Engineering with Computers (2023) 39:1317–1327
https://doi.org/10.1007/s00366-021-01522-4

ORIGINAL ARTICLE

Application of various robust techniques to study and evaluate the role of effective parameters on rock fragmentation

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Received: 8 February 2021 / Accepted: 4 October 2021 / Published online: 19 October 2021

Abstract

In this paper, an attempt has been made to implement various robust techniques to predict rock fragmentation due to blasting in open pit mines using effective parameters. As rock fragmentation prediction is very complex and complicated, and due to that various artificial intelligence-based techniques, such as artificial neural network (ANN), classification and regression tree and support vector machines were selected for the modeling. To validate and compare the prediction results, conventional multivariate regression analysis was also utilized on the same data sets. Since accuracy and generality of the modeling is dependent on the number of inputs, it was tried to collect enough required information from four different open pit mines of Iran. According to the obtained results, it was revealed that ANN with a determination coefficient of 0.986 is the most precise method of modeling as compared to the other applied techniques. Also, based on the performed sensitivity analysis, it was observed that the most prevailing parameters on the rock fragmentation are rock quality designation, Schmidt hardness value, mean in-situ block size and the minimum effective ones are hole diameter, burden and spacing. The advantage of back propagation neural network technique for using in this study compared to other soft computing methods is that they are able to describe complex and nonlinear multivariable problems in a transparent way. Furthermore, ANN can be used as a first approach, where much knowledge about the influencing parameters are missing.

Keywords Blasting · Rock fragmentation · Robust techniques · Open pit mine

1 Introduction

Blasting is still practiced for fragmenting rocks in surface and underground mining projects. A huge amount of energy is generated during the blasting process and only a small portion of this energy is effectively used to fragment and displace the rock mass and the rest of the energy is wasted in the form of undesirable events, such as air blast, fly rock, ground vibration, etc. [1–9]. Therefore, optimizing blast design parameters should be targeted to get the best possible rock fragmentation to be efficient for subsequent operations, including loading, hauling and crushing [10–12]. As a matter of fact, there are several influencing uncontrollable (rock mass properties) and controllable (blast geometry) factors affecting fragmentation quality making blast design a process with high complexity [13–15].

Investigating 432 blasting events, Mehrdanesh et al. attempted to evaluate the effect of rock mass properties on fragmentation. They concluded that in comparison of controllable parameters, uncontrollable parameters are more effective on rock fragmentation. Their study results showed that, from the rock mass properties 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 blast geometry group, stemming, spacing and hole diameter are the least important parameters on the quality of rock fragmentation [13]. Numerous empirical Formulas have been

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introduced to model rock fragmentation due to blasting. However, due to the complex nature of the fragmentation and limitation of effective variables in conventional models, these formulas are not adequately accurate. Consequently, they will not be capable to predict rock fragmentation suitably. It seems that more precise techniques are needed to predict the rock fragmentation [16].

Nowadays, artificial intelligence (AI) is being applied in a range of geo-engineering projects and AI is a fruitful approach to cope with such types of problems [17–21]. In this regard, a number of research studies have been carried out to utilize various AI tools to improve blast design parameters obtained from conventional and empirical methods [13, 22–24]. Table 1 briefly summarizes some researchers' work in rock fragmentation, where they have used different AI tools and techniques. In this paper, for which four different mines were adopted as case studies, various techniques including regression analysis, classification and regression tree, support vector regression and artificial neural network

