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Application of Artificial Neural Networks to Predict Blast-Induced Ground Vibration in a Diamond Mine

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***Abstract*— In this paper, ground vibration that is induced by blasting was predicted using data gathered from a diamond mine. Artificial neural network (ANN) is used to train the model from the 94 blast dataset using Levenberg–Marquardt algorithm, and we tested and verified the built model. Different ANN models were compared using Root mean square error (RMSE) and coefficient of determinant (R^2), and the optimum ANN model was selected. Blasthole depth, blasthole diameter, burden, spacing, stemming length, powder factor, maximum charge and distance from the blast face to the monitoring point were used as input parameters. Ground vibration was the output parameter that was predicted using the built model. Processes in building the machine learning model are presented, together with prediction results and are compared against each other.**

Keywords*— Artificial neural network, blasting, ground vibration

I. Introduction

Drilling and blasting is the most common economical viable method of rock fragmentation in mining, quarrying and civil engineering projects like road or dam construction and tunneling. During blasting, about 20-30 % of explosive energy generated is the on that actual breaks the rocks whereas the rest result in adverse environmental impacts such as ground vibration, backbreak, airblast, flyrock etc [1-3].Excessive generation of ground vibration due to blasting can result in harmful effects on nearby habitants and even damage to structures [4-10]. Hence the prediction of blast-induced ground vibration is vital way of controlling and prevent undesirable effects of blasting. Ground vibrations are measured in terms of peak particle velocity (PPV) in millimeters per second (mm/s) at a certain ground locations. Ground vibrations are influenced by controllable parameters and uncontrollable parameters. Controllable parameters are those that are man-made, mostly associated with explosive characteristics and blast design parameters such as explosive energy, charge per delay, blasthole diameter, blasthole depth, stemming etc. Uncontrollable parameters are those that are naturally occurring such as rock characteristics and geological conditions. The magnitude of the ground vibration at any locations is influenced by the following;

- Frequency: is the number of oscillations per second the wave undergoes. (measured in(Hz)
- Wave displacement : The distance a wave moves before returning to its
- original position (measured in mm)
- Wave velocity: the rate of change of displacement (measured in mm/s).
- Wave acceleration: This is the rate of change of velocity (measured in mm/s^2)

Several researchers has developed empirical formulas to predict induced ground vibrations however this empirical formulas do not include many factors that affect the blasting outcomes. Hence, the need to use more robust techniques that will incorporate many factors that affect the blasting outcome such as artificial neural network (ANN). Artificial neural network is a machine learning technique that was introduced in the 1980s. This technique is capable of developing the relationship between the inputs and outputs parameters without prior physics about them.

In this paper, a new ANN model is developed to predict blast-induced ground vibration in Orapa diamond mine. Also, different developed ANN models were compared with each other to determine the optimum ANN model.

A. The study area

Orapa mine is open mine and expected to reach the depth of 450m by 2026. The mine is situated in Botswana in Southern Africa as shown in Figure 1. It is about 240 km west of Francistown and was discovered by De Beers geologists in 1967 led by Manfred Marx. Also, it was official opened by the first the first President of Botswana, His Excellency Sir Seretse Khama in July 1971. The mine lies on igneous rocks known as kimberlite which bears diamonds and it was intruded about 92 million years ago. The Orapa kimberlite has two coalescing diatremes with preserved crater sedimentary facies named southern and northern lobes which lie on a 1.18 square kilometres at ground level.

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Figure 1. Location of Orapa Diamond Mine in Botswana, Southern Africa

