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Assessment of Blast-induced Ground Vibration using Different Predictor Approaches- A Comparison

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Blasting is a mechanism of rock fragmentation. Usages of high explosive causes ground vibration, air noise, back breaks, over breaks as well as fly rock. Excessive blast-induced vibrations cause severe damage to nearby structures and residents in and around mine. So, it is essential to the precise prediction of ground vibration to reduce the ecological damage. Vibrations are expressed in terms of peak particle velocity (PPV). The aim of this study was to assess and predict the ground vibration at different explosive quantities and distances, applications of generalized regression neural network (GRNN) as well as empirical predictors were used. A total of fourteen blast events were collected at various strategic and valuable locations in the site, out of these ten blast events were considered for training and reaming for validate of the GRNN model. A three-layer GRNN with 2-14-1 architecture was developed and trained with Levenberg–Marquardt algorithm. Five emphircal predictor equations were proposed by the United States Bureau of Mines (USBM), Ambraseys-Hendron, Langefors-Kihlstrom, Central Mining Research Institute (CMRI) predictor and Bureau of Indian standard were applied to governing a relation between peak particle velocity and its influencing parameters. The obtained results reveal that the proposed GRNN model can predict the PPV accurately as compared to the other predictor models available. Obtained results were compared based on evaluation performance models such as coefficient of determination (R^2) and mean square error (MSE) between monitored and predicted values of PPV. It was observed that GRNN approach provides high R^2 (0.9988) and low MSE (0.0001) among all other empirical predictor approaches for accurate prediction of ground vibration.

1. Introduction

Mineral resources are the backbone of any industrial nation and industry needs metal and non-metals as raw material. These are extracted by both underground and open cast mining methods. In both cases, blasting mechanism was practiced to fragment the rock-mass. During the charging of holes with explosive, larger amount of energy was released in the form of pressure and temperature of about 50Gpa and 5000k respectively (Parida and Mishra, 2015). Only 20% of explosive energy was utilized for an actual fragment of the rock mass and remain dissipates in the form of ground vibration, fly rock, air noise, over break etc.(Cheng and Huang, 2006). Excessive intensity levels of blast-induced ground vibration can damage to or failure of structures. The intensity of ground vibration levels depends on various influencing parameters like distance, an explosive charge, spacing, burden and hole depth, etc. Ground vibrations are quantified by means of particle velocities at particular ground locations. Presently, the most widely considered term to measure the ground vibration is PPV and It is defined as the maximum speed at which each particle passes or moves in a ground to its inactive state. Thus, it is very important to evaluate and predict the blast-induced vibrations to know the safe pin point levels for reducing damage levels.
Various scientists, academicians, and researchers were proposing a number of empirical predictors approach for the estimation as well as prediction of ground vibration due to blasting and are summarized in Table 1. Proposed predictors are able to predict the PPV based on two parameters such as a maximum explosive charge per delay and distance between the blasting sources to monitored point at the particular site.

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Table 1: Different empirical predictor equations

Predictor name	Equation
USBM (Duvall and Fogelson, 1962)	$V = K\left[\frac{D}{\sqrt{Q_{max}}}\right]^{-B}$
Amraseys-Hendron (Ambraseys and Hendron, 1968)	$V = K\left[\frac{D}{(Q_{max})^{\frac{1}{3}}}\right]^{-B}$
Langefors-Kihstrom (Langefors and Kihstrom, 1963)	$V = K[\sqrt{(Q_{max}/\ D^{\frac{2}{3}})}\ ]^{B}$
Bureau of Indian standard (Bureau of Indian standard, 1973)	$V = K[(Q_{max}/\ D^{\frac{2}{3}})]^{B}$
CMRI (Roy, 1991)	$V = n + K\left[\frac{D}{\sqrt{Q_{max}}}\right]^{-1}$

Where, V is PPV (mm/s), *Q* is maximum charge per delay (kg), *D* is the distance between the blasting face to vibration monitoring point (m), *K*, *B* and n are site constants and scaled distance $SD = \frac{\mathrm{Qmax}^{k1}}{D^{k2}}$ (k_1 and k_2 are predefined). The flaws of existing predictor approaches provide different predictor values of safe PPV vis-à-vis safe maximum charge per delay for the particular site and no uniformity in the predicted results. It is essential to evaluate and predict the PPV accurately. Therefore, many researchers are using soft computing techniques like artificial neural network (ANN), support vector machine algorithm (SVM), fuzzy theory, etc. for various applications.

