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ORIGINAL CONTRIBUTION

Prediction of Back Break Using Sensitivity Analysis and Artificial Neural Networks

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Abstract Back break is a negative event produced during blasting operation, which cannot be avoided completely. Large quantity of potential waves released in explosive bore hole, which cross over last row of blast hole. Back break prediction is need of hour, which influences prominently in drilling operations by seizing-up drill bits and escalates mine economics and as well generation of rock boulders. Therefore, in this paper an accurate back break prediction was predicted by using back propagation neural networks (BPNN) and ML techniques like decision tree regressor (DTR) and linear regression (LR) algorithms. To prepare the model dataset for training and testing, 119 blast datasets were collected at JVROCP-II extension project, SCCL. In these analyses the most influential parameters of back break were burden, spacing, stemming length, bench height, number of holes and powder factor. To predict back break a BPNN was used and developed in MATLAB software and compared with ML models such as DTR and LR model in Python. ANN produced a better result in terms of R^2 value as 0.96, and DTR and LR models produced 0.93 and 0.72, respectively. Similarly, in terms of RMSE and VAF ANN produced 0.7 and 94%, which is superior than other two models. ANN gives a better result than DTR and LR techniques, in predicting back break with accuracy of 94%.

Keywords Back break · Linear regression · ANN · Sensitivity analysis

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Introduction

During blasting activity various undesirable events occur which includes, airborne pressure, below surface tremors, fly rocks, and especially back break, is noticed after explosion events and ought to be minimized or eradicated. Numerous studies have been performed by many scholars to identify the variables that could influence the probability of back break fractures in opencast. A investigation of the associated literature reveals the role that various factors are responsible in generating negative waves. These traits may be employed to establish three different groupings.

From the first group, various factors like burden, stemming length, explosive consumption per blast(PF), spacing (distance between holes), total number of holes, hole distance, max charge per delay, blasting effected distance have the most influencing impacts on the back break during blasting [1]. Manoj khandelwal explained that a high stiffness ratio is responsible for minimizing back break, and also included the note gradually increase in back break occurring due to increase in spacing and burden height and explosive quantity [2]. Mukul Sharma made a experimental study on blasting he focused and monitored ground vibration (which indirectly links to back break) was independent of the burden. They established that the extent of rock mass rupture associated with the exploding hole at the exact moment of the detonation influences the ground motion [3]. Murthy described that improper delay among different rows was the important reason for the back break occurrence. Additionally, they claimed that when blast patterns expand, the likelihood of back break also increases [4]. In open-pit mines, adopting regulated blowing methods such as line slicing, before separating ground, shaped exploding and intermittent air particle factor (PF) in the final configuration of blasting ports

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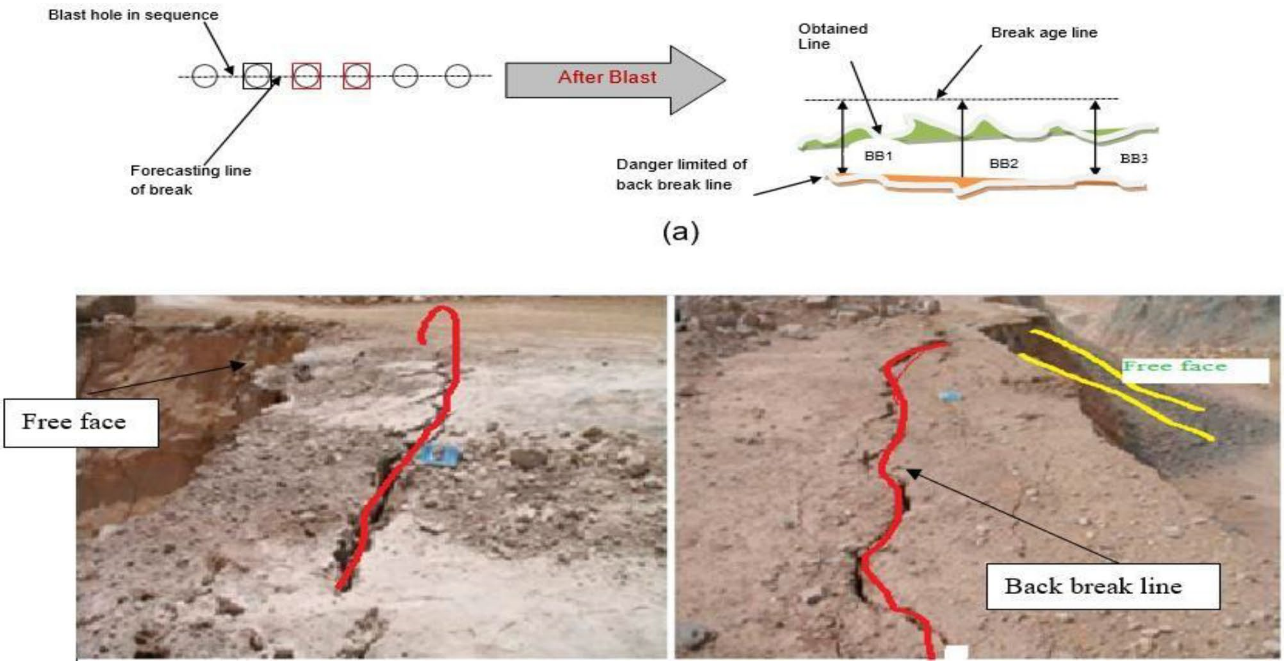


Fig. 1 Wave propagation direction indicating both forward and backward waves including back break layout

can minimize walls impact and back break. Controlled blasting procedures suggested for reducing trench walls and back crack damage, shaped exploding and intermittent air particle factor (PF) in the final configuration of blasting ports can minimize walls impact and back break. Controlled blasting procedures are suggested for reducing trench walls and back break effect [2, 5–9]. Figure 1 represents surface wave propagation and back break layout.

Various factors which is related to blasting or explosive usage links directly or indirectly is going to influence back break which includes explosive type and its quality, strength of rock, spacing to burden ratio, coupling ratio, etc. All these parameters are divided based on both controllable and uncontrollable factors. All the explosives are not same in terms of physical strength and power; distinct explosives generate different blasting pressures; if we consider ANFO detonation in hole is different from other lawful exploding substances for illustration, it generates a lower velocity than dynamite. Low combustion velocities are generated by less dense explosions. Bahandari determined that the lesser the exploding hole pressure, the lower effect caused by back break [13]. Various properties that influence the back break are shown in Fig. 2. One of the important effective factors on the back break strength is the coupling ratio, which describes the degree of immediate contact of the explosive pattern walls of the exploding hole [15] (Table 1).

