Revista Minelor – Mining Revue
ISSN-L 1220-2053 / ISSN 2247-8590
vol. 30, issue 3 / 2024, pp. 86-96

A MATLAB-BASED NEURAL NETWORK MODEL FOR PREDICTING BLAST-INDUCED GROUND VIBRATION

T. PRADEEP[1], N. SRI CHANDRAHAS[2], Yewuhalashet FISSHA[3], K. SRAVAN KUMAR[4], K.P. RAGHAVENDRA[5]*

[1]Mining Engineering Department, Malla Reddy Engineering College, Hyderabad, India
[2]Mining Engineering Department, Malla Reddy Engineering College, Hyderabad, India
[3]Department of Geosciences, Geotechnology and Materials Engineering for Resources, Graduate School of International Resource Sciences, Akita University, Akita, Japan
[4]Mining Engineering Department, Malla Reddy Engineering College, Hyderabad, India
[5]Mining Engineering Department, Malla Reddy Engineering College, Hyderabad, India

DOI: 10.2478/minrv-2024-0029

Abstract: *This research delves into using an artificial neural network (ANN) to forecast blast-induced ground vibration, vital for controlling the impact of blasting on nearby residential areas. By leveraging data from Singareni mines, the ANN model incorporates various input parameters to predict ground vibration intensity (peak particle velocity). With a dataset of 150 entries and sensitivity analysis, the ANN demonstrates a robust regression coefficient of 0.92, signifying its predictive strength. Comparative analysis favors the ANN model, showcasing its potential in mitigating adverse effects on residential zones, marking a significant stride in managing blast-induced ground vibration prediction using ANN.*
Keywords: *ANN, Back Propagation, Induced Ground Vibration, MATLAB and Regression Analysis*

1. Introduction

The continuous rise in demand for coal and other minerals has led to the expansion of opencast mines, resulting in a greater need for vast quantities of explosives for blasting operations. Currently, explosives are the primary energy source for breaking and excavating rocks. When an explosive substance detonates in a blast hole, it releases a substantial amount of energy in the form of pressure and temperature almost instantaneously. Despite significant advancements in explosive technology, optimizing the use of explosive energy remains challenging due to the complex properties of different rock types [1, 2, 3, 4, 5]. A major portion of the energy generated during blasting is often lost, leading to undesirable effects such as back breaks, fly rock, induced ground vibration, and air overpressure, as illustrated in Figure 1. Only a small fraction of this energy is effectively utilized for fracturing and moving the rock mass [6].

The earth's trembling propagates in a wave-like manner, radiating from the epicenter similar to ripples created when a stone is dropped into a body of water. This wave-like motion transmits significant energy through surface structures, causing them to vibrate. If the frequency of ground vibrations matches the natural frequency of the structures, resonance can occur, potentially amplifying the vibration’s amplitude beyond the initial ground vibration’s amplitude [7]. Duhamel's integral has found significant application in blast engineering. Research studies [8] have demonstrated its effectiveness in analyzing structural responses to blast waves. For example, [9] utilized Duhamel's integral to predict displacements and accelerations in structures subjected to explosive events, underscoring its value in assessing potential damage. According to Duhamel's integral principle of structural dynamic response under a general load [10] Duhamel's Integral Formulation: In the context of blast loading, Duhamel's integral is expressed as follows:

$$u(t) = \int_t^0 h(t-\tau)\cdot g(\tau)\,d\tau \quad \text{…………….. Eq} \qquad (1)$$

where:

- $u(t)$ represents the response of the structure at time
- $h(t-\tau)$ is the response function of the structure to a unit impulse at time
- $g(\tau)$ is the time history of the applied load.

[*] Corresponding author: N. Sri Chandrahas, assoc.prof. Ph.D. eng., Mining Engineering Department, Malla Reddy Engineering College, Hyderabad, India, srichandru2009@gmail.com