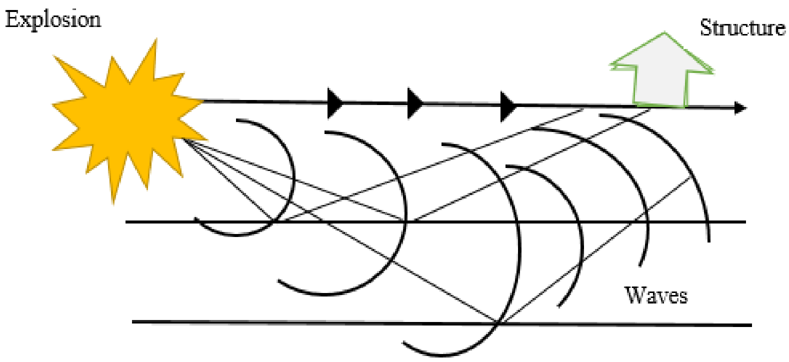

Figure 1.1. Ground vibration caused by blasting

B. Mechanism of ground vibration

When an explosive detonates within a blasthole, a large amount of chemical energy is released at high pressure thereby forming a hot gas [11]. After detonation, two forms of energy are generated; gas pressure energy and shock wave energy [12]. The shock wave energy greatly affects the walls of the blasthole and crushes it up. The damaged area surrounding the blasthole is called the crushed zone. Fracturing will result beyond the crushed zone caused by elastic and plastic waves and form what is called nonlinear zone [13]. Elastic waves propagate beyond this zone as shown in (Figure 1.1) while plastic waves lessen in this zone. As the elastic wave propagates beyond the nonlinear zone, this motion is referred to as peak particle velocity. Although, the intensity of ground vibration diminishes with distance, large amount usage of explosive can still cause damage to the nearby natural and man-made structure as result of dynamic stress being more that the material strength [14].

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II. METHODS AND MATERIALS

A. *Artificial Neural Network*

The prediction ability of ANN is based on preceding learning [15]. Once the network has been developed and trained, any similarities in the new datasets presented, the pattern will be detected and new predictions will be made. Therefore, ANN has being used successfully across many different displaces and research as well. Eren et al. [16] applied the ANN system to predict densities and particle size distributions in mineral processing industry. The ANN system was used to predict ground subsidence in a metal mine by Zhao and Chen [17]. They found out that ANN model prediction results were highly accurate and consistent with the measured values. Therefore, ANN system proved it can used to monitor mine ground subsidence. Lal and Tripathy [18] predicted dust concentration using artificial neural network in an open cast coal mine in Jharkhand, India. ANN technique have also being used by many researchers for prediction of wide range of parameters from simple to complex [19, 20].

The neural network must be trained before the new datasets can be interpreted. There are many algorithms that are used to train the neural networks, however the most used algorithm is back-propagation which is robust, versatile plus it provides effective learning for multiple layer neural networks. The back-propagation neural networks are made up of three layers which are: input layer, hidden layer and output layer. Each layer consists of basic processing units called neurons. These neurons connects to next layer via approximate weights, i.e. the output of the neurons in the input layer serves as the input for the hidden layer neurons and similar with the connection between the hidden layers and the output layers. The number of input neurons is the equal with the number input variables and it is the same as number of output neurons and the output variables. However, the problem to be solved determines the number of hidden layers and neutrons in them. A typical structure of neural network is shown below in Figure 2.

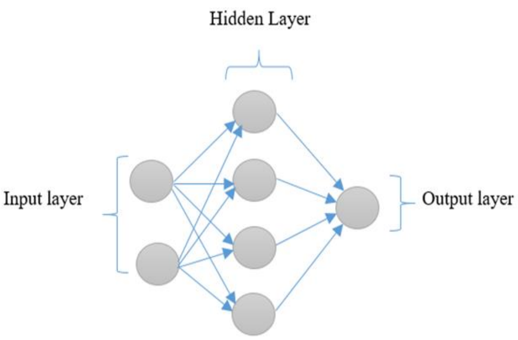

Figure 2. A typical structure of neural network

In this study a back propagation neural network is used with 'Levenberg-Marquardt' algorithm and different transfer functions to determine the optimum predictive model. Transfer functions include tan-sigmoid and log-sigmoid.

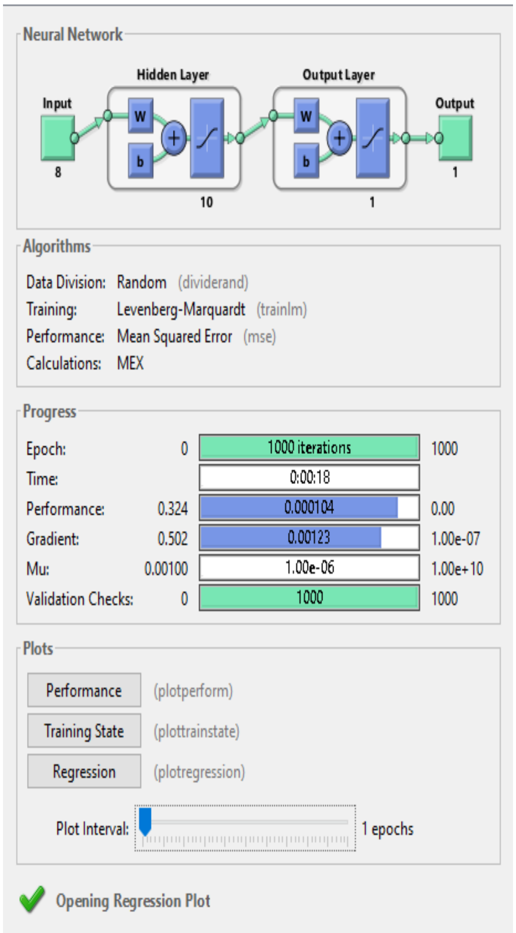

Figure 2. Training of back-propagation the neural network

B. *Datasets*

A total of 104 blasting datasets was provided by Orapa Diamond mine. For development of the ANN model, training and testing, 94 datasets was used while 10 datasets was used for checking the prediction accuracy of the developed ANN model. The ANN model was built with eight input parameters and one output parameter as shown in Table 1.The neural network architecture is shown in Figure 2.

