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Predicting blast-induced ground vibrations at limestone quarry from artificial neural network optimized by randomized and grid search cross-validation, and comparative analyses with blast vibration predictor models

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Abstract. The demand for cement and limestone crushed materials has increased many folds due to the tremendous increase in construction activities in Pakistan during the past few decades. The number of cement production industries has increased correspondingly, and so the rock-blasting operations at the limestone quarry sites. However, the safety procedures warranted at these sites for the blast-induced ground vibrations (BIGV) have not been adequately developed and/or implemented. Proper prediction and monitoring of BIGV are necessary to ensure the safety of structures in the vicinity of these quarry sites. In this paper, an attempt has been made to predict BIGV using artificial neural network (ANN) at three selected limestone quarries of Pakistan. The ANN has been developed in Python using Keras with sequential model and dense layers. The hyper parameters and neurons in each of the activation layers has been optimized using randomized and grid search method. The input parameters for the model include distance, a maximum charge per delay (MCPD), depth of hole, burden, spacing, and number of blast holes, whereas, peak particle velocity (PPV) is taken as the only output parameter. A total of 110 blast vibrations datasets were recorded from three different limestone quarries. The dataset has been divided into 85% for neural network training, and 15% for testing of the network. A five-layer ANN is trained with Rectified Linear Unit (ReLU) activation function, Adam optimization algorithm with a learning rate of 0.001, and batch size of 32 with the topology of 6-32-32-256-1. The blast datasets were utilized to compare the performance of ANN, multivariate regression analysis (MVRA), and empirical predictors. The performance was evaluated using the coefficient of determination (R^2), mean absolute error (MAE), mean squared error (MSE), mean absolute percentage error (MAPE), and root mean squared error (RMSE)for predicted and measured PPV. To determine the relative influence of each parameter on the PPV, sensitivity analyses were performed for all input parameters. The analyses reveal that ANN performs superior than MVRA and other empirical predictors, andthat83% PPV is affected by distance and MCPD while hole depth, number of blast holes, burden and spacing contribute for the remaining 17%. This research provides valuable insights into improving safety measures and ensuring the structural integrity of buildings near limestone quarry sites.

Keywords: artificial neural network; blast-induced ground vibrations; grid search method; peak particle velocity; randomized and sensitivity analysis

1. Introduction

Large-scale mining has become commonplace to fulfill the growing energy needs (e.g., from coal sources) and the demand of structural as well as architectural materials (e.g., limestone and other decorative rocks) for the rapidly expanding construction industry. Blasting operation is one of the most common and economical methods used worldwide for excavation of rocks in different fields like mining, civil, and tunneling engineering. A large quantity of explosive energy is required to dislodge and shatter the rock mass from the quarry sources of such materials. Many studies indicate that a meager 20-30% of total explosive energy produced during blast hole detonation is utilized for crack development and rock breakage, while the remaining energy is dissipated in the generation of undesirable ground vibrations, air-blast, fly rock, and noise (Cheng *et al*. 2000, Faradonbeh *et al*. 2016, Hino 1956, McKenzie 1990). Of these, the blast-induced ground vibrations (BIGV) are the main concern for the mining sector. The most significant negative impact of BIGV is the damage and possible collapse of the structures around the blasting quarry, often leading to confrontations and law-suites between mine owners/managers and the nearby residents and businesses (Dowling 1985).

In addition to the direct impact of the high-intensity ground vibrations from rock-blasting on the nearby

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residents' dwellings and their businesses, allied harm to the water conduits, buried utilities, aquifers and ecology of the nearby mines area cannot be undermined. A lack of surveilling and control of the BIGV can further lead to deforestation and back break (Duvall 1963). This back break is known to create problems for planning of the next round of blasts and is also responsible for poor rock fragmentation. There is, hence, a need to design and implement a system of monitoring and mitigating the BIGV in different mining industries.

The propagation mechanism of the BIGV resembles that of the ripples of water spreading outwardly from the impact point of stone pelting into a pond. The structures that fall along the paths of the propagating waves of BIGVs experience vibration energy of different frequencies (Siskind 1980). Structure collapse when the frequency of the BIGV matches with their natural frequency. Peak particle velocity (PPV) and frequency are the two most important parameters used to assess ground vibrations. Several variables affect the propagation of blast vibrations, e.g., mechanical properties of the rock mass, blast design, and characteristics of the explosive used (Wiss and Linehan 1978). Rock mass classification plays a vital role in assessing the blastability of tropically weathered limestone.

The classification system, as presented by (Bhatawdekar *et al*. 2021), helps optimize rock engineering design in challenging tropical environments, ensuring effective blasting operations. Maulidhar (2020) focuses on the environmental impact of blasting on tropically weathered rock. By considering the findings from this study, which explores blast fragmentation in a V-Type firing pattern, valuable insights can be gained into the potential environmental effects of blasting in tropical regions. Additionally, the paper (Bhatawdekar *et al*. 2019) introduces an advanced Building Information Model (BIM) specifically designed for drilling and blasting activities in tropically weathered rock. The BIM framework incorporates geological and geotechnical data, blast design parameters, and other relevant information to enhance the efficiency and effectiveness of drilling and blasting operations, ultimately improving productivity and safety in the context of tropically weathered rock conditions. Due to heterogeneous nature, the rock mass demonstrates variations in both composition and geological discontinuities. Consequently, the spatial variability of properties is a common characteristic found in the most rock mass (Khandelwal and Singh 2006). Based on the rock mass properties, optimization of blast design parameters and explosive energy are necessary to mitigate the undesirable effects of BIGV (Singh and Sastry 1986). Venkatesh *et al*. (1999) examines and addresses the impact of blasting operations in a limestone quarry, specifically focusing on ground vibrations and flyrock. It provides comprehensive assessments and effective mitigation measures to enhance safety and sustainability in quarrying activities.Researchers have employed various empirical approaches for prediction of the PPV (Ambraseys and Handron 1968, Standard 1973, Davies *et al*. 1964, Duvall *et al*. 1959, Ghosh and Daemen 1983, Gupta *et al*. 1988, Langefors and Kihlström 1963, Roy 1993). The two common parameters used in all such empirical predictions are: maximum charge per delay (MCPD) and distance from the blast face to monitoring point. Interestingly, however, predictive findings for the same excavation site from different studies and investigations are known to have yielded divergent values of PPV (Arthur *et al*. 2022). This inconsistency can be attributed to lack of completeness of these empirical models, where some of the other important and affective parameters were not incorporated. Hence, a robust scheme and codes thereof, capable of integrating several influencing parameters and variables, are needed for reliable and coherent predictive results of both PPV and frequency. The inter- and intra-relationships among these varied parameters are indeed very complicated. Thus, simple empirical predictors are not competent to accounts for such problems.

