Minimisation of Surface Mining Costs using Artificial Neural Network

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Abstract: *Costs of surface mining unit operations are controlled by rock fragmentation distribution. The costs can be reduced if the muck pile does not contain oversize fragments which require crushing and grinding. The oversize fragments can be reduced by adjusting the surface mine blast design so that their number in the muck pile is minimum. This paper explains the application of the Artificial Neural Network (ANN) for the minimisation of oversize fragments so that overall cost is minimum. It was observed that the trained neural network model estimated the boulder count with sufficient accuracy and it provides a feasible choice to the field engineers to optimize the blast design so that the boulder-count is the minimum and subsequently the improving the efficiency of downstream operations and their costs*

Keywords: *Artificial neural network, Blasting, Rock fragmentation, Boulder count.*

1. Introduction

Production of mineral from a mine involves a number of unit operations downstream to drilling and blasting. Drilling and blasting claim around 20% share of the total operating costs, the efficiency of other downstream operations and ultimately their costs – which account for almost 80% of the total operating cost, depend largely on the fragmentation distribution resulting from blasting. This requires the breakage in such a way that the oversize fragments are minimum. Thus, minimisation of oversize fragments (boulder) is always one of the objectives in any production blasting. The objective can be achieved by improving the efficiency of drilling and blasting. Rock fragmentation is a complex phenomenon and it depends upon many factors. These factors can be grouped in four different categories: rock geotechnical parameters such as density, hardness, compressibility; explosive parameters such as density, velocity of detonation; technical parameters such as delay interval, primer strength and location and geometrical parameters such as burden, spacing, and stemming [1]. Concept of Artificial Neural Network (ANN) has been applied to model the fragmentation [2]-[12] etc. ANN is suitable in such a case because a large number of affecting variables and their complicated mutual dependence is not reflected in the output of empirical modeling. Fragment size or as the sieve analysis of the muckpile can be obtained from the developed ANN based fragmentation models. Mining engineers are interested in knowing the boulder count so that they can plan the secondary breakage operations to reduce the downstream operation costs. Therefore an ANN model has been developed to predict the boulder count. The data sets required for the development of the model have been generated from the Limestone quarries.

2. Description Of The Sites

The ANN model described in this paper has been developed from the blast records generated from Baikunth, Hirmi, Sonadih and Rawan Limestone quarries. The quarries are situated in Raipur district of Chhattisgarh province of India and are located within a radius of 20 km. The geotechnical properties of the deposits are summarized in Table 1.

TABLE 1: Geotechnical Properties of Limestone Deposits (*Mean values).

Name of the Quarry	Uniaxial * Compressive strength (M Pa)	Density* (g/cc)	Young's * Modulus (G Pa)	Porosity* (%)	Vertical * Spacing between Joints (m)	Horizontal* Spacing between Joints (m)
Baikunth	38	2.25	46	6	1.0	0.6
Rawan	43	2.38	49	5	1.5	0.9
Sonadih	45	2.35	48	7	1.4	0.8
Hirmi	44	2.40	50	5	2.0	1.0

Thus, the deposits of the four quarries have a similar geotechnical set-up and are competent. The holes are drilled in two to three rows on staggered pattern. Row to row delay with cord relays is maintained at 50 ms whereas the delay with shock tube initiation is 42 ms. Blasts are carried out either with Ammonium Nitrate- Fuel Oil mixture or with Site-Mixed Emulsion Explosive. The other details of blast practice are given in Table 2.

