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Title Page

A neural network approach to predict blast induced ground vibration using MATLAB

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Abstract:

Ground vibration is unavoidable event occurred due to blasting which needs to be controlled mandatorily, because it could pose negative impacts on the nearby dwellings and resident areas. The use of explosives during blasting is still being considered to be one of the most important applicable alternatives for conventional methods. In this paper, an attempt has been made to predict blast-induced ground vibration using artificial neural network (ANN) considering a case study at singareni mines. To construct the model maximum charge per delay, distance from blasting face to the monitoring point, stemming, diameter of hole, scale distance, spacing and burden were taken as input parameters, whereas, peak particle velocity (PPV) is considered as an output parameter. A database consisting of 150 datasets was collected at different strategic and vulnerable locations in and around the project. From the prepared database, 80 percent data of 130 datasets were used for the training and testing of the network, whereas 20 randomly selected datasets were used for the validation of the ANN model having 10 hidden networks, which includes 7 input parameters and 1 output parameters where trained using 150 experimental monitor blast records collected from KK Open cast mine of Singareni Collieries Company Limited in Telangana. Sensitivity analysis has also been conducted to ascertain the relation between the influences of each input parameter related to blasting (PPV). In a conclusion various statistical method are compared with ANN and found coefficient of regression is 0.93 and maximum and minimum error by using ANN is -0.064 and 0.0654 and recommended empirical methods to approach the best method.

Key words: ANN, Back Propagation, Induced Ground Vibration, MAT LAB and Regression Analysis.

1. INTRODUCTION

Demand for coal and other minerals has increased continually, which has resulted in the creation of opencast mines, where the need and use of enormous quantities of explosives for blasting is increased, **specifically** in India. At the moment, explosives are the most important power source needed to break and excavate rocks. Instantaneously, after an exploding substance ignites in a blast hole, a significant quantity of energy is released in the form of pressure as well as temperature. Although explosive technology has advanced significantly, little progress has been made in the Utilizing of explosive energy because of the complexity of different rock properties [1-3]. The majority of this total power that propagated through hole during blasting may produce negative consequences such back breaks collapse, air generated blasts, and ground shaking. etc. has shown in fig 1 below while only a little part is really used to shatter and move the rock mass.[4]

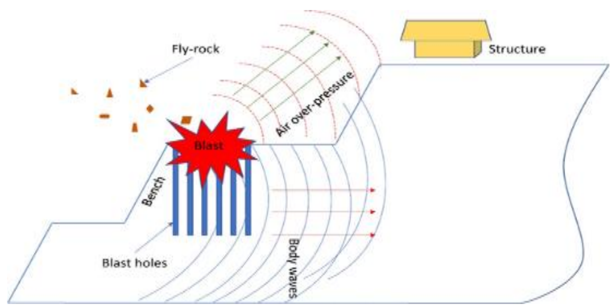

Figure: 1 Adverse effect caused by blasting operation

The earth trembling truly moves in a wave-like manner, radiating from the zone like undulations Formation just like when a stone is placed to a body of water. The surface structures are also subjected to vibration, as the huge amount of energy flows through them. Which leads to result in a resonance if the ground vibration's frequency coincides with the frequency of the structures, and as a result, the expected vibration's amplitude may be greater than the initial ground vibrations' amplitude. [5]. Peak particle velocity (PPV), frequency and air blast is frequently used criteria for evaluating ground vibrations. Development of these potential vibration in ground is determined by a large number of linked factors such as physio and technical specifications of rock mass (geology, strength, hardness, degree of saturation. etc.), explosive attribution and blast design [6-7].It is important to predict the influence of these factors on explosion for productive utilization of blasting power in a rock mass in order to minimize the blast induced negative effects [8]. Some ground vibration parameters like MCD, distance between hole, spacing of hole, explosive length of charge in hole shown in fig 2.

