Evaluation of Safe Explosive Charge in Surface Mines using Artificial Neural Network

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Abstract: The present paper mainly deals with the prediction of maximum explosive charge used per delay (Q_{MAX}) using artificial neural network (ANN) incorporating peak particle velocity (PPV) and distance between blast face to monitoring point (D). 150 blast vibration data sets were monitored at different vulnerable and strategic locations in and around major coal producing opencast coal mines in India. 124 blast vibrations records were used for the training of the ANN model vis-à-vis to determine site constants of various conventional vibration predictors. Rest 26 new randomly selected data sets were used to test, evaluate and compare the ANN prediction results with widely used conventional predictors. Results were compared based on coefficient of correlation (R) and mean absolute error (MAE) between calculated and predicted values of Q_{MAX}.

1 INTRODUCTION

The exploitation of economic minerals from earth crust is increasing day by day at a faster pace since last decade to fulfill the increasing demand of minerals. This has led to the substantial increase in the consumption of explosive. When an explosive detonates in a blast hole, a tremendous amount of energy, in terms of pressure (up to 50 GPa) and temperature (up to 5000 K), is released (Hino, 1956; McKenzie, 1990; Cheng and Huang, 2000). Although, significant developments have taken place in explosive technology, the explosive energy utilization has not made much progress due to the complexity of the various rock parameters. Only a fraction of explosive energy (20-30%) is used in the actual breakage and displacement of the rock mass, and the rest of the energy is spent in undesirable effects like ground vibrations, fly rocks, noises, back breaks, over breaks, etc. (Hagan, 1973; Dowding, 1985).

As the ground vibration is the most important environmental effect of blasting operation some regulations related to structural damages caused by ground vibration have been developed (Alipour and Ashtiani, 2011). The regulations are primarily based on the peak particle velocity (PPV) resulted from blasting operations. To come out with proper amounts of maximum charge per delay which produces limited ground vibration, several empirical conventional vibration predictors are available proposed by different researchers (Duvall and Petkof, 1959; Langefors and Kihlstrom, 1963; Ambraseys and Hendron, 1968; Bureau of Indian Standard, 1973; Pal Roy, 1993). These conventional predictors are normally used for estimating PPV of ground vibration by blasting. All the predictors estimate the PPV mainly based on two parameters (maximum charge used per delay and distance between blast face and monitoring point). For the same excavation site, different predictors give different values of safe PPV vis-à-vis safe charge per delay. There is no uniformity in the predicted result by different predictors (Khandelwal and Singh, 2009; Khandelwal, 2010). It is well known that the PPV is influenced by various geological, geotechnical, blast geometry and explosive parameters, which have not been incorporated in any of the available predictors. It seems that there is a great need to evaluate the efficiency and credibility of various empirical conventional predictors to calculate maximum charge per delay.

In the present paper, an attempt has been made to predict the Q_{MAX} using artificial neural network (ANN) by incorporating peak particle velocity

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(PPV) and distance from blast face to monitoring point (D). Prediction capability of ANN is also compared by various available conventional predictors based on coefficient of correlation and mean absolute error.

2 SITE DESCRIPTION

The field study was conducted at three different opencast coal mines of Sinagreni Collieries Company Limited (SCCL), Andhra Pradesh, India. The SCCL area is mostly covered by limestone of Pakhals in the western and southern parts and slowly grades into the sandstone of Gondwana series in North-easterly direction. The other geological units found within the project area are Talcher and Barakars. Kamthis are observed away from the project area in northern and eastern directions.

The limestone is massive, flaggy and at places striking in NW-SE direction, dipping towards NE with dip amount varying from 350 – 400. At the contact zone between limestone and sandstone, calaceous beds are observed within grades into sandstone. The sandstone is soft and coarse grained. The various units of lower Gondwana are abutting each other in different directions due to structural disturbances in that area.