The frequent use of modern soft-computing approaches has globally augmented the efficiency and accuracy of the predictive solutions in a wide variety of applications (Khandelwal 2010). Examples of such approaches in the field of ground engineering include artificial neural network (ANN), support vector machines (SVM), genetic algorithm (GA), multivariant adaptive regression splines (MARS) for permeability prediction in discontinuous rocks (Qureshi *et al.* 2022), ultimate limit state reliability-based optimization (Mehmood *et al.* 2022) and maximum likelihood classification (MLC). ANN, which is a sub-branch of artificial intelligence (AI), is advantageous over the empirical models due to its ability to deal with complex sets of parameters which cannot be accounted for in most of the empirical models. ANN are networks of linked neurons that entail signal exchange between neurons. After a successful training phase, ANN systems are good in non-linear fits as well as recognizing patterns, and the outputs may be predicted given new sets of inputs (Khandelwal *et al*. 2004).

ANN is known for good mapping capabilities, generalization, robustness as well as high-speed information processing. Once ANN is trained with labeled datasets, it has the ability to predict or solve problems of unlabeled datasets (Rajasekaran and Pai 2003).

This research paper aims to predict blast-induced ground vibrations (BIGV) at limestone quarries in Chakwal, Pakistan using an artificial neural network (ANN). With the increasing demand for cement and limestone crushed materials, construction activities have soared, leading to a rise in cement production industries and rock-blasting operations. However, the safety procedures for BIGV have not been adequately developed or implemented. The ANN model, developed using Python and Keras, will utilize input parameters such as distance, maximum charge per delay (MCPD), hole depth, burden, spacing, and number of blast holes to predict the peak particle velocity (PPV) as the output parameter. The performance of the ANN model will be compared with other methods, and sensitivity analyses will be conducted to assess the influence of each parameter on the PPV. The study will contribute to improving safety procedures and ensuring the structural safety of nearby buildings in quarry sites.

2. Artificial neural network

Artificial neural networks (ANNs) are computational models inspired by the human brain. They consist of interconnected neurons arranged in layers (Tsoukalas and Uhrig 1996). ANNs have become essential tools for understanding and solving complex problems. These mathematical models can recognize patterns, learn from data, and make predictions on unlabeled datasets after being trained on labeled data. The design of artificial neural networks (ANNs) involves comparing the network's output with the desired target values and adjusting the network until the output matches the target (Rojas 2013). This characteristic makes ANNs effective for interpolation, particularly in datasets with nuisance factors. Researchers in recent years have utilized the advanced capabilities of ANNs to estimate blast-induced ground vibration (BIGV) peak particle velocity (PPV) in cases where attenuation equations (AEs) were not effective due to dataset noise (Amnieh *et al*. 2010, Khandelwal and Singh 2009).

In the study conducted by (Arthur *et al*. 2022), three artificial intelligence (AI) approaches (Gaussian process regression, extreme learning machine, and backpropagation neural network) were used to estimate ground vibrations caused by blasting. Data from 101 blasting datasets were collected, and a comparison was made with a multivariate regression analysis and a nonparametric regression technique. The study found that the gaussian process regression model exhibited superior predictive capability with high variance accounted for (VAF), R, and R^2 values and low MSE. his makes GPR, as suggested by Arthur *et al*. (2022) an effective method for forecasting blast-induced ground vibration. In the study conducted by (Lawal *et al*. 2022), GPR, ANN, and response surface method (RSM) were used to predict rock properties based on P-wave velocity and rock density. GPR outperformed ANN and RSM, providing highly accurate results with correlation coefficients above 99% for all predicted properties and RMSE values below 5. Sensitivity analysis revealed that P-wave velocity had the strongest influence on rock mechanical properties. As suggested by Lawal *et al*. (2021) these models offer reasonable predictions for important mechanical properties of sedimentary rock.

A review paper by (Bhatawdekar *et al*. 2021) focuses on blast-induced air and ground vibrations and provides an overview of soft computing techniques used in their prediction and assessment. Soft computing approaches, such as artificial neural networks and genetic algorithms, have shown promise in modeling and predicting the effects of blasting on air and ground vibrations. The paper discusses the application of these techniques and highlights their advantages in addressing the complexities and uncertainties associated with blast-induced vibrations. Lawal *et al*. (2021) proposed GPR to predict peak particle velocity (PPV) for blast induced ground vibrations (BIGV) in Obajana limestone quarry, Nigeria. They used grey-wolf optimization (GWO) to optimize blast design parameters.

By utilizing inputs such as burden, spacing, hole depth, stemming length, and no of blast holes obtained from the quarry, the GPR model accurately predicted PPV with a R^2 of approximately 1 and VAF of about 100%. The GWO algorithm determined that reducing the number of holes by 45% and charge per delay by 8% could lead to significant 94% reduction in PPV. This study demonstrates the suitability of the proposed models for both PPV prediction and blast design parameter optimization.

Murlidhar *et al*. (2021) research paper introduces a novel approach using a Harris Hawks optimization-based multi-layer perceptron neural network for predicting the distance of flyrock resulting from mine blasting. The study aims to enhance the accuracy of flyrock prediction, which is crucial for ensuring safety in mining operations. The findings highlight the effectiveness of the proposed method in predicting flyrock distance and its potential for improving blast management practices in rock mechanics and geotechnical engineering. Lawal and Idris (2020) developed a mathematical model of ANN for prediction of PPV from 88 datasets using the feed-forward back-propagation type of supervised learning algorithm, where weights of the network are adjusted via the back-propagation technique to improve its performance. R^2 was determined for performance evaluation on 14 datasets outside the one used in developing the models.

Rajabi and Vafaee (2020) predicted the ground vibrations at a dam site, also using the BP neural network approach. They used 64 datasets to measure the coefficients of the empirical models and to make the ANN model followed by testing their performance and accuracy on 16 different datasets. Rana *et al*. (2020) predicted the ground vibrations PPV at a tunneling project using three different soft computing tools, namely, decision tree (DT), ANN, and multivariate regression analysis (MVRA). A database consisting of 137 vibration records was randomly divided into training and testing sets for model generation. The model's performance was compared with other empirical vibrations predictors. Nguyen *et al*. (2019) compared the predictions of ground vibrations using four advanced computational models with those obtained from empirical techniques. ANN, k-nearest neighbor (KNN), support vector machine (SVM), and classification and regression tree (CART) computational models were used. Mean absolute error (MAE), RMSE and R^2 were implemented as model evaluators, wherein data from 68 blasting events were used (80% to build the models, and 20% for testing their performances). Shahri and Asheghi (2018) used two different ANN models, namely, multilayer perceptron (MLP) and generalized feed-forward neural network (GFNN) to assess and predict PPV at an earth dam. They used R^2 as performance evaluator for the tested models. Murlidhar *et al*. (2019) presents two hybrid models based on artificial neural networks (ANN) for predicting the interlocking of shale rock samples. The models incorporate genetic algorithm (GA) and fuzzy inference system techniques. Compared to traditional laboratory methods, these models offer a more efficient and cost-effective approach for determining rock shear strength parameters. The results demonstrate the reliability of the hybrid models, with the adaptive neuro-fuzzy inference system (ANFIS) showing slightly better performance than the GA-ANN technique. ANFIS proved an innovative model in field of rock mechanics.