 vol. 30, issue 3 / 2024
pp. 86-96

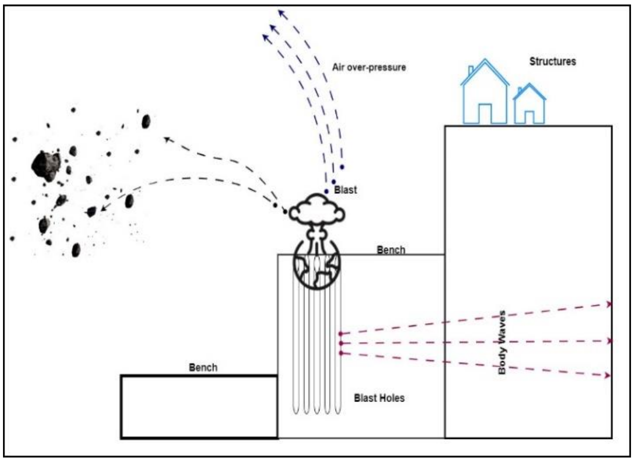

Fig. 1. Adverse effect caused by blasting operation

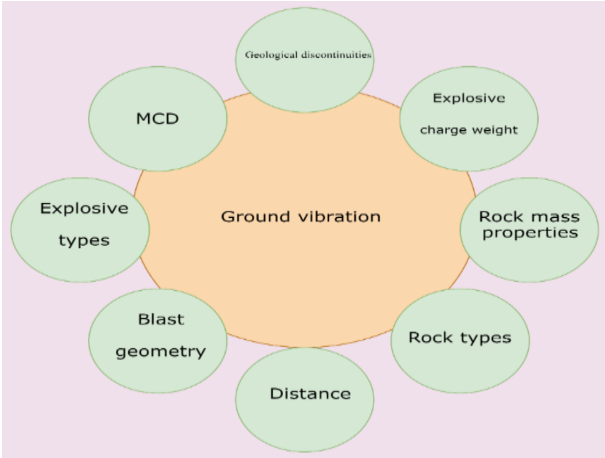

Fig. 2. Factors affecting ground vibration

Peak particle velocity (PPV), frequency and air blast are frequently used criteria's for evaluating ground vibrations. Development of this potential vibration in the ground is determined by a large number of linked factors such as physical–mechanical properties and technical specifications of rock mass (geology, strength, hardness, degree of saturation, etc.), explosive attributions, and blast design parameters [11, 12]. It is important to predict the influence of these factors on explosion for productive utilization of blasting power in a rock mass to minimize the blast-induced negative effects [13]. Some ground vibration parameters like MCD (Maximum charge per delay), the distance between hole, spacing of hole, explosive length of charge in hole shown in Figure 2.

The Maximum Charge per Delay (MCD) and blast monitoring distance are the primary parameters that determine induced ground vibration [14]. These characteristics are interdependent, meaning changes to one parameter will invariably affect the others. The behavior of ground vibration is also moderately influenced by the types of nearby rock [15]. To achieve the optimal blast with minimal vibration, it is essential to consider geophysical features during blast design. Geological discontinuities and their properties play a crucial role in the propagation of ground vibration [16]. One of the most significant factors is the distance between the motion tracking stations and the blast site. As waves dissipate and disperse over greater distances, the resulting vibration is reduced [15]. Blast geometry is vital in controlling ground vibration. Specific characteristics such as burden, hole spacing, stemming length, sub-drilling, charge length, hole diameter, and hole length can be adjusted to keep ground vibration within acceptable levels [17]. The properties of explosives also impact the magnitude and frequency of ground vibration. High-velocity explosives generate high-intensity ground vibrations, while low-velocity explosives produce lower-intensity vibrations [18].

2. Artificial Neural Network

Artificial Neural Networks (ANN), a modern branch of cognitive science, have seen substantial growth since the 1980s [19]. Today, ANN is regarded as a powerful tool for addressing complex problems. Neural networks have the capability to learn from previously observed patterns [20]. Once the algorithm has been trained with a sufficient amount of data points, it can predict outcomes for new input datasets by identifying and comparing patterns [21]. Due to its interdisciplinary nature, ANN is increasingly popular among researchers, planners, designers, and other professionals, making it an effective tool across various commercial and research fields. ANN's predictive accuracy is often reported to surpass measured values. When compared to other analytical methods, the results obtained through ANN are found to be remarkably realistic.

Saha [22] used a neural network to analyze structural hazards resulting from changes in specific parameters. Similarly, Mahil [23] utilized a neural network to estimate fundamental wave speed and rock attributes, showcasing the general mechanism of a multilayer network as depicted in Figure 3. These cases demonstrate the effectiveness of neural models in tackling problems involving numerous complex variables that affect both processes and outcomes, especially when the relationship between them is ambiguous and when experimental or historical data are available. In this study, an effort has been made to use ANN to estimate the Peak Particle Velocity (PPV) and its related frequency by incorporating appropriate rock volume, blast design specifications, and explosive characteristics.

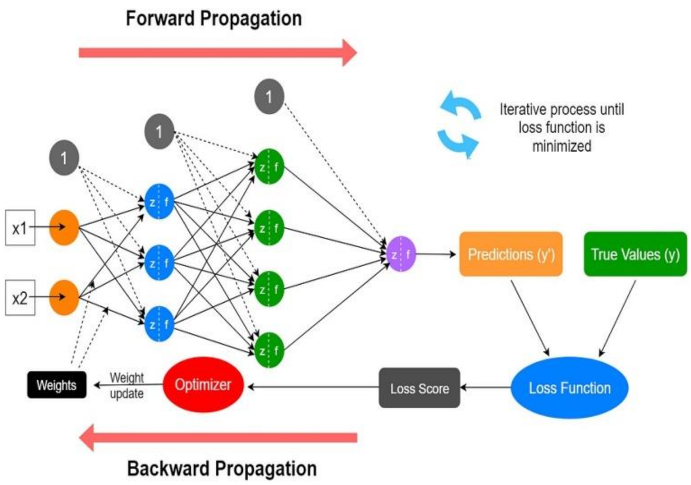

Fig. 3 Multilayer neural network architecture [1]

Ground vibration can have significant adverse effects on residential zones, impacting both structures and residents' quality of life. Studies have shown that excessive ground vibration can lead to structural damage to buildings [24] and infrastructure, including cracks in walls and foundations [25]. Moreover, prolonged exposure to high levels of ground vibration can cause discomfort and annoyance to residents, leading to sleep disturbances and increased stress levels [26] Additionally, ground vibration from construction activities or industrial operations has been linked to decreased property values in affected areas [27]. This decrease in property values can have long-term economic implications for homeowners and communities. Furthermore, certain sensitive equipment or machinery within residential areas, such as medical devices or precision instruments, may be adversely affected by even low levels of ground vibration [28].

