Prediction and Assessment of Back Break by Multivariate Regression Analysis, and Random Forest algorithm in hot strata/fiery seam of open-pit coal mine

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Research Article

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Abstract

Coal seam in mines sometimes catches fire due to its property of spontaneous heating. Drilling and blasting techniques are the most economical operation for the removal of overburden and extraction of coal in an open-pit coal mine. Blasting in a fiery seam is one the most dangerous and risky operations and various environmental and technical problems are associated with it. While blasting in a fiery coal seam, it is essential to use the minimum amount of explosive in a hole and the blast should be taken quickly. As the amount of explosive to be used must be comparatively lesser; therefore, it becomes important to perform the blasting in a manner to maximize the utilization of explosive energy. Improper utilization of energy causes back break, which is one of the technical concerns for management due to the in-stability of high wall. This study is a unique attempt to predict back break, especially in fiery coal seam through the experimental blasts and their analysis by Multivariate Regression Analysis (MVRA), and Random Forest algorithm (RFA). Total 26 blasting were conducted at open pit mine. To obtain the most optimum blast design parameter, blast design parameters were varied. The observed back break during trial blasts varies from 1.4 to 10 m. The Sensitivity analysis performed with the collected data and it has been found that stiffness ratio and stemming length are the most influential parameters on generation of back break. The MVRA and RFA analysis have been adopted for accurate prediction of back break. The results show that the RFA analysis predicts the backbreak and achieved the RMSE of ± 0.59 m while in MVRA, RMSE achieved was ± 0.99 m, making RFA more suitable method to be used for backbreak prediction in fiery seam blasting.

1. Introduction

In India, coal is a major contributor to power generation. Separation of coal from the in-situ state requires efficient techniques. The coal being the main source of energy, its demand is increasing very rapidly. The coal mines have a large production target to match the energy demand of the country. Coal has an inherent property of spontaneous heating, which causes the coal exposed for a larger time in open air burn. The seam of coal in Jharia coalfield is burning due to spontaneous heating. To break and excavate the coal out of fiery seam, the drilling blasting technique is used generally. At present, drilling and blasting are some of the cost-effective techniques for the removal of overburden (OB) and extraction of coal in open cast coal mines. Various researcher in the past have stated that only 20–30 % of explosive energy is utilized for fragmentation, and the remaining 70–80 % is used in undesirable output, i.e., ground vibration, flyrock, air overpressure, light, noise, and heat (Hajihassani et al. 2015; Ebrahimi et al. 2016a; Agrawal and Mishra 2018a).

Among all these undesirable outputs, back break is an important result of blasting, which is primarily caused by improper blast design (Agrawal and Mishra 2020). Back break is defined as the crack developed behind the last row of the production hole. It’s a significant concern for blast engineers and planners due to many reasons such as:

- Instability of high wall,

- Improper fragmentation
- Lower productivity and
- Safety.

From the literature review, it has been found that there is no particular study has been conducted to predict the back break in fiery seam blasting in coal mines of India. However, it has been recognized that various parameters influencing the generation of back break and its remedial measures have been suggested by researchers (Konya and Walter 1991; Bhandari 1997; Gates et al. 2005). Two types of parameters will influence the generation of back break, i.e., uncontrollable and controllable Parameters (Mohammadnejad et al. 2013). Uncontrollable parameters are associated with the physical and mechanical properties of a rock mass. Controllable parameters are associated with blast design and explosive parameters (Sari et al. 2014). Many researchers stated that when the length of stemming and/or burden increases, then back break also increases. Konya and Walter, (1991) stated that improper delay interval in between row to row (due to shorter delay interval, excessive confinement of gases will occur in the last row of holes) (Singh et al. 2019; Roy et al. 2020) and longer stemming length on stiff benches would generate longer back break (Agrawal and Mishra 2018b). Gates et al., (2005) stated that the leading cause of the generation of back break is shorter delay interval and when the number of rows of holes increases, then back break also increases. Monjezi et al., (2012) stated that hole depth, stemming length, spacing, and burden are the most important parameters that influence the propagation of back break (Muhammad and Shah 2017). Jimeno, Jimino and Carcedo, (1995) find out that the generation of back break is related to excessive burden and low stiffness ratio.

