast Design". Retrieved January 15, 2017, from OSMRE: www.osmre.gov/resources/blasting/btm/Module3.pdf

Oriard, L. L. (2002). "Explosive Engineering, Construction Vibrations, and Geotechnology", International Society of Explosive Engineers.

Parida A, and Mishra, (2015). "Blast Vibration Analysis by Different Predictor Approaches- A Comparison", *Earth and Planetary Science*, **11**: 337-345

Picton, P. (2000). "Neural Networks", 2nd ed. Palgrave, New York

Ragam, P. Devidas S. N. (2018). "Evaluation and Prediction of Blast–Induced Peak Particle Velocity using Artificial Neural Network: A Case Study".

Rajak, M. K, Subramanian, K.S. S and Prince, M.J.A. (2018). "The Effects of Air Decking Technique of Blasting in Surface Mine- A Brief Review".

Ripley, B. (1996). "Pattern Recognition and Neural Networks", Cambridge University Press, Cambridge

Saadat, M., Khandelwal, M and Monjezi, M. (2014). "An ANN-based Approach to Predict Blast-Induced Ground Vibration of Gol-E-Gohar Iron Ore Mine, Iran", Journal of Rock Mechanics and Geotechnical Engineering, **6**(1): 676-76, 10.106/j.jrmge.2013.11.001

Shelp M L, Upton B, Zhan G, and Sibliski U. (2009). "Mine Water Management in Modern African Mining Operations" International Mine Water Association, http://www.imwa.info. Accessed on 20th July, 2024.

Singh T. N (2014). "Application of Artificial Neural Network for Blast Performance Evaluation". *International Journal of Research in Engineering and Technology*, **3**(5): 564:574, 10.15623/ijret.2014.0305104

Singh, T. N. and Singh, V. (2004). "An Intelligent Approach to Prediction and Control Ground Vibration in Mines". *Geotechnical and Geological Engineering*: Springer, **23**: 249-262. 10.1007/s10706-004-7068-x

Siskind, D. E., Stachura, V., Stagg, M. S., Kopp, J. W. and Dowding, C. H., (1980). "Structural Response and Damage Produced by Ground Vibration from Surface Mine Blasting", *United States Bureau of Mines: Report of Investigation* 8508.

Suskind, D. E., Stagg, M. S., Kopp, J. W. and Dowding, C. (1980). "Structural Response and Damage Produced by Ground Vibration From Surface Mine Blasting". *United States Bureau of Mines: Report of Investigation* 8508.

Tanzania Bureau of Standards (2011) TZS 1471: 2011," Tolerance Limits for Environmental Vibration", *The Environmental Management Division Standard Committee, Dar es Salaam*

Taylor, R. (2010). "Macraes Phase III Vibration and Air Blast Assessment", Oceana Gold (New Zealand) Limited, Orica Mining Services

Tiile, R. N (2016). "Artificial Neural Network Approach to Predict Blast-Induced Ground Vibration, Airblast and Rock Fragmentation, Missouri: Curtis Laws Wilson Library.

United Republic of Tanzania (2015). "The Environmental Management Act", Government Notice No. 32 Published in 30/01/2015; the Environmental Management (Standards for the Control of Noise and Vibrations Pollution).