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ORIGINAL ARTICLE

Evaluation of effect of rock mass properties on fragmentation using robust techniques

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Abstract

In the civil and mining projects, blasting operation is important from technical and economical point of view. There are several parameters which affect the result of operation such as desired fragmentation and undesired phenomena, e.g., ground vibration, fly rock, etc. From these parameters, rock mass characterizations can be considered as more influential as compared to the blasting pattern. In other words, it can be said that pattern specifications should primarily be designed according to the rock mass properties to reach the main objective of the operation, i.e., rock fragmentation. Complex nature of the problem needs to implement robust approaches such as artificial intelligence-based techniques. In this paper, an attempt has been made to develop some models by which the impact of each and every parameter influencing the result of blasting operation can be evaluated. For this research work, 432 datasets from 14 mines situated in the different parts of the world has been collected. In developing of the models, 19 parameters such as uniaxial compressive strength, tensile strength, brittleness, Point Load Index, Young's modulus, Poisson's ratio, rock quality designation, cohesion, friction angle, burden, spacing and stemming were incorporated. Regression analysis, decision tree and artificial neural network methods were employed for developing the models for predicting fragmentation. Determination coefficient (R^2) for artificial neural network modeling, multivariate linear regression and decision tree was computed 0.98, 0.83 and 0.45, respectively, showing accuracy of network modeling over the other applied methods. In addition, it was revealed that the most influential parameters on fragmentation are Point Load Index, uniaxial compressive strength, Poisson's ratio, cohesion and rock quality designation, respectively, and the least effective ones are stemming, spacing and hole diameter, respectively.

Keywords Rock mass properties · Rock fragmentation · Robust techniques

1 Introduction

Blasting is a dominant practice for fragmenting rocks in mining and civil projects. In this operation, only a small portion of the explosives' energy is really consumed in the process of rock fragmentation [1, 2] and the rest of it is exhausted in the form of unwanted events such as ground vibration, air overpressure, fly rock and back break [3–6]. Since, in the open pit mines, destination of the blasted rock is the primary crusher for which size distribution of the feed is very important, therefore, blast design should be managed in such a way that crusher performance be reasonable to maintain the whole process economical from mine to mill [7, 8]. However, it should be mentioned that getting a specific size distribution normally is not an easy task because there are some effective factors that not in the hand of blast engineer. Broadly, the most relevant factors affecting the result of a blast can be divided in two categories: uncontrollable (rock mass properties) and controllable (blast geometry and explosive specifications) [9, 10]. Nowadays, Artificial Intelligence (AI) such as artificial neural network (ANN) is utilized for solving complicated problems in various fields of science and engineering [11–14]. Specifically, many research works are available regarding implementation of AI in prediction of rock fragmentation [15]. In this paper, it was tried to recognize the most effective parameters on rock fragmentation by using various approaches of conventional (regression analysis) and machine learning (ANN and decision tree) methods.

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2 Artificial neural network

Artificial neural network is actually an imitation of the human brain [16]. It contains several interconnected layers. In each layer there exist computational components known as neurons. ANN can be applied for solving problems with high non-linearity. Robustness of the ANN can be highlighted in its capability of function approximation and feature selection [17–22]. The first step in applying ANN is training which require datasets including inputs and outputs. There are several tactics that can be considered in the training process of the multi-layer perception (MLP), however, back propagation algorithm has more benefits comparing to the other available approaches. MLP network contains at least three main parts known as input, transitional and output layers. Number of the neurons in the transitional layer is determined according to the nature of the problem in hand. In the training, a weight is primarily given to each of the connections between the existing nodes in each of the layers. This initial weight should be modified to examine the efficiency of the network [23–25].