Ragam and Nimaje (2018a) developed a multilayer perceptron (MLP) based back propagation (BP) neural network model and to predict the ambiguous ground vibration at ACC Dungri lime stone mine, India. The observed results ensure the ANN model provides accurate results compared to other conventional models. Ragam and Nimaje (2018b) used an ANN model to estimate the PPV levels at Mine-A, Inida and the results of ANN was more close to observed PPV values among other models. Nimaje and Tripathy (2017) employed radial basis function neural network (RBFNN) to predict the fire risk of Indian coals and revealed that RBFNN model provides superior results over statisitcal models. Ahmad et al. (2017) were propsed multple neural network (MNN) to predict the combustion efficiency from the boiler. Liu and Wang (2016) introduced the support vector regression (SVR) model based on ant colony optimization for forecasting the concentration of pollutants in the air.

In the current study, the blast experiment test was conducted at IDL Explosive Limited and recoreded fourteen blast events at different distances from the blast-source. The GRNN model along with five empirical predictor approaches are used for evaluation and prediction of the ground vibration levels and compared the results.

2. Blast site description

The ground vibration phenomenon due to blasting was studied at IDL Explosives Limited (IDL). The blast site location coordinates are 22°11'12.8"N 84°52'28.4"E and located at Sonaparbat area, Rourkela, India. IDL is the leading manufacturing of explosives and accessories located at the outskirt of Rourkela, which houses services for the production of a total range of packaged explosives and non-explosive emulsion matrix, an intermediary for delivery of bulk explosives along with accessories. The blast sitemap is depicted in Figure 1. Explosion clad plates are manufactured to use in various applications. The cladding is being conducted on the sand base surface which is spread uniformly and the plates are cladded with the help of explosives in form of a powder which is initiated by the remote device. The pressure released from this cladding by the explosives joins two different metal plates. This process generates sound and ground vibration due to blasting in the surroundings.

3. Instrumentation and data collection

Blasting events are monitored with the help of seismograph (make: Instantel. Inc, Canada- Miniamate plus along with two geophones and one microphone). In this study, total 14 blast events were recorded over a period of one month. Figure 2 depicts the monitoring of ground vibration with the seismograph instrument. The PPV data was monitored at various distances from the blast source with respect to the maximum charge per delay and the results are listed in Table 2.

Figure 1: Site Map of IDL–Explosives Ltd

Figure 2: Monitoring of ground vibration with minimate plus seismograph

Table 2: Recorded PPV data at various distances at varying explosive charge

S.No	Distance (m)	Max. Explosive per delay (kg)	PPV (mm/s)
1	354	540	1.48
2	493	180	1.02
3	500	300	1.78
4	90	500	1.11
5	50	564	0.64
6	200	720	0.32
7	195	777	0.57
8	100	1020	0.32
9	540	1320	0.25
10	150	1500	0.19
11	530	1520	0.38
12	90	1850	0.44
13	270	1990	0.32
14	270	2750	0.19

Note: Table 2 monitored data was listed based on day wise collection of results

4. Data analysis

4.1 Prediction of PPV using empirical predictor approaches

All the empirical predictor approaches must have site-specific constants (Table 1). The specific constants are varied based on changes in ground vibration. The site constants (K, B, and n) are calculated by plotting graph between scaled distance and PPV on the log-log scale using the following Eq(1) and Eq(2)

$$\log v = \log k - B \ \log SD \tag{1}$$

The general equation of the straight line is

$$y = mx + C \tag{2}$$

Table 3: Calculated values of site constants

Predictor equation	K	B	n
USBM	14.36	-0.80	--
Langefors-Kihlstrom	0.374	0.7766	--
Amraseys-Hendron	51.39	0.913	--
Bureau of Indian standard	0.374	0.3883	--
CMRI Predictor (n=0)	14.361	--	-1

Here, PPV and SD data should exhibit a straight line on a log-log graph. Therefore, intercept $C = \log k$ and slope $-B = m$. K, B, and n were determined by multiple regression analysis using SPSS-20 package. Figures 3- 7 graphically represented the correlation between measured and predicted PPV by different SD laws. Table 3 illustrates the site constants for different predictor models. The Amaresyes-Hendron and USBM have quite remarkable R^2 while Langefors-khilstom and Bureau of Indian Standard are having less R^2.