In conclusion, the utilization of Artificial Neural Networks (ANN) has emerged as a focal point in the field of blast engineering, aiming to achieve accurate and

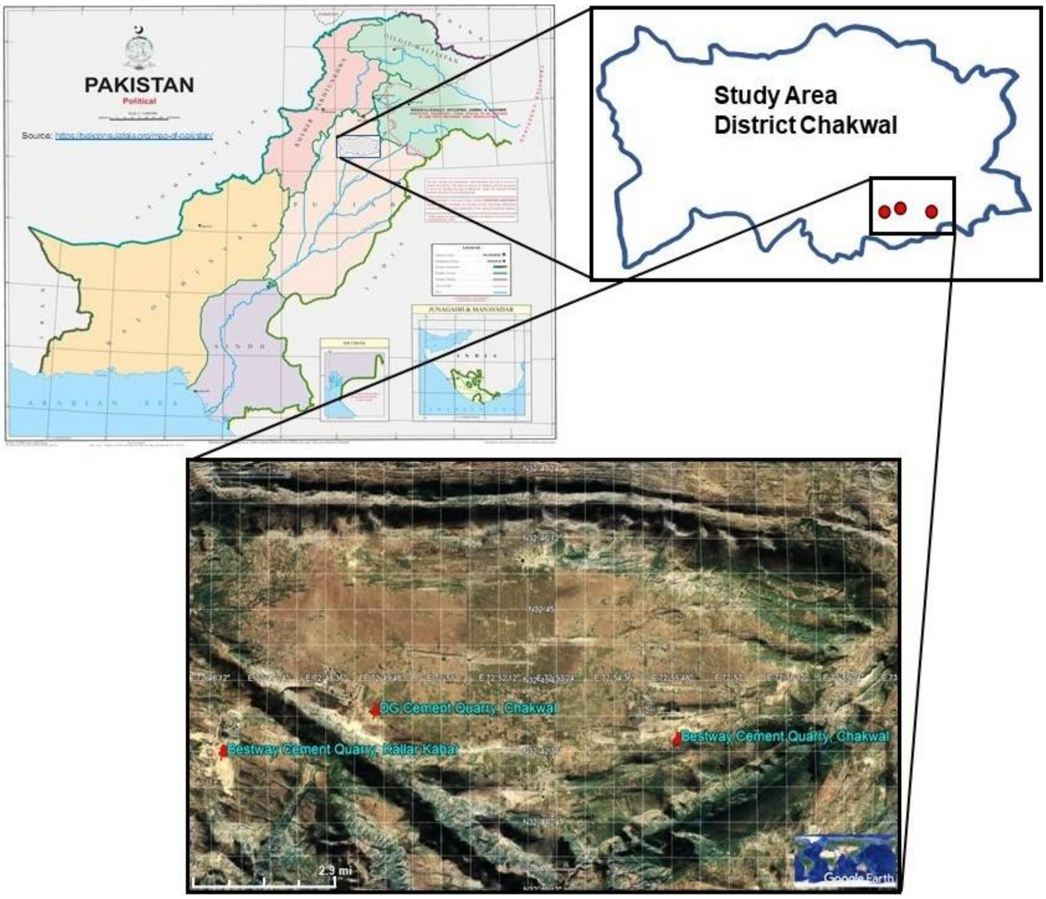

Fig. 1 Locations of the blast sites at the cement quarries in Chakwal District, Punjab, Pakistan

efficient prediction models. This study successfully harnesses the power of ANN to estimate flyrock distance resulting from mine blasting, a critical factor for enhancing safety and minimizing environmental consequences in mining activities. By integrating ANN with advanced techniques such as the Equilibrium Optimizer, the research introduces a novel approach that enables precise flyrock distance estimation (Bhatawdekar *et al*. 2023). Furthermore, the study explores the application of tree-based predictive models for estimating air overpressure induced by mining blasts, contributing to improved blast management strategies and the evaluation of air quality impacts (Ramesh *et al*. 2021). Additionally, the research delves into the advanced analysis of collision-induced blast fragmentation in a V-type firing pattern, providing insights into optimizing blast designs to achieve desired fragmentation outcomes (Chouhan *et al*. 2022). These cutting-edge techniques collectively demonstrate a dedication to mitigating environmental effects and advancing sustainable practices within the mining industry.

3. The study area, and the blast design parameters

The study was conducted at three different cement quarries located in the Chakwal District, Punjab Province of Pakistan. The quarries, namely DG Cement, Chakwal, Bestway Cement, Chakwal, and Bestway Cement KallarKahar, were specifically identified as illustrated in Fig. 1. The proximity of the quarries to surrounding

Table 1 Locations of the limestone quarry sites, and their blasting benches in the study area.

Limestone Quarry Site Designation	Geographic Location		No. of Blasting Benches	Designations of Blasting Benches
	Latitude (N)	Longitude (E)		
DG Cement, Chakwal	32.71909°	72.82640°	4	777; 766; 838; 812
Bestway Cement, Chakwal	32.71110°	72.93107°	2	5; 6
Bestway Cement, KallarKahar	32.707484°	72.773639°	2	3; 5

Table 2 Rock Mass Properties of limestone quarries

Rock Property	DG Cement Chakwal	Bestway Cement Chakwal	Bestway Cement Kallarkahar
Rock Formations	Sakesar Limestone		
UCS (MPa)	109.8	59.0	67.497
BTS (MPa)	5.84	6.35	-
Dry Density (g/cm^3)	2.67	2.61	2.65
Porosity (%)	0.798	3.475	-
RQD (%)	79.5	76.23	67.45

Table 3 Range of blast design parameters for blasting benches 777, 766, 838 and 812 at the limestone quarry of DG Cement, Chakwal

Parameter	Symbol	Range	Unit
Bench height	H	10-14	M
Hole diameter	D	90-100	Mm
Spacing	S	4-5	M
Burden	B	3-5	M
Hole diameter	D	90-100	Mm
Sub-drilling	J	0.5	M
Stemming length	S_T	3	M
High Explosive	HE	150-575	Kg
ANFO*	BA	232-2900	Kg
Blast holes	N_h	4-41	no.
Max. charge/delay	Q_{max}	60-90	Kg
Blast rows	N_r	1-2	no.
Depth of hole	H_L	11-14	m

*ANFO: Ammonium Nitrate Fuel Oil. It is a blasting agent in the mining and construction industries

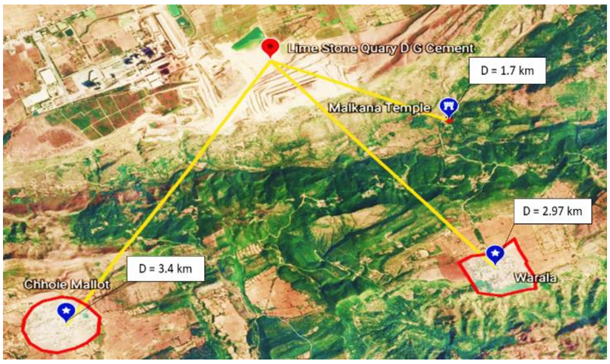

Fig. 2 Satellite imagery showing villages located around the limestone quarry of DG Cement, Chakwal [Google Earth]

Fig. 3 Satellite imagery showing villages located around the limestone quarry of Bestway Cement, Chakwal [Google Earth]

villages and towns is shown in Figs. 2-4. The precise geographic locations in terms of latitudes and longitudes, the number of blasting benches and their designations is presented in Table 1. The rock and rock mass properties (including unconfined compressive strength (UCS), Brazilian tensile strength (BTS), dry density, porosity and rock quality designation (RQD)) of the limestone rock exposed at the selected query sites are presented in Table 2.