Artificial Intelligence and Machine Learning Approaches in Blasting

In nearly every field including engineering, science, education, medicine, business, accounting, finance, marketing, economics, stock market and law, artificial intelligence (AI) has emerged as a key research area [16, 17]. Research in the domain of mining and geotechnical applications has recently emphasized the effectiveness of artificial intelligence (AI) technologies [18, 19]. There are many empirical models created to estimate the fragmentation of rock caused by mine blasting [20]. Artificial intelligence-based algorithms like ANN, FIS, GEP, Regression, XG Boost, Random Forest, AMC and K-NN algorithms have been employed in several research segments to solve and back break [21, 22]. Using 415 blast design data, two models—FIS, an artificial intelligence method and regression—were built to predict rock fragmentation in an Iranian mine. The research found that the FIS method fits well in predicting outcomes [23]. Similar to this, many approaches studies have found models can accurately forecast back break depending on input factors like weight, spacing and explosive quantity [24]. For instance, predictive maintenance models based on machine learning algorithms have been developed to increase the dependability of equipment and minimize the time required for it to break down [25]. Machine learning has also been used in mineral exploration and resource estimation, as

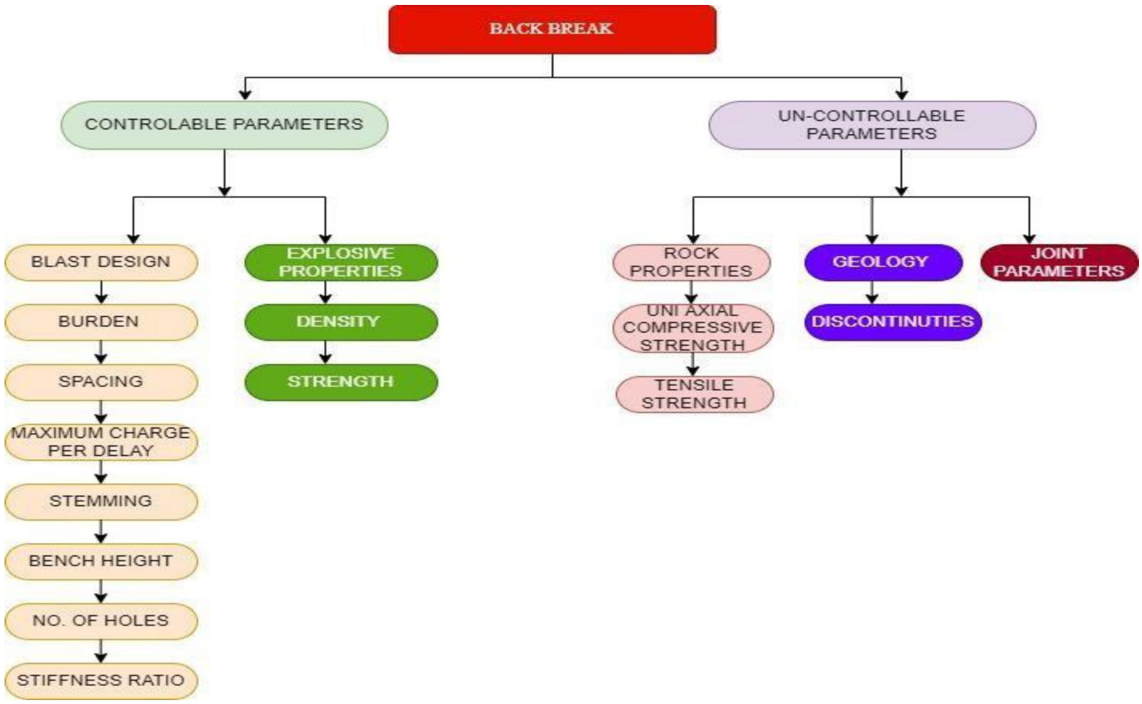


Fig. 2 Back break properties describing both controllable and uncontrollable factors

Table 1 Summary for machine learning techniques on blasting

References	Number of datasets	Input parameters	Models	Performance index
Taheri et al. [21]	89	MCPD, D	ANN, ABC-ANN, empirical model	$R^2=0.92$
Arthur et al. [22]	101	MCPD, D, PF, SL B, S, AD	GPR, BPNN, MARS, ELM, MVRA	$R^2=0.99$ MSE = 0.09 R = 0.99 VAF = 99.17%
Khandelwal [23]	128	B, S, D, CL, MCPD	ANN, empirical model	MAE = 0.18 CoD = 0.91
Bakhshandeh et al. [24]	30	S, D, T, N, MCPD	ANN, MVRA, empirical model	$R^2=0.977$ Error = 0.0164
Saadat et al. [25]	69	D, MCPD, HD	ANN, MLR, empirical model	$R^2=0.95$ MSE = 0.00072
Lawal [26]	100	D, MCPD	ANN, MLR	$R^2=0.9164$, RMSE = 2.90 VAF = 98.74 MAPE = 7.14
Zhang [27]	175	PF, T, B, S H, D, MCPD	PSO-XG Boost, empirical models	$R^2=0.96$ RMSE = 0.58 MAE = 0.34 VAF = 96.08
Rana et al. [28]	137	MCPD, HDM, CPH, HD, TC, D, NH, TS	ANN, MVRA, CART, empirical predictor	RMSE = 1.56 $R^2=0.95$

stated by [26–32]. The significance of the function that machine learning techniques play in the mining sector is highlighted by these applications.

Decision Tree Regressor

A well-liked technique for machine learning called decision trees can be utilized for regression as well as classification issues. They are an ideal choice for newcomers to the discipline of machine learning since they are simple to understand, decipher and employ. In this comprehensive guide, we will cover every aspect of the decision tree algorithm, including its fundamental concepts, numerous decision tree types, how decision trees are put together and how to evaluate and optimize decision trees.

Using decision trees, machine learning tries to minimize any imbalance or ambiguity in the dataset. In this study, a decision tree algorithm was created and used to estimate back break during blasting in SCCL mines. The outcomes of the simulation were compared to those generated by multivariate logistic regression modeling using actual, appropriate information sample domain and tree structure shown in Fig. 3.

As previously established, the "results" addressed in this piece are related to the outcomes linked to the evaluation or test information collection [20]. But in the present investigation, assessments of performance between both tools—DT and ANN—as also as for the two tools—SVM and RF—are reported in previous studies with all of the measurement of error included provided. Those comprised the relationship coefficient (R), the root average squared error (RMSE), the mean absolute error in degrees (MAE), in addition to the utmost exaggeration and underweight estimation drawbacks. The significance of these performance gauges is clear. Individualized proportional errors for the two approaches used in the present investigation, DT and ANN and linear regression, respectively, will be investigated.