Previously various attempt has been made by the researcher for prediction of backbreak using multiple regression analysis (Monjezi et al. 2010; Khandelwal and Monjezi 2013) and artificial intelligence (AI) techniques such as artificial neural networks (Agrawal and Mishra, 2018; Esmaeili et al., 2012; Monjezi et al., 2013, 2014; Monjezi and Dehghani, 2008; Sayadi et al., 2013), fuzzy set theory (Monjezi et al. 2010), neuro-genetic approach adaptive neuro-fuzzy inference system, support vector machine (Monjezi et al. 2010; Khandelwal and Monjezi 2013; Mohammadnejad et al. 2013), genetic programming (Saghatforoush et al. 2016) hybrid artificial neural network and bee colony algorithm (Ebrahimi et al. 2016b), and hybrid artificial neural network and ant colony optimization. Faramarzi et al., (2013), presented a new model for risk assessment and backbreak prediction in bench blasting based on the concept of rock engineering systems (RES). Bhagade and Murthy, (2020) applied a geo engineering approach for controlling backbreak and enhancing fragmentation at dragline bench blasting. Hasanipanah and Bakhshandeh Amnieh, (2020) employed genetic algorithm and imperialist competitive algorithm for prediction and proposed RES based fuzzy approach for evaluation of backbreak. Furthermore, Sari et al., (2014) developed a stochastic model for prediction of backbreak in open pit mines based on Monte Carlo simulation technique. Based on above discussion, it seems that the RFA have not been used for prediction of BB in hot strata. Therefore, this study has been conducted to established model of RFA and to assess the performance of RFA comparing with MVRA model. In recent years this algorithm is used in different field by various researcher (Lan et al. 2020; Dong et al. 2011;

Zhou et al. 202; Bienvenido-Huertas et al. 2020; Pahlavan-Rad et al. 2020). Table 1 shows some recent work for the prediction of back break by soft computing technique

1.1 blasting in hot strata/ fiery seam

As per DGMS circular 4 (2006) blasting will be done within 2 hours, start from the first hole charging to firing and the temperature of the hole must be below than the 80° C due to safety reasons. In India various incident has been recorded due to blasting in hot strata because detonation will be done due to high temperature. For blasting in hot strata, less amount of explosive will be utilized for speedy completion of work. blasting operation. Table 1 shows some recent work for the prediction of back break by soft computing technique.

Table 1
Recent work for prediction of back break using soft computing techniques and their performances.

Reference	Technique	Input	R^2
Ghasemi, Amnieh and Bagherpour, (2016)	RT, ANFIS	B, S, ST, PF, K	$R^2_{RT} = 0.972$ $R^2_{ANFIS} = 0.998$
Ghasemi, (2017)	PSO	B, S, ST, PF, K	$R^2 = 0.98$
Saghatforoush et al., (2016)	ANN	B, S, ST, PF, HL	$R^2 = 0.83$
Shirani Faradonbeh et al. 2016	GP	B, S, ST, PF, K	$R^2 = 0.98$
Hasanipanah et al. 2017	ANFIS-PSO	B, S, ST, PF	$R^2 = 0.92$
ANN-Artificial Neural Network; PSO-Particle Swarm Optimization; RT-Regression Tree; ANFIS-Adaptive neuro-fuzzy inference system; GP-Genetic Programming; B-burden; S-spacing; ST-stemming length; PF-Powder Factor; HL-hole length; K-stiffness ratio.			

2. Site Details

The trial blast has been conducted at ASP Colliery is under administrative control of M/s Bharat Coking coalfields limited, a subsidiary of Coal India Limited. This is located in the East Jharia area, which is located in the south of Dhanbad, Jharkhand. The **Details of the blasting are as given below in** Table 2: **-**

Table 2
Details of the blasting

Parameters	Dimensions
Bench height	6.0 m
Drilling Pattern	Staggered
No. of holes per round	9 to 30
No. of rows per round	2 to 3
Hole diameter	150 mm
Detonator type	Electronic delay detonator
Hole to hole delay	25 ms
Row to row delay	92 ms
Booster	150 gm Emulsboost
Explosive type	Site mixed emulsion

3. Research Methodology And Experimental Blasting

After an intensive literature review, it has been found that the burden, spacing, stemming length, powder factor, and stiffness ratio are parameters mostly used for prediction of back break.

The trial blasts were conducted at ASP colliery, BCCL (Figure 2). The mine is fiery and the coal seam is under fire due to which the temperature of overburden (OB) rock has also increased, therefore, detailed precautionary measures while charging and firing shots has been taken. The following precautionary measures were taken:

- Temperature at the bottom of the holes has been measured accurately using laser thermometer to determine whether fire exists, holes were charged if the temperature in the hole was below 80°
- It was ensured that all Explosive, detonators and emulsion boosters were proper tested in an approved laboratory in respect of temperature sensitivity, impact sensitivity for safe handling in mines.
- No sleeping of holes was practiced to avoid any mishappening in mines due to explosive in hot strata and seam.
- The holes were charged with minimum required explosive and blasts were taken immediately after (within 2 hours) charging and other safety protocols.

For this study, 26 blasting data are collected at ASP colliery as given in Table 2.