The respective ranges of blast design parameters for the selected query sites are presented in Tables 3 through 5.

Table 4 Range of blast design parameters for blasting benches 5 and 6 at the limestone quarry of Bestway Cement, Chakwal

Parameters	Symbol	Range	Unit
Bench height	H	10-18	M
Hole diameter	D	115	mm
Spacing	S	4-5	M
Burden	B	3-4	M
Sub-drilling	J	0-0.5	M
Stemming length	S_T	3	M
High Explosive	HE	270-705	Kg
ANFO*	BA	1250-4500	Kg
Blast holes	N_h	21-45	no.
Max. charge/delay	Q_{max}	60-119	Kg
Blast rows	N_r	2-4	no.
Depth of hole	H_L	10-18.5	m

Table 5 Range of blast design parameters for blasting benches 3 and 5 at the limestone quarry of Bestway Cement, KallarKahar

Parameters	Symbol	Range	Unit
Bench height	H	13-18	m
Hole diameter	D	90	mm
Spacing	S	4	m
Burden	B	3	m
Sub-drilling	J	0.5	m
Stemming	S_T	3	m
High Explosive	HE	148.5-201.5	Kg
ANFO*	BA	1620-3100	Kg
Blast holes	N_h	27-31	no.
Max.charge/delay	Q_{max}	65-106	Kg
Blast rows	N_r	2	no.
Depth of hole	H_L	13.5-18.5	m

Fig. 4 Satellite imagery showing villages located around the limestone quarry of Bestway Cement, KallarKahar [Google Earth]

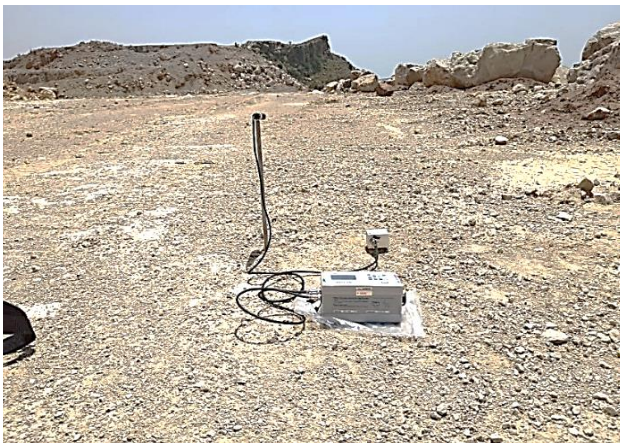

Fig. 5 Monitoring of BIGV at Bestway Cement limited, Chakwal

4. Blast vibrations dataset

A total of 110 blast vibrations dataset were recorded from 40 blasts in the three cement quarries as per ISRM (Dowding 1992). SME explosives and a NONEL initiation system were used in all three quarries. Ground vibrations were recorded with the GDS Korea Wave ONRe instrument as shown in Fig. 5. Three devices were used to monitor the BIGV with each blast, and PPV was recorded at various intervals.

Blast-induced ground vibrations (BIGV) have been monitored at limestone benches which are towards the nearest structures or villages. Therefore, blast vibration data from three cement factories were used collectively for neural network training. The heatmap plot between different variables using 110 blast datasets is shown in Fig. 6. The heatmap plot shows the correlation between variables in the form of colors and their values. High values have a greater correlation between variables and vice versa. The heatmap plot generated from the data obtained at all three-cement quarry indicates a weak correlation between PPV, blast hole numbers, and distance. The heterogeneous characteristics of the quarry site, including varying rock composition and geological structures, may cause unpredictable propagation of seismic waves and affect PPV measurements.

For neural networks, inputs are blast design and distance parameters. Values of blast design parameters were acquired from all three cement quarries. Prior to the detonation, the distance from the blast to the stationed point was also measured on-site using the engineer's chain. Table 6 shows the descriptive statistics of different parameters for ANN. It is based on field data collection from various cement quarries. The parameters were scaled between 0 and 1 using standard scaler imported from scikit learn library in Python.

Blastability index, Young Modulus, Poisson ratio, and P-wave velocity as well as rock quality designation (RQD), and geological strength index (GSI) are all important geological parameters for predicting peak particle velocity (PPV) (Kumar and Bhargava 2016). The variation of these parameters at different cement quarries are not varied so much due to the same lithology and working on similar bench-type material. Their influence was not undertaken for the prediction of PPV during ANN analysis. Therefore, these are not considered in the neural network model of the current analysis but should be used as input parameters if the variability is large.

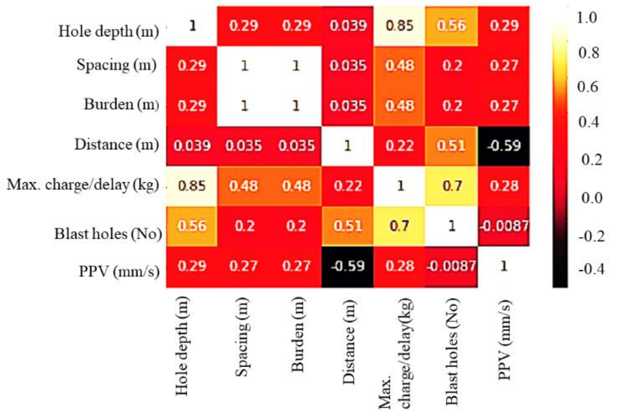

Fig. 6 Heatmap plot between different variables using 110 blast vibrations dataset

Table 6 Descriptive statistics of parameters form the blast vibrations dataset

Parameters	Mean	Median	Mode	Std. deviation	Min.	Max	Unit
Max. charge/ delay	79	77	72	25.9	16	119	kg
Distance	250.2	213	180	137.6	49	762	m
Hole depth	12.4	12.5	12.5	3.3	5.4	18	m
Blast holes	19.4	21	1	14.7	1	45	no.
Burden	3.5	3.5	3.5	0.4	2.7	4	m
Spacing	4.5	4.5	4.5	0.4	3.7	5	m
PPV	5.9	3.95	1.5	5.6	0.3	23.5	mm/s

5. Optimization of hyperparameters and nodes in activation layer for ANN

Optimized hyperparameters are necessary for the development of the ANN. The hyperparameters include batch size, learning rate, dropout rate, regularization, number of epochs for training network, and activation function. In the optimization algorithm, the learning rate is very crucial. The algorithm may not identify the ideal local minima if the learning rate is too high. Similarly, if the learning rate is too low, the algorithm may take longer to iterate, resulting in more computational power and time.

