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Airblast Prediction in a Blasting Operation Using Artificial Intelligence

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***Abstract*—This paper presents the use of artificial neural network (ANN) to predict airblast that is induced by blasting in a diamond mine. A total of 94 blasting datasets were used to develop and train the ANN models using Levenberg–Marquardt algorithm. The input parameters were: burden, spacing, blasthole depth, blasthole diameter, stemming length, distance from the blast face, powder factor, and maximum charge. Airblast was the output parameter. Its values were predicted after the model was built. The ANN model with 8-12-1 architecture proved to have a better performance when compared to other ANN models. Comparisons were based on coefficient of determinant (R^2) and root mean square error (RMSE). The processes of building and characterization of the machine learning model are shown together with results on prediction accuracy. Each result is compared against different ANN architecture, transfer functions, and number of hidden neurons**

***Keywords*— Airblast, artificial neural network, blasting**

I. INTRODUCTION

Blasting is the most common technique used in mining and civil engineering for rock fragmentation. Airblast or air overpressure is the one of the most hazardous effects of blasting operation on the environment. The noise generated during the blast can result in complaints from nearby local inhabitants and impact the personnel negatively psychologically. Also, more than 80% of the energy released during blasting results in adverse environmental effects such as airblast, ground vibration and flyrocks etc [1-3], as illustrated in Figure 1.

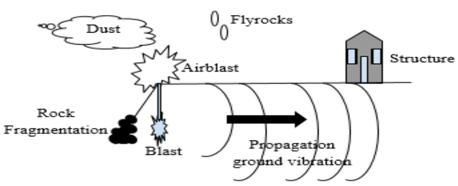

Figure 1. Environmental effects of blasting

Therefore, it is vital to predict blast-induced airblast to insure safe blasting operation. During blasting, airblast is generated when explosive gases get released into the atmosphere and create air pressure waves [4]. In blasting operation, airblast or air-overpressure is mainly a resultant of the following [5-7]

- Air pressure pulse (APP): displacement of the rock at bench faces as the blast progresses.
- Stemming release pulse (SRP): escape of gases from the blasthole when the stemming is ejected.
- Gas release pulse (GRP): escape of gases through rock fractures.
- Rock pressure pulse (RPP): induced by ground vibration.

Moreover, airblast is influenced by many factors which are divided into controllable and uncontrollable factors as shown in studies [8-12]. Controllable factors include blast design parameters such as burden and spacing, charge depth, stemming, maximum charge per delay, detonator accuracy and direction of initiation. However, uncontrollable factors include atmospheric conditions, weak strata, overcharging and conditions caused by secondary blasting. Various researchers has shown the predictive ability of the artificial intelligence methods across different fields of studies. Khandelwal and Kankar [9] predicted airblast using empirical models and support vector machine (SVM).They developed the models using 75 datasets. The results showed that SVM had high prediction accuracy as compared to empirical formulas. Armaghani et al [10] used a hybrid Al-based predictive model to predict blast induced air overpressure (AOp) at granite quarry site in Malaysia. The hybrid Al-based predictive model results were highly accurate as compared to conventional predictors.

ANN is the widely used soft computing method for prediction and this the first time ANN is applied to predict blast-induced airblast in a diamond mine according to the authors knowledge. The Orapa mine is located Orapa mine is located in Botswana, Southern Africa. It is situated 240 km west of Francistown in the Central District of Botswana as shown in Figure 1.1. It is positioned between the latitude and longitude of 21° 18′ 30″ S and 25° 22′ 10″ E respectively.

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Figure 1.1 Map of Botswana showing the location of Orapa Diamond Mine

Orapa mine is a conventional open pit mine as demonstrated in Figure 1.2. The mine operates a four-shift system with 8 hours per shift. The mine operations start with drilling of the blastholes, charging blastholes with explosives and detonating blastholes. The resulting rock fragments from the blasting are loaded into dump trucks using hydraulic excavators. The waste material is hauled to waste dumps while the ore is transported directly to the crusher or to the stockpile. Dewatering is one of the processes that is also done as mining progresses to control water inflows thus creating workable dry conditions and reducing pore water pressure which affects slopes significantly.