Table 2: Trail blasts data generated at ASP colliery

Sl. No.	Burden (B)	Spacing (S)	Stemming Length (ST)	Powder Factor (PF)	Stiffness ratio (K)	Backbreak (BB)
Training dataset						
1	2.50	3.00	3.20	1.51	1.88	6.33
2	2.40	2.50	4.00	0.94	2.33	4.70
3	2.90	2.50	4.20	1.41	1.79	3.20
4	2.80	3.00	4.00	1.75	1.79	3.00
5	3.00	2.80	4.10	1.46	1.90	2.00
6	2.20	4.00	4.20	1.28	2.64	10.00
7	2.60	3.00	2.50	1.89	1.50	4.00
8	3.00	3.00	4.10	1.45	1.83	3.20
9	2.30	3.00	4.20	1.06	2.52	6.40
10	2.50	3.00	4.00	1.19	2.16	4.00
11	2.50	2.50	3.90	0.95	2.20	2.80
12	2.20	2.70	4.10	0.91	2.68	4.00
13	2.70	2.90	4.10	1.13	2.11	4.60
14	3.00	3.20	4.30	1.41	1.97	4.30
15	2.50	3.00	3.90	1.57	2.04	3.80
16	2.80	2.80	3.80	1.65	1.82	1.40
17	3.00	2.50	4.00	1.14	1.87	7.00
18	2.50	2.50	3.60	1.12	2.00	6.70
19	3.20	3.60	3.00	1.84	1.34	3.20
20	3.20	3.60	3.60	1.90	1.56	2.70
Testing Dataset						
21	3.00	2.50	4.20	1.23	1.66	3.00
22	3.00	3.50	4.00	1.84	1.87	3.10
23	2.50	2.70	4.10	1.13	2.28	3.90
24	2.20	3.00	3.70	1.12	2.41	5.00
25	2.90	3.20	4.10	1.46	1.97	3.94
26	2.40	2.60	4.00	1.00	2.33	4.00

The collected dataset has been randomly divided into two sets one is training dataset set and other is testing data set. The ratio of training and testing data set is 80-20%, i.e., 20 & 6.

For measurement of back break, a reference line / station point has been fixed at a certain distance from the last row of the blast hole and measurement of back break has been done at three point, i.e. two at the edges point and one at the middle point. For final value of back break, arithmetic mean has been taken. Measurement of back break at field is showing in Figure 3. There was an uneven generation of back break due to existing inner cracks due to the developed gallery. An attempt has been taken by considering most influential blast design parameters for prediction of back break.

4. Data Compilation And Analysis

In this study, 26 number of blasting data were used as model input parameters and the statistical information of various parameters of data collected as given in Table 3.

Table 3 Summary sheet of data collected at ASP Colliery, BCCL

Category	Parameters	Symbol	Min	Max	Mean	Standard deviation
Input	Burden (m)	B	2.20	3.20	2.68	0.31
	Spacing (m)	S	2.50	4.00	2.95	0.39
	Stemming length (m)	ST	2.50	4.30	3.88	0.41
	Powder Factor (m^3/kg)	PF	0.91	1.90	1.36	0.31
	Stiffness Ratio	K	1.34	2.68	2.02	0.33
Output	Back break (m)	BB	1.40	10.00	4.24	1.78

4.1 Prediction of Back break by Multivariate regression analysis (MVRA)

This method used for the prediction of dependent (Back break) variable through in incorporating all the independent (burden, spacing, stemming length, powder factor, and stiffness ratio) variables i.e. one or more and provide a relationship of them. This method is widely use in the field of mining to solve the various problems. This can be used for the prediction of dependent (output) variable through in incorporating all the independent (input) variables i.e. one or more and provide a relationship of them (Khandelwal and Monjezi, 2013; Monjezi et al., 2010b; Sari et al., 2014).

The equation obtained using MVRA for prediction of back break is as follows:

$$BB = 28.47 - 6.04 \times B + 4.28 \times S + 1.02 \times ST - 7.31 \times PF - 7.19 \times K \qquad \text{Eq (1)}$$

Where,

BB is Back break (m),

B is Burden (m),

S is Spacing (m),

ST is Stemming Length (m),

PF is Powder Factor (m^3/kg),

K is stiffness ratio (m/m).

Figure 4 shows the relationship between the measured and predicted back break and in MVRA the R^2 value is 0.6535 which shows poor interconnectivity.

4.2 Prediction of Back break using Random Forest Algorithm (RFA)

The Random Forest algorithm has proposed by Breiman and produces the predictions from multiple decision trees in a forest. This algorithm uses the Ensemble learning technique and based on the bagging algorithm. It creates the forest with several trees of the subsection of data and combination of all of trees will produce the output. In this model, the training data set is utilized for training the classification/regression model (Garai et al. 2018). This algorithm has various advantages such as the Random Forest algorithm can solve the classification and regression problem, handle the missing values automatically and handle nonlinear parameters efficiently (Figure 5).

Weka software is used for Random Forest classification algorithms. Weka is an extensive collection of machine learning algorithms and a beneficial data mining tool for developing a prediction model by classify the accuracy based on datasets. In this study, Kernel type filter with Random Forest classification algorithms is used. The performance of the RF shows in the “classifier output” panel.

For model training, the same training data set has been used to train the predictive model for RF, and the testing dataset used to test and validate the RFA model.

Figure 6 shows the relationship between the measured and predicted back break and in RFA the R^2 value is 0.8792 which shows good interconnectivity.