The activation function is also important. Because it introduces non-linear relationships between input and output mapping, the result would be a simple linear function if it wasn't applied.

5.1 Tuning of hyperparameters in Keras

Keras Regressor has been used for selecting optimized parameters for training ANN with sequential model and dense layers. Adam was used as an optimization algorithm

Table 7 Optimized hyperparameters obtained using random search method

Search Method	Hyper-parameters	Range	Optimized value
RSCV	Activation function	ReLu, Tanh, Linear	ReLu
	Batch size	16, 32, 64, 128	32
	No. of epochs	100, 200, 300, 400, 500	500
	Learning rate	0.1, 0.01, 0.001	0.001

Table 8 Optimized number of nodes obtained for hidden layers using Grid Search Method

Search Method	Optimized hyper parameters	Range of node in activation layers	Optimized nodes	Mean	Std. deviation
GSCV	ReLu	8,16,32	32	1	0.3
	32	16,32,64	32		
	500 0.001	32, 64, 256	256		

for the neural network. The parameters (activation function, batch size, epochs, and learning rate) were defined with different ranges as shown in Table 7. The model is fitted using the randomized search cross-validation (RSCV) technique with 10 folds. After successful training of defined randomized search on the datasets (X_train, Y_train), the best score with the best parameters was obtained as shown below in Table 7.

5.2 Tuning of nodes in hidden layers

Setting up the architecture for training a neural network is the most difficult task and time-consuming in Keras. It takes sometimes an overnight run in Python for finding the best nodes and parameters for training neural networks. Once the best hyperparameters are obtained for the neural network then, a number of nodes for each layer is obtained from different search methods. The complexity of the training data determines the structure of the model. The model complexity is defined by the number of nodes in each activation layer. The increase in the number of nodes in each activation layer determines the non-linear relationship between input and output dataset (Franklin 2019). In literature, various search methods are available for a selection of optimum nodes in activation layers, like for loop, grid search method etc. In this study Grid search method was used for optimization of nodes while following the steps listed below:

1. Import all necessary packages from different libraries of machine learning
2. Define the sequential model with five layers and activation function
3. Use optimized hyperparameters in that model
4. Use Adam as an optimizer
5. Fit the defined model in Keras Regressor
6. Define the range of grid search parameters for different layers
7. Make a dictionary of these parameters
8. Fit all parameters in GSCV with default k-folds
9. Lastly, fit the grid on training datasets

Following the above-mentioned steps, the mean and standard deviation of the best-fit nodes were obtained. These are shown in Table 8 below.

6. Development of ANN model

For successful development of the neural network, it should be first trained on a trained dataset before using for the unlabeled dataset. There are various types of learning algorithms available in the literature for the training of the neural network. It is well known that neural network performs well for large dataset and also solve complex problems. Following steps were taken before training neural networks in Python:

1 Import necessary packages from different libraries
2 Import blast datasets into Python in the form of a CSV format and convert them into arrays
3 Preprocess the data to remove the outliers, nuisance
4 Split dataset into input and output target variables
5 Divide dataset into training and testing using scikit learn library
6 Scale down the input data to bring in same magnitude while importing standard scaler

Once the above steps are followed, a platform was set up for the development of a neural network. The architecture of the developed ANN is shown in Fig. 7. Python programming language was used for the development of the ANN model. In this study, the network is developed in the Keras library while importing sequential models with Dense layers.

The sequential model was used with dense layers because it was developed in the form of layers to layers. The rectified linear unit (ReLu) activation function is a mathematical operation used in machine learning to introduce non-linearity in neural networks. It is applied to each layer, including the output layer. ReLU activation function returns the input value unchanged when it is positive and sets it to zero when it is negative. In simpler terms, ReLu lets positive numbers pass through unchanged, while it sets negative numbers to zero. This function is preferred in neural networks due to its simplicity and effectiveness in learning complex patterns. By Using ReLu, the network becomes capable of capturing intricate relationships within the data and mitigating issues like the vanishing gradient problems. Optimization algorithm Adam was defined with a learning rate of 0.001. Adam optimizer, which is the most advanced optimizer used for deep learning networks has the ability to combine the best properties of two algorithms AdaGrad and RMSProp.

The model was compiled with an optimizer, training loss function, and metric function for the evaluation of the training neural network model. MAE was taken as a training loss function while mean squared error (MSE), mean absolute percentage error (MAPE), and RMSE was used for evaluation of the training model. Finally, the model was fitted on the trained dataset, with validation data (X-test, y-test) for model evaluation with defined epochs of 500 and batch size of 32. The analysis for the ANN model was highlighted in two stages, namely: training and testing.

6.1 Training of the developed ANN model

Before training the ANN model, the data was divided using train_test_split while importing scikit learn library in Python. The ANN model was trained with 85 percent data in model training. The training dataset contained 93 samples of blast vibration. During the training process, the loss function was used in order to determine the training model performance. MAE was taken as an evaluator for model training, while R^2, MSE, MAPE, and RMSE were taken as metric loss functions to check the model performance on others loss functions as well. Referring to Fig. 8 below, the yellow line represents training loss while the red line shows the validation loss. The training loss rapidly decreases from 0-100 epochs, while after that, further decrease is minimal, which ensures the presence of global minima. The R^2, MAE, MSE, MAPE, and RMSE between the predicted and measured values for the training dataset were used as a measure of performance as shown in Table 9.

The performance evaluation of the neural network model with a 6-32-32-256-1 architecture revealed promising results. The validation curve closely aligned with the training curve throughout the initial 500 epochs, indicating that the chosen architecture effectively mitigated the risk of overfitting. Moreover, I closely monitored the margin between the training and validation loss and observed that it remained stable until approximately 400 epochs as shown in Fig. 8. However, beyond this point, the margin started to widen, signaling a potential risk of overfitting. To ensure the model's generalization ability, I made the decision to halt the training at 500 epochs, preventing the model from becoming overly sensitive to the training data. This cautious approach was taken to maintain the model's reliability and ensure its ability to make accurate predictions on unseen data (Fig. 9).

