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A Principal Component-Enhanced Neural Network Framework for Forecasting Blast-Induced Ground Vibrations

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Abstract: Blast-induced ground vibration, a by-product of rock fragmentation, presents significant challenges, particularly in areas adjacent to residential structures, where excessive vibration can cause structural damage and propagate cracks. This study proposes a novel framework integrating Principal Component Analysis (PCA) and Artificial Neural Networks (ANN) to predict Peak Particle Velocity (PPV), a critical metric for assessing ground vibration intensity. Field data were gathered from Singareni coal mines, capturing a range of blasting parameters, including burden, spacing, explosive quantity, and maximum charge per delay. PCA was employed to identify and retain the most influential variables, reducing dimensionality while preserving essential information. The optimised subset of features was subsequently used to train the ANN model. The model's performance was evaluated using regression analysis, yielding a high coefficient of determination ($R^2 = 0.92$), indicating its robustness and accuracy in predicting PPV. A comparative analysis with conventional empirical equations demonstrated the superiority of the ANN model, which consistently provided more precise estimates of vibration intensity. The integration of PCA not only improved model performance but also enhanced computational efficiency by eliminating redundant parameters. This research underscores the potential of combining advanced statistical techniques with machine learning models to improve the predictability of blast-induced ground vibrations. The proposed framework offers a practical tool for mine operators to mitigate the environmental impact of blasting activities, particularly in sensitive areas.

Keywords: Artificial Neural Networks (ANN); Principal Component Analysis (PCA); Ground vibration prediction; Peak Particle Velocity (PPV); Blast design; MATLAB; Regression analysis

1 Introduction

The increasing demand for coal and other minerals has led to the expansion of opencast mines, resulting in the heightened use of explosives for blasting operations. Explosives remain the primary energy source for breaking and excavating rock. Upon detonation within a blast hole, explosives release immense amounts of energy in the form of pressure and temperature almost instantaneously. Despite advancements in explosive technologies, efficiently utilizing the energy from explosives remains a challenge due to the varying characteristics of different rock types [1–5]. A significant portion of the energy generated during blasting is often lost, leading to undesirable outcomes such as back breaks, fly rock, ground vibration, and air overpressure, as depicted in Figure 1. Among these, ground vibration is particularly serious, as it not only results in wasted energy but also poses a significant risk to the stability of nearby structures, especially residential buildings. Ground vibrations can propagate over large distances, causing structural damage, inducing cracks in buildings, and potentially jeopardizing the safety of local communities. Only a small percentage of the energy is effectively used to fracture and displace the rock mass, making the control of ground vibrations crucial to minimizing both operational inefficiencies and the negative impacts on surrounding areas [6].

Ground vibration caused by blasting propagates as waves from the blast site, much like the ripples that form when a stone is thrown into water. These waves transmit considerable energy through surface structures, causing them to vibrate. When the frequency of these vibrations aligns with the natural frequency of the structures, resonance can occur, amplifying the vibrations and potentially increasing their amplitude beyond the initial ground motion [7]. Duhamel's integral has been widely used in blast engineering to analyse how structures respond to blast-induced waves. Research [8] has shown its effectiveness in predicting structural responses. For instance, the study [9] applied Duhamel's integral to forecast displacements and accelerations in structures impacted by explosions, highlighting its importance in evaluating potential damage. According to the principle of structural dynamic response under a general load [10], Duhamel's integral in blast loading scenarios is expressed as follows:

$$u(t) = \int_{t}^{0} h(t-\tau) \cdot g(\tau) d\tau \tag{1}$$

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.