Two predictive model were used i.e. Random Forest, and Multivariate regression analysis and their results (coefficient of Determination (R^2), and Root mean square error (RMSE) mentioned at Table 4. A Graphically representation of measured back break and predicted back break by RFA, and MRA is shown in Figure 7. The prediction of back break by RFA is close to the measured back break. Sensitivity analysis was done by cosine amplitude method to get the idea for most influential parameters for generation of back break and found that stiffness ratio and stemming length are most influential parameters.

Table 4 Performance of prediction of back break by various models

Model	R^2	RMSE	Rank
MVRA	0.6535	0.99	2
RFA	0.8792	0.59	1

5. Sensitivity Analysis:

Sensitivity analysis is a technique to find out the most influential input parameters on output. For this purpose, Cosine amplitude method has been applied. The following equation has been illustrated:

$$R = \frac{\sum_{i=1}^{n}(x_i \times y_i)}{\sqrt{\sum_{i=1}^{n} x_i^2 \times \sum_{i=1}^{n} y_i^2}} \qquad (2)$$

Where, x_i, y_i, n are input, output and numbers of a dataset, respectively. The relationship in between input and output parameters are shown in Fig. 8. This figure shows that stemming length and stiffness ration are most influential parameters on BB generation.

6. Discussion

In this study, trial blasts were conducted with utmost safety in hot strata/fiery seam conditioned mining and the blasts results has been monitored. The prediction of backbreak has been done in hot strata condition. For this purpose, two technique has been used, one is MRA, i.e., statistical analysis and other is Random Forest, a branch of AI. In this analysis 26 blast were investigated in ASP Colliery, BCCL (India) and blasting parameters, namely, burden, spacing, stemming length, powder factor and stiffness ratio were recorded. Considering this as a model input parameter and backbreak is output parameters. The collected dataset has been divided into two groups, i.e., training and testing at a ratio of 80% & 20%, respectively. Statistical performance like coefficient of determination (R^2) and root mean square error (RMSE) were performed to evaluate the performance capacity of the predictive models.

Theoretically the value of R^2 and RMSE is one and zero for the best predictive models. The performance capacity of the both models has been captured in Table 4. That shows that the value of R^2 for RFA and MRA is 0.8792 and 0.6535 and RMSE is ± 0.59 m & ±0.99 m respectively. The values of RMSE revealed that the performance capacity for prediction of backbreak by RFA is superior than the MRA.

For better comparison, a graph has been plotted in between measured and predicted backbreak by RFA and MRA and represented in Fig. 7 for better understanding. A sensitivity analysis has been performed in

between inputs and output parameters that reveals that stemming length and stiffness ratio are more influential parameters for generation of backbreak.

7. Conclusion

The trials blasting conducted at hot strata/ fiery seam of ASP colliery, BCCL, a study has been conducted to precisely predict the backbreak using different techniques, the following conclusions have been drawn:

- For prediction of back break at fiery coal seam blasting, the Random Forest Algorithm technique can be used efficiently.
- From sensitivity analysis, it has been found that stiffness ratio and stemming length are most influential parameters for generation of back break. Therefore, during designing blast round these parameters must be taken in consideration.
- The MVRA model developed here in this study will help in suitable blast design modification for minimizing the back break & optimizing explosive energy for achieving required rock fragmentation and will improve the overall productivity of mines.

Declarations

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CONFLICT OF INTEREST STATEMENT

The authors declare no conflict of interest in preparing this article.

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Figures

Figure 1

Backbreak at ASP Colliery, BCCL.

Figure 2

Drilling and blasting operations on working bench

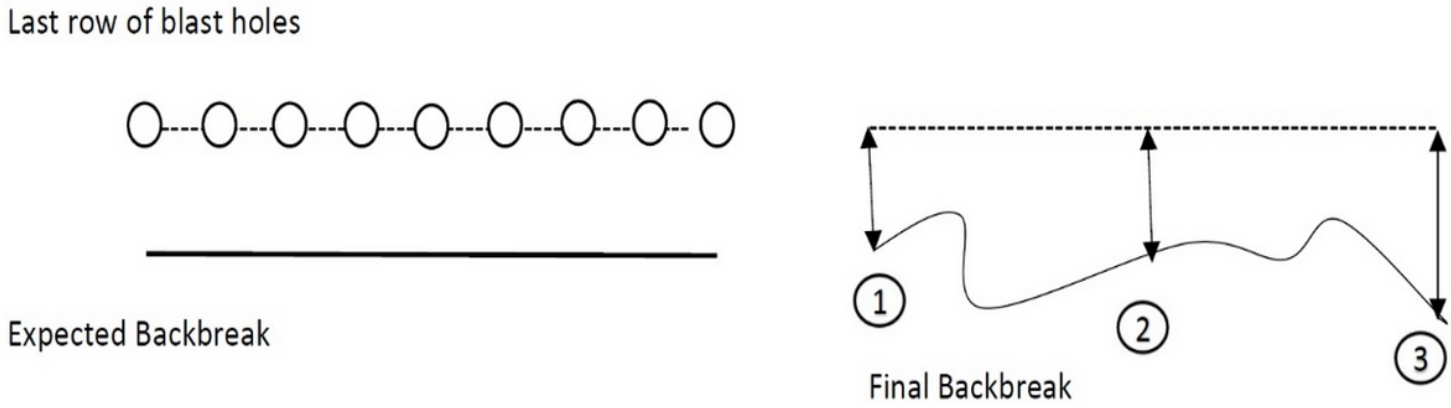

Figure 3

Measurement of back break in field (Bhagade and Murthy 2020).