Table 1 Summary of researches regarding rock fragmentation prediction

References	Controllable variables	Uncontrollable variables	Method
Monjezi et al. 2009 [12]	B, S, St, PF, L, B/S	–	Fuzzy logic
Bahrami et al. 2011 [25]	B, S, St, SD, PF, L, MC, D, BI	–	ANN
Sayadi et al. 2013 [16]	B, S, L, SD, PF	–	ANN
Karami and Afiuni-Zadeh 2013 [26]	B, PF, S/B, N, St/B, MC	UCS	ANFIS
Shams et al. 2015 [27]	B, S, D, PF, St	SHV, J	FIS
Bakhtavar et al. 2015 [28]	B/S, St, t, P, N, D, L, BI	E, UCS	E, UCS
Ebrahimi et al. 2016[29]	B, S, St, L, PF	–	ANN-BCA
Trivedi et al. 2016 [30]	Q, QL, L, B, S, St, PF, D	σ_c, RQD	MLR
Singh et al. 2016[31]	B/D, S/B, St, H/B, ET, INI, PF	–	Empirical
Hasanipanah et al. 2016 [32]	B, MC, PF, S/B, St/B, H/B, N, INCL, D, B/D	–	RES
Hasanipanah et al. 2016 [32]	PF, B, St, S/D	UCS, Jp, RQD, JS, ρ, JPO	RES
Prasad et al. 2017 [33]	B, L, St, PF	–	Empirical
Hasanipanah et al. 2018 [24]	PF, St, S, B, MC,	–	PSO-ANFIS
Mehrdanesh et al. 2018 [13]	B, S, L, D, St, PF	PL, UCS, UTS, BT, ρ, E, V_p, SHV, υ, RQD, C, ϕ, XB	ANN
Asl et al. 2018 [34]	B, S, L, Sub, St, P, PF	GSI	ANN-FFA
Murlidhar et al. 2018 [35]	P, PF, B/D, S/B, H/B, St/B	BS, RQD	ANN-ICA

ANFIS adaptive-network-based fuzzy inference system, *BCA* bee colony algorithm, *MLR* multivariate linear regression, *RES* rock engineering system, *PSO* particle swarm optimization, *FFA* fire fly algorithm, *ICA* imperialist competitive algorithm, *B* burden, *S* spacing, *St* stemming, *L* hole length, *PF* powder factor, *D* hole diameter, *SHV* Schmidt hardness value, *J* density of joint, *MC* maximum charge used per delay, *S/B* spacing to burden ratio, *St/B* stemming to burden ratio, *H/B* stiffness factor, *N* number of rows, *INCL* blast-hole inclination, *ET* explosives amount and type, *INI* initiation mode, *Q* charge per hole, *QL* linear charge concentration, σ_c unconfined compressive strength, *RQD* rock quality designation, *E* modulus of elasticity, *t* delay timing, *BI* blastability index, *P* specific charge per delay, *UCS* uniaxial compressive strength, *PL* point load strength, *UTS* uniaxial tensile strength, *BT* brittleness, ρ density, V_p P wave velocity, υ Poisson's ratio, *C* cohesion, ϕ friction angle, X_B mean in situ block size, BS block size, *Sub* sub-drilling, *GSI* geological strength index, *JP* joint persistency, *JS* joint spacing, *JPO* joint plane orientation ratio to bench face, *SD* specific drilling were applied to predict rock fragmentation in the open pits blasting operation.

2 Artificial neural network

Artificial neural network is a branch of artificial intelligence [36–38]. It is made of a multilayer topology in which the layers are connected to each other. The first layer is considered for placing inputs, whereas the last one is for output(s). In addition to the mentioned layers, there are one or more layers known as hidden (transitional) layers which are placed in between the first and last layer. In fact, the hidden layers' components known as neurons are responsible for the required computations. Number of the neurons in each hidden layer is determined by a try and error mechanism. When facing very low correlation ANN would be the best possible solution as compared to the available conventional alternatives [12, 13]. Amongst various advantages of ANN modeling, function approximation and feature selection can be considered as a specific capability [39–41].

To start working with ANN, a reasonable number of data sets (a set of inputs and their respective outputs) should be collected and used for training various network architectures from which the best combination would be selected. Artificial neural network (ANN) is increasingly being used to solve various nonlinear complex problems, such as rock fragmentation. However, it is not clear that what appropriate sample size should be there when using ANN in this context. The amount of data required for ANN learning depends on many factors, such as the complexity of the problem or the complexity of the learning algorithm. Till now, it is not clear that how much sample data should be there in a predictive modeling problem. However, there are some empirically established rule-of-thumb are there to estimate sample size requirements when using ANN. For example, one rule-of-thumb is that the sample size needs to be at least a factor of ten times the number of features. During this process, first, the connections between the neurons should be assigned a random weight, thereafter the initial given weights would be updated in each modeling run to gain the best possible efficient network. The next important item which should be thought of is adopting a proper method of training such as a back propagation algorithm with many advantages as compared to the other existing approaches [42–45].