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Table 1. The range of parameter

Type of data		Parameters	Range
Input	1	Burden (m)	4-8
	2	Stemming length (m)	4-8
	3	Spacing (m)	4-7
	4	Hole depth (m)	6.54 -18.43
	5	Hole diameter (mm)	150 – 250
	6	Distance (m)	438 - 1500
	7	Maximum charge per delay (kg)	27- 61.4
	8	Powder factor (kg/m^3)	0.3 - 61.4
Output	1	Ground vibration (PPV), mm/s	91.5 – 126.7

III. RESULTS AND DISCUSSION

An ANN model 6 of 8-10-1 network architecture of transfer function of TRANSIG was found to be the optimum model as illustrated in Table 2. A pictorial representation of the optimum neural network architecture is shown in Figure 3. The coefficient of determination (R^2) of the optimum model is 0.945. This index is closer to 1 and this means it has the higher the prediction accuracy compared to other models. Ground vibrations was predicted by optimum artificial neural network using 10 new datasets that have not being used before. The predicted ground vibrations were compared with the measured ones as shown in Figure 4. It evidently shows by the R^2 that the predicted values by the optimum ANN model are closer to the measured values as shown in Figure 3.1 and it was 0.9849.This index shows that the chosen ANN model has an excellent prediction capabilities. Also, the root mean square error (RMSE) between the measured values and the optimum ANN predicted values was at the lowest with 0.24 and close to zero, thus providing to be a great predictive model.

Table 2. Different ANN models

Model	Transfer function	Network architecture	(R^2)
1	TRANSIG	8-20-1	0.935
2	TRANSIG	8-13-1	0.889
3	LOGSIG	8-10-1	0.860
4	LOGSIG	8-12-1	0.939
5	LOGSIG	8-16-1	0.848
6	TRANSIG	8-10-1	0.945

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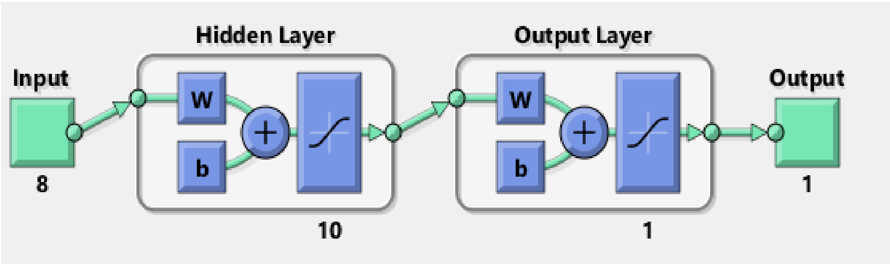

Figure 3. The optimum neural network achitecturure

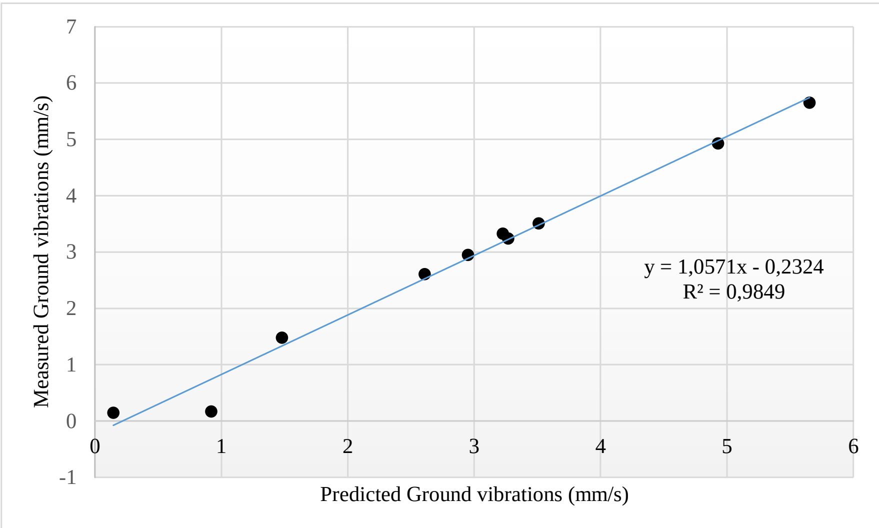

Figure 3.1. The relation between the measured and the predicted ground vibrations by ANN

IV. CONCLUSION

Based on the study, it shows that ANN model with network architecture of 8-10-1 with two hidden layer and transfer function of tran-sigmod has been found to be the excellent predictive model by merging back-propagation neural network with ‘Levenberg-Marquardt’ algorithm. Also, the optimum ANN model proved to be the best because of its highest coefficient of determination.

