Assessment of Maximum Explosive Charge Used Per Delay in Surface Mines

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Abstract: - The present paper mainly deals with the prediction of safe charge of explosive used per delay ($Q_{\text{max}}$) using artificial neural network (ANN) incorporating peak particle velocity (PPV) and distance between blast face to monitoring point (D). 120 blast vibration data sets were monitored at different vulnerable and strategic locations in and around a major coal producing opencast coal mines in India. 100 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 20 new randomly selected data sets were used to compare the ANN prediction results with widely used conventional predictors. Results were compared based on coefficient of determination ($R^2$) between measured and predicted values of $Q_{\text{max}}$. It was found that coefficient of determination between measured and predicted $Q_{\text{max}}$ by ANN was 0.894, whereas it was ranging from 0.023 to 0.417 by different conventional predictor equations.

Key-Words: - Safe explosive charge used per delay; peak particle velocity; distance between blast face to monitoring point; conventional vibration predictors; artificial neural network

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 [1-3]. 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. [4-5].

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 [6]. 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 [7-10]. 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 [11-12]. 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.

Progress has been made in recent years in ability to predict the $Q_{\text{max}}$, but the state of the art is deficient in many ways. On the basis of detailed investigation, a viable approach for the prediction is necessary, and an Artificial Intelligence (AI) comes in handy to fulfill this approach. In the present paper, an attempt has been made to predict the safe charge of explosive per delay using artificial neural network (ANN) by incorporating peak particle velocity (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 determination.

2 Site description

The study was conducted at Jayant opencast mine of Northern Coalfields Limited (NCL), which is a subsidiary company of Coal India Limited. It is located at Singrauli, Distt. Sidhi (M.P.), India. The area of NCL lies geographically between latitudes of 24° 0’ to 24° 12’ and longitudes 82° 30’ to 82° 45’ and belongs to Gondwana super group. The dip of the strata is gentle and varying from 2° to 5°. The coalfield can be divided into two sub basins, viz. Moher sub-basin (312 sq. km.) and Singrauli Main basin (1890 sq. km.). The field is divided into 11 major mining blocks namely Kakri, Bina, Marrack, Khadia, Dhudhichua, Jayant, Nighahi, Amlohri, Moher, Gorbi and Jhingurdah. The overburden in this area is mostly medium to coarse-grained sandstones, carbonaceous shales and shaly sandstones. Nonel and MS connectors are used for initiation. The inter-hole delay was 17-25 ms, whereas, inter-row delay was 2-4 times the inter-hole delay.

3 The Philosophy of Artificial Neural Network

The technique of artificial neural networks (ANNs) is an effective alternative methodology. The artificial intelligence information-processing structures are still very primitive compared to biological ones [13]. There is a wide scope to solve problems by the ANNs particularly to approximate nonlinear behavior without a prior knowledge of interrelations among the elements within a system [14]. Moreover, it has been proven that a feedforward ANN with an arbitrary number of processing units is a universal function approximator [15].

3.1 Feed Forward Back Propagation Neural Network

Feed forward neural networks are being widely used for solving various ticklish problems, such as pattern recognition, function approximation, dynamic modeling, data mining, time series forecasting, etc. Feed forward networks have one or more hidden layers of sigmoid neurons followed by an output layer of linear neurons. Multiple layers of neurons with nonlinear transfer functions allow the network to learn nonlinear and linear relationships between the input and the output vectors [16]. In light of Kolmogorov’s theorem, multilayer feed forward network can be viewed as exact representation of input-output mapping. Further modification over Kolmogorov’s theorem is made by [17] to obtain the exact representation equation. To overcome the difficulty of exact mapping, approximate representation is obtained. Multilayer feed forward found its mathematical form here. A multilayer feed forward network when learns by back propagation, in which error propagates back is called feed forward back propagation (FFBP). Kolmogorov’s theorem however, fails to provide not only number of layers but also number of neurons necessary in each hidden layer.

3.2 Learning of Feed Forward Back Propagation Network

Training of the network is basically a process of arriving at an optimum weight space of the network. The descent down the error surface is made using the following rule:

$$\Delta w_{ij} = \eta \left( \frac{\partial E}{\partial w_{ij}} \right)$$

Where,

- $\eta$ is the learning rate parameter.
- $w_{ij}$ is the weight of the connection between the $i^{th}$ neuron of the input layer and the $j^{th}$ neuron of the hidden layer.