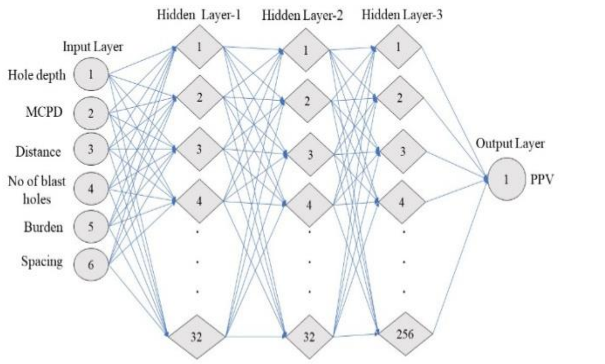

Fig. 7 Architecture developed for training neural network model

Table 9 Different loss function evaluators used in training model performance

Model Stage	R^2	MAE	MSE	MAPE	RMSE
Training	0.98	0.26	0.39	6.9	0.62

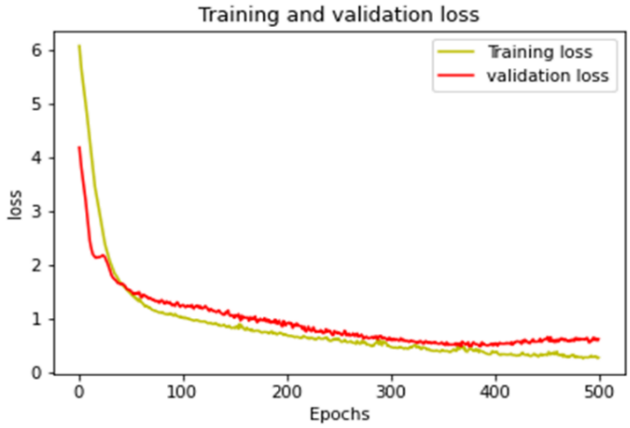

Fig. 8 Training and validation loss for each epoch during training

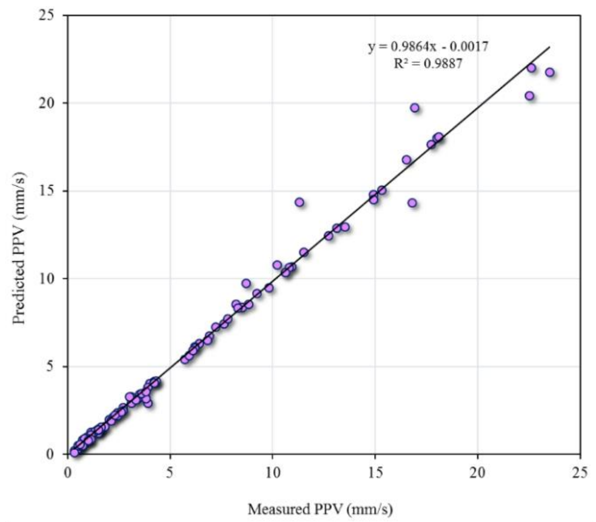

Fig. 9 The relationship between the measured and predicted PPV by trained ANN model

6.2 Testing of developed ANN model

The 15 percent dataset that was not used to train the neural network was selected to test the model. The testing loss on the developed trained ANN model is shown with a red curve in Fig. 10.

The Figure shows that the testing loss on new datasets decreases with increase in epochs following the same general trend as observed in the training loss. The testing data contained 17 samples of the blast vibration dataset. The results are presented in Table 10 to show the functionality of the network. The R^2, MAE, MSE, MAPE, and RMSE between the predicted and measured values for the testing dataset were used as a measure of performance. The performance of the testing dataset on a trained neural network model is demonstrated in Fig. 10 along with their R^2 value.

Table 10 Different loss functions are used for evaluating training model performance

Model Stage	R^2	MAE	MSE	MAPE	RMSE
Testing	0.92	0.61	0.75	21.6	0.87

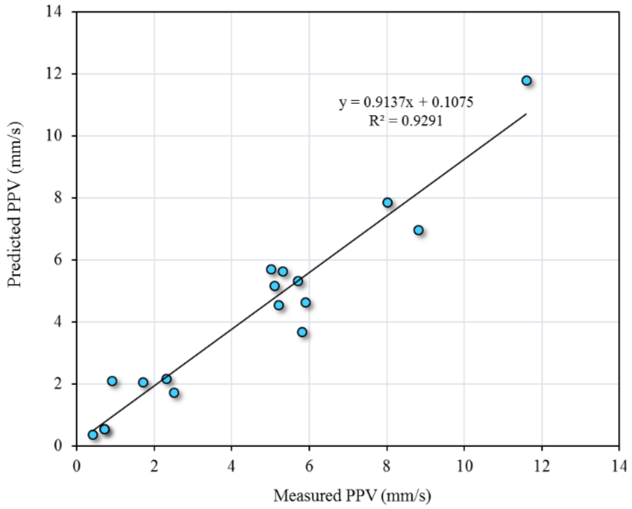

Fig. 10 The relationship between the measured and predicted PPV by trained ANN model on test dataset

Table 11 Different loss functions are used for evaluating MVRA model performance

Model	R^2	MAE	MSE	MAPE	RMSE
MVRA	0.47	2.8	11.7	127	3.4

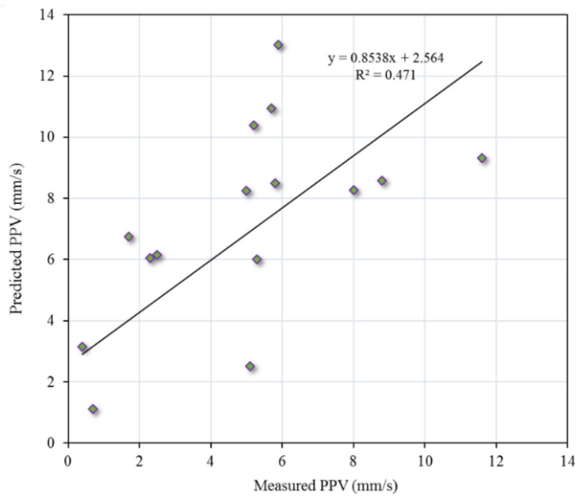

Fig. 11 The relationship is shown by the MVRA model on 17 blast vibration datasets.

7. Prediction by multivariate regression analysis

Prediction of PPV of blast vibrations can also be done with MVRA. MVRA is also capable of predicting PPV because it can also take into account all the affective parameters of PPV and is not restricted to only two parameters like other empirical models. The mathematical equation for PPV was determined using MVRA on 93 blast vibration datasets. Following equation was developed for the prediction of PPV.

$$PPV = 3.2 - 0.2\,[HD, m] + 1.09\,[S, m] + 0\,[B, m] - 0.03\,[D, m] + 0.11\,[Q\_max, kg] + 0.04[No\ of\ BH] \tag{1}$$

It is important to note that the burden values in equation 1 from the multivariate regression analysis (MVRA) show zero coefficient values, indicating the absence of a linear relationship between burden and PPV. One possible reason for this is that burden values vary significantly. In our study, we found that the variations in burden values were not substantial, which may have contributed to the absence of clear linear relationships. Another factor to consider is that linear regression analysis may not effectively capture complex non-linear relationships, which could have affected our findings in this analysis.

Furthermore, Eq. (1) is employed to evaluate the performance of the developed model on the same testing dataset that was previously used in the evaluation of the artificial neural network (ANN). The relationship between the measured and predicted PPV using the multivariate regression analysis (MVRA) is depicted in Fig. 11. The R^2 value obtained for MVRA is 0.47, indicating that the equation for PPV derived from MVRA does not achieve the desired level of accuracy. The MAE, MSE, MAPE, and RMSE for predicted PPV using MVRA analysis is calculated as shown in the Table 11.