Regression Analysis

Regression analysis is expanded to include a greater quantity of uncorrelated feature in the investigation of prediction in a process known as multivariable regression. Using this method, the relationship between the required (uncorrelated) and predicted (dependent) factors can be easily ascertained. Eight variables, including burden, bore positioning, hole dimension, specific cutting, stemming dimension, quantity of explosive per delay, rock volume and powder factor(ton/kg), have been taken into consideration in the present investigation to determine back break. Regression equation and multiple variable flow chart for parameters are given in Fig. 4

$$B_1 = b_1 = \sum \left[\left(x_i - x \right) \left(y_i - y \right) \right] \Big/ \Sigma \left[\left(x_i - x \right)^2 \right] \quad (1)$$

where xi and yi are the observed datasets. And x and y are the mean value.

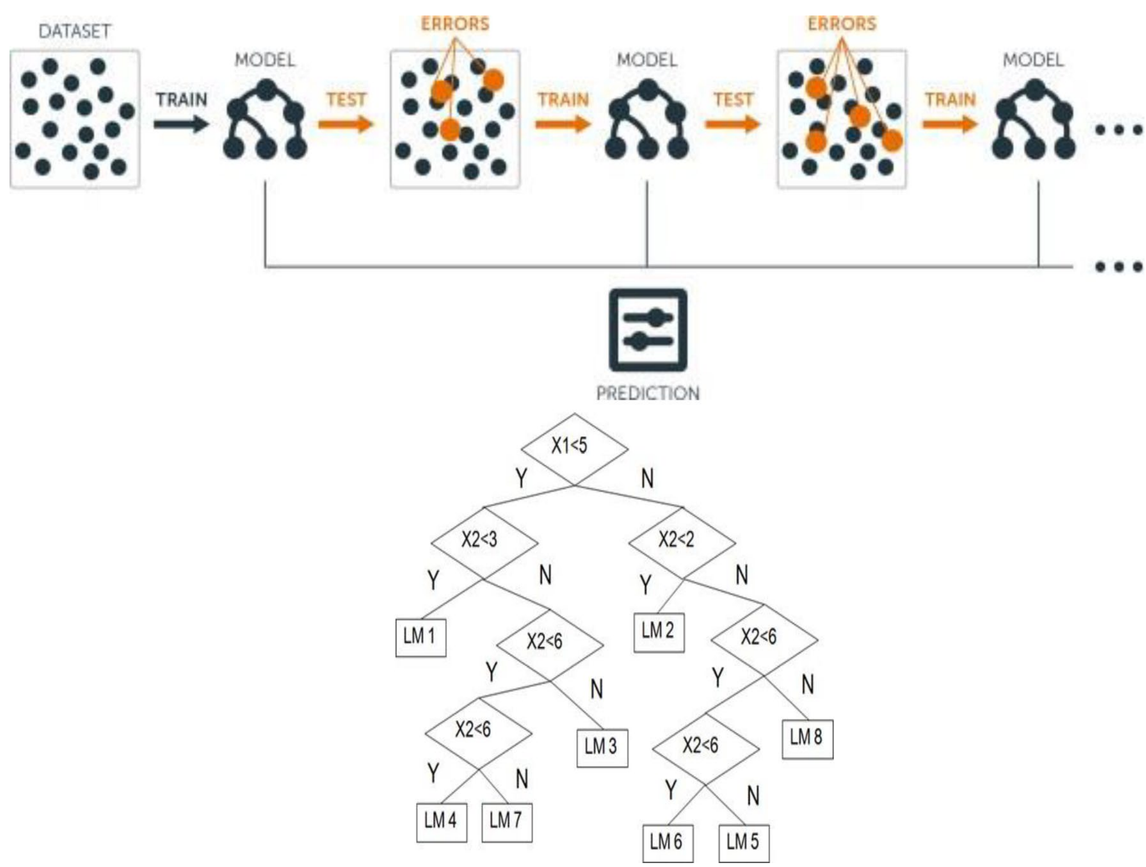


Fig. 3 **a** Sample domain data, **b** tree structure showing various parameters representing data

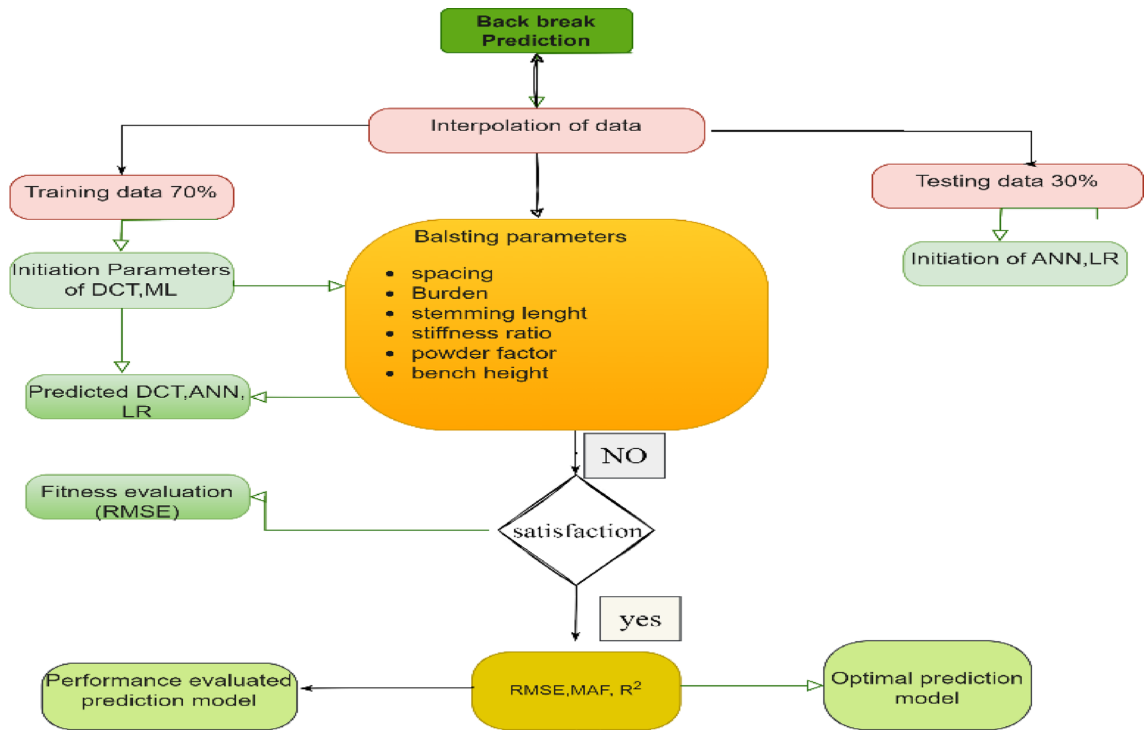


Fig. 4 Stepwise procedure representing ANN, LR and machine learning showing RMS

Artificial Neural Network

Artificial neural network (ANN) is a contemporary field regarding cognitive science that has expanded significantly since the 1980s [21]. ANN is now thought of as one of the clever instruments for understanding critical problems. Neural networks can pick up new information from previously observed patterns [22].