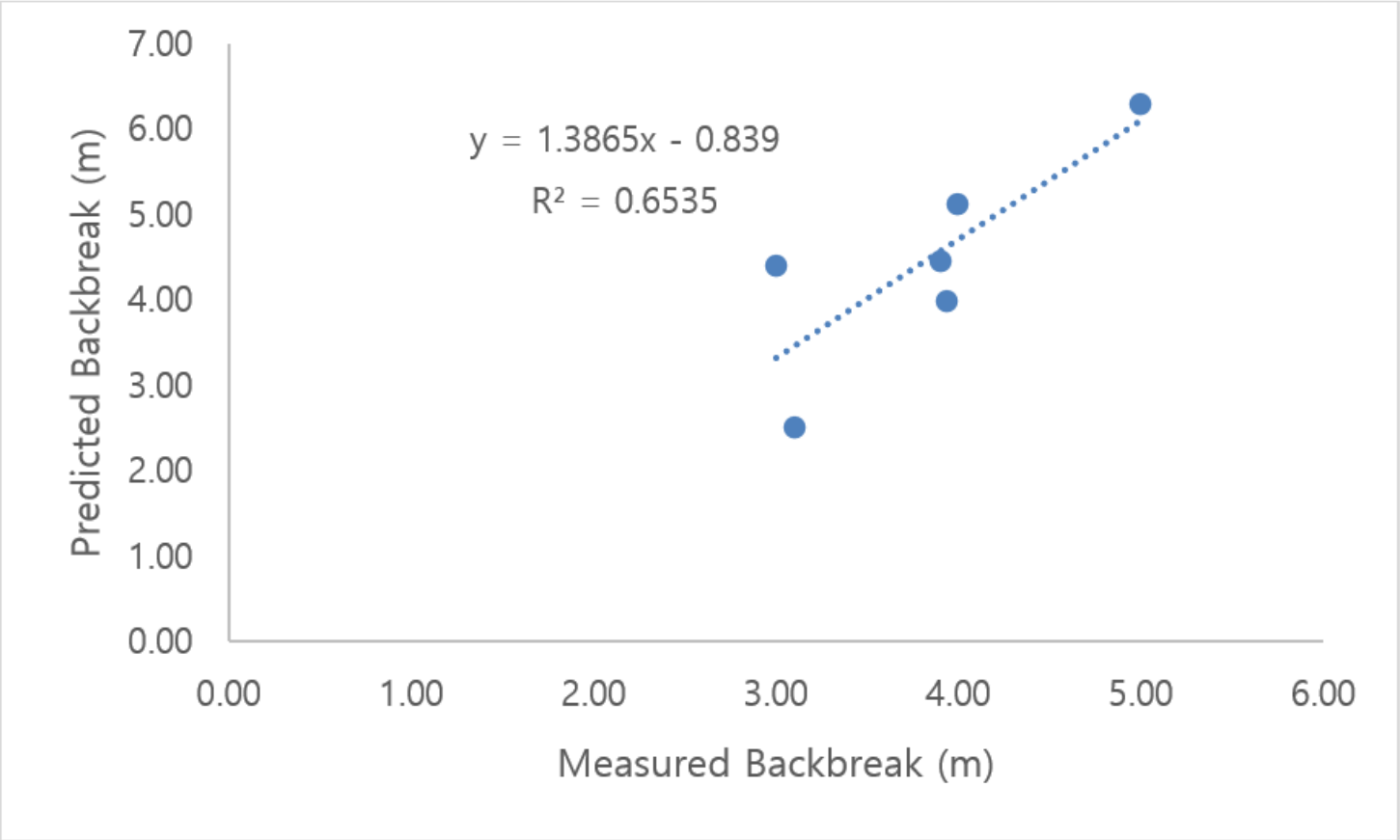

Figure 4

MVRA predicted vs. Measured back break at ASP, Colliery