A trained network can be examined by comparison of the model outputs with that of the measured outputs. To do this four statistical indices including determination coefficient (R^2), mean absolute error (MAE), root mean square of errors (RMSE), and variance account for (VAF) can be calculated [46–50]. The following formulae are the mathematical expressions of the aforesaid indices:

Fig. 1 Location map of studied mines

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

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

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

$$\text{MAE} = \frac{1}{N} \sum_{i=1}^{N} \left|(O - O')\right|, \tag{4}$$

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

3 Case study

In this paper, the required database is obtained from four different open pit mines [13]. All the mines are situated in Iran (Fig. 1) and considered to be the main sources of copper and iron ore in the country. Table 2 gives some descriptions about the mines.

4 Collection of data sets

In this research, the database has been collected by performing 353 blasting operations in 4 mines mentioned in chapter 3. Descriptive information of the data sets is given in Table 3. Controllable parameters including burden, spacing, stemming, bench height, hole diameter, powder factor and uncontrollable rock characteristics comprising universal

Table 2 Various mines and rock formation of case studies

Row	Case studies	Location	Latitude	Longitude	Rock type
1	Chadormalou	Iran-Yazd	32.31	55.53	Magnetite, hematite, rhyolite
2	Gol-e-gohar	Iran-Sirjan	29.28	55.83	Magnetite
3	Sarcheshme	Iran-Kerman	29.95	55.86	Porphyry sarcheshmeh, andesite
4	Songun	Iran-Tabriz	38.69	46.71	Monzonite

Table 3 Variables used for developing models

Variables	Controllability	Number	Symbol	Mean	Min	Max	Std. dev
Burden (m)	Controllable inputs	353	B	4.98	1.90	7.50	1.27
Spacing (m)		353	S	6.02	2.30	10.00	1.62
Height of Bench (m)		353	H	13.25	5.00	17.90	2.41
Hole Diameter (mm)		353	D	181.97	76.00	250.80	60.35
Stemming (m)		353	T	5.10	1.80	8.00	1.55
Powder factor (kg/m^3)		353	PF	0.59	0.23	1.48	0.30
Point Load Strength	Uncontrollable inputs	353	Is_{50}	5.47	2.00	8.00	1.71
Uniaxial compressive strength (MPa)		353	UCS	118.83	35.00	200.00	44.53
Uniaxial tensile strength (MPa)		353	UTS	11.69	2.80	23.00	5.91
Density (t/m^3)		353	ρ	3.47	2.50	4.80	0.71
Young`s modulus (GPa)		353	E	47.81	20.00	70.00	14.40
P-Wave velocity (km/s)		353	V_p	4.03	3.00	4.80	0.40
Schmidt hardness value		353	SHV	43.65	20.00	57.00	8.54
Poisson's ratio		353	υ	0.22	0.20	0.27	0.02
Rock quality designation		353	RQD	77.59	45.00	95.00	12.34
Cohesion (MPa)		353	C	0.29	0.15	0.38	0.05
Friction angle		353	φ	36.16	28.00	46.00	5.89
Mean in-situ block size (m)		353	X_B	0.58	0.36	1.00	0.09
Mean blasted particle size (m)	Output	353	X_{50}	0.29	0.04	0.51	0.10

Table 4 Comparison of different neural network structures

No.	Architecture	Hidden activation	Output activation	Train				Test			
				MAE	RMSE	VAF (%)	R^2	MAE	RMSE	VAF (%)	R^2
1	18-14-1	Sine	Tanh	0.080	0.095	17.3	0.213	0.077	0.093	15.0	0.190
2	18-14-1	Sine	Tanh	0.070	0.085	32.8	0.560	0.068	0.085	27.5	0.491
3	18-8-1	Sine	Tanh	0.050	0.063	62.7	0.630	0.050	0.065	57.4	0.627
4	18-17-1	Sine	Exp	0.036	0.050	81.1	0.814	0.034	0.048	78.8	0.790
5	18-17-1	Sine	Tanh	0.033	0.043	83.1	0.832	0.035	0.044	80.4	0.809
6	18-9-1	Sine	Exp	0.030	0.039	85.9	0.861	0.033	0.041	82.7	0.830
7	18-8-1	Sine	Tanh	0.027	0.035	88.4	0.885	0.027	0.034	88.5	0.890
8	18-10-1	Exp	Sine	0.018	0.023	95.1	0.951	0.023	0.029	91.7	0.919
9	18-12-1	Exp	Sine	0.021	0.026	93.7	0.937	0.020	0.025	93.4	0.939
10	18-14-1	Tanh	Tanh	0.006	0.008	99.5	0.995	0.007	0.009	98.6	0.986

compressive strength (UCS), uniaxial tensile strength (UTS), Is50, density, Young's modulus, P-wave velocity, Schmidt hardness value, Poisson's ratio, rock quality designation (RQD), cohesion and friction angle were considered to the inputs.