TABLE 2: Blast Practice Details

Name of the Quarry	Dia (mm)	Spacing (m)	Burden (m)	Depth (m)	Explosive type	Primer	Initiation method	Secondary breakage method
Baikunth	115	5.0-6.0	3.0-4.0	8.0	ANFO	Cartridge booster/Cast booster	Cord relays	Secondary blasting/ Rock breaker
	152	6.5-7.0	4.5-5.0		SME	Cast booster	Shock tubes	
Rawan	152	7.0	4.0	8.0	SME	Cast booster	Shock tubes	Rock breaker
Sonadih	100	4.0	3.0	9.0	SME	Cast booster	Shock tubes	Rock breaker
Hirmi	115	4.0	6.0	8.0	ANFO	Cartridge booster/Cast booster	Cord relays	Rock breaker
	152	7.0	5.0		SME		Shock tubes	

3. Data Collection

Research [13] indicates that the following factors affect the fragmentation in competent rocks:

a) Explosive energy per unit volume of rock mass, i.e. specific charge

b) Explosive distribution within the rock mass

c) Type of explosive

d) Delay timing

e) Joint system and its orientation with respect to blast direction.

The specific charge is logically correlated with the number of holes/row, number of rows, average depth, average spacing, average burden and total quantity of explosive fired in one round. On the similar considerations the type of the explosive replaces the VoD and the density of the explosive. The explosive distribution is represented by the diameter of the blast hole and the stemming height. The geotechnical parameters and the delay practice were similar in the referred mines hence they have not been considered as an input variable. The input variables are therefore the number of holes per row, number of rows, average spacing, average burden, average depth, diameter, average stemming, type of the explosive and the total charge. The target variable is the boulder (size >1 m) count as the maximum feed size of the crushers of the quarries is 1 m. Three hundred blasts have been monitored to generate the records. Out of these, 191 records were used for training, 77 records for validation and 32 for testing of the ANN model. The Range of the data used for the development of the models is presented in Table 3.

TABLE 3: Range Of The Data Used For The Development Of Models

Input Variables	Value			
	Minimum	Maximum	Mean	Standard Deviation
Diameter, mm (*D*)	100	152	Not Applicable	
Average burden, m (*B*)	2.80	4.65	3.73	0.61
Average spacing, m (*S*)	3.70	6.80	4.89	0.78
Average depth, m (*H*)	7.00	9.75	8.66	0.61
Average stemming, m (*T*)	2.60	4.30	3.33	0.39
Number of holes/row (*N*)	9	57	25	8.13
Number of rows (*n*)	2	3	Not Applicable	
Type of the explosive	ANFO and SME			
Quantity of explosive fired per round, kg (*Q*)	1287	9567	4109	1897
Target variable	Value			
	Minimum	Maximum	Mean	Standard Deviation
Boulder count (*N'*)	39	250	122	45.82

4. ANN Model

The ANN model described in this paper was developed using the syntax available in ANN tool box of MATLAB. A back-propagation neural network was selected due to its simplicity and uniform approximation of any continuous function. The number of neurons in the input layer was nine and the number of neurons in the output layer was one. Levenberg–Marquardt (LM) algorithm is used for training the network because it has good generalization ability and has the capability of providing good predictions. Generally, Log-Sigmoid ((Logsig), Hyperbolic tangent Sigmoid (Tansig), Positive Linear (Poslin) and Linear (Purelin) transfer functions are used in back propagation neural network (BPNN) [10]. The network was optimised for the number of hidden layers and type of the transfer function. As a result of optimization, a BPNN model (Fig 1) with one hidden layer with two neurons in it, Levenberg-Marquardt as training function and purelin function as transfer function is finalized.

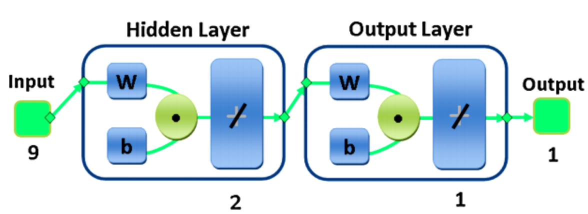

Fig 1. Developed Artificial Neural Network

152 and 100 mm diameter holes and the predictions are compared with target variables of these 32 records. The capability of the neural network is evident from Table 4 and Fig 2 and 3.