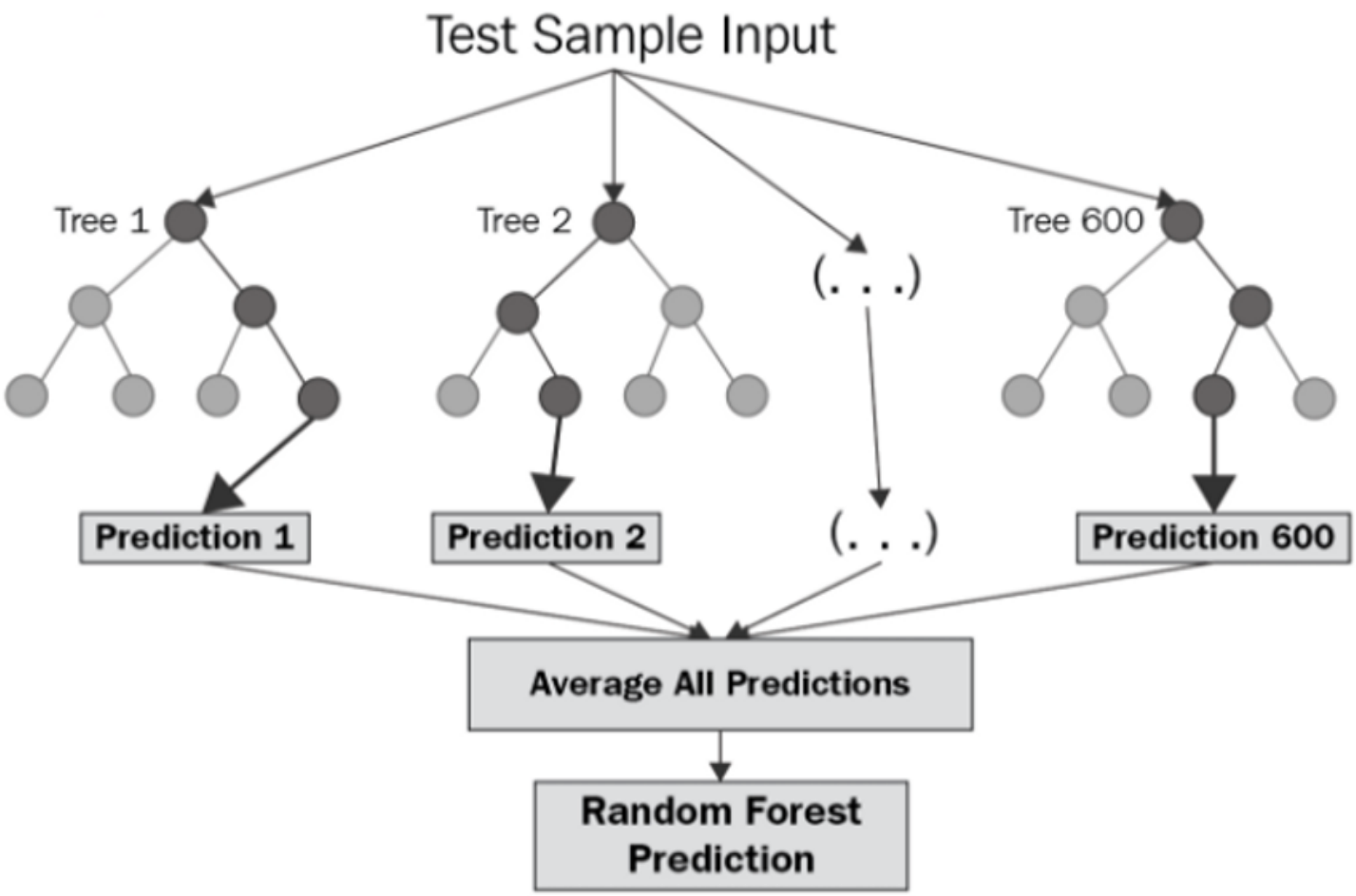

Figure 5

Model structure of RFA for prediction of Back break (Source: Internet).