In this research, image analysis techniques were applied to calculate size distribution using Split-Desktop software. Fragmentation has been calculated on the basis of 50% of passing size (X_{50}). Finally mean-blasted particle size (X_{50}) was selected as output in the modeling process.

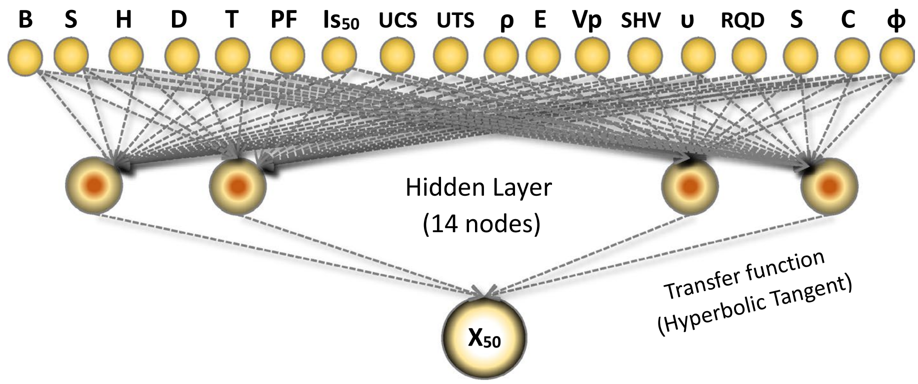

Fig. 2 Architecture of the optimum ANN model

5 ANN architecture

In this study, a total number of 353 data sets were used for training and testing groups. Back propagation approach was implemented for the model training. To have an applicable database and to improve efficiency of the training process, the whole data sets were normalized between values of − 1 and 1 [51]. After preprocessing of the data sets, to find out the best possible model with maximum accuracy and minimum error, numerous networks were created by varying pertinent elements, such as number of hidden layers and their respective neurons [52]. MAE, RMSE, VAF and R^2 were determined for the various network topologies (Table 4). As it is seen in this table, the best model is a back propagation network with an architecture 18-14-1 and a hyperbolic-tangent transfer function in both the hidden and output layers (no.10). From Fig. 2, an optimum architecture of the ANN model is depicted. The determination coefficient was computed 0.9947, which is adequate to show competency of the developed ANN model.

6 Multivariate regression analysis (MRA)

Multivariate regression analysis was used to evaluate the relationship between the inputs and output. MRA is considered as a conventional method of trend analysis in scientific tasks [53–55]. Using Statistica 12.0 software [56–58], regression analysis was performed to develop a mathematical function for predicting mean size of the fragment size (X_{50}) (Eq. 5). As it is deduced from this equation, burden, spacing mean in-situ block size, uniaxial compressive strength, Schmidt hardness value, cohesion, Young's modulus and density have a direct relevance with X_{50}, whereas bench height, hole diameter, stemming, powder factor, Poisson's ratio, UTS, Is_{50}, friction angle, P-wave velocity and RQD are indirectly effective in the X_{50} magnitude. The determination coefficient and RMSE were computed 0.8863 and 0.026, respectively, which indicates the relatively lower performance of the developed MRA model compared to the ANN model:

$$\begin{aligned} X_{50} = &0.01(B) + 0.009(S) - 0.003(H) - 0.0005(D) \\ &- 0.001(\mathrm{ST}) - 0.33(\mathrm{PF}) - 0.001(\mathrm{Is}_{50}) \\ &+ 0.002(\mathrm{UCS}) - 0.005(\mathrm{UTS}) + 0.022(\rho) \\ &+ 0.002(E) - 0.1(V_{\mathrm{p}}) + 0.007(\mathrm{SHV}) \\ &- 0.524(\vartheta) - 0.001(\mathrm{RQD}) + 0.515(C) - 0.004(\varphi) \\ &+ 0.4\left(X_{\mathrm{B}}\right) + 0.233 \end{aligned} \tag{5}$$

7 Classification and regression tree

Decision tree (DT) is fundamentally a branch of hierarchical approach which is used worldwide due to its capability to cope with classification-based problems. Structure of a tree contains different parts including, root, branches, leaves and nodes. DT is an ascending way of solution in which the root is placed at the topmost of the tree. In this technique, solution process is started with selecting a random node as a potential root for the tree. Each node represents a variable of the problem in hand and is divided into two branches. Division of the nodes is done with help of one of the independent variables. It is noted that a range has to be selected during the division process using a try and error mechanism. The selected range should be such a way that model performance indices such as root mean square error (RMSE) be minimized for each and every node [59, 60].