The model accuracy is studied by considering the model outputs and the actual measured outputs. Coefficient of determination (R^2), root-mean-square error (RMSE), mean absolute error (MAE) and variance account for (VAF) (Eqs. 1–4), are normally used to observe the model performance [26]:

$$R^2 = 1 - \frac{\sum_{i=1}^{N} (y - y')^2}{\sum_{i=1}^{N} (y - \tilde{y})^2}, \tag{1}$$

$$\mathrm{VAF} = \left[1 - \frac{\mathrm{VAR}(y - y')}{\mathrm{VAR}(y)}\right] \times 100, \tag{2}$$

$$\mathrm{RMSE} = \sqrt{\frac{1}{N}\sum_{i=1}^{N} (y - y')^2}, \tag{3}$$

$$\mathrm{MAE} = \frac{1}{N}\sum_{i=1}^{N} (y - y'), \tag{4}$$

where y, $y'$and $\tilde{y}$are the measured, predicted and mean of the y values, respectively, and N is the total number of data.

3 Case studies

In this research, the blast database is taken from previous study results collected in various mines and rock formation in the world [27–38] that were combined with blast data collected from the open pit mines of Iran to create the blast database as given in Table 1.

4 Collection of datasets

Descriptive statistics of the input and output variables are given in Table 2. Parameters such as burden, spacing, stemming, height of bench, hole diameter, powder factor, UCS, UTS, brittleness, Is_{50}, Density, Young's Modulus, P-wave velocity, Schmidt hardness value, Poisson's ratio, RQD, Cohesion and friction angles were used as inputs and X_{50} was selected as output.

5 ANN architecture

In this study, a total of 432 datasets were randomly split into training and testing groups. Training of the model was accomplished by back propagation procedure using 342 datasets. The entire datasets were normalized to values between − 1 and 1 to improve the efficiency of the training process. Afterwards, several models with different network elements (number of neurons in hidden layer, transfer function, etc.) were constructed to find out the most appropriate configuration with lowest error. MAE, RMSE, VAF and R^2 were determined for the various network structures (Table 3). From this table, it is seen that the best case is a back propagation network with an architecture 19-28-1 having the hyperbolic-tangent transfer function in hidden layer and exponential transfer function in output layer (No.12). Figure 1 shows the optimum architecture of ANN model. An illustrative plot of

Table 1 Various mines and rock formation of case studies

Row	Case study	Rock type	Location
1	Akdaglar	Blocky sandstone	Turkey-Istanbul
2	Bealton	Diabase	USA-Virginia
3	Chadormaloo	Magnetite, hematite, rhyolite	Iran-Yazd
4	Dongri-Buzurg	Quartzite muscovite gneiss	India-Nagpur
5	Golegohar	Magnetite	Iran-Sirjan
6	Mrica	Andesite	Indonesia
7	Murgul	Dacite	Turkey-Istanbul
8	Ozmert	Blocky sandstone	Turkey-Istanbul
9	Pittsboro	Basalt	USA-Virginia
10	Reocin	Massive dolomite	Spain-Cantabria
11	Sarcheshme	Porphyry Sarcheshmeh, andesite	Iran-Kerman
12	Soma	Lignite with calcite-filled joints	Turkey-Istanbul
13	Songun	Monzonite	Iran-Tabriz