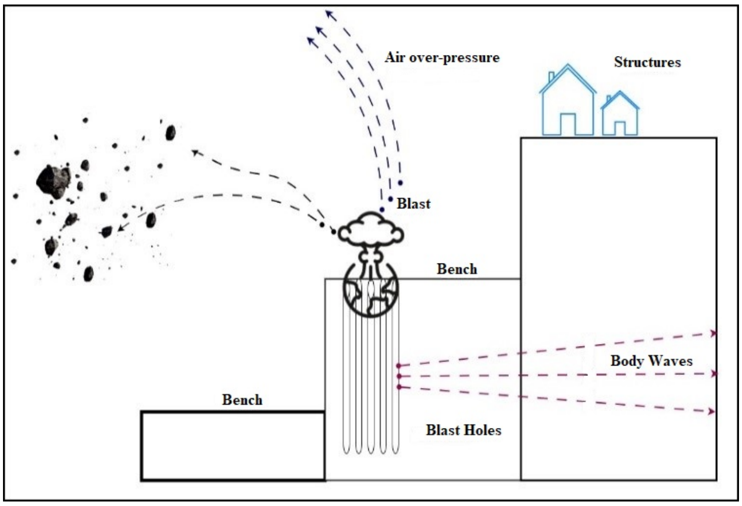


Figure 1. Adverse effect caused by blasting operation

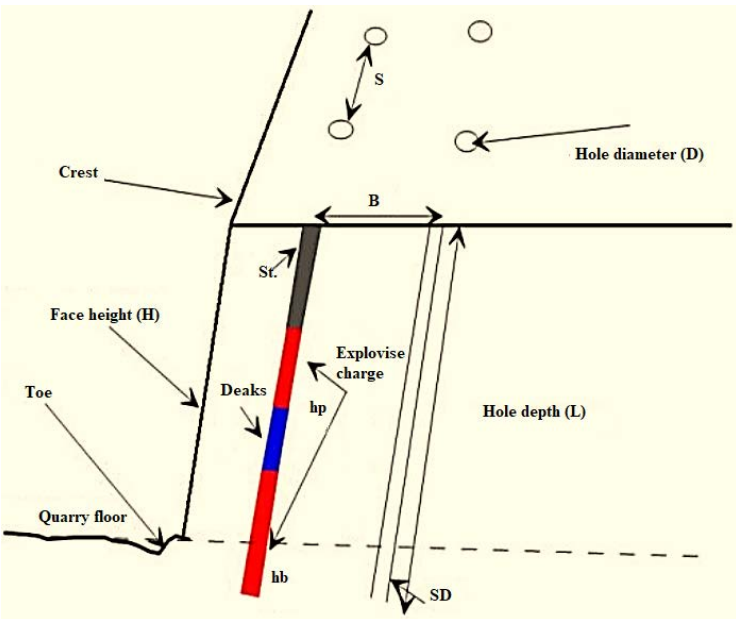


Figure 2. Factors affecting ground vibration

PPV, frequency, and air blast are commonly used criteria for assessing ground vibrations. The development of these vibrations is influenced by a variety of interconnected factors, including the physical and mechanical properties of the rock mass (such as geology, strength, hardness, and saturation levels), the characteristics of the explosives used, and the parameters of the blast design [11, 12]. It is crucial to predict how these factors affect blasting to maximize the efficient use of explosive energy while minimizing the negative impacts of blast-induced vibrations [13]. Key ground vibration parameters include the maximum charge per delay (MCD), the spacing between blast holes, and the charge length of explosives within the blast holes, as illustrated in Figure 2.

MCD and the distance from the blast site to the monitoring point are the primary factors influencing ground vibrations [14]. These factors are interdependent, meaning adjustments to one will impact the others. The type of rock in the surrounding area also moderately affects ground vibration behaviour [15]. To achieve optimal blasting with minimal vibration, it is essential to incorporate geophysical considerations into the blast design. Geological discontinuities and their properties significantly influence how ground vibrations propagate [16]. The distance between the blast site and motion tracking stations is another key factor, as the intensity of vibrations diminishes over longer distances due to wave dissipation and dispersion [15]. Blast geometry also plays a crucial role in controlling ground vibrations. Factors such as burden, hole spacing, stemming length, sub-drilling, charge length, hole diameter, and hole depth can be adjusted to keep ground vibrations within acceptable limits [17]. Additionally, the properties of the explosives themselves affect the intensity and frequency of the ground vibrations; high-velocity explosives produce stronger vibrations, while low-velocity explosives generate lower-intensity vibrations [18].

2 ANN

ANN, a modern branch of cognitive science, have experienced significant growth since the 1980s [19]. Today, ANN is recognized as a powerful tool for solving complex problems. Neural networks have the ability to learn from previously observed data patterns [20]. Once trained with a sufficient amount of data, ANN can predict outcomes for new datasets by identifying and matching patterns [21]. Due to its interdisciplinary nature, ANN has gained widespread popularity among researchers, planners, designers, and professionals across various fields, proving to be highly effective in both commercial and research applications. Its predictive accuracy is often reported to surpass measured values, and when compared to other analytical methods, ANN consistently delivers highly realistic results.

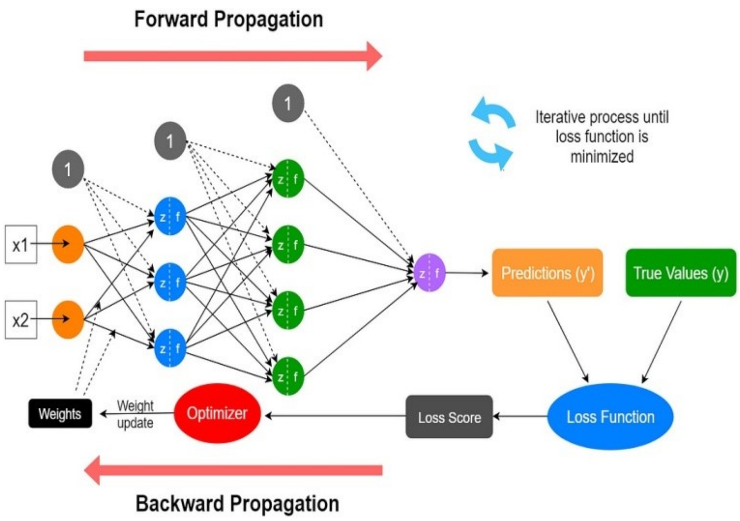


Figure 3. Multilayer neural network architecture [1]

Nguyen and Bui [22] employed a neural network to analyze structural hazards arising from changes in specific parameters, while Jaroonpattanapong and Tachom [23] used a similar approach to estimate fundamental wave speed and rock characteristics, illustrating the workings of a multilayer network, as shown in Figure 3. These examples highlight the effectiveness of neural models in solving problems that involve numerous complex variables, particularly when the relationships between these variables are unclear and experimental or historical data are available. In this study, an attempt has been made to use ANN to predict PPV and its associated frequency by incorporating factors such as rock volume, blast design specifications, and explosive properties.

