Evaluation of blast-induced ground vibration predictors

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Abstract

The present paper mainly deals with the prediction of blast-induced ground vibration level at a Magnesite Mine in tecto-dynamically vulnerable hilly terrain in Himalayan region in India. The ground vibration was monitored to calculate the safe charge of explosive to avoid the continuous complaints from the nearby villagers. The safe charge of explosive and peak particle velocity (PPV) were recorded for 75 blast events (150 blast data sets) at various distances. These data sets were used and analysed by the widely used vibration predictors. From the four predictors, vibration levels were calculated and compared with new monitored 20 blast data sets. Again, the same data sets were used to validate and test the three-layer feed-forward back-propagation neural network to predict the PPV values. The same 20 data sets were used to compare the results by the artificial neural network (ANN). Among all the predictors, a very poor correlation was found, whereas ANN provides very near prediction with high degree of correlation.

Keywords: PPV; Predictor equation; Artificial neural network; Explosive charge

1. Introduction

Drilling and blasting combination is still an economical and viable method for rock excavation and displacement in mining as well as in civil construction works. The ill effects of blasting, i.e. ground vibrations, air blasts, fly rocks, back breaks, noises, etc. are unavoidable and cannot be completely eliminated but certainly minimize up to permissible level to avoid damage to the surrounding environment with the existing structures [1,2]. Among all the ill effects, ground vibration is major concern to the planners, designers and environmentalists [3]. A number of researchers have suggested various methods to minimize the ground vibration level during the blasting. Ground vibration is directly related to the quantity of explosive used and distance between blast face to monitoring point as well as geological and geotechnical conditions of the rock units in excavation area.

Geological and geotechnical conditions and distance between blast face to monitoring point cannot be altered but the only factor, i.e. quantity of explosive can be estimated based on certain empirical formulae proposed by the different researchers [4–7] to make ground vibrations in a permissible limit. An appropriate and rock friendly blasting can be only alternative for smooth progress of the rock removal process.

In the present investigation, few important and widely used predictors have been used to predict the peak particle velocity (PPV) and computed results are compared with actual field data. The same input–output data sets have been also used for the prediction by artificial neural network (ANN). The basic idea is to find the scope and suitability of the ANN for prediction of PPV over the widely used vibration predictors.

2. Mechanism of ground vibration

When an explosive charge detonates in the blast hole, intense dynamic stresses are set up around it due to sudden acceleration of the rockmass by detonating gas pressure on hole wall. The strain waves transmitted to the surrounding rock sets up a wave motion in the ground [8]. The strain energy carried out by these strain waves fragments the rock mass due to different breakage mechanism such as crushing, radial cracking, and reflection breakage in the
presence of a free face. The crushed zone and radial fracture zone encompass a volume of permanently deformed rock. When the stress wave intensity diminishes to the level where no permanent deformation occurs in the rockmass (i.e., beyond the fragmentation zone), strain waves propagate through the medium as the elastic waves, oscillating the particles through which they travel (Fig. 1). These waves in the elastic zone are known as ground vibration, which closely confirm to the visco-elastic behaviour. The wave motion spreads concentrically from the blast site in all directions and gets attenuated due to spreading of fixed energy over a greater mass of material and away from its origin [9]. Even though, the ground vibration attenuates exponentially with distance but due to large quantity of explosive, it can still be high enough to cause damage to buildings and other man-made and natural structures by causing dynamic stresses that exceed material strength [10].

3. Different vibration predictor equations

<table>
<thead>
<tr>
<th>Name of predictor equation</th>
<th>Equations</th>
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<tbody>
<tr>
<td>USBM (Duvall and Fogelson, 1962)</td>
<td>( v = K \left( \frac{R}{\sqrt{Q_{\text{MAX}}}} \right)^{-B} )</td>
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<tr>
<td>Ambraseys–Hendron (1968)</td>
<td>( v = K \left( \frac{R}{Q_{\text{MAX}}^{1/3}} \right)^{-B} )</td>
</tr>
<tr>
<td>Langefors–Kihlstrom (1978)</td>
<td>( v = K \left( \frac{Q_{\text{MAX}}}{R^{1/2}} \right)^B )</td>
</tr>
<tr>
<td>Indian Standard Predictor (1973)</td>
<td>( v = K \left( \frac{Q_{\text{MAX}}}{R^{1/2}} \right)^B )</td>
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where \( v \) is the peak particles velocity (mm/s), \( Q_{\text{MAX}} \) the maximum charge per delay (kg), \( R \) the distance between blast face to vibration monitoring point (m), and \( K \) and \( B \) the site constants, which can be determined by multiple regression analysis.