In general, this area consists of soft soil upto 2 m depth followed by medium to coarse grained grey sandstone overburden along with shale and thick coal bands of varying thickness of 17.67 to 49.58 m. Thickness of top seam is varying from 1.4 to 4.4 m and the bottom seam thickness is varying from 2.75 to 5.07 m. The partition thickness consisting of mostly medium grained grey sandstone and it is varying from 4.87 to 13.0 m.

3 THE PHILOSOPHY OF ARTIFICIAL NEURAL NETWORK

An artificial neural network can be considered as a soft tool to model the brain reflection (solution) to the given problems. Wide range of capabilities of the neural networks such as generalization, classification, noise reduction and prediction have made the method applicable for solving problems in various fields of science and technology. In the neural networks, deduction is performed using highly interconnected computing cells known as "neurons", which in fact are mathematical functions of linear or nonlinear (Haykin, 1994). The computing cells are usually set in three or more successive layers, known as network architecture or topology (Rafiq et al, 2001; Dreyfus, 2004). Number of the neurons in the extreme outmost layers is equal to the problem independent and dependent variables. On the other hand, number of the intermediate (hidden) layer(s) and number of their respective neurons is dependent to the problem environment. In fact hidden layer(s) can be considered as the computational units of a network.

Feed-forward network with error back propagation algorithm is the most commonly used in solving complicated problems. In these networks that are also called multilayer perceptrons (MLPs), often one or more hidden layers of sigmoid neurons followed by output(s) linear neuron(s) give the best results (Babuska, 2004; Tawadrous, 2006; Demuth and Beale, 2008).

During training process, the network is given values of both the independent and actual measured dependent variables. When the difference between the model predicted values with that of the real values reaches to a predefined threshold, the training process is stopped (Babuska, 2004). Prior to start network training, both the input and output values should be normalized (Rafiq et al, 2001; Demuth & Beale, 2008). Following training, the network performance is tested applying testing datasets. To get a more coherent result, the testing datasets should not be incorporated for learning the network. For a full coverage of data variability, these datasets are selected from the sorted original database using a random mechanism.

4 DATA SET

One of the most important stages in the ANN technique is data collection. In the present study, 150 blast vibration records were monitored at different vulnerable and strategic locations in and around the mines as per ISRM (1992) standards. Among which, 124 blast vibration data sets were chosen for the training of the network and rest 26 data sets were used for the testing of the ANN network. The data was divided into training and validation datasets using sorting method to maintain statistical consistency. The range of distance of monitoring point from blasting face and PPV is 35 – 8400 m and 0.31 – 92.30 mm/s respectively, whereas range of QMAX is 75 – 6000 kg.

5 NETWORK ARCHITECTURE

Baheer (2000) and Hecht-Neilsen (1987) indicated that one hidden layer may be sufficient for most problems. Two hidden layers may be necessary for a learning function with discontinuities (Masters, 1994). Lippmann (1987) and Rumelhart et al. (1986) indicated that there is rarely an advantage in using more than one hidden layer. Therefore, one hidden layer was preferred in this study. However, the number of neurons is the most critical task in the ANN structure. The heuristics proposed for this purpose are summarized in Table 1.

Table 1: The heuristics proposed for the number of neuron to be used in hidden layer(s) (Ni: number of input neuron, N0: number of output neuron)

Heuristic	Calculated number of neuron for this study	Reference
≤ 2 x Ni+1	5	Hecht-Nielsen (1987)
3Ni	6	Hush (1989)
(Ni + N0)/2	2	Ripley (1993)
2Ni / 3	1	Wang (1994)
√(Ni x N0)	2	Masters (1994)
2Ni	4	Kannellopoulas and Wilkinson (1997)

As can be seen from Table 1, the number of neurons that may be used in the hidden layer varies between 1 and 6, depending on the proposed heuristics in the literature. The ANN structures were trained by using number of hidden neurons defined above. By considering the findings obtained from different trials, the ANN structure consisting of one hidden layer with 6 neurons (Fig. 1) was selected for the given problem. The datasets were normalized between zero and one considering the maximum values of input parameters.

Feed forward back propagation neural network architecture (2-6-1) is adopted due to its appropriateness to predict the Q_{MAX}. Pattern matching is basically an input/output mapping problem. The closer the mapping, better the performance of the network is.