Once an adequate amount of data points have been used to train the algorithm, it could be able to forecast about one output related to fresh input datasets with compare patterns [23]. ANN is growing in popularity among academics, planners, designers and other professionals as a useful tool for finishing their work because of its transdisciplinary nature. As a result, ANN is effectively used in many commercial and research fields. ANN's prediction of statistics data is reportedly more accurate than measured values. Obtained data are compared to the other analytical methods; they discovered that results are incredibly realistic.

By using a neural network [24] analyzed a hazard to the structure brought on by changes in the mentioned parameters. Likewise, utilizing a brain network, [27] estimated the fundamental wave speed and rock attributes the general mechanism of a multilayer network as shown in Fig. 5. These illustrations exhibit the superiority of neural models in handling issues where a large number of complicated variables affect both the procedure and outcomes, when the relationship between the process and the results is ambiguous, and when experimental or historical data are available. In the current study, an effort has been made to use ANN to estimate the back break and its related frequency using appropriate rock volume, blast design specifications and exploding characteristics.

Materials and Methods

Field and Data Collection

Singareni Coal Mines Firm Limited (SCCL), the only coal-producing committed company in southern India, is owned equally by the governments of India and Telangana.

Jalagam Vengalarao opencast coal mine OC project is located between the Indian villages of Komapalli between the districts of Khammam in Telangana Latitude: 17° 12″ 38.84″ N Longitude: 80° 47″ 39.22″ E and is bounded by North Latitude 80° 47″ 19.31″ and 17° 12″ 38.84″ N and East Longitudes 79° 26′ 32″ and 79° 28′ 47″ and falls in the survey of India. No. 56 M/8 of the topo map shown in Fig. 6, and the environmental clearance was obtained for the expansion project including coal washery, vide MOEF & CC. In the JVR OC Mine (I&II Expansion), coal will be mined with a mix of shovels and dumpers in an open-pit

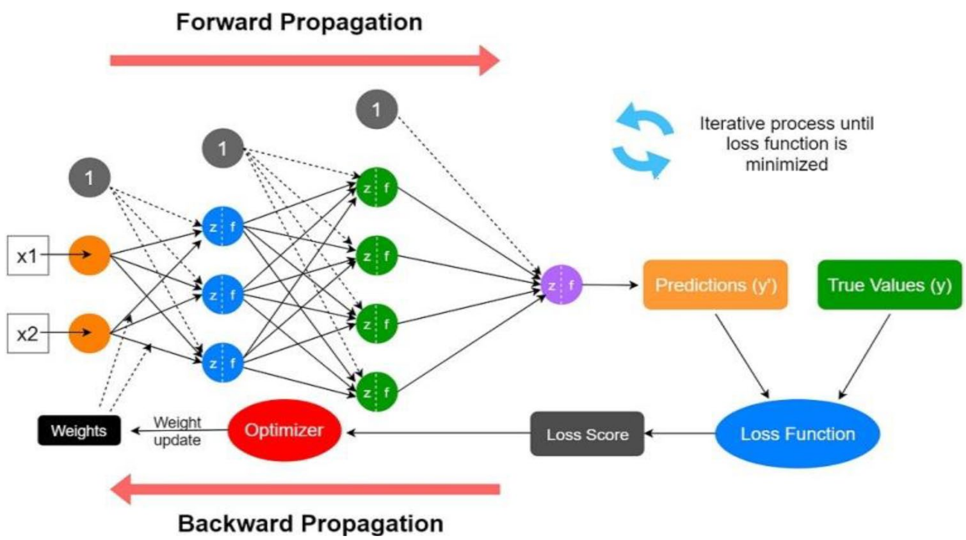


Fig. 5 Multilayer neural network architecture

Fig. 6 Satellite view and existing plan of JVR opencast

mining technique. The procedure of Jig and Drum Washing will be applied in the coal washery.

Blast Data Collection

A total number of 119 dataset has been collected from JVR opencast mine, which includes six input parameters burden, spacing, stemming, bench height, stiffness ratio and number of holes and one output parameter, back break. The dataset was prepared and used for prediction by using MATLAB and Python software. Data collection and back break observation done in blasting area are shown in Fig. 7.

Three datasets have been collected via the SCCL mine's blasting events and utilized to develop the decision tree model, the linear regression and artificial neural network

Fig. 7 Estimating distance of back break created during blasting

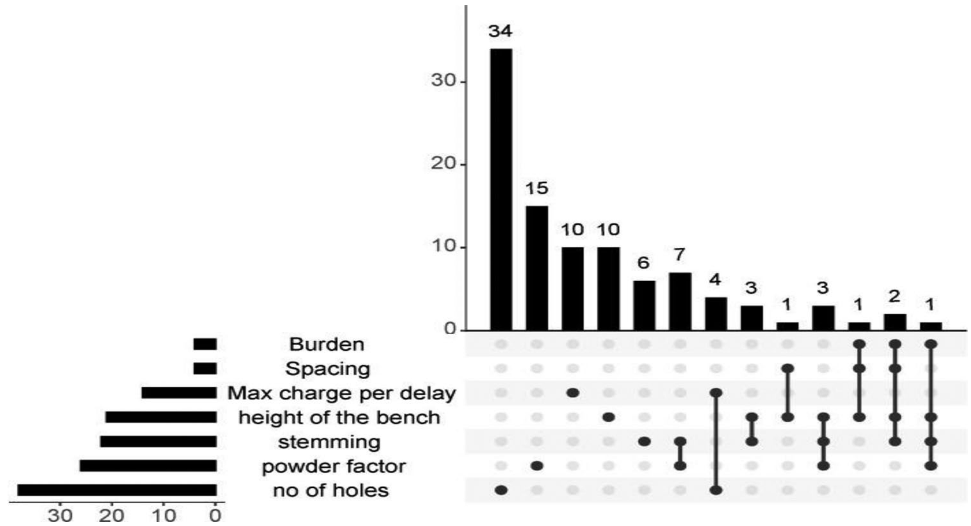


Fig. 8 Relation among dependent variable showing most influenced parameter

Table 2 Blasting pattern information of the JVR opencast mine

Parameter	Description
Explosive type	SMS
Blast hole pattern	Staggered
Bench height	5 (m)
Hole diameter	(150 mm)
Rows per blast	2–7
Number of holes	120

(ANN) prediction for back break. Blast data variability is presented in Fig. 8 and Tables 2 and 3.