4.2 Prediction of PPV using GRNN

GRNN is a one-pass neural network with highly parallel construction. Specht (1991) proposed GRNN, is a variation of the radial basis function neural network (RBF).Basically, it is an algorithm based on function approximation (estimation) which is a statistical technique named as kernel regression (Xue and Yang, 2014). The training of GRNN is very quick and data needs propagated only once forwarded, unlike other neural network algorithms. A typical architecture of GRNN is depicted in Figure 9. The desired output is determined by taking an average of assigned weights of training output data set. The weight of each output is calculated using the Euclidean distance function between the training and testing data. If the Euclidean distance is more than the total weighs at the output is very less otherwise the additional weight should be assigned to output.

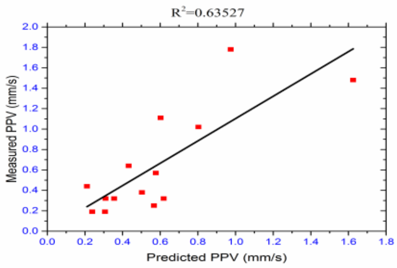

Figure 3: USBM predictor

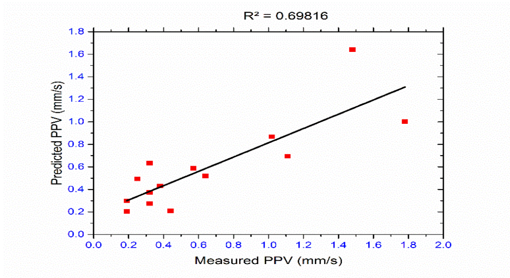

Figure 4: Amraseys-Hendron Predictor

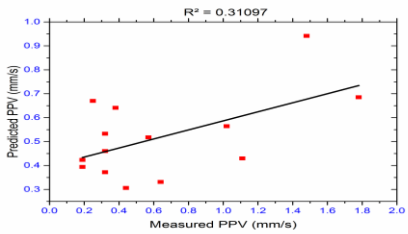

Figure 5: Langefors-khilstom Predictor

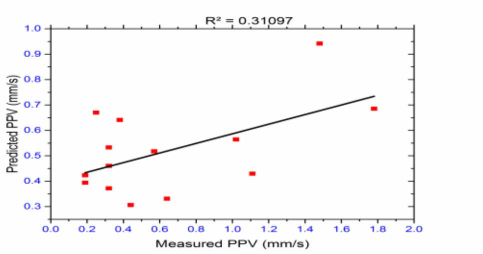

Figure 6: Bureau of Indian Standard Predictor

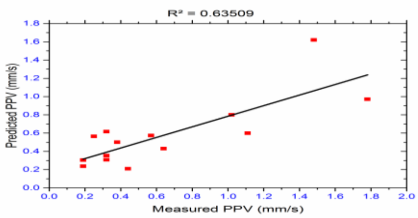

Figure 7: CMRI Predictor

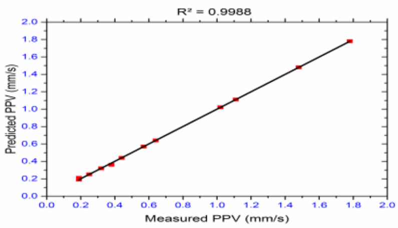

Figure 8: GRNN model

A GRNN contains four layers: an input layer, a pattern layer, summation layer and an output layer. The size of input neurons in input layer depends on the total number of the observed parameters. The input layer feeds the input to pattern layer and each neuron presents a training pattern and output. The main purpose of pattern layer is calculating the Euclidean distance along with activation function and forwarded to the summation layer (Alawode and Alawode, 2014). The summation layer has two sub-parts: numerator (N) and denominator (D). The numerator part consists of addition(summation) of the multiplication of training output data along with activation function and denominator part having the addition of all specified activation function. This summation layer feeds both the data of numerator part and denominator part to the output layer. The output layer is consisting of one neuron which determines the output by merely dividing the output of each numerator part (N) to each of denominator part (D), yielding the predicted output Y(x) to an unknown input vector x as

$$Y(x) = \frac{\sum Y_i \, e^{-\left(\frac{d_i^2}{2\sigma^2}\right)}}{\sum e^{-\left(\frac{d_i^2}{2\sigma^2}\right)}} \tag{3}$$

$$d_i^2 = (x - x_i)^T (x - x_i) \tag{4}$$

Where x is the input sample and x_i is the training sample and Yi is output sample. d_i^2 is the Euclidian distance from x_i to x. $e^{-\left(\frac{d_i^2}{2\sigma^2}\right)}$ which is an activation function. Basically, activation function is the weight of the input data. Here, the unknown spread parameter is constant (σ). It can be adjusted by training process to an optimum, where the error should be minimized. The procedure of training is to find out the optimum of σ. It varies between 0.0001 to 1. The best practice is to minimize the MSE. All fourteen data sets were divided into training and testing datasets as per the thumb rule. The Training of the network was carried out on 70% data sets and the remaining data sets were used for testing and evaluation of the network using MATLAB 2015b. The prediction response of developed GRNN model is graphically represented in Figure 10.