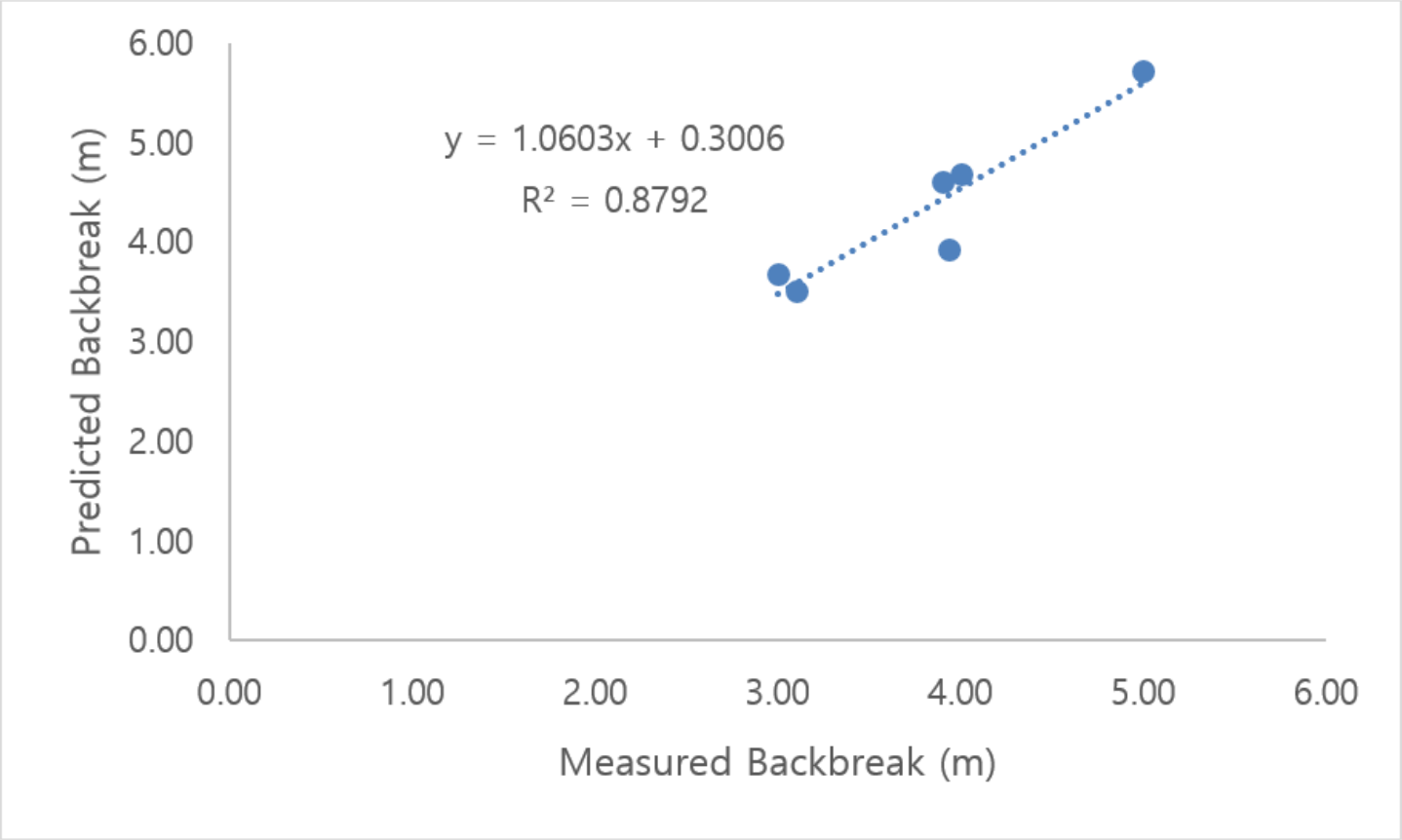

Figure 6

RFA Predicted vs. Measured back break at ASP, Colliery.