The figures (Fig. 9) depict the discernible relationships between back break and other blast design parameters, specifically burden and spacing. These relationships are illustrated through heatmap plots and violin plots, showcasing the statistical significance and correlations among these variables. The graphical representations serve to elucidate the interdependencies and influences of burden and spacing on the observed back break outcomes, providing a visual insight into the complex interactions within the blasting process.

Sensitivity Analysis

After training in ANN, sensitive analysis intended to perform to understand the uninfluencing trend exists among dependent and independent variables.

The last step of modeling is to assess the sensitivity analysis of the model output taking consideration of input parameter to identify effective parameter among other six input parameters. It was unfolded that burden is the most impacting and crucial on generation of back break as shown in Fig. 10.

Model Training and Testing

A total of six input parameters (spacing, burden, stemming length and powder factor) and one output parameter (back break) collected from the mine were utilized to create a three-layered neural network that propagates backward (BPNN) in MATLAB programs. Two models based on intelligent retrieval understanding, statistical regression (LR) and decision tree regressor, are additionally employed for the forecasting, and for that purpose, an estimation programming has been created utilizing both approaches in Python Jupiter notebook

The total 119 datasets were split into training (70%), testing (15%) and validation sets using MATLAB with NNTOOL. This tool enabled the network interface to be generated and published by entering the parameters as input and the targeted variable as the result. The chosen learning operation was TRAINLM, which utilizes the Levenberg–Marquardt optimization algorithm to modify bias and weight variables for improved efficiency.

The system type selected for this task was feedforward replication. The learning algorithm used during training was Learngdm, a gradient descent with momentum. To construct the network, an appropriate performance function, the number of layers, the number of cells and the propagation pattern were determined using statistics such as the mean squared error (MSE). After successfully creating the network, training was performed. The sigmoid function was employed for prediction, and its equation is shown in Fig. 11. Please provide the correct sigmoid equation (Eq. 2) for a more accurate interpretation of your statement.

$$F(I) = 1/1 + e\infty I \tag{2}$$

Table 3 Blast data used for training and testing

Bench height, m	Spacing, m	Burden, m	Stemming, m	Powder factor, te/kg	Back break, m
6.00	2.5	2	4	1.50	1
6.00	2.5	2	4	1.50	1
2	2	2	4	0.50	0
6	2.5	2	4.5	1.33	1
4	2.5	2	6	0.67	0
6	2.5	2	5	1.20	1
4	2.5	2	5	0.80	0
6	2.5	2	5.3	1.13	2
5	2.5	2	4.5	1.11	2
6	2.5	2	6	1.00	2
6	2.5	2	5	1.20	1
3.5	2.5	2	3	1.17	2
5	2.5	2	5	1.00	1
5	2.5	2	4	1.25	1
6	2.5	2	5	1.20	1
6	2.5	2	5	1.20	4
5	2.5	2	3	1.67	3
6	2.5	2	5.4	1.11	3
6	2.5	2	3	2.00	3
6	2.5	2	3	2.00	3
5	2.5	2	3	1.67	3
6	2.5	2	3	2.00	0
6	2.5	2	3	2.00	0
5	2.5	2	5	1.00	0
2.3	2	2	5	0.46	3
4.35	2.5	2	4.5	0.97	1
2.5	2	2	4.4	0.57	2
6	2.5	2	5	1.20	2
3.5	2	2	5	0.70	2
2.5	2	2	5	0.50	2
6	2.5	2	5	1.20	4
4	2.3	2	5	0.80	3
2.5	2	2	5	0.50	3
3	2	2	5	0.60	2
6	2.5	2	5	1.20	2
5	2.5	2	5	1.00	2
5	2.5	2	5	1.00	3
4	2.5	2	5	0.80	3
4	2.5	2	5	0.80	3
6	2.5	2	5	1.20	4
5	2.5	2	5	1.00	3
6	2.5	2	5	1.20	3
2	2	2	5	0.40	3
6	2.5	2	4	1.50	3
6	2.5	2	4	1.50	2
5	2.5	2	4	1.25	1
6	2.5	2	4	1.50	0
6	2.5	2	4	1.50	1
5	2.5	2	4	1.25	0

Table 3 (continued)

Bench height, m	Spacing, m	Burden, m	Stemming, m	Powder factor, te/kg	Back break, m
3.5	2.5	2	4	0.88	2
3.5	2.5	2	4	0.88	2
6	2.5	2	5	1.20	2
2	2	2	5	0.40	1
6	2.5	2	4	1.50	2
6	2.5	2	4	1.50	1
5	2.5	2	4	1.25	1
6	2.5	2	4	1.50	1
6	2.5	2	4	1.50	4
3	2	2	3	1.00	3
6	2.5	2	4	1.50	3
2.5	2	2	4	0.63	3
4	2.5	2	4	1.00	3
2.5	2	2	4	0.63	3
6	2.5	2	3	2.00	0
3	2	2	3	1.00	0
5	2.5	2	3	1.67	0
6	2.5	2	4	1.50	3
6	2.5	2	4	1.50	1
6	2.5	2	4	1.50	1
6	2.5	2	4	1.50	0
2.5	2	2	4	0.63	1
6	2.5	2	5	1.20	0
6	2.5	2	5	1.20	2
5	2.5	2	5	1.00	2
6	2.5	2	5	1.20	2
6	2.5	2	5	1.20	1
5	2.5	2	5	1.00	2
5	2.5	2	5	1.00	1
6	2.5	2	5	1.20	1
5	2.5	2	55	0.09	1
2.5	2	2	5	0.50	4
6	2.5	2	5	1.20	3
4	2	2	5	0.80	3
6	2.5	2	5	1.20	3
5	2.5	2	5	1.00	3
6	2.5	2	5	1.20	3
6	2.5	2	5	1.20	0
5	2.5	2	5	1.00	0
4	2.5	2	5	0.80	0
4	2.5	2	4	1.00	0
2.5	2	2	4	0.63	0
6	2.5	2	3	2.00	0
3	2	2	3	1.00	3
5	2.5	2	3	1.67	1
6	2.5	2	4	1.50	1
6	2.5	2	4	1.50	0
6	2.5	2	4	1.50	1
6	2.5	2	4	1.50	0

Table 3 (continued)