Figure 1.2. Ariel view of Orapa open pit mine

Airblast or air overpressure is the one of the most hazardous effects of blasting operation on the environment. During blasting, airblast is generated when explosive gases get released into the atmosphere and create air pressure waves. These generated explosive gases have energy that leads to the rise of air pressure level above the normal atmospheric pressure. Atmospheric pressure wave can be subcategorized into two: audible and sub-audible [11].Audible pressure waves are those with high frequency sound while sub-audible pressure waves have low frequency sound. Blast induced airblast is a shock wave which is refracted horizontally by density variations in the atmosphere and gradually dies out with distance and time. The minimum frequency of sound that a human being can hear is 20 Hz and below that it cannot be heard. Airblast is measured in terms of Pascal (Pa) and Decibels (dB) [12]. Air blast results in inhabitants' annoyances and potential structural damage when air overpressure wave's energy is higher than the atmospheric pressure. Table I below shows the types of impacts that different levels of airblast can cause [13].

Table I. Airblast levels and their impacts

Airblast level	**Impacts**
<110 dB	Non
110-130 dB	Window Vibration
130-150 dB	Glass Break
180 dB	Structural damage

II. METHODS AND MATERIALS

A. Artificial Neural Network

Artificial neural network is one of the artificial intelligence method what mimics how the human brain works introduced in the early 1980s. ANN is defined by four stages which are choosing the network architecture, training, testing and validating datasets [14]. ANN is applicable in situations whereby the relationship between the inputs and outputs datasets is complex and nonlinear [15]. The most common used ANN type is the multilayer feed forward and has three layers that are interconnected to each other by neurons [16]. This three layers are input layer, hidden layer and the output layer. A typical ANN model is shown in Figure 2. The input layer receives the raw data (n) and then transmit it through neurons to the hidden layers via connection weights. The output of each hidden neurons is produced after transfer function such as the sigmoidal function to the hidden neurons net input. The process continues until the desired output is produced.

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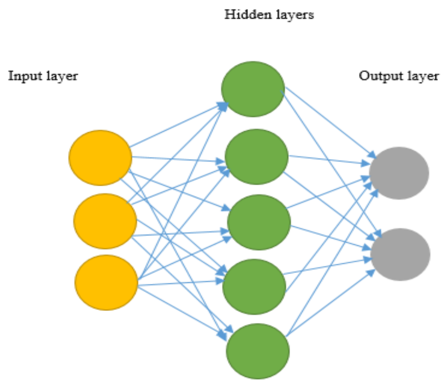

Figure 2. Typical ANN model

B. Training of the neural network

Firstly, neural network can be trained with back-propagation algorithm before new datasets are imported. There many algorithms used for training the neural network but for solving the predicting problems back-propagation algorithm is mostly used [17].The training of the network by back-propagation involves the following four steps (14)

1) Initialization of weights,
(2) feed-forward,
(3) back-propagation of errors, and
4) Updating of weights and biases.

Also, Levenberg–Marquardt algorithm can used for training the network as it fastest method with high accuracy. It is a built in function on MATLAB software [18]. Therefore, in this study it is used to train the network. The ANN behavior mostly depend on weights and transfer function. The transfer function output is multiplied weights connecting the hidden layer and the output layer to generate the network output. The commonly used transfer functions are tan-sigmoid, log-sigmoid and linear transfer function in back-propagation as shown in Figure 2.2, 2.3 and 2.4 respectively.

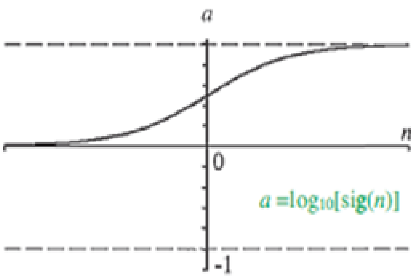

Figure 2.2. log-sigmoid function used for hidden layers [19]

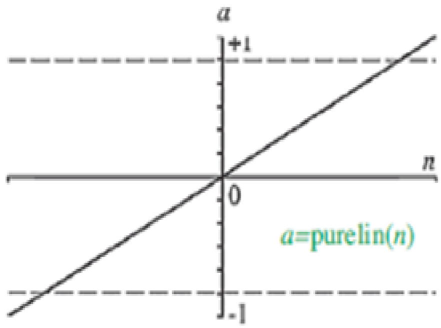

Figure 2.4.Liner transfer functions used for the output layer [19]

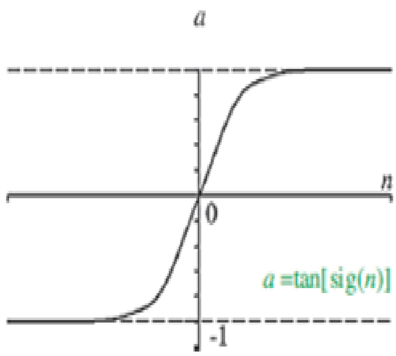

Figure 2.3. tan-sigmoid function used for hidden layers [19]