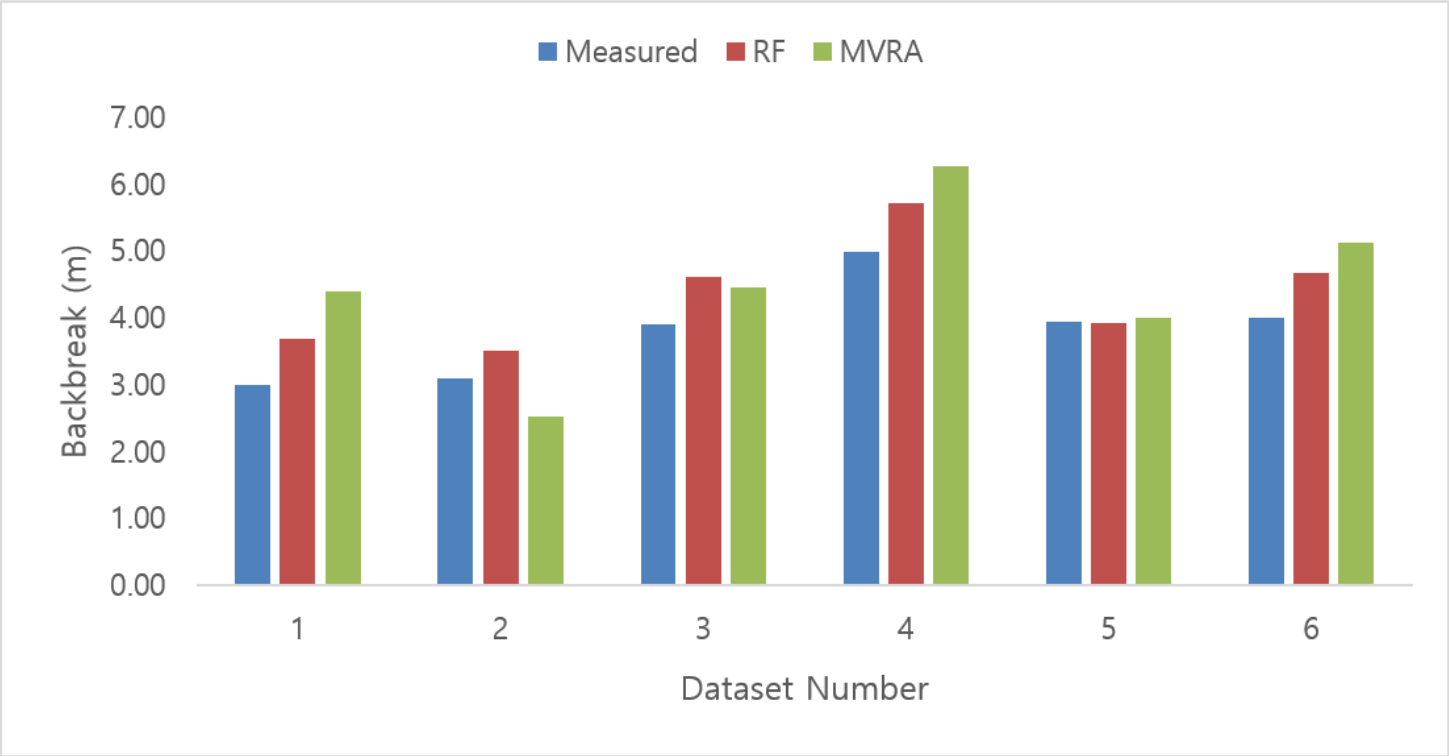

Figure 7

Representation of measured and predicted back break by MRA and RFA.

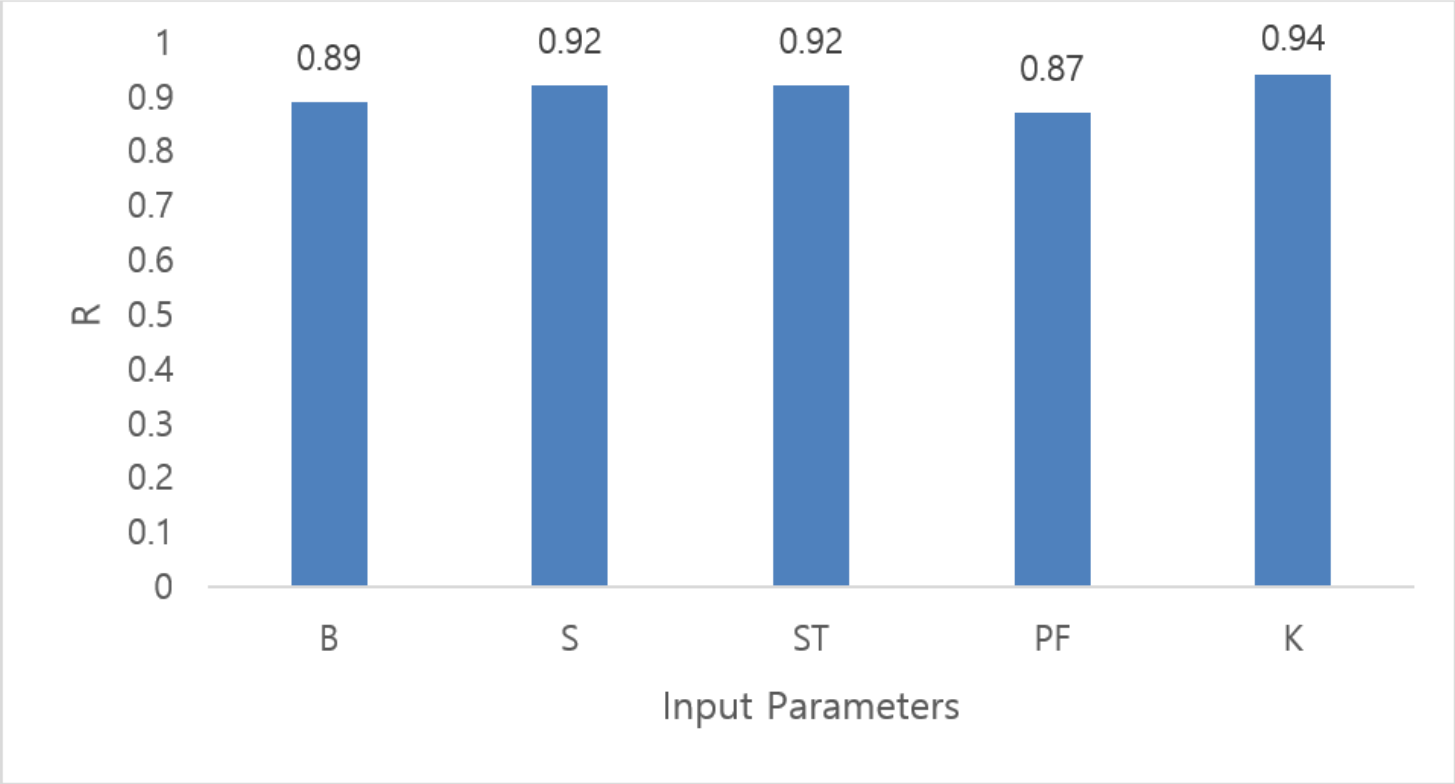

Figure 8

Relationship in between input parameters and backbreak.