3. Materials and Methods

3.1 About the site

The investigation was carried out in the KK OC project, Singareni Coal Fields, which belongs to an Indian government-owned enterprise 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. Geological map and location is shown in figure 4 and 5.

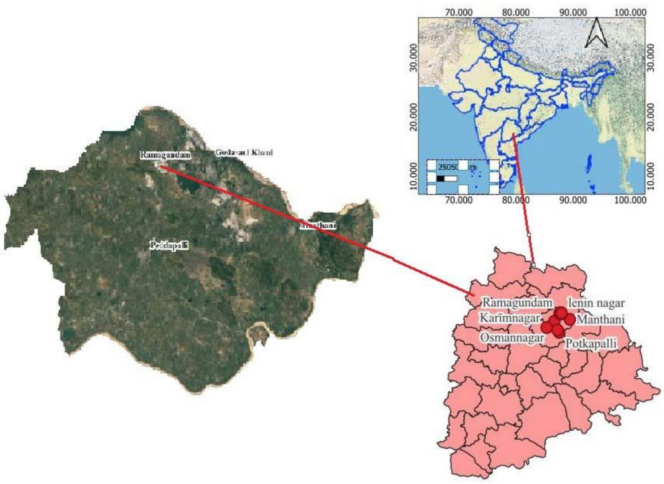

Fig. 4. Google location of the mine

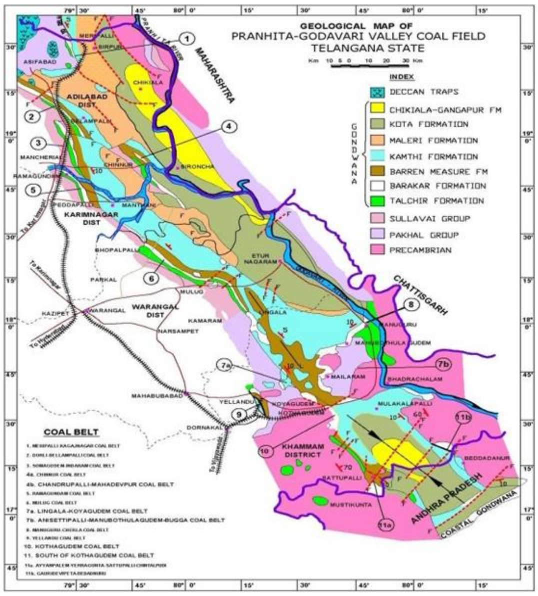

Fig. 5. Geological Map of KK opencast mine

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 Godavari River running in the south.

 vol. 30, issue 3 / 2024
pp. 86-96

3.2. Data Collection

The height of the study benches was 17 meters. The alluvium soil and sandstone comprised the friable rock strata. The blast hole measured 250 mm in diameter and 18 meters in depth. Site Mixed Emulsion was the explosive (SME). The firing pattern was a line that was started with a cast booster and NONEL initiation mechanism, while the drilling pattern was square. Sandstone had a density of 2.3 g/cc. Figures 6 and 7 display, OB bench, blast site, and blast parameters. burden (m), spacing (m), blast hole length (m), blast hole diameter (mm), total explosive (kg), charge per hole (kg), stemming length (m), firing pattern, and structural elements like joints were among the blast design characteristics that were gathered during the visit.

Fig. 6. OB sandstone bench

Fig. 7. Blast site

In the region, the geological state of the rock mass was isotropic in all directions. To ensure consistency in the vibration monitoring measurements, the observation point locations were selected at an identical angle to the blast site. Any insignificant impact of the variations in angle has been disregarded. At the experimental drilling sites, random benches were used to gather samples related to the qualities of the rock.

3.3. Ground Vibration Measurement

The ground vibration was recorded using an engineering seismograph called Minimate, as Figure 8 (a & b) illustrates. To keep direct contact with the earth, the transducer was securely pressed into the ground while fastened to spikes, as shown in figures 8a & 8b.

Fig.8 (a & b). Data collection using Minimate blaster

Given that the distance between the blast area and the monitoring station stayed constant during the research, the maximum charge per delay was between 110 and 210 kg. 500 meters was the measurement distance. The seismograph recorded vector sum velocity (VS) and PPV for the longitudinal (R), vertical (V), and transverse (T) components during the blasts.