This method is also employed for regression analysis [61–65]. Due to various merits of classification and regression tree (CART) over other decision tree algorithms, it is normally preferred to be applied by many researchers [66–68]. In this paper, Matlab software was used to predict rock fragmentation incorporating the CART method. Developed decision tree for predicting X_{50} is shown in Fig. 3.

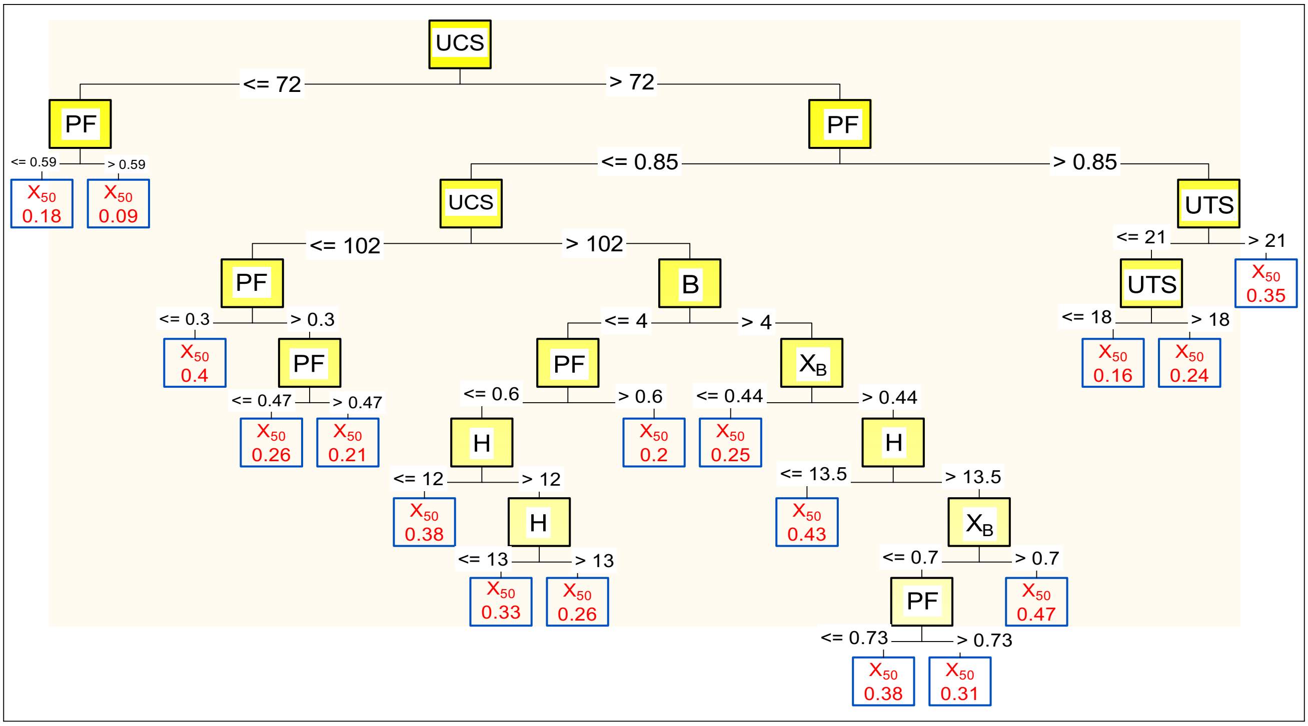

Fig. 3 Developed CART model for predicting X_{50}

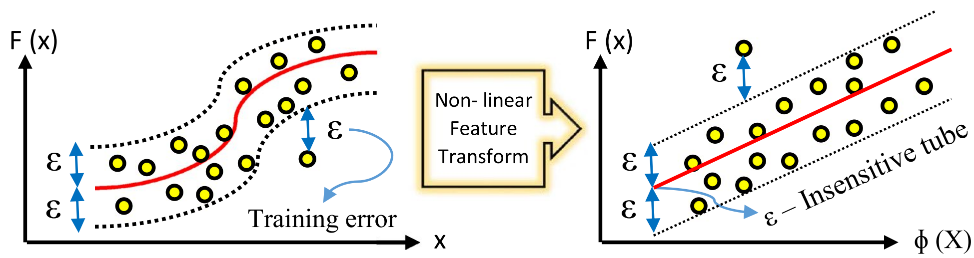

Fig. 4 Graphic description of the SVR model

8 Support vector regression

Support vector machine is applicable for solving both the classification and regression problems. In machine learning, support vector machines (SVM), which is well-known to handle structural risk minimization, is widely used in different fields of investigation [69–71]. Support vector regression (SVR), a subdivision of SVM, is suitable for dealing with