Ground vibrations can have significant negative impacts on residential areas, affecting both buildings and the well-being of residents. Research shows that excessive ground vibration can cause structural damage, including cracks in walls and foundations [24, 25]. Prolonged exposure to high vibration levels can also lead to discomfort, sleep disturbances, and increased stress among residents [26]. Additionally, ground vibrations from industrial or construction activities have been linked to reduced property values in affected areas [27], which can have long-term economic consequences for homeowners and communities. Furthermore, even low levels of ground vibration can disrupt sensitive equipment or machinery in residential zones, such as medical devices or precision instruments [28].

3 Materials and Methods

3.1 About the Site

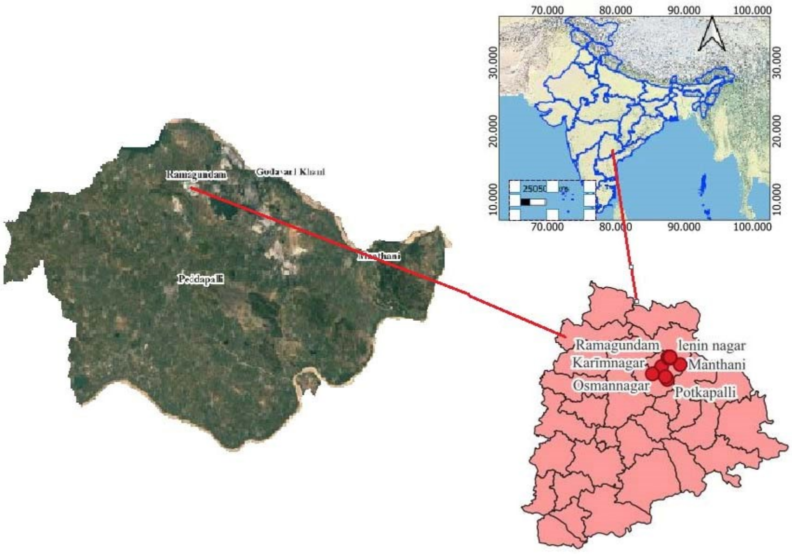


Figure 4. Google location of the mine

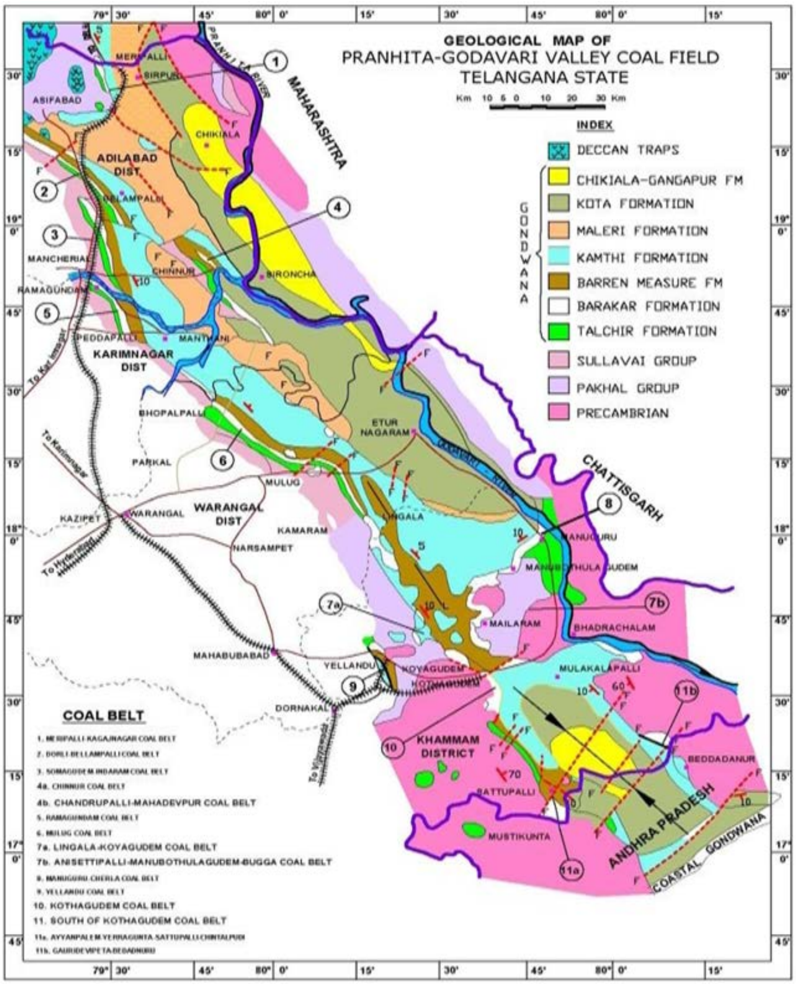


Figure 5. Geological map of KK opencast mine

The study was conducted at the KK OC project in the Singareni Coal Fields, a government-owned enterprise located in the state of Telangana, India. The KK OC project is situated in the northern part of the Somagudem Indaram coal belt, near the village of Mandamarri in Mancherial district. It is geographically positioned between latitudes 18°59'44" and 19°03'42" North, and longitudes 79°26'32" and 79°28'47" East, as shown in the Survey of India Topographical Map No. 56M/8. The geological map and location details are illustrated in Figures 4 and 5.

The mine's local relief varies from 120 meters above sea level in the south to 270 meters in the north, with an average gradient of 5.7 meters per kilometer, sloping towards the Godavari River, which flows to the south.

3.2 Data Collection

The study benches had a height of 17 meters, with friable rock strata consisting of alluvial soil and sandstone. The blast holes were 250 mm in diameter and 18 meters deep, and the explosive used was Site Mixed Emulsion (SME). A line firing pattern was employed, initiated with a cast booster and a NONEL system, while the drilling pattern followed a square configuration. The sandstone had a density of 2.3 g/cc. Figures 6 and 7 provide an overview of the overburden (OB) bench, the blast site, and the blast parameters. During the site visit, various blast design parameters were recorded, including 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 such as joints.