3.4. Principle Component Analysis (PCA)

Principal component analysis was used in XLSTAT for this inquiry to understand how independent and dependent variables affected trends for the ultimate choice of blast design in software that would be used for experimental blasts. The hole width, burden, spacing, front row burden, decking, stemming, firing pattern, total average explosive quantity, and total explosive quantity were selected to load PCA (Principle Component Analysis) as the input data for loading from the blast design parameters.

The correlation circle that the PCA in software package generates serves as the starting point for interpretation; the values within the circle will direct the process moving forward. When examining the link

vol. 30, issue 3 / 2024
pp. 86-96

between independent and dependent variables, the software package correlation circle is an invaluable tool. Three segments comprise the interpretation: the positively correlated, negatively correlated, and orthogonally correlated segments.

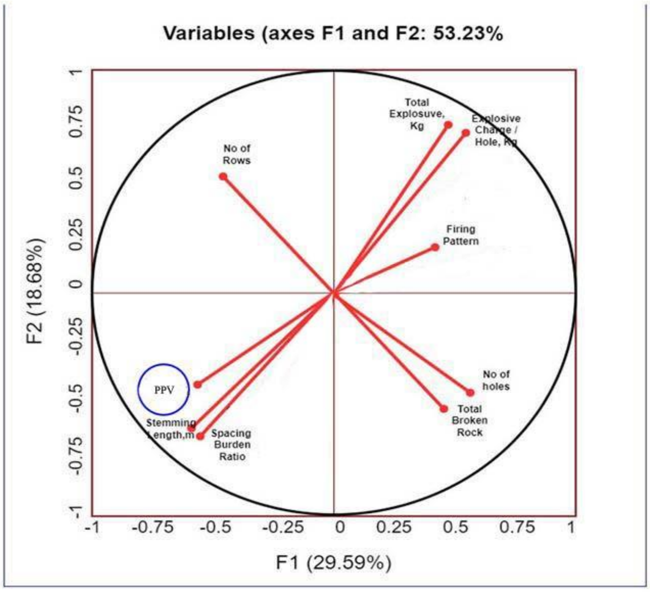

Fig. 9. Correlation Circle Diagram of blast design parameters

Positively correlated variables are those that are found close together and in the same quadrant; negatively correlated variables are those that are found in the opposite quadrant, and orthogonally related variables are those that are found next to the quadrant. Positive correlation denotes a proportionate link, negative correlation denotes an inversely proportional relationship, and orthogonal correlation denotes no relationship at all between the variables [29]. The relationship between the number of holes, the load, the spacing, the front row burden, the stemming, the firing pattern, the hole depth, and the explosive quantity (independent variables) has been determined using XLSTAT [30]. From Figure 9, It is observed that Peak Particle Velocity (PPV) has a positive relationship with stemming length, burden, and spacing, while there is a negative relationship between explosive quantity per hole, total explosive, and firing pattern. Therefore, PPV tends to increase with higher values of the other independent parameters.

4. Machine Learning Models

4.1. ANN Approach to predict PPV

Artificial Neural Networks (ANNs) are computational models inspired by the human brain's neural structure [31]. The ANN predicts pattern outcomes based on prior learning. Once trained, it detects similarities in new patterns, adjusting results accordingly, offering interpolation capabilities. Training the ANN involves the backpropagation algorithm. The feed-forward Backpropagation Neural Network (BPNN) consists of an input layer, hidden layer, and output layer. Neurons within these layers connect using weighted connections. Neurons in the input layer pass information to those in the hidden layer, and similarly, connections occur between the hidden and output layers [32, 33, 34]. The problem determines the number of hidden layers and their neurons. In this study, a BPNN with a 'log-sigmoid' transfer function was employed, the mathematical equation for the sigmoid function is 1/(1+e(-x) as presented in figure 10. Where x represents the input value and e denotes the constant 2.718.

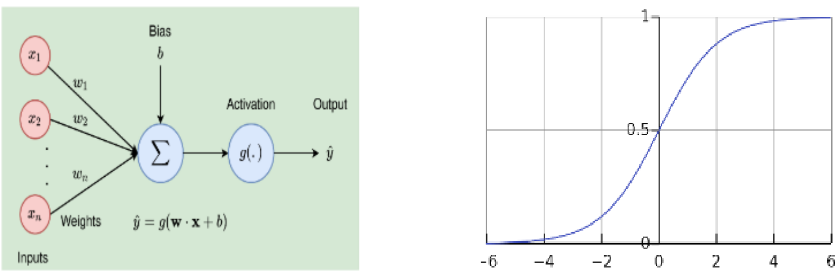

Fig. 10. Activation function and sigmoid equation for prediction in ANN in MATLAB

vol. 30, issue 3 / 2024
pp. 86-96

After experimenting with various combinations, the optimal model comprised two hidden layers, each with ten neurons. Table 1 displays the input and output parameters utilized in the ANN model. Training involved 150 datasets, while 30 datasets were reserved for testing and validation. Figure 11 depict the neural network's architecture and performance during training. The regression plots in Fig. 12 showcase the selected network's proficiency across training, testing, and validation stages.

The connections between the results and hidden components follow a similar logic [35]. Every pattern pair of training exemplars 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 [36, 37].