4. The study area

The Dharapani Magnesite Mine is situated about 7 km from Pithoragarh town of Uttarakhand State in India. The mining area is hilly, having high ridges and hillocks separated by valley and depression. The area comprises mainly meta-sedimentary and metamorphic rocks. The area stratigraphically belongs to the lesser Himalaya, which is considered to be young dynamic mountain chain. The thickness of rock unit is variable from 5 to 8 m. Magnesite bands occur in the form of discontinuities bands spreading over the length and breadth of the area [11]. The magnesite ore bodies are associated with dolomitic rock. The general dip of ore bodies and associated formation varies, from 20° to 60° (with local variation) is towards the North-East. Isoclinal folds and joints have been observed on the exposed face of the mine.

The deposit is being worked by opencast mining method with 7–8 benches. The 6–7 m high benches are excavated by drilling and blasting. The explosive used in mine is indomite (slurry) cartridges and blasted simultaneously in staggered pattern of drilling (Figs. 2 and 3). The mine produces approximately 30,000 t/year magnesite. The 75...
blast events were monitored and recorded on different locations with the help of SINCO-6 seismograph having two transducers for PPV measurement and one additional for air blast [12]. These data sets were used for prediction, training and validation. The 10 blast events (20 data sets) further recorded were used for the estimation as well as for ANN validation with predictors.

The two villages Bhurigon and Tarigon are 300–350 m away from the blast site and always vulnerable and suspicious about the blast vibration. Mines management always received complaint from the villagers regarding blast vibration. To overcome from the difficulties, the blasts were monitored and safe charge of explosive was estimated.

5. Artificial neural network (ANN)

The ANN is a new branch of intelligence science and has developed rapidly since the 1980s. Neural network has the ability to learn from the pattern acquainted before [13]. Once the network has been trained, with sufficient number of sample data sets, it can make predictions, on the basis of its previous learning, about the output related to new input data set of the similar pattern [14]. Therefore, ANN is being successfully used in many industrial areas as well as in research areas also. Singh et al. [15] predicted the strength properties of schistose rocks by neural network. The stability of waste dump from dump slope angle and dump height is investigated by Khandewal and Singh [16]. They found very realistic results as compared to the other analytical approach. Singh et al. [17] computed the P-wave velocity and anisotropic properties of rocks by neural network. Many others researchers have also used this technique for the prediction of various complex parameters from simple input parameters [18,19].

A network first needs to be trained before interpreting new information. Several different algorithms are available for training of neural networks but the back-propagation algorithm is the most versatile and robust technique, which provides the most efficient learning procedure for multi-layer neural networks. Also, the fact that back-propagation algorithms are especially capable to solve predicting problems makes them so popular. The feed forward back-propagation neural network (BPNN) always consists of at least three layers: input layer, hidden layer and output layer. Each layer consists of number of elementary processing units, called neurons, and each neuron is connected to the next layer through weights, i.e. neurons in the input layer will send its output as input for neurons in the hidden layer and similar is the connection between hidden and output layer. Number of hidden layer and number of neurons in the hidden layer changes according to the problem to be solved. The number of input and output neurons is same as the number of input and output variables.

To differentiate between the different processing units, values called biases are introduced in the transfer functions. These biases are referred to as the temperature of a neuron. Except for the input layer, all neurons in the back propagation network are associated with a bias neuron and a transfer function. The bias is much like a weight, except that it has a constant input of 1, while the transfer function filters the summed signals received from this neuron. These transfer functions are designed to map a neurons’ or layers’ net output to its actual output and they are simple step functions either linear or non-linear functions. The application of these transfer functions depends on the purpose of the neural network. The output layer produces the computed output vectors corresponding to the solution.