The number of training cycles is important to obtain proper generalization of the ANN structure. Theoretically, excessive training, which is also known as over-learning, can result in near-zero error on predicting training data. However, this over-

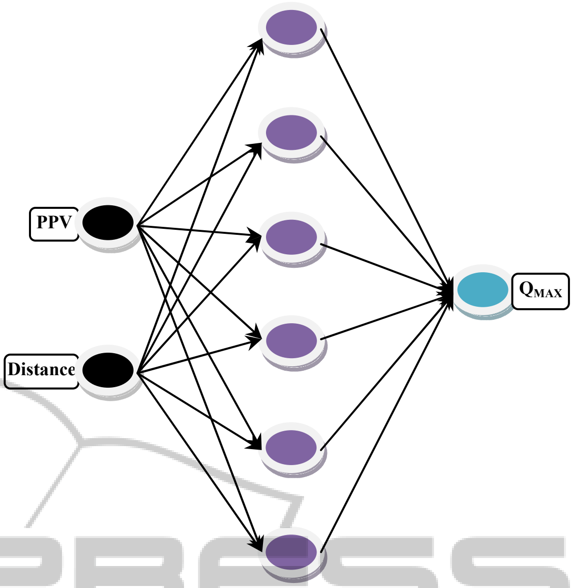

Figure 1: Suggested ANN for the case study.

learning may result in loss of the ability of the ANN to generalize from the test data, Fig. 2 (Basheer and Hajmeer, 2000). The increasing point in the error of the test data or the closest point to the training curve is considered to represent the optimal number of cycles for the ANN architecture.

All the input and output parameters were normalized between 0 and 1. Equation 10 was used for the scaling of input and output parameters.

Normalized value = (max. value – unnormalized value) / (max. value – min. value)

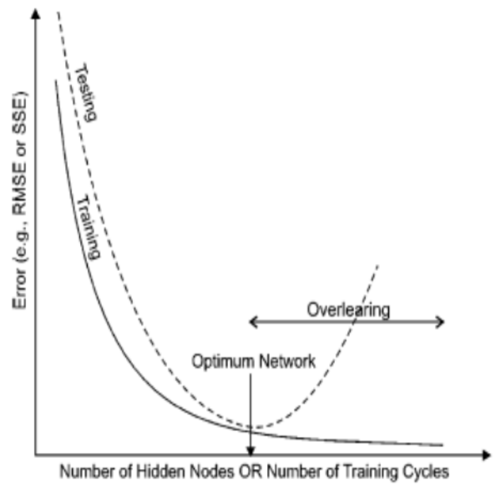

Figure 2: A criteria for termination of training and selection of optimum network architecture (Basheer and Hajmeer, 2000)

6 TESTING AND VALIDATION OF ANN MODEL

To test and validate the ANN model, a data sets were chosen, which was not used while training the network, was employed. As Bayesian interpolation (MacKay, 1992) has been used, there was no danger of over-fitting or under-fitting problems. Fig. 3 illustrates the calculated and predicted QMAX. Here, coefficient of correlation is as high as 0.985, whereas, MAE is 94.36.

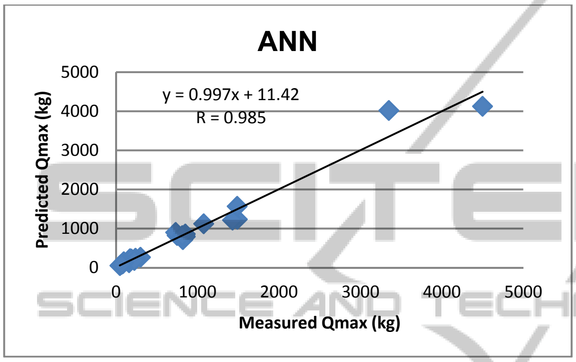

Figure 3: Calculated vs. predicted Q_{MAX} by ANN.