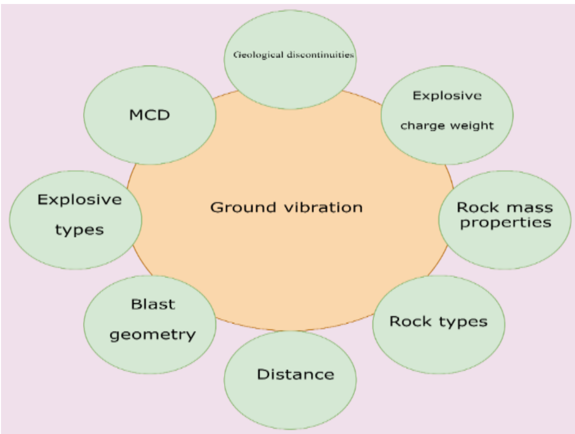

Figure: 2 Factors affecting ground vibration

frequency (air blast)[9]MCD, blast distance, and monitoring station are the primary determining parameters. Each of the characteristics listed above depends on the others and is generally linked. Changes to one parameter will also affect other parameters. A moderate amount of ground vibration behavior is influenced by the nearby rock kinds [10]. To produce the best blast with the least amount of vibration, geophysical features should be considered while constructing any blast. Additionally, geological discontinuity and its properties plays a crucial in the propagation of ground vibration [11].One of the factors with the greatest impact is the separation between the motion tracking station and the blast area. Because waves dissipate and disperse more over a greater distance, vibration will be reduced [12].For the purpose of controlling ground vibration, blast geometry is quite important. Specific characteristics can be used to minimize ground vibration under control levels, including burden, spacing of hole, stemming length, sub-drilling, length of charge, diameter of hole, and hole length [13]. Explosives do have influence on the magnitude and frequency of ground vibration. High velocity of detonation explosive generates high intensity ground vibration, and low velocity of detonation explosive generates low intensity ground vibration.

2.1. NEURAL NETWORKS IN MATLAB

Artificial neural network (ANN), a contemporary field regarding cognitive science that has expanded significantly since the 1980s [14]. ANN are now thought of as one of the clever instruments for understanding critical problems. Neural networks can pick up new information from previously observed patterns [15]. Once an adequate amount of data points has been used to train the algorithm it could be able to forecast about one output related to fresh input datasets with compare patterns [16]. ANN is growing in popularity among academics, planners, designers, and other professionals as a useful tool for finishing their work because of its transdisciplinary nature. As a result, ANN is effectively used in many commercial and research fields. ANN's prediction of statistics data is reportedly more accurate than measured values. Obtained data is compared to the other analytical method; they discovered that results are incredibly realistic.

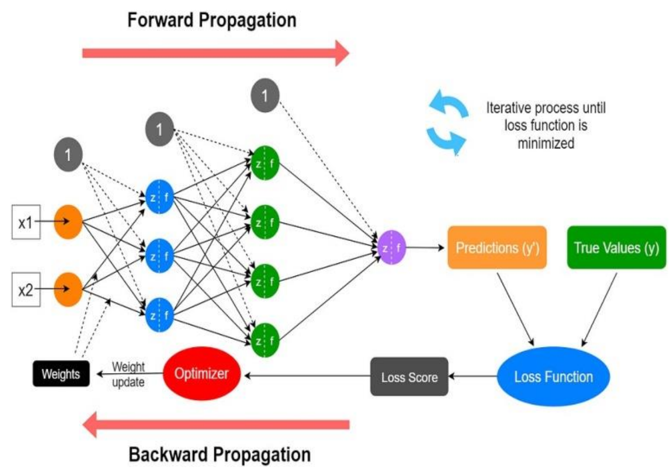

Figure: 3 Multilayer neural network architecture

By using a neural network, Saha [17] analyzed a hazard to the structure brought on by changes in mentioned parameters. By means of a brain network, mahil [18] estimated the fundamental wave speed and rock attributes the general mechanism of multilayer network is shown in figure 3. These illustrations exhibit the superiority of neural models in handling issues where a large number of complicated variables affect both the procedure and outcomes, when the relationship between the process and the results is ambiguous, and when experimental or historical data are available. In the current study, an effort has been made to use ANN to estimate the PPV and its related frequency using appropriate rock volume, blast design specifications, and exploding characteristics.