Table 2 Variables used for developing models

Parameter	Controllability	Symbol	Mean	Min	Max	Std. Dev	
Inputs	Burden (m)	Controllable	B	4.69	1.90	7.50	1.45
	Spacing (m)		S	5.65	2.20	10.00	1.84
	Height of bench (m)		H	12.81	5.00	21.00	2.88
	Hole diameter (mm)		D	171.11	76.00	250.80	63.43
	Stemming (m)		T	4.77	1.50	8.00	1.66
	Powder factor (Kg/m^3)		PF	0.58	0.20	1.48	0.28
	Point load strength	Uncontrollable	Is_{50}	4.88	1.00	8.00	2.14
	Uniaxial compressive strength (MPa)		UCS	106.97	30.00	200.00	50.19
	Uniaxial tensile strength (MPa)		UTS	10.30	1.50	23.00	6.44
	Brittleness		BT	11.90	8.18	20.00	2.94
	Density (t/m^3)		ρ	3.28	1.90	4.80	0.81
	Young's modulus (GPa)		E	43.12	13.30	70.00	17.51
	P-Wave velocity (Km/s)		V_p	3.81	2.20	4.80	0.66
	Schmidt hardness value		SHV	39.32	10.00	57.00	13.21
	Poisson's ratio		υ	0.23	0.20	0.31	0.03
	Rock quality designation		RQD	71.91	35.00	95.00	17.86
	Cohesion (MPa)		C	0.27	0.05	0.40	0.09
	Friction angle		φ	34.46	22.00	46.00	6.88
	Mean in-situ block size (m)		X_B	0.69	0.36	1.90	0.32
Output	Mean-blasted particle size (m)		X_{50}	0.27	0.04	0.51	0.11

Table 3 MAE, RMSE, VAF and R^2 for some of the models

No	Architecture	Hidden activation	Output activation	MAE	RMSE	VAF	R^2
1	19-27-1	Exponential	Sine	0.001	0.034	81.138	0.818
2	19-2-1	Sine	Sine	0.055	0.090	18.532	0.259
3	19-6-1	Exponential	Tanh	0.001	0.017	95.296	0.953
4	19-22-1	Logistic	Tanh	0.000	0.018	94.849	0.949
5	19-13-1	Sine	Sine	0.014	0.077	6.345	0.128
6	19-11-1	Sine	Logistic	0.029	0.096	37.352	0.247
7	19-3-1	Tanh	Sine	0.002	0.025	89.501	0.899
8	19-30-1	Sine	Exponential	0.023	0.057	55.605	0.559
9	19-2-1	Logistic	Exponential	0.002	0.023	91.721	0.922
10	19-30-1	Tanh	Sine	0.002	0.034	81.273	0.823
11	19-22-1	Tanh	Sine	0.001	0.037	78.211	0.790
12	19-28-1	Tanh	Exponential	0.0003	0.010	98.516	0.986
13	19-5-1	Tanh	Tanh	0.002	0.020	93.344	0.934
14	19-3-1	Tanh	Tanh	0.003	0.025	90.139	0.905
15	19-10-1	Sine	Exponential	0.003	0.063	34.792	0.350

measured versus predicted fragmentation using the ANN model is reported in Fig. 2. The result showed that the training R^2 was 0.99, which indicates that the designed ANN was capable to predict the fragmentation with the least error.

6 Multivariate linear regression (MLR)

Multivariate linear regression analysis was used to assess the mapping between the input and output parameters.