In the region, the geological condition of the rock mass was isotropic in all directions. To maintain consistency in vibration monitoring, the observation points were chosen at identical angles relative to the blast site. Minor variations in angle were considered negligible. At the experimental drilling sites, samples related to rock properties were collected from randomly selected benches.

Figure 6. OB sandstone bench

Figure 7. Blast site

3.3 Ground Vibration Measurement

Ground vibrations were recorded using an engineering seismograph known as Minimate, as depicted in Figure 8. To ensure proper contact with the ground, the transducer was securely fastened to spikes and firmly pressed into the soil, as shown in Figure 8.

Since the distance between the blast site and the monitoring station remained constant throughout the study, the maximum charge per delay (MCD) ranged from 110 to 210 kg, with a measurement distance of 500 meters. The seismograph recorded vector sum velocity (VS) and PPV for the longitudinal (R), vertical (V), and transverse (T) components during the blasts. Field-obtained results of PPV are presented as violin graphs in Figure 9.

Figure 8. Data collection using Minimate blaster

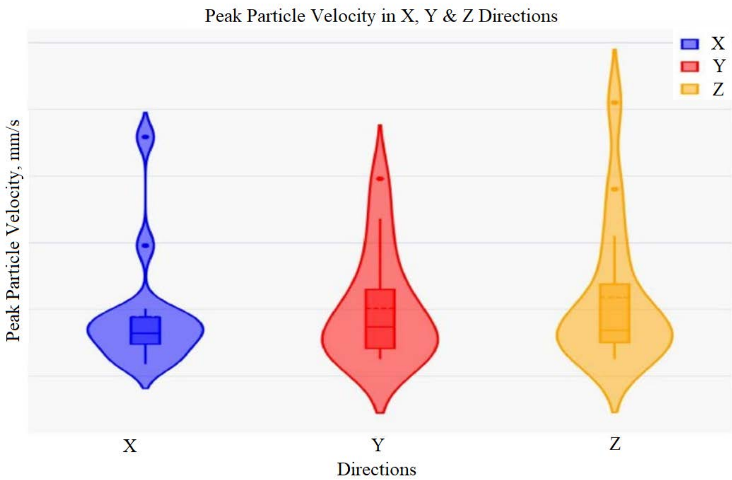


Figure 9. Blast site

3.4 PCA

In this study, PCA was conducted using XLSTAT to assess how independent and dependent variables influenced trends in determining the optimal blast design for the experimental blasts. The input data for the PCA was selected from various blast design parameters, including hole width, burden, spacing, front row burden, decking, stemming, firing pattern, total average explosive quantity, and total explosive amount.

The correlation circle generated by the PCA software serves as a foundational element for interpretation, guiding the analysis based on the values within the circle. This correlation circle is an essential tool for examining the relationships between independent and dependent variables. The interpretation consists of three segments: positively correlated, negatively correlated, and orthogonally correlated segments.

Positively correlated variables are those that appear close together in the same quadrant, while negatively correlated variables are located in opposite quadrants. Orthogonally related variables are found adjacent to the quadrants. A positive correlation indicates a proportional relationship, a negative correlation signifies an inversely proportional relationship, and orthogonal correlation suggests no relationship exists between the variables [29]. Using XLSTAT, the relationships among the number of holes, load, spacing, front row burden, stemming, firing pattern, hole depth, and explosive quantity (independent variables) were analyzed [30].