7 ESTIMATION OF MAXIMUM CHARGE PER DELAY BY CONVENTIONAL PREDICTORS

Table 2 illustrates the various available conventional vibration predictor equations proposed by different researchers (Duvall and Petkof, 1959; Langefors and Kihlstrom, 1963; Ambraseys and Hendron, 1968; Bureau of Indian Standard, 1973; Pal Roy, 1993). These predictors have been employed to calculate the safe quantity of charge that can be blasted per delay, with minimum abuse in the surrounding rock mass.

Empirical equations are versions of the following general form that typically are used by investigators (Davies et al, 1964)

$$PPV = K.D^{A}.Q_{MAX}^{B}$$

Where,

v = Peak particles velocity (PPV), mm/s,
Q_{MAX} = Maximum charge per delay, kg,
D = Distance between blast face to vibration monitoring point, m, and
K, A, B, and n = Site constants.

Table 2: Different conventional predictors.

Name	Equation
USBM (Duvall and Petkof, 1959)	$v = K\,(D/\sqrt{Q_{MAX}})^{-B}$
Langefors – Kihlstrom (1963)	$v = K\,[\sqrt{(Q_{MAX}/D^{2/3})}]^{B}$
Ambraseys – Hendron (1968)	$v = K\,[D/(Q_{MAX})^{1/3}]^{-B}$
Bureau of Indian Standard (1973)	$v = K\,[(Q_{MAX}/D^{2/3})]^{B}$
CMRI Predictor (Pal Roy, 1993)	$v = n + K\,(D/\sqrt{Q_{MAX}})^{-1}$

All the conventional vibration predictors have site specific constants. The value of site constants also varied as the ground conditions changed. Moreover, these are derived based on only two parameters, i.e. QMAX and the distance from monitoring point to blast face.

These conventional vibration predictors have been advocated in order to analyse the blast data. The site constants of these predictors were determined from the multiple regression analysis of the 124 blast vibration cases. The calculated values of site constants as well as their respective coefficient of correlation (R) for the various predictor equations are given in Table 3.

Figs. 4-8 demonstrate the prediction capability of various conventional predictors to predict QMAX. Here, coefficient of correlation is ranging from 0.752 to 0.316, which is maximum for the CMRI predictor, whereas minimum for the Langefors-Khilstrom and Bureau of Indian Standard predictor. Mean absolute error was ranging from 633.44 to 2910.97. It was maximum for Bureau of Indian Standard predictor whereas minimum for USBM predictor.

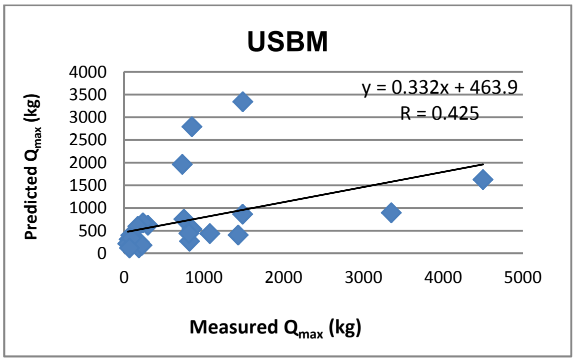

Figure 4: Calculated vs. predicted Q_{MAX} by USBM predictor.

Table 3: Calculated values of site constants.

Name of Predictor	Site Constants			Final Q_{MAX} Equation
	K	B	n	
USBM	166.34	1.291		$Q_{MAX} = D^2(v/166.34)^{2/1.291}$
Langefors – Kihlstrom	0.93	0.857		$Q_{MAX} = D^{2/3}(v/0.93)^{2/0.857}$
Ambraseys – Hendron	1093.96	1.424		$Q_{MAX} = D^3(v/1093.96)^{3/1.424}$
Bureau of Indian Standard	0.929	0.428		$Q_{MAX} = D^{2/3}(v/0.929)^{1/0.428}$
CMRI Predictor	165.9		-3.284	$Q_{MAX} = D^2(v+3.284/165.9)^2$