Bench height, m	Spacing, m	Burden, m	Stemming, m	Powder factor, te/kg	Back break, m
2.5	2	2	4	0.63	2
6	2.5	2	5	1.20	2
6	2.5	2	5	1.20	2
5	2.5	2	5	1.00	1
6	2.5	2	5	1.20	2
6	2.5	2	5	1.20	1
5	2.5	2	5	1.00	1
5	2.5	2	5	1.00	1
6	2.5	2	5	1.20	4
5	2.5	2	55	0.09	3
2.5	2	2	5	0.50	3
6	2.5	2	5	1.20	3
4	2	2	5	0.80	2
6	2.5	2	5	1.20	1
5	2.5	2	5	1.00	2
6	2.5	2	5	1.20	1
6	2.5	2	5	1.20	2
5	2.5	2	5	1.00	1
6	2.5	2	5	1.20	1

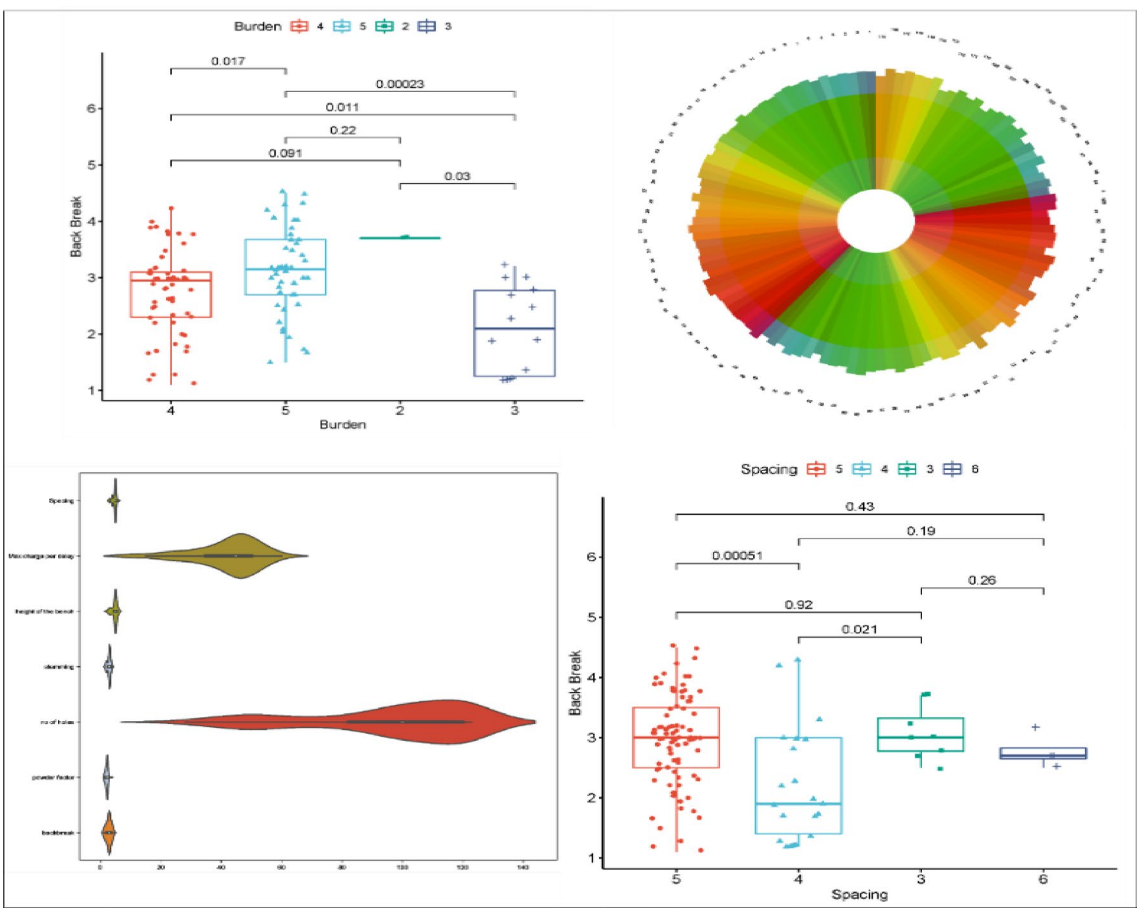


Fig. 9 Dataset observation from a) heat plots, b) violin plot

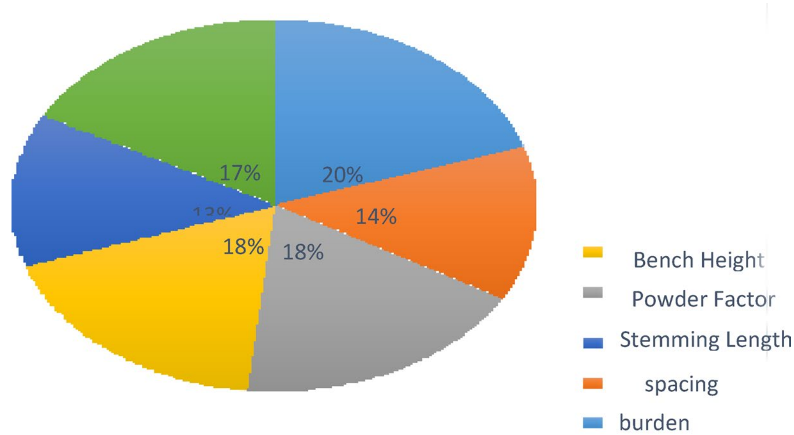


Fig. 10 Pie chart plot represents relation among parameters

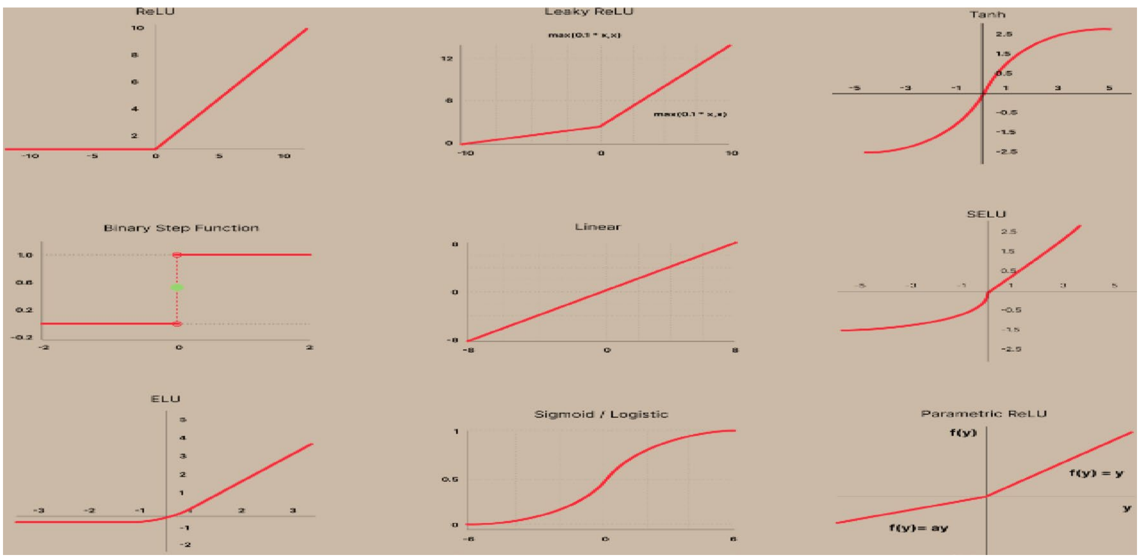


Fig. 11 Sigmoid activation function linear and binomial

In this investigation, the back break was anticipated with code written in MATLAB and statistical techniques, combining the decision tree analysis (DCT) and logistic regression (LR) models and ANN. The total number of 119 datasets was divided between datasets for training (20%) and test datasets (80%). Datasets used for model are shown in Table 3.