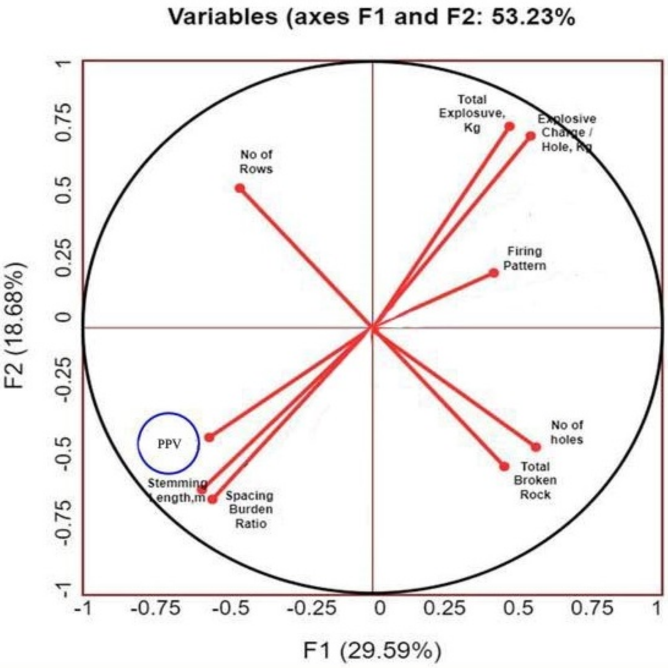
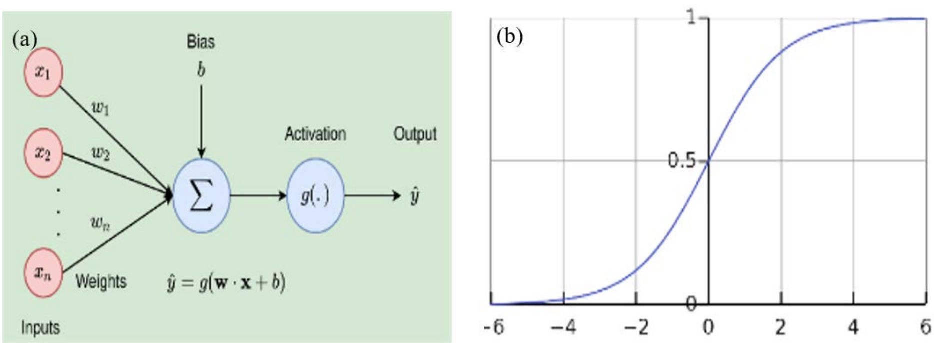


Figure 10. Correlation circle diagram of blast design parameters

From Figure 10, it is evident that PPV shows a positive correlation with stemming length, burden, and spacing. Conversely, a negative correlation exists between explosive quantity per hole, total explosive, and firing pattern. Therefore, PPV tends to increase as the values of the other independent parameters rise.

4 Machine Learning Models

4.1 ANN Approach to Predict PPV



(a) (b)

Figure 11. Activation function and sigmoid equation for prediction in ANN in MATLAB

ANNs are computational models designed to mimic the neural structure of the human brain [31]. ANNs predict outcomes based on patterns learned from prior data. Once trained, they can identify similarities in new patterns and adjust their results accordingly, allowing for interpolation capabilities. The training process involves the backpropagation algorithm. A feed-forward Backpropagation Neural Network (BPNN) is composed of an input layer, one or more hidden layers, and an output layer. Neurons within these layers are interconnected through weighted connections. Information from the input layer is transmitted to the hidden layer, and connections also exist between the hidden and output layers [32–34]. The specific problem being addressed dictates the number of hidden layers and the neurons within them.

In this study, a BPNN utilizing a 'log-sigmoid' transfer function was implemented, represented mathematically by the Eq. (2) as shown in subgraph (a) of Figure 11 and subgraph (b) of Figure 11, where x represents the input value and e is the mathematical constant approximately equal to 2.718.