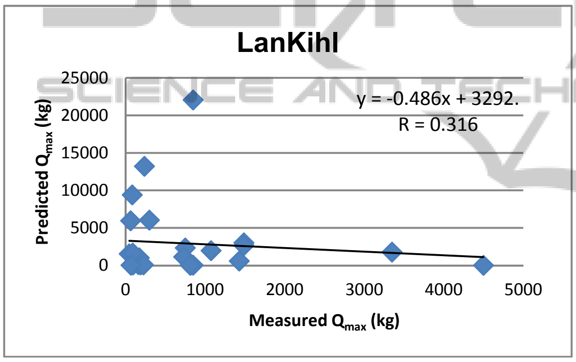

Figure 5: Calculated vs. predicted Q_{MAX} by Langefors – Kihlstrom predictor.

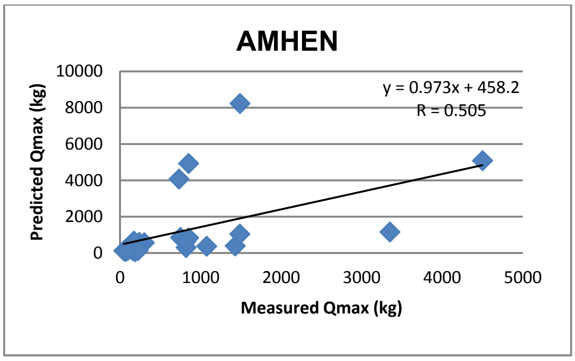

Figure 6: Calculated vs. predicted Q_{MAX} by Ambraseys-Hendron predictor.

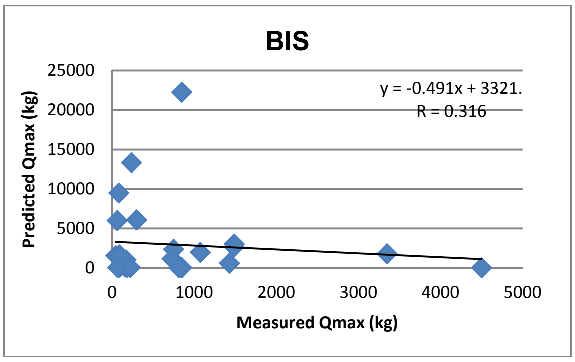

Figure 7: Calculated vs. predicted Q_{MAX} by Bureau of Indian Standard predictor.

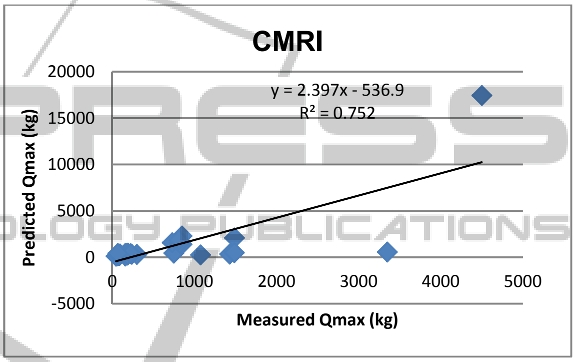

Figure 8: Calculated vs. predicted Q_{MAX} by CMRI predictor.

8 CONCLUSIONS

A number of researches have been established to formulate the PPV and QMAX in the blast-induced vibrations. All the conventional predictors have site specific constants and these are not able to predict the safe charge for even other similar geo-mining conditions. The predictor equations proposed by various researchers show good correlation in calculation of PPV and a low correlation while calculating maximum safe charge per delay, as these calculates QMAX by back calculation.

The main aim of this study was to predict QMAX which is one of the most important factors in blast pattern designing. ANN method has been found application on various engineering areas, particularly where the problem is involved with complexity and uncertainty. In this study, a three layer feed forward back propagation neural network model has been employed to predict the QMAX. Results were also compared with different available conventional vibration predictors. The ANN model predicts QMAX value as an output parameter for a given PPV and distance from the blast face. The comparison shows that results from ANN model are close to the real ones that are desirable. ANN results indicate very close agreement for the QMAX with the field data sets as compared to conventional predictors.

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