3. MATERIALS AND METHODS:

3.1 Field data collection

The investigation has carried out in singareni coal fields, Indian government-owned enterprise It is situated in the state of Telangana. KK OC project is located in Northern part of Somagudem Indarm coal belt near Mandamarri village in Mancherial district and is bounded by North Latitude

18°59'44" and 19°03'42" and East Longitudes 79° 26'32" and 79°28'47" and falls in the survey of India. No. 56M/8 of the topo map. Khan, Kalyani the terrain in the Open Cast project region is gently undulating. Geological map and location has shown in figure 4 and 5.

The local relief of the mine ranges from 120 meters over the average sea level in the south to 270 meters above mean sea altitude in the north, with an average slope of 5.7 meters per kilometer towards the Go davari River running in the south.

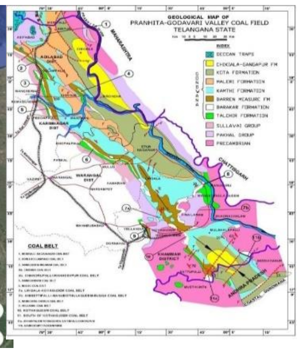

Figure: 4 Google location of mine 5: Geological Map of KK opencast mine

The KK-1 and KK-5 Mines' strike expansion is in this regionand coal fragments after blasting and data collection by minimate blaster is shown in figure 6.

Figure:6 Data collection using minimate blaster

3.2 Implementation And Brief Survey of ANN:

A cell must teach prior it gets interacted with fresh data. Different varieties of algorithms are available for network training, the mechanism for reverse propagation; however it is the approach that is most flexible and long lasting, offering the most efficient learning process considering layered networks. Additionally, the popularity of back-propagation algorithms can be attributed to their exceptional ability of handling predictive problems. In mechanism for forward propagation, the information layer, unseen layer, and return layer are always present (BPNN). The mathematical equation for the sigmoid function is 1/(1+e(-x)). Where x represents the input value and e denotes the constant 2.718. For binary classification and statistical regression issues, the function converts any input value to a number between 0 and 1. Activation function and mathematical equation of ANN for prediction of data set are shown below in fig 7.

Biases, or values with this name, are added to the transfer functions to distinguish between the various processing components. A neuron's temperature is defined as these anomalies.

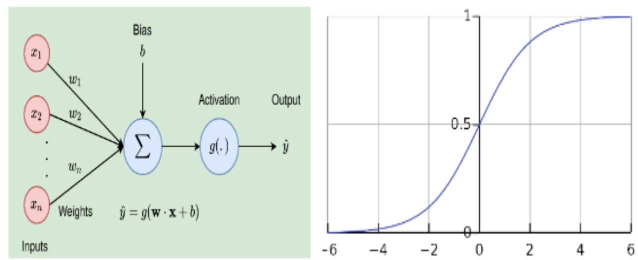

Figure: 7 Activation function and sigmoid equation for prediction in ANN in MATLAB