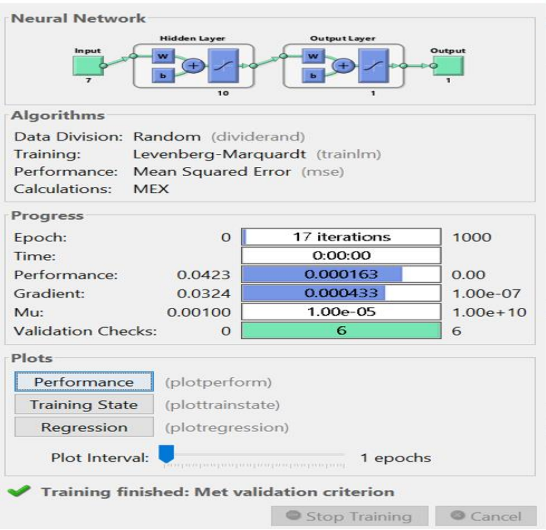

Fig. 11. Neural Network Architecture with 1000 iterations for Mean Squared Error (MSE) calculation

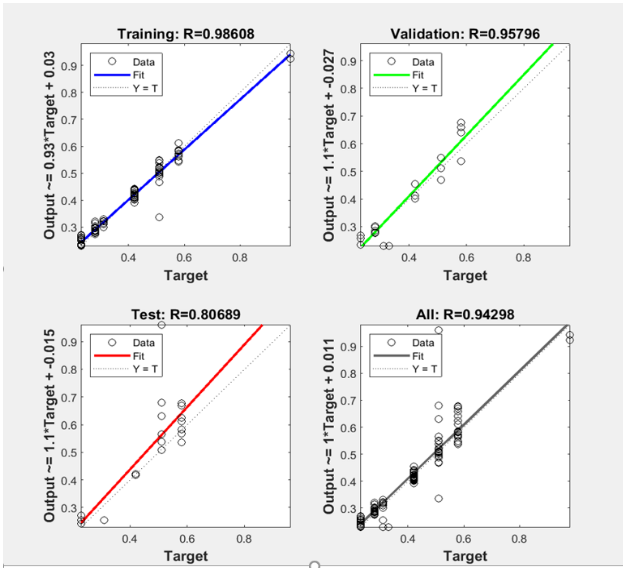

Fig.12. Neural Network Regression fitting Plot indicting R^2

4.2. Multivariate Regression Analysis (MVRA)

Regressions analysis using more than two parameters is 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 [38]. 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 [39]. The same datasets and input factors that were used for ANN predictions were also used for MVRA [40, 41]. It validates all the input parameters to read and validate the input data and found output data is compared with previously obtained data values. The multivariate equation insisted in this research work is given below equation (2).

$$y = \beta 0 + \beta 1x1 + \cdot\cdot\cdot + \beta pXp \tag{2}$$

vol. 30, issue 3 / 2024
pp. 86-96

The equation expresses a linear relationship between the dependent variable (y) and multiple predictor variables (x1, x2, ..., xp) weighted by their respective regression coefficients (β1, β2, ..., βp), along with the intercept (β0).

Table 1: Input Parameters for Network and Range

S. No.	Input Parameter	Range
1	Spacing Burden Ratio	1.1 - 1.3
2	Stemming Length, m	4 - 5
3	Firing Pattern	L, V, D
4	Explosive Quantity, Kg	500 - 600
5	Total Quantity of Explosive, Kg	30,000 - 33,000
6	Distance of monitoring point from blasting face(m)	500 - 1000
7	Maximum charge per delay(m)	40 - 120

5. Results and Discussions

This section presents and discusses the findings from the study on neural network modeling technique for forecasting blast-induced ground vibration using MATLAB. The study initially assessed the neural network model's effectiveness by comparing its predictions to real ground vibration data obtained at several blasting sites from Singareni Coal Field. In addition, the study conduct sensitivity analysis to identify important input factors that have a major impact on prediction accuracy. These evaluations provide light on the durability and reliability of the constructed neural network model for forecasting ground vibration levels in response to various blasting situations.

In this work, RMSE & R^2 calculations were performed using the following equations (3) & (4):

$$\text{RMSE} = \frac{1}{n}\sum_{i=1}^{n}(\text{Yi} - \text{Yi})2 \tag{3}$$

Here, n is the total number of data points, yi denotes the actual values, and Yi denotes the expected values. Consequently, the mean squared error (MSE) between the expected and actual values.

$$R^2 = 1 - \frac{\sum \text{i}(\text{yi} -\hat{}\,\text{yi})2}{\sum \text{i}(\text{yi} -\bar{}\,\text{y})2} \tag{4}$$

The data is denoted as n, yi & ˆ yi, where ˆ yi stands for the mean and represents and projected values, respectively. Metrics like RMSE and R^2 were calculated on the training and testing data sets to identify the optimal algorithm for developing a formula to predict fragmentation and ground vibration.