interpolative and extrapolative problems using a specific predictive model. In this SVR technique, Vapnik–Chervonenkis (VC) theory is considered as the base for formulization [72–74]. Reasonable generalization reaches when VC dimension is quite low which in turn causes the error probability to be definitely low [75, 76]. Also, in this technique, a "loss function" is applied for regression estimation and function approximation. The function is defined as the difference between predicted

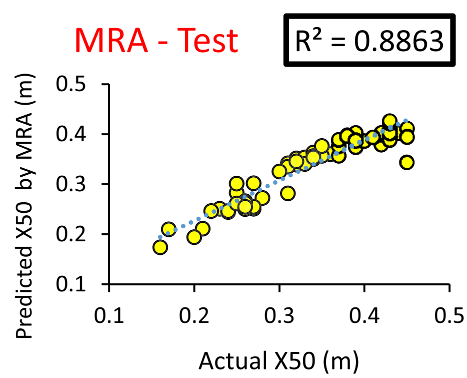

Fig. 5 Scatter plot of the predicted vs. actual X_{50} for the MRA model (test)

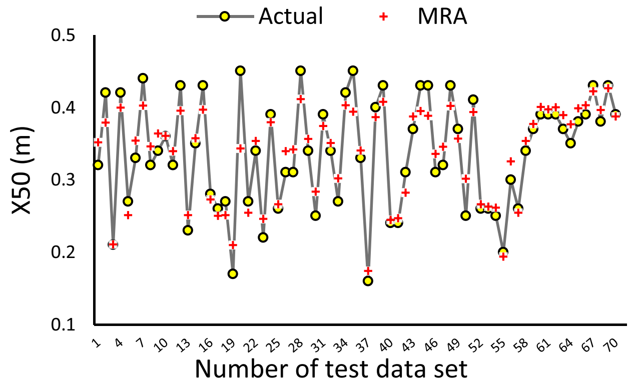

Fig. 6 Comparison of predicted and measured outputs for the MRA model

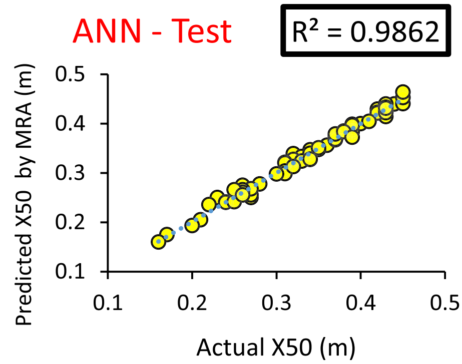

Fig. 9 Scatter plot of the predicted vs. actual X_{50} for the ANN model (test)

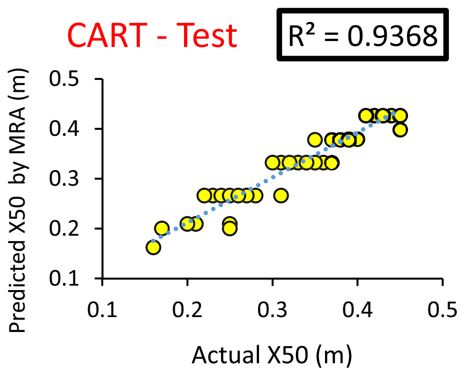

Fig. 7 Scatter plot of the predicted vs. actual X_{50} for the CART model (test)