$$\int \frac{1}{1+e(-x)} dx \tag{2}$$

Table 1. Input parameters for network and range

Sl. 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

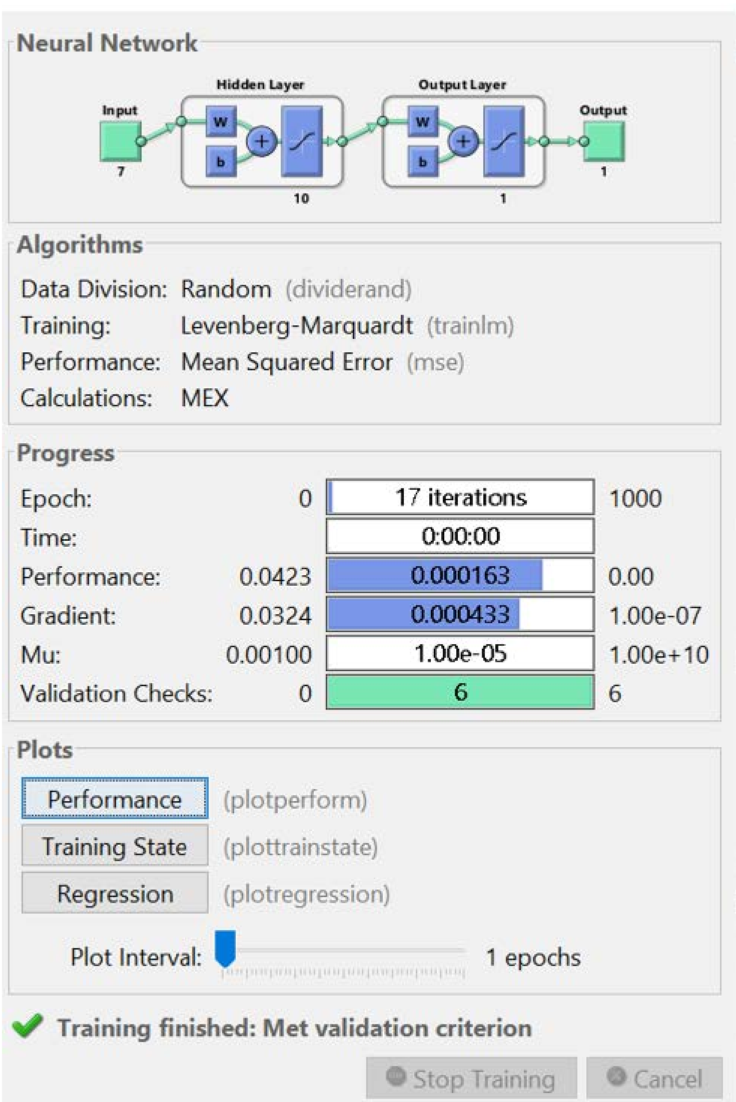


Figure 12. Neural network architecture with 1000 iterations for Mean Squared Error (MSE) calculation

After testing various configurations, the optimal model consisted of two hidden layers, each containing ten neurons. Table 1 outlines the input and output parameters used in the ANN model. The training process utilized 150 datasets, while an additional 30 datasets were set aside for testing and validation. Figure 12 illustrates the architecture of the neural network and its performance during the training phase. The regression plots in Figure 13 demonstrate the effectiveness of the selected network throughout the training, testing, and validation stages.

The connections between the outputs and hidden components operate on a similar principle [35]. Each pair of training examples provided to the network for learning undergoes this process repeatedly. Each complete pass through a training pattern is termed a cycle or epoch. The user-defined objective is considered achieved when the error falls within an acceptable range; the process is repeated as many times as needed to meet this goal [36, 37].

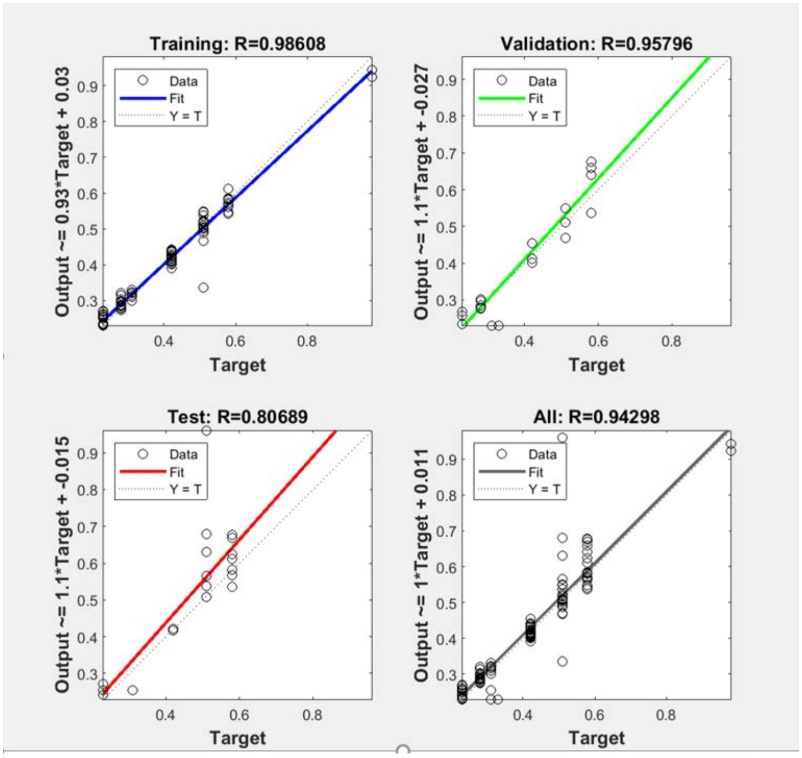


Figure 13. Neural network regression fitting plot indicting R^2

4.2 Multivariate Regression Analysis (MVRA)

Regression analysis involving more than two parameters is employed to enhance understanding of the relationships between independent variables and the modified value. In linear regression, a straight-line equation represents the relationship among the variables. MVRA is applied to identify the best-fitting solution when multiple independent variables are present [38]. By utilizing the least squares method, multiple regression analyses generate solutions for the datasets. This process involves constructing a regression matrix and using the backslash operator to solve for the coefficients, thereby establishing and solving simultaneous equations [39]. The same datasets and input variables used for the ANN predictions were also applied in the MVRA [40, 41]. This validates all input parameters, allowing for the verification of the input data and the comparison of the derived output data with previously obtained values. The multivariate equation proposed in this research is expressed in the following Eq. (3).

$$y = \beta 0 + \beta 1x1 + \cdots + \beta pxp \tag{3}$$

The equation expresses a linear relationship between the dependent variable (y) and multiple predictor variables ($x1, x2, ..., xp$) weighted by their respective regression coefficients ($\beta 1, \beta 2, ..., \beta p$), along with the intercept ($\beta 0$).