During training of the network, data are processed through the input layer to hidden layer, until it reaches the output layer (forward pass). In this layer, the output is compared to the measured values (the “true” output). The difference or error between both is processed back through the network (backward pass) updating the individual weights of the connections and the biases of the individual neurons. The input and output data are mostly represented as vectors called training pairs. The process as mentioned above is repeated for all the training pairs in the data set, until the network error converged to a threshold minimum defined by a corresponding cost function; usually the root-mean-squared error (RMS) or summed squared error (SSE).

In Fig. 4 the jth neuron is connected with a number of inputs

$$x_i = (x_{i1}, x_{i2}, x_{i3}, \ldots x_{in}).$$

The net input values in the hidden layer will be

$$Net_j = \sum_{i=1}^{n} x_i w_{ij} + \theta_j,$$

where $x_i$ is the input units, $w_{ij}$ the weight on the connection of $i$th input and $j$th neuron, $\theta_j$ the bias neuron (optional), and $n$ the number of input units.

So, the net output from hidden layer is calculated using a logarithmic sigmoid function as follows:

$$O_j = f(Net_j) = 1/1 + e^{-(Net_j + \theta_j)}.$$

The total input to the $k$th unit is

$$Net_k = \sum_{j=1}^{n} w_{jk} O_j + \theta_k,$$

where $\theta_k$ is the bias neuron, $w_{jk}$ the weight between $j$th neuron and $k$th output.

So, the total output from $i$th unit will be

$$O_i = f(Net_i).$$

In the learning process, the network is presented with a pair of patterns, an input pattern and a corresponding desired output pattern. The network computes its own output pattern using its (mostly incorrect) weights and thresholds. Now, the actual output is compared with the
desired output. Hence, the error at any output in layer $k$ is
\[ e_l = t_k - O_k, \]
where $t_k$ is the desired output and $O_k$ the actual output.

The total error function is given by
\[ E = 0.5 \sum_{k=1}^{n} (t_k - O_k)^2. \]

Training of the network is basically a process of arriving at an optimum weight space of the network. The descent down error surface is made using the following rule:
\[ \nabla W_{jk} = -\eta (\delta E / \delta W_{jk}), \]
where $\eta$ is the learning rate parameter and $E$ is the error function.

The update of weights for the $(n+1)$th pattern is given as
\[ W_{jk}(n+1) = W_{jk}(n) + \nabla W_{jk}(n). \]

Similar logic applies to the connections between the hidden and output layers. This procedure is repeated with each pattern pair of training exemplar assigned for training the network. Each pass through all the training patterns is called a cycle or epoch. The process is then repeated as many epochs as needed until the error is within the user specified goal is reached successfully. This quantity is the measure of how the network has learned.

6. Network architecture

Feed forward network is adopted here as this architecture is reported to be suitable for problem based on problem identification. Pattern matching is basically an input/output mapping problem. Closer the mapping, better performance of the network.

The architecture of the network is tabulated below:

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<table>
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<tbody>
<tr>
<td>1</td>
<td>No. of input neurons: 2</td>
</tr>
<tr>
<td>2</td>
<td>No. of output neurons: 1</td>
</tr>
</tbody>
</table>

7. Results and discussion

7.1. Prediction by USBM equation

The USBM equation for PPV is
\[ v = K[R/\sqrt{Q_{\text{MAX}}}]^{-B}. \]
The site constants $K$ and $B$ can be determined by plotting the graph between the square-root-scaled distance $[R/\sqrt{Q_{\text{MAX}}}]$ and PPV on log-log scale (Fig. 5). The value of $K$ is 47.92 ($10^{1.6805}$) and the value of $B$ is $-0.5529$.

Now the USBM equation for the particular site is
\[ v = 47.92[R/\sqrt{Q_{\text{MAX}}}]^{-0.5529}. \]
The above equation has been used for the prediction of PPV of 20 data sets. Fig. 6 shows the measured and predicted PPV by USBM equation in 1:1 slope line. It shows wide variation from the 1:1 slope line and indicates poor correlation between measured and predicted values of PPV.