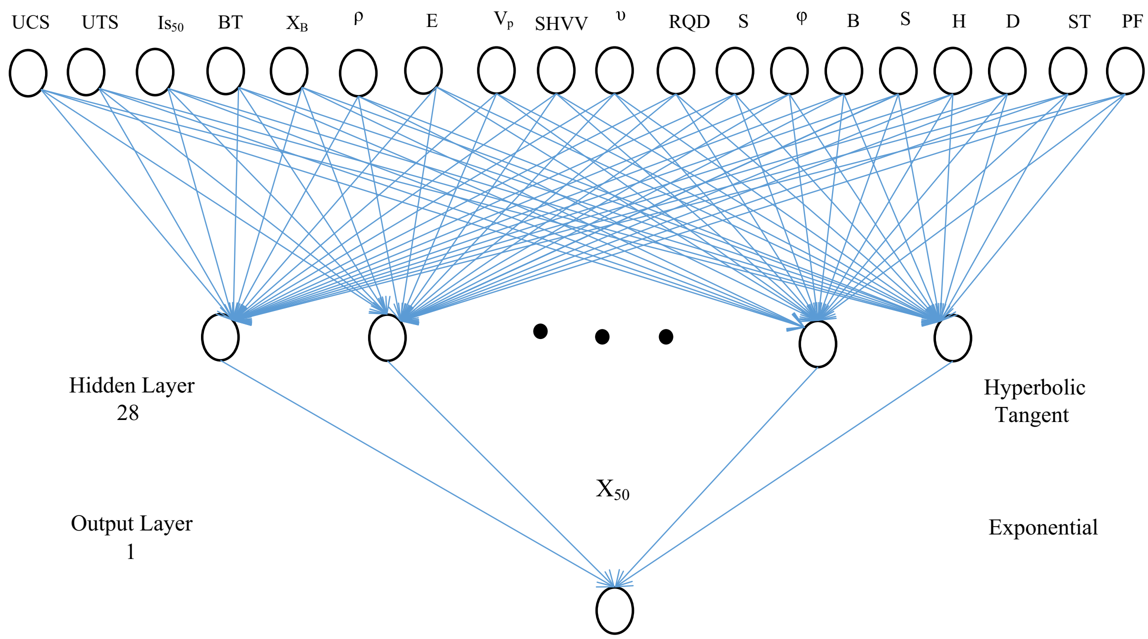

Fig. 1 Architecture of ANN model

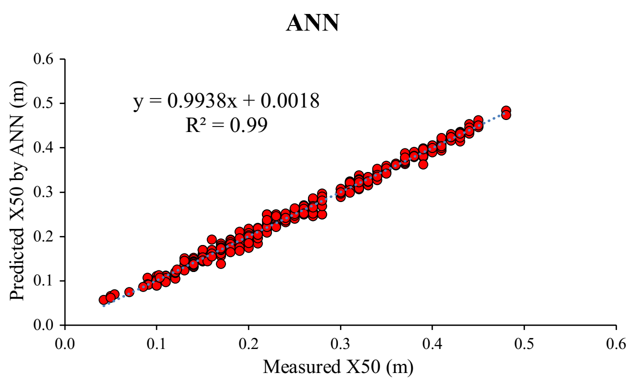

Fig. 2 Correlation between measured and predicted X_{50} in ANN model (Training accuracy)

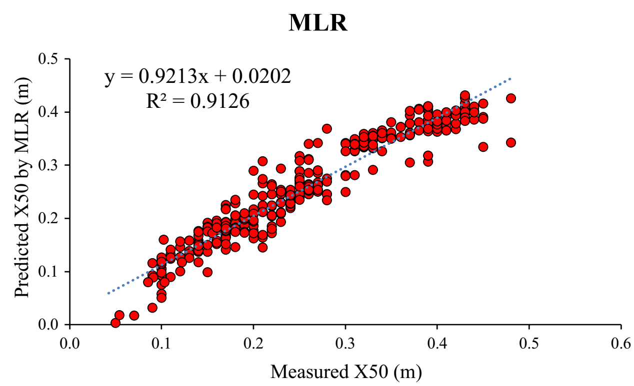

Fig. 3 Correlation between measured and predicted X_{50} in MLR model

MLR is widely used in various branches of science and technology [39, 40]. Equation 5 shows the results obtained from the regression analysis. Correlation between measured and predicted fragmentation using the MLR model is shown in Fig. 3.

$$\begin{aligned} X_{50} = {} & 0.009(B) + 0.004(S) - 0.003(H) - 0.0002(D) \\ & - 0.001(\mathrm{ST}) - 0.33(PF) + 0.165(X_B) - 0.002(IS_{50}) \\ & + 0.004(\mathrm{UCS}) - 0.014(\mathrm{UTS}) - 0.006(\mathrm{BT}) \\ & - 0.024(\rho) - 0.0008(E) - 0.12(V_p) + 0.006(\mathrm{SHV}) \\ & + 0.035(\vartheta) - 0.003(\mathrm{RQD}) + 0.68(C) + 0.005(\varphi). \end{aligned} \tag{5}$$

As shown in Eq. 5, parameters including burden, spacing, mean in-situ block size (X_B), uniaxial compressive strength (UCS), Schmidt hardness value (SHV), Poisson's ration (υ), cohesion (C) and friction angle (φ) have a direct relationship with X_{50}. Whereas, bench height, hole diameter, stemming, powder factor, UTS, brittleness, Is_{50}, density, Young's modulus, P-wave velocity and RQD have an inverse relationship with X_{50}.