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 is relatively smaller compared to those of the MVRA model for the same parameters. In addition, the coefficient of determination (R^2) 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, the ANN model predicts outputs with suitable accuracy compared to the MVRA model. Computed prediction by the ANN model as seen in Table 5 is the best with R^2 of 0.92. MVRA model also predicted better than other predicted equations. Various predictive equations are compared with obtained mine data to show the accuracy of PPV during blasting is shown in figure 13 and in table 2.

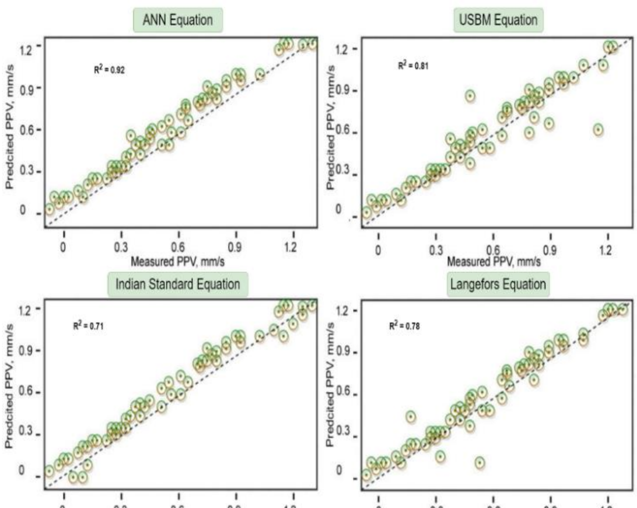

Fig. 13. Performance R^2 values for various models

vol. 30, issue 3 / 2024
pp. 86-96

Similarly, it observed among ANN and MVRA, ANN produced finest RMSE value of 0.5, which generated a low value when compared to MVRA as shown in figure 14.

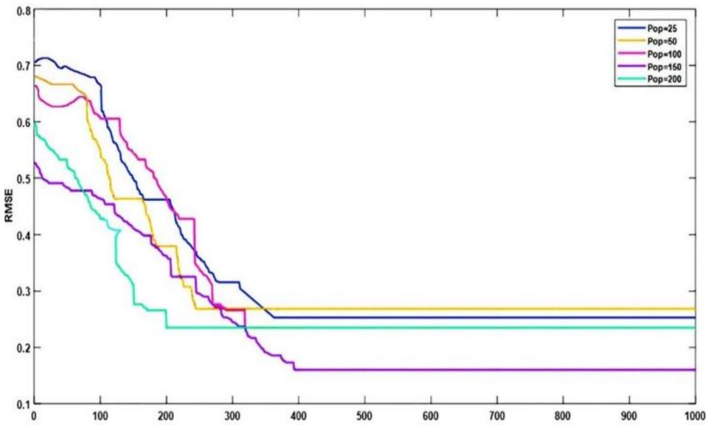

Fig. 14. ANN RMSE output values for PPV

Table 2. PPV Recorded and Predicted Values

S. No	Recorded PPV,mm/s	ANN Predicted PPV, mm/s	Error ANN	MVRA Predicted PPV, mm/s	Error MVRA
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

Table 2 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 other various predicted equation, and geological constants of other than ANN & MVRA, equations are presented in table 3.

The numerical model's correctness and effectiveness are established through rigorous internal validation processes, sensitivity analyses, and comparisons with empirical models and field data, all detailed within the main manuscript. These comprehensive analyses demonstrate the reliability of our neural network-based approach in predicting blast-induced ground vibration accurately.

Table 3. PPV predicted equations and their site constants for KK OCP mine [4]

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. Conclusion

The study aimed to enhance fragmentation, minimize blast damage (Peak Particle Velocity), and ensure the safety of residents near blasting activities. An effective ANN model was developed and applied on-site. Comparative analysis between ANN predictions, empirical methods, and MVRA predictors was conducted. Using the ANN model, a series of blasts were optimized and compared against a set of un-optimized blasts.

- The study conducted principal component sensitivity analysis on various parameters and successfully identified pivotal factors influencing blast outcomes. Stemming length, firing pattern, total explosive quantity, and spacing burden ratio were found to exert considerable influence on peak particle velocity among other parameters.

vol. 30, issue 3 / 2024
pp. 86-96

- The R^2 values among all models like MVRA, USBM, Langefors, Ambraseys- Hendron, and Bureau of Indian standard, ANN produced a superior coefficient of regression value of 0.92, which resembles a stronger prediction model than others.
- ANN performs better in training, testing, validation, and in overall category with the values of 0.98, 0.95, 0.8 and 0.945 respectively, then MVRA in predicting peak particle velocity.
- Likewise, in terms RMSE, ANN produced a finest lower value of 0.5 than MVRA.
- The ANN with the set of real blast datasets like spacing burden ratio, stemming length, firing pattern, maximum charge per delay, explosive quantity, and distance from the blasting site are quite useful in predicting PPV for practicing mining engineers at the field.

To summarize, the current study presents an optimal performance ANN model for forecasting ground vibration during blasting. This work will assist mining engineers and designers in estimating ground vibration during blasting. It is also proposed that the ANN model be utilized to address various geotechnical challenges.