8. Prediction of PPV using blast vibration predictors

Various common blast vibration predictors which are most widely used by researchers as shown in Table 12. In order to determine the site constants [K, β, α, and A] for various empirical vibration predictors, MVRA was performed on the same datasets which were used for the development of the ANN model. Excel software was used for 93 blast vibration datasets to determine the site constants. The site constants were obtained after analysis for different empirical predictors as shown in Table 13.

Empirical models in blast vibration prediction are built upon simplified relationships derived from observations or mathematical formulas. These models often make assumptions and have certain limitations that hinder their ability to accurately represents the complexities of the blasting process. As a result, when comparing the predicted and actual peak particle velocity (PPV) values using these empirical models, we may observe a negative slope as illustrated in Figs. 12 and 13. This negative slope signifies a mismatch between the predicted and actual PPV values, highlighting the limitations of the empirical models in capturing the true underlying relationships present in the data. In other words, the negative slope suggests that the empirical models are not able to accurately predict the actual PPV values and may not fully account for all the factors influencing blast vibrations.

Additionally, Figs. 12 and 13 illustrate the performance

Table 12 Common empirical blast vibration predictor for prediction of PPV (Khandelwal and Singh 2009)

Empirical Model	Equation
USBM Standard (Duvall *et al*. 1959)	$V = K\left[\frac{R}{Q_{max}}\right]^{-B}$
Langefors-Kihlstrom (Langefors and Kihlström 1963)	$V = K\left[\left(\frac{Q_{max}}{R^{\frac{3}{2}}}\right)^{\frac{1}{2}}\right]^{B}$
Ambraseys and Hendron (1968)	$V = K\left[\frac{R}{(Q_{max})^{\frac{1}{3}}}\right]^{B}$
Bureau of Indian Standard (Standard 1973)	$V = K\left[\left(\frac{Q_{max}}{R^{\frac{2}{3}}}\right)\right]^{B}$
General Predictor (Davies *et al*. 1964)	$V = kR^{-B}(Q_{max})^{A}$
Ghosh-Daemon (Ghosh and Daemen 1983)	$V = K\left[\frac{R}{(Q_{max})^{0.5}}\right]^{-B} e^{-\alpha R}$
Gupta (Gupta *et al*. 1988)	$V = K\left[\frac{R}{(Q_{max})^{0.5}}\right]^{-B} e^{-\alpha(\frac{D}{Q})}$

Table 13 Common empirical blast vibration predictors and their site constant values

Empirical Model	Site constants			
	K	β	A	α
USBM	8.73	-0.269		
Langefors-Kihlstrom	6.86	0.332		
Ambraseys-Hendron	11.09	-0.281		
Bureau of Indian Standard	3.19	0.198		
General Predictor	5.57	-0.02	0.1	
Ghosh-Daemon	6.68	0.008		-0.0029
Gupta	6.68	-0.016		-0.0019

of various empirical predictors for the prediction of PPV using R^2, MAE, MSE, MAPE, and RMSE as model performance evaluators. In statistics, the R^2 value is frequently utilized as a measure of the strength of linear relationships between variables. However, for non-linear relationships, the R^2 value may not accurately represent the strength of the relationship (Wheelwright *et al*. 1998). The Langefors-Kihlstrom predictor showed a higher R^2 values of 0.51, whereas the general predictor resulted in a very low value of 0.04.

The site and geological constants, "k" and "B" in the blast vibration empirical models, were determined using the same dataset employed for the ANN model. The analysis was conducted using SPSS software, and the results are summarized in Table 13. Log-log plots were developed using SPSS software to analyze the relationships between blast design parameters and ground vibrations. Regression analysis on the log-log plots yielded the values of "k" and "B," enabling more accurate predictions of blast vibrations while considering site and geological factors.

9. Results and discussion

Figs. 12 and 13 shows a comparison of ANN, MVRA, and PPV predicted by various empirical blast vibration predictors. Here, the ANN predictions are closer to the measured PPV, but the traditional empirical predictors and MVRA predictions show significant variability. Fig. 14 shows that the PPV predicted by ANN most closely matches the measured PPV values, while the other empirical predictors showed a very high degree of error.

This is because the other common predictors do not account for all the parameters that affect the vibrations. MVRA also shows poor R^2 value with others loss functions despite taking all affective input parameters which affect PPV. ANN outperforms MVRA and other commonly used vibration predictors. Different evaluating loss functions are used to demonstrate the performance of various predictor models as shown in Table 14. The predicting performance of ANN is outstanding, and it compares favorably to field data.

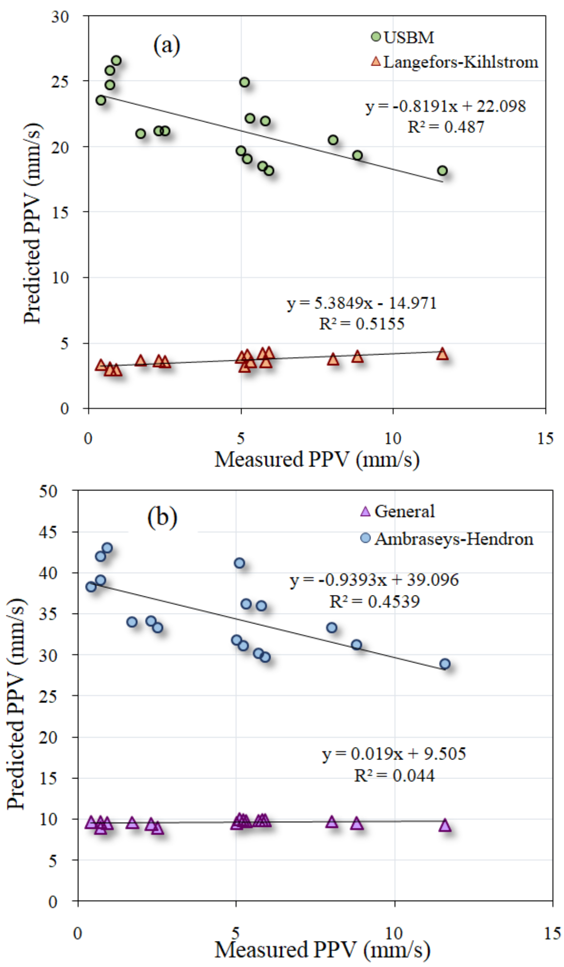

Fig. 12 The relationship is shown by USBM (Duvall *et al*. 1959) and Langefors-Kihlstrom (Langefors and Kihlström 1963) for measured with predicted PPV (a)and Ambraseys-Hendron (Ambraseys and Hendron 1968) and General predictor (Davies *et al*. 1964) for (b)

Table 14 Different prediction models of peak particle velocity (PPV) with various loss functions were evaluated on testing datasets