5 Results and Discussions

This section presents and discusses the results from the study on the neural network modeling technique for predicting blast-induced ground vibration using MATLAB. The study began by evaluating the neural network model's performance by comparing its predictions with actual ground vibration data collected from various blasting sites in the Singareni Coal Field. Additionally, sensitivity analysis was conducted to identify the key input factors that significantly influence prediction accuracy. These evaluations shed light on the robustness and reliability of the developed neural network model for forecasting ground vibration levels in different blasting scenarios.

In this research, calculations for RMSE and R^2 were carried out using the following Eqs. (4) and (5):

$$\mathrm{RMSE} = \frac{1}{\mathrm{n}} \sum_{\mathrm{i}=1}^{\mathrm{n}} (\mathrm{Yi} - \mathrm{Yi})2 \tag{4}$$

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

$$\mathrm{R}^2 = 1 - \frac{\sum \mathrm{i}\,(\mathrm{yi} - {}^\wedge\mathrm{yi})\,2}{\sum \mathrm{i}\,(\mathrm{yi} - {}^-\mathrm{y})\,2} \tag{5}$$

The data is represented by n, yi, and $^\wedge\mathrm{yi}$, where $^\wedge\mathrm{yi}$ stands for the mean and represents and projected values respectively.

Metrics such as RMSE and R^2 were calculated on both the training and testing datasets to determine the optimal algorithm for developing a formula to predict fragmentation and ground vibration.

Table 2. PPV recorded and predicted values

Sl. 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

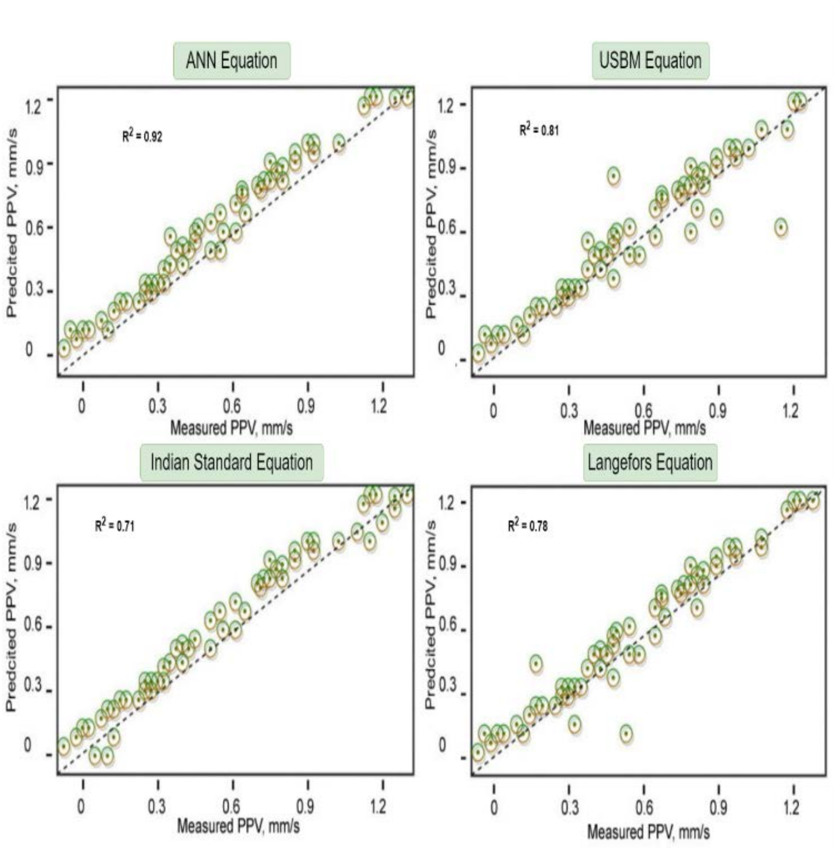


Figure 14. Performance R^2 values for various models

The ANN model demonstrates higher accuracy compared to the MVRA model, as evidenced by the relatively smaller root mean square error (RMSE) for various parameters in the ANN model compared to those in the MVRA model for the same parameters. Furthermore, the coefficient of determination (R2) for the parameters predicted by the ANN model, based on the trained data, approaches unity more closely than those of the MVRA model. This indicates that the ANN model provides predictions with greater accuracy compared to the MVRA model. The predictions made by the ANN model, as shown in Table 2, yield an R^2 value of 0.92, making it the most effective. The MVRA model also outperforms other predictive equations. A comparison of various predictive equations with the collected mine data, illustrating the accuracy of PPV during blasting, is displayed in Figure 14 and Table 2.