The update of weight for the $(n+1)^{th}$ pattern is given as:

$$w_{ij} (n+1) = w_{ij} (n) + \Delta w_{ij} (n)$$

Similar logic applies to the connection between the hidden and the output layer.
The error $E$ is the mean squared error and is determined by the following relation:

$$E = \sum [O_k(n) - O'_k(n)]^2 \quad (3)$$

Where,

$O_k(n)$ is the output determined by the network for the $n^{th}$ pattern and $O'_k(n)$ is the corresponding output given in the training data set.

The weight change rule is a development of the perception learning rule. Weights are changed by an amount proportional to the error at that unit times, the output of the unit feeding into the weight.

The output unit error is used to alter weights on the output units. Then, the error at the hidden nodes is calculated (by back – propagating the error at the output units through the weights), and the weights on the hidden nodes altered using these values.

For each data pair to be learned a forward pass and backward pass is performed. This is repeated over once again until the error is at a low enough (or is given up). The input and the hidden layers consists of linear processing units as neurons, whereas, the output layer consists of non-linear processing units as the neurons. The non-linear function used is the logarithmic sigmoid function and is defined as:

$$f(\text{net}) = \frac{1}{1 + e^{-\text{net}}} \quad (4)$$

Where,

$f(\text{net})$ is the weighted sum of the inputs for a processing unit.

Thus, the outputs are determined for each epoch, the mean square error calculated and the weights updated till a user specified error goal or epoch goal is reached successfully.

4 Data Set

One of the most important stages in the ANN technique is data collection. In the present study, 120 blast vibration records were monitored at different vulnerable and strategic locations in and around the mines as per ISRM [18] standards. Among which, 100 blast vibration data sets were chosen for the training of the network and rest 20 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. Datasets for validation were extracted at regular intervals from the sorted database and the remaining datasets were used for the training and testing of ANN model vis-à-vis to determine site constant of various conventional vibration predictors. The range of distance of monitoring point from blasting face and PPV is 35 – 640 m and 1.97 – 82.0 mm/s respectively, whereas range of explosive charge used per delay ($Q_{max}$) is 25 – 606.25 kg.

5 Network Architecture

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

A three layer feed-forward back-propagation neural network was developed to predict the $Q_{max}$. The input layer has 2 input neurons and the output layer has 1 neuron, whilst the hidden layer comprises 6 hidden neurons (Fig. 1).

All the input and output parameters were scaled between 0 and 1. Equation 5 was used for the scaling of input and output parameters.

$$\text{Scaled value} = \frac{(\text{max. value} - \text{unnormalised value})}{(\text{max. value} - \text{min. value})} \quad (5)$$

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. The results are presented in this section to demonstrate the performance of the networks. Coefficient of determination ($R^2$) between the predicted and measured values is taken as the measure of performance. As Bayesian interpolation [19] has been used, there was no danger of over-fitting or under-fitting problems. Fig. 2 illustrates the measured and predicted $Q_{\text{max}}$. Fig. 2 clearly indicates the ability of ANN for the prediction of $Q_{\text{max}}$. Here, coefficient of determination is as high as 0.894.

Fig 2 Measured vs. predicted $Q_{\text{max}}$ by ANN

7 Estimation of Maximum Charge Per Delay by Conventional Predictors

Table 1 illustrates the various available conventional vibration predictor equations proposed by different researchers [7-10]. 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.

Table 1 Different conventional vibration predictors

<table>
<thead>
<tr>
<th>Name</th>
<th>Equation</th>
</tr>
</thead>
<tbody>
<tr>
<td>USBM [7]</td>
<td>$v = K \left(\frac{D}{\sqrt[3]{Q_{\text{max}}}}\right)^b$</td>
</tr>
<tr>
<td>Ambraseys – Hendron [8]</td>
<td>$v = K \left(\frac{D}{Q_{\text{max}}}\right)^{1.37}f$</td>
</tr>
<tr>
<td>Bureau of Indian Standard [9]</td>
<td>$v = K \left(\frac{Q_{\text{max}}}{D^{2/3}}\right)^b$</td>
</tr>
<tr>
<td>CMRI Predictor [10]</td>
<td>$v = n + K \left(\frac{D}{\sqrt[3]{Q_{\text{max}}}}\right)^b$</td>
</tr>
</tbody>
</table>