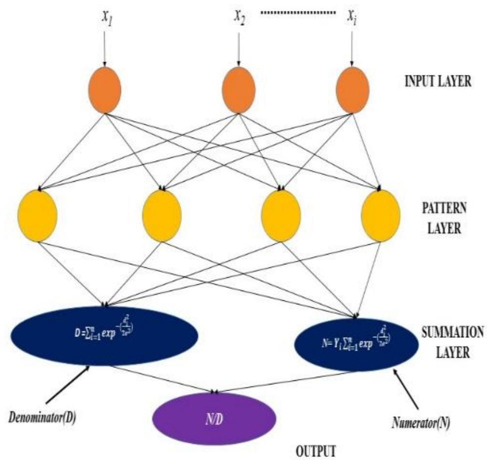

Figure 9: GRNN architecture

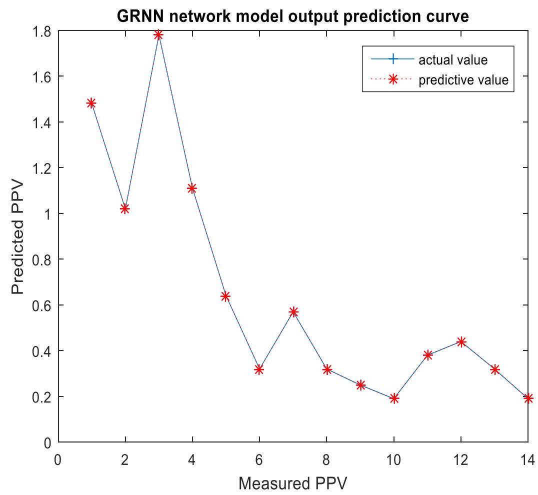

Figure 10: The response of GRNN model

5. Results and discussion

The Figure 8 shows the correlation between the measured and predicted PPV using GRNN model. The analysis of all predictor models in terms of evaluation performance models i.e. R^2 and MSE are summarized in Table 4. The graphical comparison of measured and predicted PPV of all proposed approaches are depicted in Figure 11. It was observed that the GRNN predictor approach has highest R^2 and lowest MSE as compared to other predictors.

Table 4: Correlation coefficient and error parameter

Predictor	R^2	MSE
USBM	0.63257	0.0923
Amraseys-Hendron	0.69816	0.7665
Langefors-khilstom	0.31097	0.1916
Bureau of Indian standard	0.31097	0.1916
CMRI	0.63509	0.0926
GRNN	0.9988	0.0001

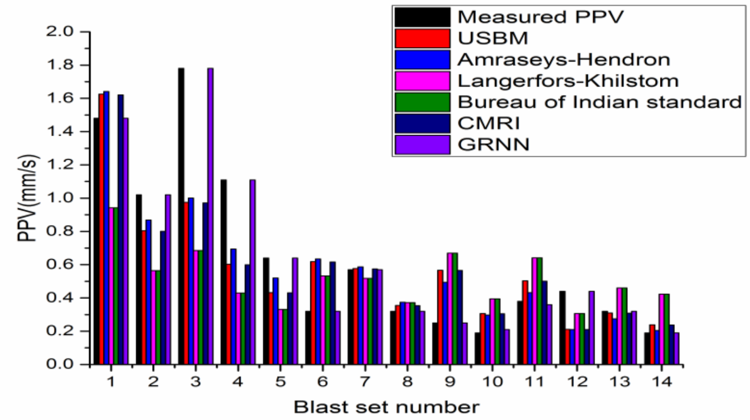

Figure 11: Comparison of measured and predicted PPV using different predictors

6. Conclusions

The blast-induced ground vibration evaluation analysis has been carried out using five established empirical predictors and GRNN model. The parameters such as distance and maximum explosive per delay were taken as input parameters and PPV as an output for all proposed predictors. The obtained results evident that GRNN model provides significant R^2 (0.998) and less MSE(0.0001) as compared to other predicted models. Therefore, it shows more accuarate and better prediction results between recorded and predicted PPVs.

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