C. Datasets

Orapa diamond mine provided a total of 104 blasting datasets. A total of 94 datasets was used for development, training and testing the ANN model whereas 10 datasets was used for validating the ANN model. Eight input parameters and one output parameter were used to build the feed forward back propagation ANN system. Input parameters were blasthole depth, blasthole diameter, stemming length, spacing, burden, and distance from the blast face, powder factor and maximum charge per delay. On the other hand airblast was regarded as the output parameter. The optimum prediction model was established by feeding input and output parameters on a MATLAB-based ANN system. The range of input and output parameters are shown in Table II.

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Table II. Range of Input and output parameters

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

Table III. Different ANN models

Model	Transfer function	Network architecture	(R^2)	(RMSE)
1	TRANSIG	8-10-1	0.935	0.385
2	TRANSIG	8-14-1	0.926	0.421
3	TRANSIG	8-12-1	0.983	0.149
4	LOGSIG	8-11-1	0.849	0.752

III. RESULTS AND DISCUSION

Optimum ANN model was selected from the models developed as shown in Table III. The selection was based on the evaluation performance using coefficient (R^2) and the root mean square error (RMSE). The ANN model 2 was chosen as then optimum model as it has R^2 an RMSE of 0.983 and 0.149 respectively. The indices shows the excellent predictive ability of the chosen model. The optimum ANN model had network architecture of 8-12-1 (8 inputs parameters, 12 hidden neurons and 1 output parameter with a transfer function of transig as illustrated in table III. Also the optimum ANN model is shown in Figure 3. Figure 3.1 demonstrates the graph between the measured airblast and predicted airblast by the optimum model on a 1:1 slope line. All the predicted data points are very close to 1:1 slope line. This shows the predictive ability of ANN to predict blasting effects such as airblast.

Figure 3. Optimum model network architecture

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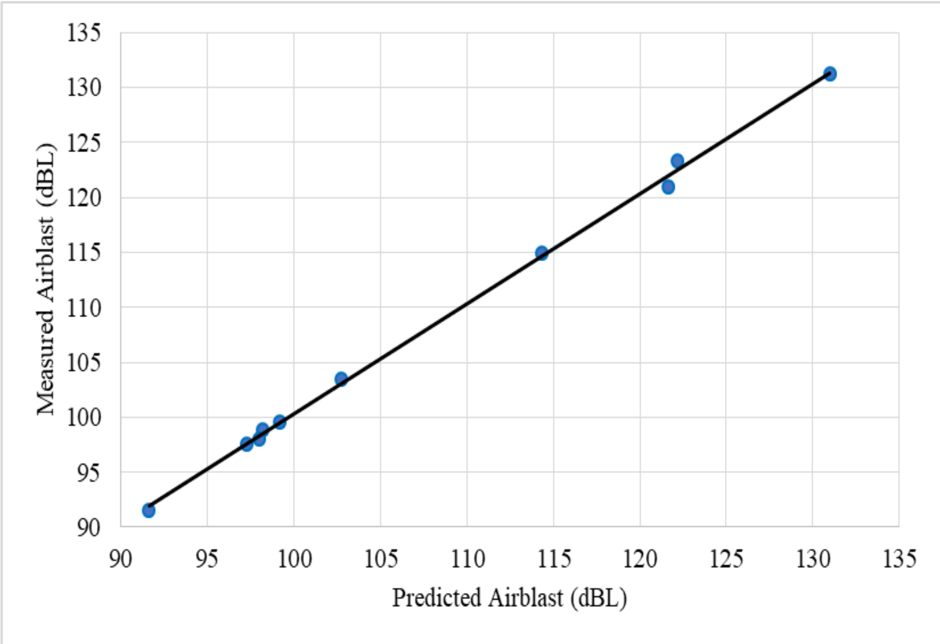

Figure 3.1. The relation between measured and predicted Airblast values by ANN model

IV. CONCLUSION

The neural network with two hidden layer, twelve hidden neurons and tran-sigmod transfer function has been found as the optimum model. Also, the predicted airblast values by the optimum ANN model shows the high degree accuracy of predictive capability of ANN when compared with the measured airblast values. Therefore, it can be concluded that ANN is an applicable tool to predict blast-induced airblast.

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