Results and Discussion

The 20% of the dataset was utilized to assess and revamp the degree of precision as well as the efficacy of the models built. During this stage, 80% of the entire dataset was randomly picked to construct an emulate for predicting back break with low RMSE value among linear regression, ANN and DT.

The performance of the proposed models was evaluated using three forms of model estimation errors which are the root-mean-square error (RSME), variance accounted for (VAF) and coefficient of determination ($R.^2$), presented in Eqs. 3, 4 and 5

$$\mathrm{RMSE} = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(\alpha - \omega)^2} \tag{3}$$

$$\mathrm{VAF} = \left(1 - \frac{\mathrm{var}(\alpha - \omega)}{\mathrm{var}(\alpha)}\right) * 100 \tag{4}$$

$$R^2 = 1 - \frac{\sum i(y_i - \hat{y}_i)2}{\sum i(y_i - \bar{y})^2} \tag{5}$$

Examining a variety of populations between sizes of 25 and 200 repetitions, ANN achieved the most favorable results for back break predictions, with the R^2 and lowest RMSE values obtained for ANN that are 0.986 and 0.7. Various models of RMSE outputs are presented in Figs. 12, 13 and 14.

Similarly, the performance of the three models was assessed through the utilization of variance accounted for (VAF) and R-squared ($R2$) metrics. This evaluation aimed to gauge the robustness and accuracy of the models in predicting back break, as expressed by Eqs. 4 and 5. The corresponding output results are visually depicted in Figs. 15, 16, 17, 18 and 19 and Table 4.

Six input parameters were taken for ANN and ML techniques, which are burden, spacing, stemming length, height of the bench, powder factor and number of holes and back break as output parameter for both as well. The coefficient of regression for all the models used for prediction is shown in the figures for the comparison, and after comparing all the regression parameters, it was shown that ANN is the best soft computing technique suitable for prediction of back break. From the above plot it is clear that regression plots obtained from both ANN and Excel are the same ($R2 = 0.97$,0.72 and0.79) and for visualization obtained and predicted data were programmed in violent plots to show distribution of statistical dataset shown in Figs. 17, 18 and 19.

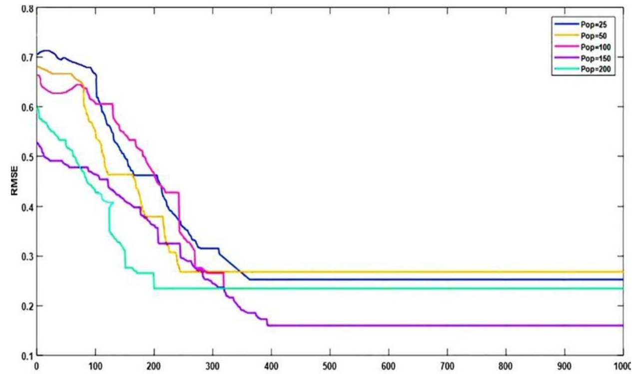
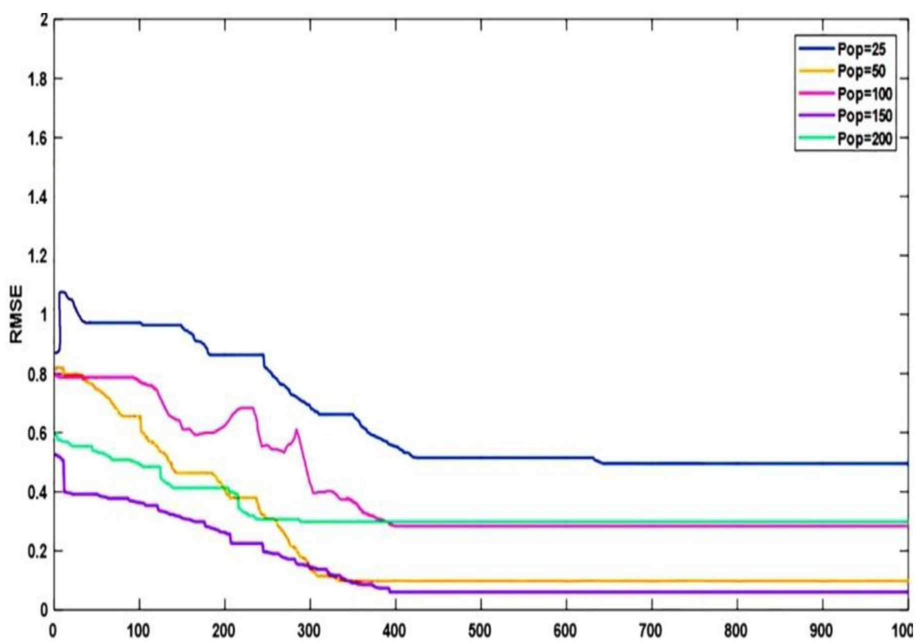


Fig. 13 ANN model RMSE output values comparison with various populations for back break on testing datasets

Conclusion

In this study, a predictive modeling technique employing a MATLAB-based artificial neural network (ANN) was employed to forecast back break. Specifically, a three-layered backpropagation neural network was constructed for this purpose. To elucidate the relationship trends among blast design parameters, a sensitivity analysis was conducted. The curated dataset was utilized in machine learning models, including linear regression and decision tree, in

Fig. 12 Regression model RMSE output values comparison with various populations for back break on testing datasets