7 Classification and regression tree (CART)

The decision tree is one of the hierarchical techniques extensively used for classification and regression because of its

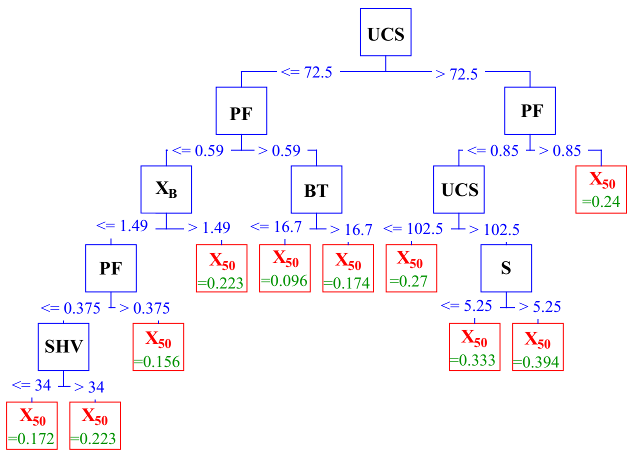

Fig. 4 CART model developed for predicting the X_{50}

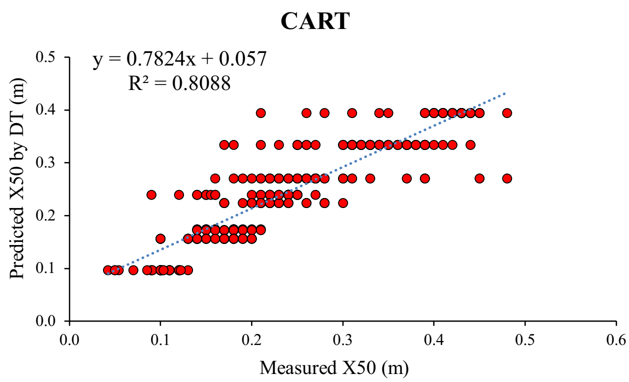

Fig. 5 Correlation between measured and predicted X_{50} in CART model

interpretability and efficacy [41]. There are several decision tree algorithms that can be applied to regression problems, however, CART (classification and regression tree) has substantial advantages comparing to the other existing approaches [42–45]. In this paper, MatLab software was used to predict rock fragmentation using CART model. Figure 4 shows the appropriate tree built for predicting the X_{50}. The correlation between measured and predicted X_{50} using CART model is shown in Fig. 5.

8 Performance evaluation of the models

Model evaluation of the obtained MLR, CART and ANN models was performed applying 90 test datasets which were not used in the model development. Table 4 shows the calculated values of validation indexes for all three models. According to Table 4, it can be seen that

Table 4 Calculated validation indices for the ANN, MLR and DT models

Model	MAE	RMSE	VAF (%)	R^2
MLR	0.001084	0.0331	83.41	0.836
CART	0.007254	0.064	38.69	0.453
ANN	0.000093	0.0095	98.607	0.986