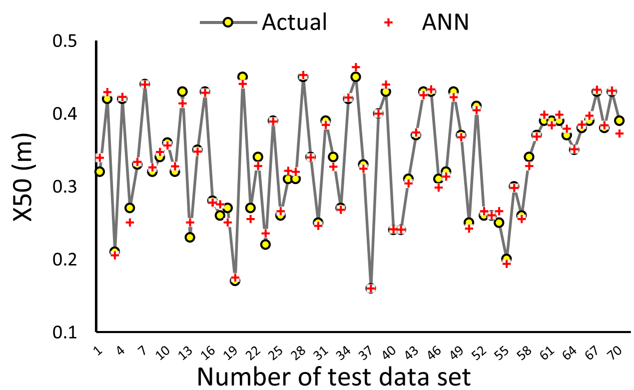

Fig. 10 Comparison of predicted and measured outputs for the ANN model

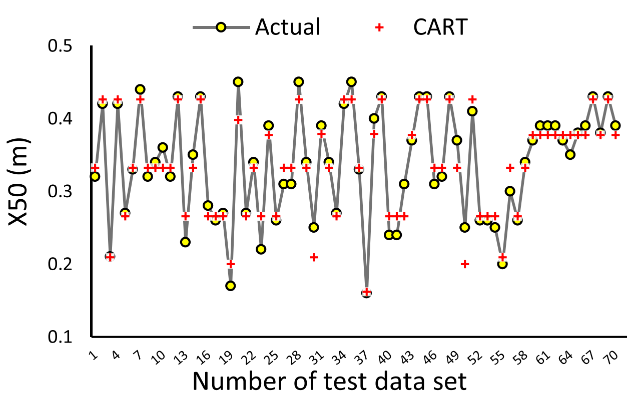

Fig. 8 Comparison of predicted and measured outputs for the CART model

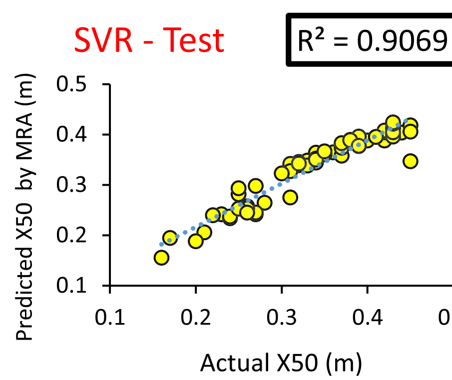

Fig. 11 Scatter plot of the predicted vs. actual X_{50} for the SVR model (test)

value and tube radius (ε). Figure 4 shows the idea of the ε-insensitive loss function. As it is seen in this figure, samples situated out of the $\pm\varepsilon$ margin, would be considered non-zero slack variables and are kept apart from computations. It is obvious that the amount of loss function would be zero within ε-insensitive tube. It is noted that further details about SVM and SVR can be found out in the literature [77].

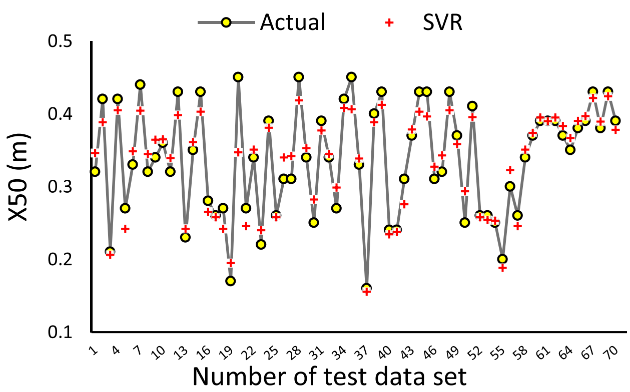

Fig. 12 Comparison of predicted and measured outputs for the SVR model

contrary, efficiency of the conventional MRA is very low amongst the other utilized models. The MRA is bound to follow some valid statistical relations, whereas ANN is unbiased and can make its own relationship based on the sample data sets and due to that it has been found that ANN gives much better results compared to MRA in complex engineering problems. Rock fragmentation is also a very complex and complicated problem, influenced by several controllable and uncontrollable factors. Furthermore, results showed that facing problems with high complexity and nonlinearity such as fragmentation modeling, non-linear methods with high flexibility such as ANN have higher capabilities compared to classical linear methods such as MRA.