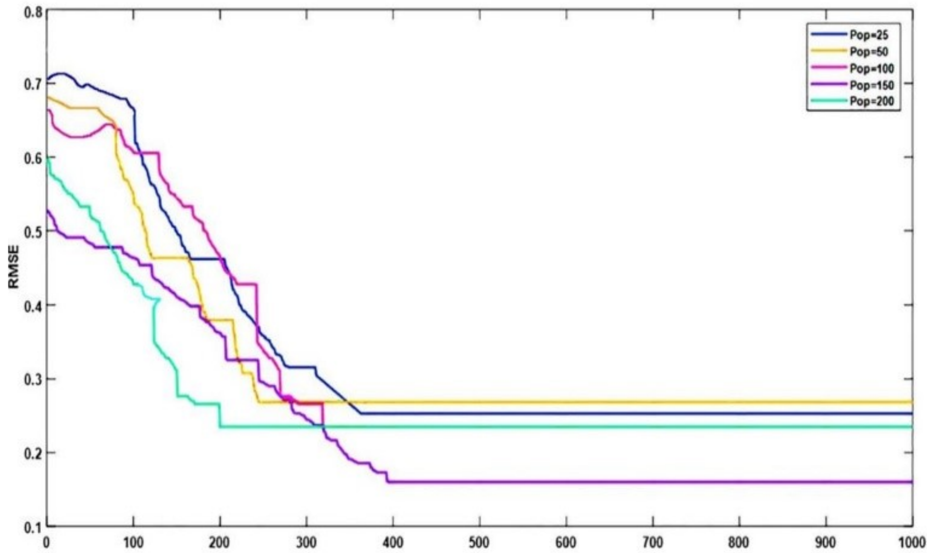


Figure 15. ANN RMSE output values for PPV

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

Empirical Names	Equation	Site Constants K	Site Constants B	Prediction Output Value
USBM	$V = K[R/Qmax] - B$	4.95	-0.57	0.81
IangefQR	$V = K[Qmax/R2/3)1/2)$ B	1.84	-0.296	0.78
Ambrasexs-Hendron	$V = K[R/Qmax)1/3) - B$	0.446	0.697	0.30
Bureau of Indian standard	$V = K(Qmax/R2/3)B$	0.654	0.233	0.71

Likewise, the comparison between the ANN and MVRA models revealed that the ANN achieved the best RMSE value of 0.5, indicating a lower error compared to the MVRA model, as illustrated in Figure 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 the ANN model predict PPV is very close to measured data than other various predicted equations, 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.

6 Conclusion

The study focused on improving fragmentation, reducing blast-induced damage (PPV), and ensuring the safety of residents living near blasting operations. An effective ANN model was developed and implemented on-site, allowing for a comparative analysis between ANN predictions, empirical methods, and MVRA predictors. The study involved optimizing a series of blasts using the ANN model and comparing them to a set of unoptimized blasts.

- Principal component sensitivity analysis was conducted on various parameters, successfully identifying key factors that influence blast outcomes. Among these parameters, stemming length, firing pattern, total explosive quantity, and spacing-burden ratio were found to significantly impact PPV.

- The R^2 values across various models, including MVRA, USBM, Langefors, Ambraseys-Hendron, and the Bureau of Indian Standards, demonstrated that the ANN model achieved a superior coefficient of regression value of 0.92, indicating a stronger predictive capability than the other models.
- The ANN outperformed the MVRA in training, testing, validation, and overall performance, achieving values of 0.98, 0.95, 0.80, and 0.945, respectively, in predicting PPV.
- Additionally, in terms of RMSE, the ANN produced an optimal lower value of 0.5, compared to the MVRA model.
- The ANN, utilizing real blast datasets such as spacing-burden ratio, stemming length, firing pattern, maximum charge per delay, explosive quantity, and distance from the blast site, proved to be a valuable tool for predicting PPV for mining engineers in the field.

In summary, this study presents a highly effective ANN model for forecasting ground vibrations during blasting operations. The findings will assist mining engineers and designers in estimating ground vibration levels, and it is recommended that the ANN model be applied to address various geotechnical challenges.

7 Future Scope of Work

- Gather data from multiple mines, incorporating a range of geo-blast design parameters as inputs for the algorithm.
- Develop a hybrid algorithm for predicting PPV.
- Create a web-based interface for PPV prediction, allowing practicing engineers to easily access predictions with just a few clicks.

Author Contributions

Writing—original draft preparation, NCH, TP, and YF; writing—review and editing, TP and YF. All authors have read and agreed to the published version of the manuscript.

Informed Consent Statement

Ethical approval Authors state that the research was conducted according to ethical standards.

Data Availability

The data used to support the findings of this study are available from the corresponding author upon request.

Conflicts of Interest

The authors declare that they have no conflicts of interest.

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