Model	R^2	MAE	MSE	MAPE	RMSE
ANN	0.92	0.7	0.75	21.6	0.87
MVRA	0.47	2.8	11.7	127	3.4
USBM	0.48	17.1	320.5	1215.8	17.9
L-Kihlstrom	0.51	2.5	8.6	129.5	2.9
A-Hendron	0.45	30.5	974.8	2027	31.2
Indian Standard	0.47	2.5	9.1	136.6	3
General Predictor	0.04	5.4	35.8	434.7	5.9
G-Daemen	0.24	10.9	172.9	916.3	13.1
Gupta et.	0.51	3.5	17	308.7	4.1

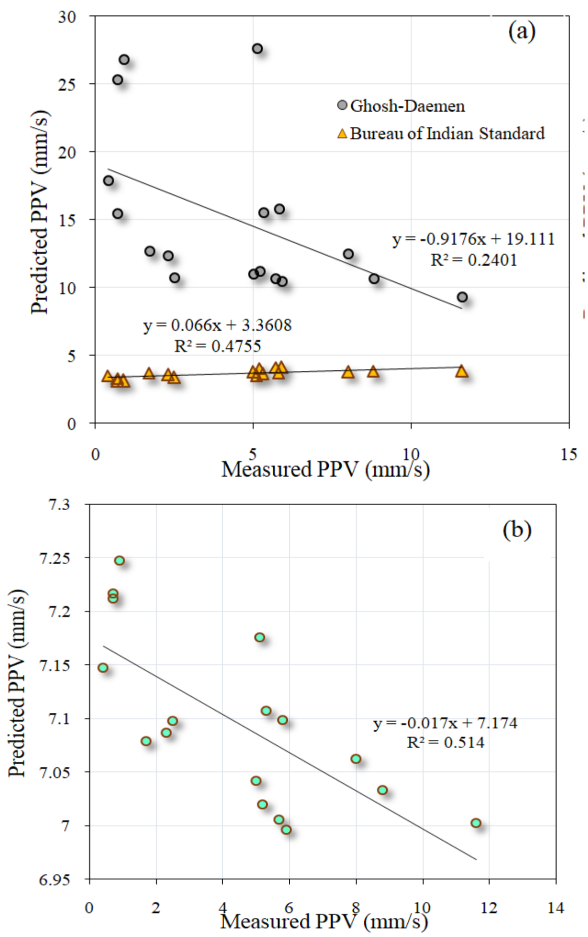

Fig. 13 The relationship is shown by Ghosh-Daemen (Ghosh and Daemen 1983) and Bureau of Indian Standard (Standard 1973) for measured with predicted PPV (a) and Gupta (Gupta *et al*. 1988) for (b)

10. Sensitivity analysis for the blast datasets

To determine the relative influence of each parameter on the PPV, sensitivity analysis was done on all six input parameters. It was performed for individual parameters in Python programming while importing Pandas library once the neural network was trained well. The analysis indicates that distance between the blast face to the stationed point,

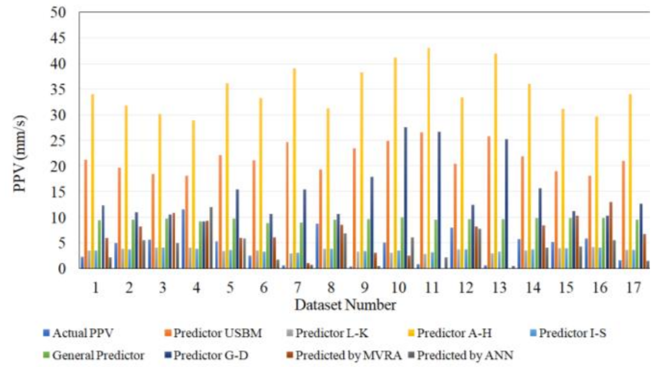

Fig. 14 Comparison of various predictors for prediction of PPV

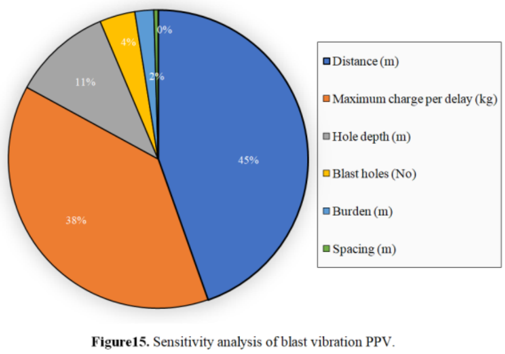

Fig. 15 Sensitivity analysis of blast vibration PPV

the maximum charge per delay, and the hole depth are the most effective input parameters for the blast vibration PPV, as shown in Fig. 15. Spacing, number of blast holes, and the burden are the least effective input parameters in that study. Therefore, it can be conveniently deduced that most of the cement factories located in geological settings similar to that of Chakwal District, Pakistan should focus on these three input parameters in their blasting design for their limestone quarry sites to minimize damage possibilities for the structures located nearby.

11. Conclusions

The study was aimed at predicting the blast-induced ground vibrations in different limestone cement quarries of Chakwal District, Pakistan towards developing a blast design to ensure the safety of structures around the blast quarry sites. Three different vibration prediction models were employed to select an optimum solution for the site. After analysis, it was found that using deep neural network methodology in Python, ANN outperforms other methods. The hyperparameters and nodes in activation layers for ANN were optimized using randomized and grid search method with cross-validation techniques. After developing the optimized training model on 85% of the dataset, it was tested on the remaining 15% dataset to test the model performance.

For this study, five evaluating indexes were used for different blast vibration predictors to judge the performance of the models under different loss functions. Accordingly, R^2, MAE, MSE, MAPE, and RMSE were taken into account simultaneously for the selection of an appropriate model. The ANN model has shown the highest R^2value and considerably low MAE, MSE, MAPE, and RMSE values. Thus, it was selected as a model appropriate for the prediction of BIGV at limestone quarries with similar geological and geomorphologic settings. The empirical model (Langefors-Kihlstrom) performed well in contrast to MVRA for this dataset.

This study further confirms that ANN, once trained on a labeled dataset, it has the ability to predict blast vibrations on the unlabeled dataset, and that ANNs are quite promising and satisfying in terms of prediction results. Using this approach, blast design can also be optimized for better distribution of explosive energy for rock breakage and to mitigate the blast nuisance.

Future research in this field can focus on advancing the prediction and safety measures of blast-induced ground vibrations (BIGV) at limestone quarry sites by incorporating advanced prediction techniques and tools. These may include the utilization of advanced artificial neural network (ANN) architectures, such as recurrent neural networks (RNNs) and convolutional neural networks (CNNs), which have demonstrated superior performance in various domains. By harnessing the capabilities of RNNs and CNNs, researchers can improve the accuracy and robustness of BIGV prediction models. Additionally, the integration of remote sensing technologies, such as light detection and ranging (LiDAR) and satellite imagery, can provide valuable data sources for monitoring quarry operations and assessing their impact on BIGV.

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