9 Performance evaluation of the models

Model evaluation of the developed MRA, CART, SVR and ANN models was performed with the 70 unused data sets in development process of the aforesaid models. The correlation between predicted and measured X_{50} for all the four models are shown in Figs. 5, 6, 7, 8, 9, 10, 11 and 12. Table 5 shows the calculated values of validation indexes. According to this table, performance of the ANN model with the highest accuracy and lowest is better as compared to the other employed models. On the

10 Sensitivity analysis

Normally, sensitivity analysis is performed to evaluate the effect of input variation on the relevant outputs. There are various methods of sensitivity analysis. One of the most frequently used methods is relevancy factor (RF) which is calculated by Eq. 6 [13, 78]:

Table 5 Calculated validation indices for the ANN, MRA, SVR and CART models

Model	MAE	RMSE	VAF (%)	R^2	MAE	RMSE	VAF (%)	R^2
	Train				**Test**			
MRA	0.021	0.027	93.262	0.933	0.021	0.026	87.896	0.886
CART	0.020	0.028	93.204	0.932	0.014	0.019	93.586	0.937
SVR	0.018	0.022	95.597	0.956	0.018	0.023	90.477	0.907
ANN	0.005	0.008	99.463	0.995	0.007	0.009	98.612	0.986

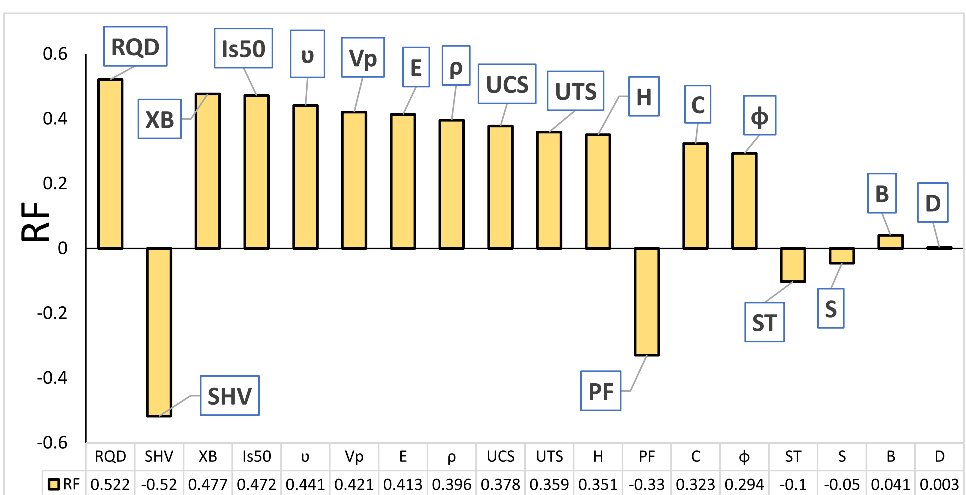

Fig. 13 Sensitivity analysis of the input variables on fragmentation

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

where $x_{l,i}$ and $\overline{x}_l$ are the ith value and the average value of the lth input variable, respectively, y_i and $\overline{y}$ are the ith value and the average value of the predicted output, respectively.

As it is seen in Fig. 13, uncontrollable parameters are more effective on fragmentation quality as compared to controllable parameters. From the uncontrollable parameters, rock quality designation, Schmidt hardness value, mean in-situ block size and point load index are more effective on rock fragmentation. Accordingly, from the controllable parameters, hole diameter, burden and spacing are the least effective on the fragmentation quality.

11 Conclusions

In this paper, artificial neural network, support vector regression, decision tree and regression analysis were implemented to investigate the effect of uncontrollable and controllable parameters on fragmentation quality in blasting operation of open pit mines. For this study, a database was prepared from four mines situated in different parts of Iran. In the first step superiority of the different models was inspected from which competence of the neural network modeling was approved. The values of MAE, RMSE, VAF and R^2 for ANN model were 0.007, 0.009, 98.612% and 0.986, respectively. In this regard, MRA modelling with the obtained values of 0.021, 0.026, 87.896% and 0.886 in the validation phase for MAE, RMSE, VAF and R^2, respectively, displayed the poorest performance. According to outcomes of the application of the network modeling, as a whole, it was concluded that in fragmentation quality uncontrollable parameters are more influential as compared to controllable parameters. Rock quality designation, Schmidt hardness value, mean in-situ block size and point load index from the former group play a vital role in the fragmentation quality and from the latter one, hole diameter, burden and spacing are the least effective parameters in this regard.

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