7. Future Scope of Work

- To collect data from various mines, include various geo-blast design parameters as inputs for the algorithm.
- To Develop a hybrid algorithm for PPV prediction.
- To Create a web-based interface for PPV prediction, enabling practicing engineers to benefit with just a few clicks.

Acknowledgments

Author contributions: TP and YF wrote introduction, literature review, and methodology; NCH, SK, and KPR proofread and added inputs in results and discussion's part.

Funding: This research received no external funding.

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

References

[1] **Abiodun Ismail Lawala, Musa Adebayo Idrisa**, 2021.
An Artificial Neural Network-Based Mathematical Model for the Prediction of Blast-Induced Ground Vibrations

[2] **lvarez-Vigil A. E.**, 2020
Predicting Blasting Propagation Velocity and Vibration Frequency Using Artificial Neural Networks

[3] **Anand Kumar, Pusker Singh, Sanjay Kumar Sharma, Nawal Kishore C. S. Singh**, 2021.
Quantitative Assessment of BIGV and Structural Response Based on Velocity and Frequency around an Opencast Mine, Department of Mining Engineering, Indian Institute of Technology (BHU), Varanasi 221 005, India

[4] **Sri Chandrahas N., Choudhary B.S., Venkataramayya M.S.**, 2023
Firing Pattern and Spacing Burden Ratio Selection in Jointed Overburden Benches Using Unmanned Aerial Vehicle and Artificial Intelligence Based Tool, Proceedings of the Second International Conference on Emerging Trends in Engineering (ICETE 2023). DOI: http://10.2991/978-94-6463-252-1_134

[5] **Chandrahas N.S., Fissha Y., Choudhary B.S., Olamide Taiwo B., Venkataramayya M.S., Adachi T.**, 2024
Experimental Data – Driven Algorithm to Predict Muckpile Characteristics in Jointed Overburden Bench Using Unmanned Aerial Vehicle and AI Tools. International Journal of Mining, Reclamation and Environment, 1–35. https://doi.org/10.1080/17480930.2024.2340876

[6] **Mishra A.K.**, 2019
An Innovative Technique of Simplified Signature Hole Analysis for Prediction of Blast-Induced Ground Vibration of Multi-Hole/ Production Blast: An Empirical Analysis.

[7] **Bansingh Z.**, 2019.
Predicting Blast-Induced Ground Vibration in Open-Pit Mines Using Vibration Sensors and Support Vector Regression-Based Optimization.

[8] **Jiang L., Zeng J., Wang G.**, 2019
A Discrete Dynamic Response Model with Multiple Degrees of Freedom for Horizontal Goaf Group, J. Rock Mech. Eng., pp. 35, 59–67

[9] **Tileylioglu S., Stewart J.P., Nigbor R.L.**, 2011
Dynamic Stiffness and Damping of a Shallow Foundation from Forced Vibration of a Field Test Structure. J. Geotech. Geoenviron. Eng., 137, 344–353. [CrossRef].

[10] **Nielsen A.H.**, 2009.
On the Use of Rayleigh Damping for Seismic Analysis. Proc. Inst. Civ. Eng. Eng. Comput. Mech., 162, 215–220. [CrossRef]

[11] **Choudhary B.S., Mishra A.K.**, 2021
Modeling the Effects of Ground Vibrations on the Surface due to Blasting in Underground Coal Mines

[12] **Armaghani D.J., Kumar D.**, 2020.
A Novel Approach for Forecasting of Ground Vibrations Resulting from Blasting: Modified Particle Swarm Optimization Coupled Extreme Learning Machine

[13] **Duvall W.I., Fogleson D.E.**, 2007
Review of Criteria for Estimating Damage Toresidences from Blasting Vibrations. USBM, RI, vol. 5968, p. 19

[14] **Dusenberry D.**, 2010
Handbook for Blast Resistant Design of Buildings, pp. 8-9

[15] **Enayatollahi I., Aghajani Bazzazi A., Asadi A.**, 2014.
Comparison between Neural Networks and Multiple Regression Analysis to Predict Rock Fragmentation in Open-Pit Mines. Rock Mechanics and Rock Engineering, Volume 47, Issue2, pp. 799 – 807

[16] **Ghosh A., Daemen J.K.**, 2004
A Simple New Blast Vibration Predictor. In: Proc. 24^{th} US Symp. Rock Mechanics, Texas, USA, pp.151–161

[17] **Ghosh S.I.**, 1973.
Criteria for Safety and Design of Structures Subjected to Underground Blast. Bureau of Indian Standard. ISI Bulletin IS-6922

[18] **Hemant A., Pradeep T.**, 2020
Blast Vibration Dependence on Total Explosives Weight in Open-Pit Blasting

[19] **Sri Chandrahas N., Choudhary B.S., Krishna Prasad N.S.R., Musunuri V., Rao K.K.**, 2021
An Investigation into the Effect of Rockmass Properties on Mean Fragmentation. Arch. Min. Sci., 66, 561–578