7.2. Prediction by Ambraseys–Hendron equation

The Ambraseys–Hendron equation for PPV is
\[ v = K[R/(Q_{\text{MAX}})^{1/3}]^{-B}. \]
The site constants $K$ and $B$ can be determined by plotting the graph between the cube root scaled distance $[R/(Q_{\text{MAX}})^{1/3}]$ and PPV on log-log scale (Fig. 7). The value of $K$ is 56.47 ($10^{1.7518}$) and the value of $B$ is $-0.4489$. 
Now the Ambraseys–Hendron site specific equation is

\[
v = 56.47\left[\frac{R}{Q_{\text{MAX}}}^{1/3}\right]^{-0.4489}.
\]

The above equation has been used for the prediction of PPV of 20 data sets. Fig. 8 shows the measured and predicted PPV by Ambraseys–Hendron equation. This also indicates poor correlation between predicted and measured value of PPV.

7.3. Prediction by Langefors–Kihlstrom equation

The Langefors–Kihlstrom equation for PPV is

\[
v = K\left[\frac{Q_{\text{MAX}}}{R^{2/3}}\right]^{1/2}.\]

The site constants \(K\) and \(B\) can be determined by plotting the graph between \((Q_{\text{MAX}}/R^{2/3})^{1/2}\) and PPV on log–log scale (Fig. 9). The value of \(K\) is 26.607 \((10^{1.425})\) and the value of \(B\) is 0.7139.
Now the Langefors–Kihlstrom site equation is
\[ v = 26.607\left(\frac{Q_{\text{MAX}}}{R^{2/3}}\right)^{1/2}0.7139. \]

The above equation has been again used for the prediction of PPV of 20 data sets. Fig. 10 shows the measured and predicted PPV by Langefor–Kihlstrom equation with poor correlation between data sets.

7.4. Prediction by Indian Standard Predictor equation

The Indian Standard Predictor equation for PPV is
\[ v = K\left(\frac{Q_{\text{MAX}}}{R^{2/3}}\right)^B. \]

The site constants \( K \) and \( B \) can be determined by plotting the graph between the \( Q_{\text{MAX}}/R^{2/3} \) and PPV on log–log scale (Fig. 11). The value of \( K \) is 7.195 \((10^{0.857})\) and the value of \( B \) is 0.1661.
Now the Indian Standard Predictor equation for the mine is

\[ v = 7.195 \left( \frac{Q_{\text{MAX}}}{R^{2/3}} \right)^{0.1661} \]

Similarly here also the above equation has been used for the prediction of PPV of 20 data sets. Fig. 12 exhibits the measured and predicted PPV by Indian Standard Predictor equation. This also indicates poor correlation between predicted and measured values of PPV.

### 7.5. Prediction by ANN

Fig. 13 demonstrates the graph between measured PPV and predicted PPV by ANN on 1:1 slope line. All predicted data points are coming very nearer to 1:1 slope line. This indicates greater capability of ANN for the prediction of PPV.
8. Comparison of results and probable causes

Fig. 14 illustrates the comparison of predicted PPV by different predictors and by ANN with measured PPV in field. Here, ANN line is following the measured PPV line in very nice manner but other PPV predictors are unable to predict the PPV which is close to the observed values in the field. If the safe charge of explosive is calculated based on the above predictors, certainly one can face problem to control the ground vibration. It may be sometime under estimate or over estimate the explosive requirement. The use of any predictor without validation causes damage to the surround and hindrance to the mine smooth working.

9. Conclusions

Based on the study, it is establish that the feed-forward back-propagation neural network approach seems to be the better option for close and appropriate prediction.
of PPV to protect surrounding environment and structure. The use of any predictor without validation may invite further complication for smooth conduct of mining operations. This study indicates that all predictors used in the paper are either over estimating or under estimating the safe explosive charge to keep the PPV under the safe limit. Both the predictions are not appropriate for the site where populations are residing very near to mine. If more number of data sets are used in ANN, the prediction will be more accurate, because it does not follow the over fitting and under fitting law of curves as in the case of vibration predictors.

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