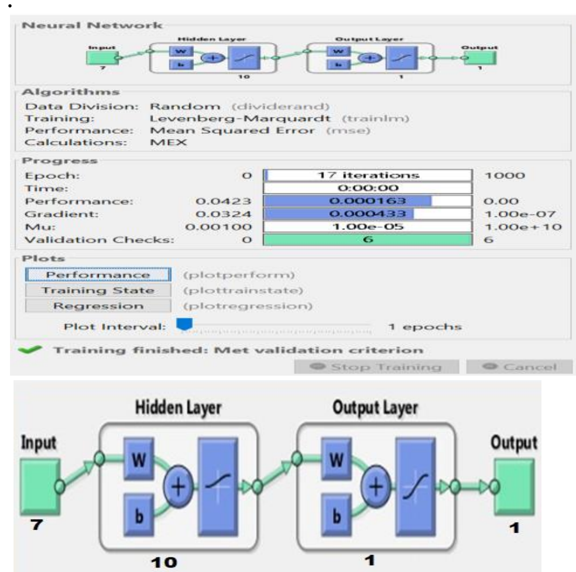

Figure: 8 Neural network Architecture showing 1000 iterations calculating MS

The reverse propagation network's entire population of neurons is attached to a biased neuron and performs an exchange function, with the exception of those in the input layer, while this neuron's transfer mechanism filters all of its impulses, the bias functions similarly to Unlike a weight, its continuous input is 1After training data in mat lab using 7 input parameters, an epoch of around 1000 repetitions has performed using 10 hidden layers showing 1 output layer Fig: 8 representing architecture of neural network are shown below

4 .Description Of Adopted Data Set for Training

The entire data of nearly 150 data sets are trained in ANN based mat lab using 7 input parameters. Obtained data is divided on basis of training and testing on 70:30 basis and remaining data for validation in MATLAB®. After the data dumped in to MAT LAB using the NN tool function. It opens the window learn intake of data for the training in feed-forward back-propagation because it is good for non-linear fittings. Trainslm is the activation function adopted because it updates random weight and bias values according to Levenberg-Marquardt equation. The connections between the results and hidden components follow a similar logic [20]. Every pattern pair of training exemplar given to train the network goes through this process again. Each iteration of every training pattern is referred to as a cycle or period. the user-specified goal is effectively reached once the inaccuracy within it is shown, the procedure is repeated as many times as necessary. This number represents the network's level of learning. After training in MAT LAB data sets ranges and their output including error is shown in Table 1 & 2 respectively.

Table: 1 Input Parameters for Network and Range

Sl.No.	Input Parameter	Range
1	Hole diameter(mm)	150–311
2	Average hole depth(m)	6–43
3	Average burden(m)	3–7
4	Average spacing(m)	4–7
5	Average charge length(m)	4–38
6	Distance of monitoring point from blasting face(m)	500–1000
7	Maximum charge per delay(m)	40-120

5. PPV Assessment Using Conventional Scaling Law Predictors

Because of insufficient knowledge of rock behavior and the challenges in obtaining accurate values for rock parameters is always a difficult task, predicting the transmission of blast-induced vibration through the ground is always a challenging factor. A number of predictor equations are suggested by many researchers for finding PPV considering mostly of 2 parameters 1. Maximum charge per delay 2. Scale distance. Because of complexity of rock behavior these 2 parameters are not adequate to predict ground vibration accurately for this ANN and MVRA is used as it can deal with complex data by taking many input parameters.

Sl no	Recorded PPV	Predicted PPV by ANN	Error ANN	Predicted PPV by MVRA	Error
1	0.23	0.2321	-0.01	0.24	-0.01
2	0.98	0.90	0.03	0.48	0.49
3	0.28	0.28	-0.03	0.40	-0.12
4	0.31	0.30	0.01	0.52	-0.21
5	0.58	0.57	0.06	0.42	0.16
6	0.98	0.97	0.03	0.51	0.46
7	0.58	0.57	0.06	0.47	0.15

It shows a comparison between measured and predicted PPV by PPV, MVRA and different predictor equations considering parameters influencing them and it shows ANN model predict PPV is very close to measured data than others various predicted equation and their geological constants are shown in table 4 belo

Table: 4 PPV predicted equations and their site constants for KK OCP mine

Emperical names	**Equation**	**Siteconstants**		**Prediction output value**
		K	**B**	
USBM	$V=K[R/Qmax]^{-B}$	**4.95**	**-0.57**	**0.81**
Langefors	$V=K[Qmax/ R^{2/3})^{1/2})^{B}$	**1.84**	**-0.296**	**0.78**
Ambraseys-Hendron	$V= K[R/Qmax)^{1/3})^{-B}$	**0.446**	**0.697**	**0.30**
Bureau of indian standard	$V=K(Qmax/R^{2/3})^{B}$	**0.654**	**0.233**	**0.71**

6.Multivariate Regression Analysis (MVRA)