[20] **Sri Chandrahas N., Choudhary B.S., Vishnu Teja M., Venkataramayya M.S., Krishna Prasad N.S.R.**, 2022
XG Boost Algorithm to Simultaneous Prediction of Rock Fragmentation and Induced Ground Vibration Using Unique Blast Data. Appl. Sci., *12*(10), 5269; DOI: https://doi.org/10.3390/app12105269

[21] **Hoang Nguyen**, 2019
Prediction of Blast-induced Air Over-pressure in Open-Pit Mine: Assessment of Different Artificial Intelligence Techniques

[22] **Hoang Nguyen, Xuan-Nam Bui B.C.**, 2020.
Soft Computing Models for Predicting Blast-Induced Air Over-Pressure: A Novel Artificial Intelligence Approach

[23] **Huay Kaepty,** 2019
Monitoring and Control Airblast Overpressures in an Open Pit Coal Mine Jaroonpattanapong , K. Tachom, Department of Mining and Petroleum Engineering, Faculty of Engineering, Chiang Mai University

[24] **Smith A. et al.**, 2018.
Impact of Ground Vibration on Residential Buildings: A Case Study, Journal of Structural Engineering, 25(3), 112-125

[25] **Jones B. et al.**, 2016
Assessment of Structural Damage Due to Ground Vibration in Residential Areas, Construction and Building Materials, 40, 225-234

[26] **Brown C., Smith D.**, 2019
Effects of Ground Vibration on Human Health: A Review, Environmental Health Perspectives, 127(4), 460-471

 vol. 30, issue 3 / 2024
pp. 86-96

[27] **Johnson E. et al.**, 2020
Economic Impacts of Ground Vibration on Residential Property Values, Journal of Real Estate Economics, 35(2), 201-215

[28] **Garcia R. et al.**, 2017
Effects of Ground Vibration on Sensitive Equipment: A Case Study in a Residential Area, Journal of Environmental Engineering, 30(4), pp. 287-299

[29] **Jahed Armaghani Marto**, 2013
Blasting Induced Flyrock and Ground Vibration Prediction through an Expert Artificial Neural Network Based on Particle Sparm Optimization

[30] **Cristianini N., Shawe-Taylor J.**, 2000
An Introduction to Support Vector Machines and Other Kernel-Based Learning Methods, Cambridge University Press, London

[31] **Sri Chandrahas N., Choudhary B.S., Venkataramayya M.S.**, 2018
Identification of Most Influencing Blast Design Parameters on Mean Fragmentation Size and Muckpile by Principal Component Analysis. International Journal of Innovative Technology and Exploring Engineering (IJITEE) ISSN: 2278-3075, Volume 8, Issue 2S2

[32] **Jian Zhou A., Yingui Qiu A., Manoj Khandelwal B.**, 2016
Developing a Hybrid Model of Jaya Algorithm-Based Extreme Gradient Boosting Machine to Estimate Blast-Induced Ground Vibrations

[33] **Khandelwal M.**, 2014
Artificial Neural Network as a Tool for Back Break Prediction. Geotechnical and Geological Engineering, 32(1), 21-30

[34] **Lima Xingping Lai**, 2019
Blast-Casting Mechanism and Parameter Optimization of a Benched Deep-Hole in an Opencast Coal Mine

[35] **Matidz Mulalo**, 2017
Assessment of Blast-Induced Ground Vibration at Jinduicheng Molybdenum Open Pit Mine

[36] **McKenzie C.**, 2008
Quarry Blast Monitoring Technical and Environmental Perspective, Quarry Management, p. 23

[37] **Mostafa T.M..**, 2009
Artificial Neural Network for Prediction and Control of Blasting Vibrations in Assiut (Egypt) Limestone Quarry, IntJRockMechMinSci46(2):426–431

[38] **Monjezi M., Bahrami A., Yazdian Varjani A.**, 2010
Simultaneous Prediction of Fragmentation and Fly Rock in Blasting Operation Using Artificial Neural Networks, International Journal of Rock Mechanics and Mining Sciences, Volume 47, Issue 3, pp.476 – 480

[39] **Monjezi M., Amiri H., Farrokhi A., Goshtasbi K.**, 2010.
Prediction of Rock Fragmentation due to Blasting in Sarcheshmeh Copper Mine Using Artificial Neural Networks, Geotechnical and Geological Engineering, 28(4), 423-430

[40] **Taiwo B.O., Yewuhalashet F., Adamolekun L.B., Bidemi O.O., Famobuwa O.V., Victoria A.O.**, 2023
Development of Artificial Neural Network Based Mathematical Models for Predicting Small Scale Quarry Powder Factor for Efficient Fragmentation Coupled with Uniformity Index Model, Artificial Intelligence Review, 0123456789 https://doi.org/10.1007/s10462-023-10524-1

[41] **Sri Chandrahas N., Choudhary B.S., Venkataramayya M.S.**, 2023
Competitive Algorithm to Balance and Predict Blasting Outcomes Using Measured Field Data Sets, Comput Geosci. https://doi.org/10.1007/s10596-023-10254-x.