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REFERENCES

[1] Cheng, G., Huang, S.L., 2000. Analysis of ground vibration caused by open pit production blast. In: Holmberg (Ed.), Explosive and Blasting Technique, Balkema, pp. 63–70

[2] Monjezi, M, Bahrami, A., Yazdian, A., Sayadi, A.R., 2009. Prediction and controlling of flyrock in blasting operation using artificial neural network. Arab. J. Geosci. doi:10.1007/s12517-009-0091-8

[3] Hakan, A.K., Konuk, A., 2008. The effect of discontinuity frequency on ground vibrations produced from bench blasting: a case study. Soil Dyn. Earthq. Eng. 28, 686–694

[4] Nateghi R, Kiany M, Gholipouri O. Control negative effects of blasting waves on concrete of the structures by analyzing of parameters of ground vibration.Tunn Undergr Space Technol 2009;24(6):608–16.

[5] Toraño J, Ramírez-Oyanguren P, Rodríguez R, Diego I. Analysis of the environmental effects of ground vibrations produced by blasting in quarries.Int J Min Reclam Environ 2006;20(4):249–66.

ISSN: 2521-2292

[6] Kahriman A. Prediction of particle velocity caused by blasting for an infrastructure excavation covering granite bedrock. Miner Resources Eng 2001;10(2):205–18.

[7] Singh PK, Vogt W, Singh RB, Singh MM, Singh DP. Response of surface structures to rock blasting. Miner Resources Eng 1997;6(4):185–94.

[8] Faramarzi F, Ebrahimi Farsangi MA, Mansouri H. Simultaneous investigation of blast induced ground vibration and airblast effects on safety level of structures and human in surface blasting. Int J Min Sci Technol 2014;24 (5):663–9.

[9] Khandelwal M, Singh TN. Prediction of blast-induced ground vibration using artificial neural network. Int J Rock Mech Min Sci 2009;46(7):1214–22.

[10] Yi CP, Lu WB. Research on influence of blasting vibration on grouted rockbolt.Yantu Lixue/Rock Soil Mech 2006;27(8):1312–6.

[11] Hopler, R.B. (Ed.) (1998) Blasters' Handbook, 17th ed., International Society of Explosives Engineers, Cleveland, OH.

[12] Djordjevic, N.M. (1995) A Study on the Blast Induced Ground Vibrations and their Effects on Structures, PhD Thesis, Julius Kruttschnitt Mineral Research Centre, The University of Queensland, Brisbane, Australia

[13] Mortazavi, A. (1999) Modelling of Rock Blasting in Jointed Media using Discontinuous Deformation Analysis, PhD Thesis, Mining Engineering department, Queen's University, Canada

[14] Siskind DE, Stagg MS, Kopp JW, Dowding CH. Structure response and damage produced by ground vibration from surface mine blasting, vol. 8507. US Bureau of Mines, RI; 1980. p. 74.

[15] Simpson PK. Artificial neural system—foundation, paradigm, application and implementations. New York: Pergamon Press; 1990.

[16] Eren H., Fung, CC.,Wong, KW., (1997). An application of Artificial Neural Network for prediction of densities and particle size distributions in mineral processing industry. IEEE Instrumentation and Measurement. Technical Conference. Ottawa, Canada

[17] Zhao, K and Chen, S (2011). Study on artificial neural network method for ground subsidence prediction of metal mine. Science Direct. Volume 2. pp 177-182

[18] Lal, B and Tripathy, S. (2012) Prediction of dust concentration in open cast coal mine using artificial neural network. Atmos Pollut Res , Volume 3, Pp 211–218.

[19] Maulenkamp F, Grima MA. Application of neural networks for the prediction of the unconfined compressive strength (UCS) from equotip hardness. Int J Rock Mech Min Sci 1999;36:29–39.

[20] Kosko B. Neural networks and fuzzy systems: a dynamical systems approach to machine intelligence. New Delhi: Prentice Hall of India; 1994. p. 12–17.