Regressions analysis using more than two parameters are used to gain a better understanding of the correlation between independent variables and standard modified value. A straight-line formula is the parameter in linear regression. To find the best-fitting solution when there are multiple independent variables and MVRA is used. By utilizing least squares fit, multiple regressions provide answers to the datasets. By creating the regression matrix and using the backslash operator to solve for the coefficient, it builds and solves the simultaneous equations. The same datasets and input factors that were used for ANN predictions were also used for MVRA. It validate all the input parameter to reading and validating the input data and found output data is compared with previous obtained data values. The multivariate equation insisted in this research work is given below equation (1)

$$y = \beta 0 + \beta 1x1 + \cdot\cdot\cdot + \beta pXp.......(1)$$

7. ANN Simulation Evaluation and Verification:

After the data trained using Neural network to demonstrate how successfully the networks worked, the findings are presented in this section. Performance metrics include (MAPE) and the connection between the projected and observed numbers (Accuracy) is recorded. The aforementioned input information served as the foundation for the prediction. One unknown layer with 10 hidden cells was used to train the network.The pattern was trained using 1000 learning data set because there was no risk of difficulties with over-fitting because we employed Bayesian regulation [30]. The particle velocity and oscillations have a correlation value of up to 0.9884 and 0.9268 for the anticipated and actual values, respectively .To determine the mean error, subtract the found value from the matching anticipated value, and later divided the result by the found value represented as a percentage. All the MSE and R values obtained after trained in mat lab is shown in fig below 9.

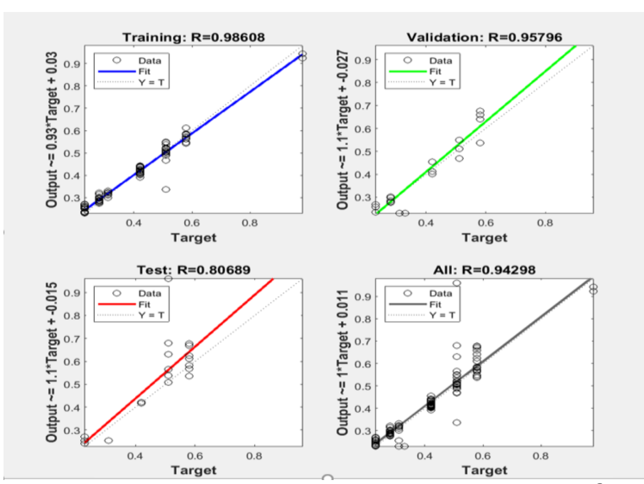

Figure: 9 Neural Network Regression fitting Plot indicting R^2

8. RESULTS AND CONCLUSION

The number of input parameters taken was seven for ANN and MVRA analysis which are hole depth, spacing, burden, bench height, maximum charge per delay, scaled distance, distance from blast site to vibration station. Table 5 shows an error calculation of PPV predicted by both ANN and MVRA for ground vibration, Air blast and frequency. It shows that the error generated from prediction in ANN is lesser than the statistical analysis. The maximum and minimum error generated by ANN are -0.064, 0.0652whereas minimum and maximum error generated by MVRA is -0.252, 1.472respectively.

RMSE and R2 were used for comparing the artificial neural network (ANN) and the MVRA models. The indexes were calculated for the different output parameters belonging to theANNandtheMVRAmodelsasshowninTable6below.

Table: 5 RMSE and R^2 values obtained from ANN and MVRA models form Blast data

Model	Blast Parameter	**RMSE**	**R^2**
ANN	Ground vibration	0.016	0.92
	Air overpressure	0.021	0.910
	Frequency	0.316	0.890
MVRA	Ground vibration	0.172	0.37
	Air overpressure	0.11	0.157
	Frequency	0.061	0.52