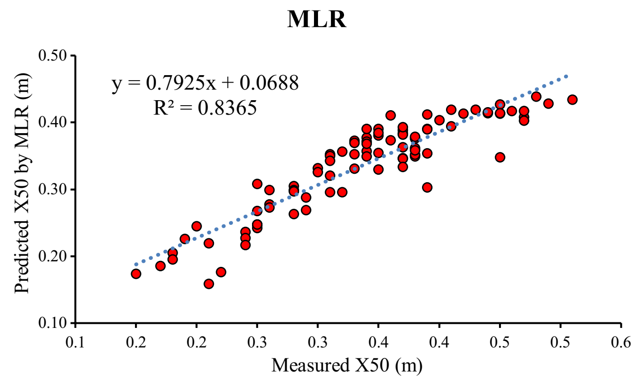

Fig. 6 Correlation between measured and predicted X_{50} in MLR model

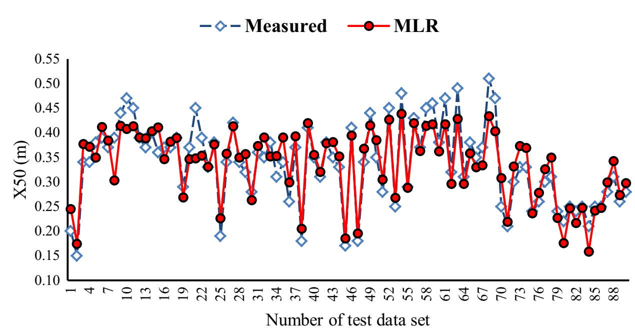

Fig. 7 Comparison of predicted and measured rock fragmentation in MLR model

the developed ANN model with the obtained values of 0.00009, 0.0095, 98.6% and 0.986 in the validation phase for MAE, RMSE, VAF and R^2, respectively, is superior compared to MLR model with these values of 0.001, 0.033, 83.41% and 0.836, respectively. Furthermore, comparing the obtained results from CART model showed the low competence of it to predict rock fragmentation precisely. The correlation between predicted and measured X_{50} using all three models are shown in Figs. 6, 7, 8, 9, 10 and 11. Altogether, these figures demonstrate that the ANN model has the best performance in prediction of X_{50} in comparison to the other models.

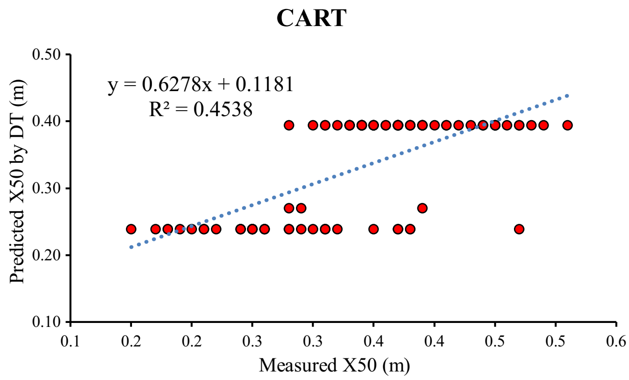

Fig. 8 Correlation between measured and predicted X_{50} in CART model

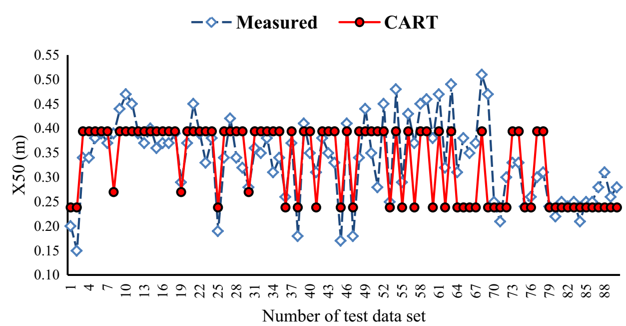

Fig. 9 Comparison of predicted and measured rock fragmentation in CART model

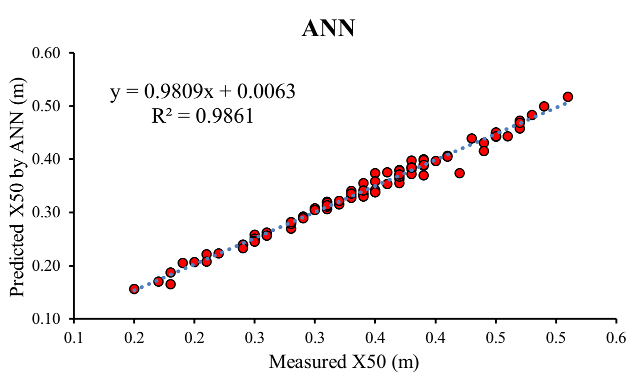

Fig. 10 Correlation between measured and predicted X_{50} in ANN model

9 Sensitivity analysis

To evaluate the influence degrees of uncontrollable and controllable parameters on rock fragmentation, a sensitivity analysis using the ANN model based on the relevancy factor (RF) was carried out [46]. The RF values can be calculated by Eq. 6:

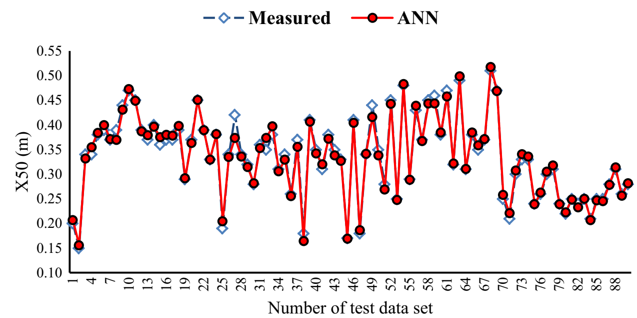

Fig. 11 Comparison of predicted and measured rock fragmentation in ANN model

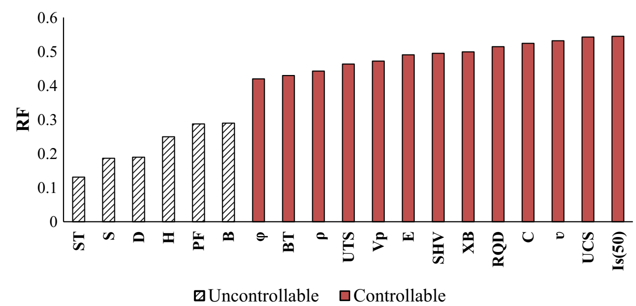

Fig. 12 Sensitivity analysis of the input parameters

$$RF = \left| \frac{\sum_{i=1}^{n} (x_{l,i} - \bar{x}_l)(y_i - \bar{y})}{\sqrt{\sum_{i=1}^{n} (x_{l,i} - \bar{x}_l)^2 \sum_{i=1}^{n} (y_i - \bar{y})^2}} \right|, \quad (6)$$

Where $x_{l,i}$ and $\bar{x}_l$ are the i_{th} value and the average value of the l_{th} input variable, respectively, y_i and $\bar{y}$ are the i_{th} value and the average value of the predicted output, respectively.

As it is observed in the Fig. 12, it was concluded that in comparison of controllable parameters, uncontrollable parameters are more effective on rock fragmentation. In this regard, from the prior group, Point Load Index, uniaxial compressive strength, Poisson's ratio, cohesion and rock quality designation, respectively, are the most important parameters on rock fragmentation and from the second group, stemming, spacing and hole diameter are the least important parameters on the quality of rock fragmentation.

10 Conclusions

In this paper, artificial neural network, decision tree and regression analysis was implemented to investigate the effect of uncontrollable and controllable parameters on the fragmentation quality in the blasting operation. For this study, a database was prepared from several mines situated in different parts of the world. In the first step, superiority of the different models was inspected from which competence of the neural network modeling was explored. The values of MAE, RMSE, VAF and R^2 for ANN model were 0.00009, 0.0095, 98.6% and 0.986, respectively. According to outcomes of the network modeling, it was generally concluded that compared to controllable parameters, uncontrollable parameters are more effective regarding fragmentation. In this respect, from the uncontrollable parameters, Point Load Index, uniaxial compressive strength, Poisson's ratio, cohesion and rock quality designation, respectively, are the most effective factors on fragmentation quality and from the controllable parameters, stemming, spacing and hole diameter are the least effective factors in this regard.

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