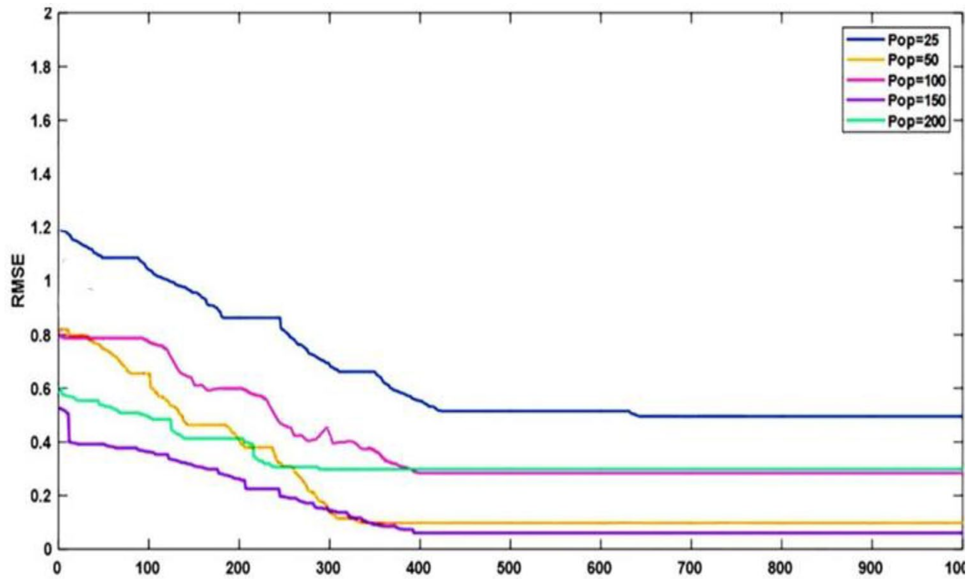


Fig. 14 Decision tree model RMSE output values comparison with various populations for back break on testing datasets

Fig. 15 Measured back break comparison with ANN, LR and DT models

addition to the MATLAB-based ANN. The key findings of the study are outlined below:

- Analysis of experimental blasts revealed that among the blast design parameters, burden exhibited a significant influence on back break.
- Sensitivity analysis confirmed that burden has a notable impact on back break.
- Among the employed machine learning models, namely ANN, linear regression and decision tree, the ANN outperformed others in predicting back break. This superiority was evident in terms of evaluation metrics for testing data, with R^2, RMSE and VAF values of 0.97, 0.7 and 86.85, respectively.

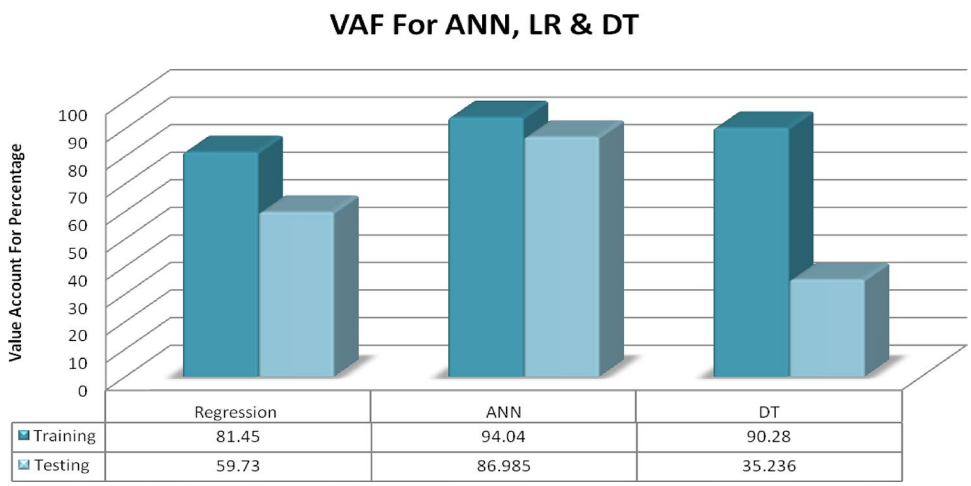


Fig. 16 Results of VAF of ANN,LR and DT

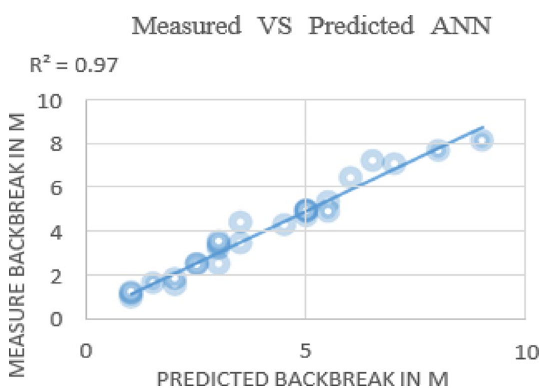


Fig. 17 Coefficient of correlation between measured and predicted back break using ANN

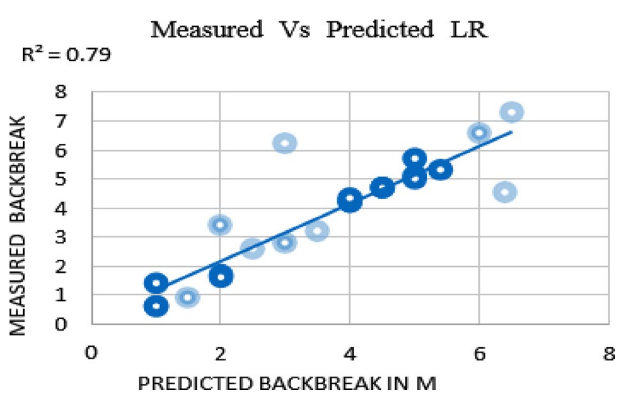


Fig. 18 Coefficient of correlation between measured and predicted back break using LR

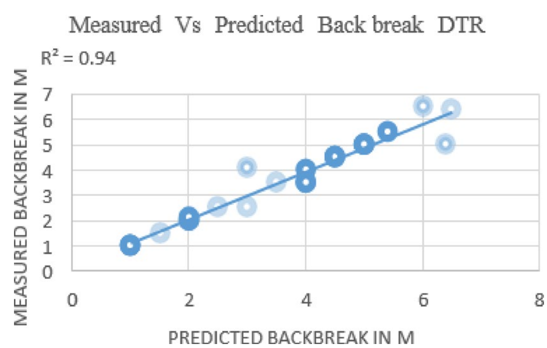


Fig. 19 Coefficient of correlation between measured and predicted back break using DTR

Table 4 Measured back break and predicted back break using ANN, LR

S. no	Measured back break	Predicted back break by ANN	Predicted back break by LR	Predicted back break by DCT
1	5	4.9825	5.3	5.5
2	5	4.7688	1.69	2
3	3.5	4.4662	3.2	3.5
4	5	5.022	4.69	4.5
5	4.5	4.3502	4.2	4
6	6	6.4817	2.6	2.5
7	5.5	5.392	4.7	4.5

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Declarations

Conflict of interest The authors declare that they have no conflict of interest.

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

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