As observed from Table 5 above, the ANN model is more accurate than the MVRA model since the root mean square error(RMSE)for the different parameters in the ANN model are relatively smaller compared to those of the MVRA model for the same parameters. In addition, the coefficient of determination (R2) for the parameters in the Ann model for prediction and estimating obtained trained data, The ANN model is closer to unity compared to those of the MVRA. Hence, ANN model predicts outputs with suitable accuracy compared to MVRA model. Computed prediction by the ANN model as seen in Table 5 is the bestwithR2of0.92.MVRAmodelalsopredictedbetterthanother predictedequation. Various predictive equations are compared with obtained mine data to show the accuracy of PPV during blasting is shown in figure11 below

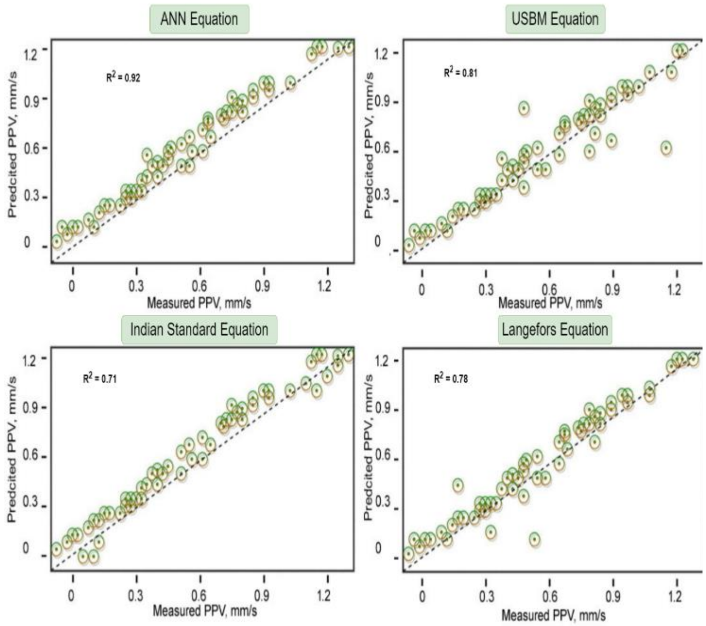

Figure:10 Performance R^2 for various models

Regression graph showing predicted PPV by ANN vs various predicted equation while determining the accuracy of measured Frequency from ANN predicted data it was shown the R^2 value has 92percentaccuracy. The maximum and minimum error generated by ANN (-0.064 ,0.0652)is lesser than Statistical analysis MVRA (0.252, 1.472) From the validation training data in ANN the regression plot, coefficient of regression is obtained as R value for PPV and frequency is 0.95796and0.8734.

Conclusions

The study's objectives were to increase fragmentation, reduce blast damage, and safeguard local residents near the blasting activities. At Mines, a perfect ANN model was developed and used. Next, the outcomes of ANN predictions were contrasted with those of empirical methods and MVRA predictors. Once more, a set of blasts were optimized using the ANN model, and the results were compared to a set of unoptimized blasts.
Below is a summary of the study's findings and how they were validated:

1. Root square error(0.0016) and R square (0.94). The creation of Network pattern models in opencast mines is, however, frequently a challenging process that necessitates a solid foundation in algorithms.

2. While comparing R2 value from collected data with ANN,MVRA and other predicted equations it shows that ANN predictions is best option when dealing with complicated data of ground vibration.

3. The most successful parameters were the separation between the blow-up face area and the observing point, the maximum delay, the powder factor, and the S/B ratio. With (0.94, 0.95,0.95,0.96) on PPV by following sensitivity analysis on different parameters.

4. The empirical method provides a quick and simple way to calculate blast-induced PPV, but further study is required to increase its accuracy. Comparing the RMSE and R2 of empirical equations and multivariate regression, an artificial neural network (ANN) model was shown to be more successful.

- **Author contributions:** TP wrote introduction, literature review, and methodology; NCH, SK, DUVDP. MN, VK & KPR proof read and added inputs in results and discussions part.

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- **Data availability:** The data used in the study are available from the corresponding author on reasonable request.
- **Declarations:** Conflict of interest: The authors declare that they have no conflict of interest. Ethical approval Authors state that the research was conducted according to ethical standards.

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