Where,$$
\begin{align*}
\nu & = \text{Peak particles velocity (PPV), mm/s,} \\
Q_{\text{max}} & = \text{Maximum charge per delay, kg,} \\
D & = \text{Distance between blast face to vibration monitoring point, m, and} \\
K, B, \text{ and } n & = \text{Site constants.}
\end{align*}
$$

Empirical equations are versions of the following general form that typically are used by investigators [20]

$$
\text{PPV} = K.D^aQ_{\text{max}}^b
$$

Where, PPV is the peak particle velocity, $Q_{\text{max}}$ is Maximum charge per delay (kg), D is distance of the measuring transducer form the blasting face (m), and K, a and b are site-specific constants, which can be determined by multiple regression analysis.

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. Maximum charge per delay and the distance from monitoring point to blast face.

Table 2 shows that the Ambraseys – Hendron and CMRI predictor has quite remarkable coefficient of determination, whereas Bureau of Indian Standard predictor has very less coefficient of determination, so it will not be able to predict the $Q_{\text{max}}$ in a proficient manner. It should be noted here that the resulted coefficient of determination is just for the equations in the form of offered one.

Table 2 Calculated values of site constants

<table>
<thead>
<tr>
<th>Name of the Predictor</th>
<th>Site Constants</th>
<th>Final $Q_{\text{max}}$ Equation</th>
<th>$R^2$</th>
</tr>
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<tbody>
<tr>
<td>USBM</td>
<td>114.025 0.923</td>
<td>$Q_{\text{max}} = D^2\left(\frac{v}{114.025.34}\right)^{2.923}$</td>
<td>0.468</td>
</tr>
<tr>
<td>Ambraseys – Hendron</td>
<td>399.945 1.079</td>
<td>$Q_{\text{max}} = D^3\left(\frac{v}{399.945}\right)^{3.1.079}$</td>
<td>0.555</td>
</tr>
<tr>
<td>Bureau of Indian</td>
<td>6.397 0.334</td>
<td>$Q_{\text{max}} = D^{2.5}\left(\frac{v}{6.397}\right)^{2.334}$</td>
<td>0.101</td>
</tr>
</tbody>
</table>
Figs. 3-6 demonstrates the prediction capability of various conventional predictors to predict $Q_{\text{max}}$. Here, coefficient of determination is ranging between 0.023 to 0.417, which is highest for the Ambraseys – Hendron predictor, whereas minimum for the Bureau of Indian Standard predictor. Though, while calculating site constants of various predictors for 100 blast cases, CMRI predictor had shown highest coefficient of determination, but for 20 randomly selected different blast cases, Ambraseys – Hendron predictor is showing highest coefficient of determination.

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**Standard CMRI Predictor**

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<tr>
<td>$Q_{\text{max}} = D^2(v+0.644/165.6)^2$</td>
<td>0.738</td>
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8 Results and Discussion

In this section, a prediction performance comparison is made between the presently constructed ANN model and the conventional predictor models. The results of applying the various conventional predictors and ANN are compared in Table 3. Table 3 shows the coefficient of determination ($R^2$) for all the 4 vibration predictors as well as for ANN model also. As seen
in this table, the applicability of ANN is far better than any of the conventional predictor equations.

<table>
<thead>
<tr>
<th>Name of Model</th>
<th>R²</th>
</tr>
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<tbody>
<tr>
<td>USBM</td>
<td>0.263</td>
</tr>
<tr>
<td>Ambraseys – Hendron</td>
<td>0.417</td>
</tr>
<tr>
<td>Bureau of Indian Standard</td>
<td>0.023</td>
</tr>
<tr>
<td>CMRI Predictor</td>
<td>0.327</td>
</tr>
<tr>
<td>ANN</td>
<td>0.894</td>
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9 Conclusions
The main aim of this study is to predict maximum charge per delay which is one of the most important factors in blast pattern designing. The ANN model predicts maximum charge per delay 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 Q_max with the field data sets as compared to conventional predictors.

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 it calculates Q_max by back calculation. If the safe charge of explosive is calculated based on the above predictors, certainly one can face problems to control the ground vibration. This may, sometimes, result in either under estimate or over estimate the explosive requirement. The uses of any predictor without validation causes damage to the surround and hinder the mine smooth working.

References