TABLE 4: Estimation Results Of Boulder Count By Ann Model

S. No.	Explosive used	Actual boulder count	Predicted boulder count by ANN	S. No.	Explosive used	Actual boulder count	Predicted boulder count by ANN
1	ANFO	94	125	17	SME	94	100
2	ANFO	99	119	18	SME	84	89
3	ANFO	148	137	19	ANFO	126	121
4	ANFO	128	131	20	ANFO	129	120
5	ANFO	113	123	21	ANFO	90	98
6	ANFO	110	120	22	ANFO	51	53
7	ANFO	144	134	23	ANFO	64	82
8	ANFO	135	139	24	ANFO	60	68
9	ANFO	139	132	25	ANFO	88	106
10	SME	70	71	26	ANFO	64	75
11	SME	61	47	27	SME	130	110
12	SME	88	102	28	SME	152	131
13	SME	39	23	29	SME	100	83
14	SME	45	24	30	SME	112	102
15	SME	66	50	31	SME	107	95
16	SME	91	89	32	SME	135	111

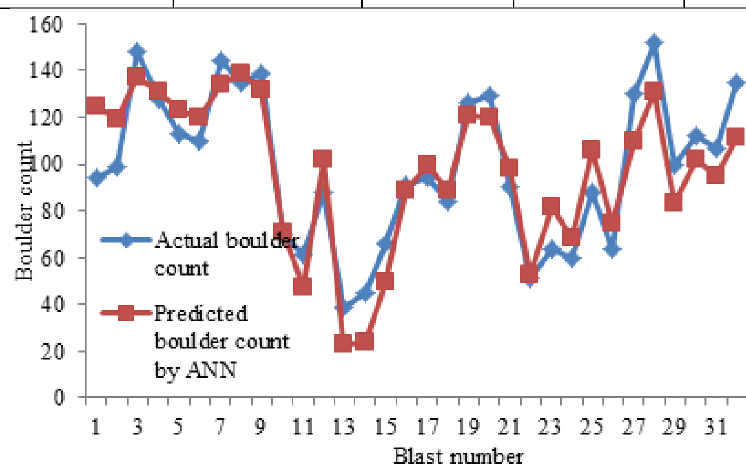

Fig 2 Predictive ability of ANN model

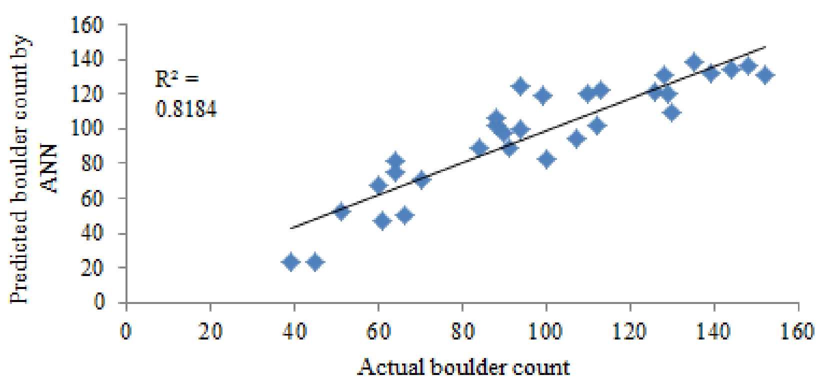

Fig. 3. Scatter obtained between the actual boulder count and the predicted boulder count by ANN.

5. Conclusion

Rock blasting is a complex operation wherein the output depends upon a number of uncontrollable parameters. Therefore an accuracy of more than 80 % in the predictions of boulder count is considered to be sufficient. It is observed that the correlation coefficient between the actual boulder count and predicted boulder count by ANN is more than 0.9; which can be considered as satisfactory. Thus, the artificial neural network seems to be a good option to predict boulder count. Different blast designs can be assessed for the boulder count. The design yielding minimum boulders can be considered as the best choice which can ultimately lead to minimum cost.

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