ISSN: 2521-2293

Prediction of blast-induced rock fragmentation at Orapa Diamond Mine using hybrid ANN models

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Abstract – This paper presents predictive models for blast-induced fragmentation at Orapa Diamond Mine in Botswana using machine learning algorithms namely artificial neural networks (ANN), particle swarm optimization artificial neural networks (PSO-ANN), and genetic algorithm artificial neural networks. A dataset consisting of 50 blasts with eight blast design parameters such as burden, spacing, hole depth, hole diameter, maximum charge per delay, stemming length, powder factor, distance from the monitoring point as input parameters, and fragmentation as the output parameter are used. The main goal of production blasting is to achieve proper fragmentation. Rock fragmentation has a direct influence on the mill throughput and diggability which in turn affect the overall mine economics. Hence accurate prediction of fragmentation is crucial in arriving at an economical outcome. Root mean square error and determination coefficient (R^2) indices were used to validate and compare the performance of the models. PSO-ANN demonstrated superiority over the other hybrid models in predicting fragmentation with the highest accuracy and lowest error. The results of sensitivity analysis showed that hole depth has the most influence on fragmentation while maximum charge per delay has the least influence on fragmentation.

Keywords - Rock fragmentation; blasting; artificial neural network; particle swarm optimisation; genetic algorithm; sensitivity analysis.

I. INTRODUCTION

The main goal of production blasting in the mining industry is to achieve proper rock fragmentation. Subsequent processes such as loading, hauling, and crushing are significantly influenced by production blasting. The quality of fragmentation is used as an indicator of the efficiency of a blast. As a result, blast design parameters play a significant role in producing the desired fragmentation [1]. Uniform particle size distribution leads to increased mill throughput due to the increased diggability of the fragmented rock that translates into the performance of the loader and excavator used. In addition, proper fragmentation eliminates the need for secondary blasting [2]. All these lead to improved overall plant or mine economics. Hence accurate prediction of rock fragmentation plays a significant role in the economies of operating the mines.

Parameters influencing rock fragmentation are divided into three categories, namely, rock mass properties, blast geometry, and explosive properties [3-6]. From the literature, there are several empirical models developed for forecasting blast-induced rock fragmentation [7-10]. Empirical models are only able to consider a few effective parameters thus making them inaccurate and unreliable. Furthermore, acquiring all the relevant effective parameters is not possible as their non-linear relationships are not known or are difficult to quantify [11-12].

To overcome the limitations of empirical models, the application of artificial intelligence techniques has been highlighted by several researchers in the field of engineering and rock mechanics [13-18]. Zhou et al. [19] predicted blast-induced rock fragmentation using artificial neural network (ANN), support vector regression (SVR), adaptive neuro-fuzzy inference system (ANFIS), adaptive neuro-fuzzy inference system combined with genetic algorithm (ANFIS-GA), and adaptive neuro-fuzzy inference combined with firefly algorithm (ANFIS-FFA). ANFIS-GA performed better compared to the other models in predicting rock fragmentation. ANN and multivariate regression analysis (MVRA) was applied in forecasting rock fragmentation by Monjezi et al. [20]. Burden-to-spacing ratio, hole diameter, stemming, total charge per delay, powder factor, maximum holes per delay, point load index, and delays between the rows were considered as inputs in their study. The ANN method showed superiority over MVRA in predicting rock fragmentation with an R^2 value of 0.985 and an RMSE value of 0.995.

Bahrami et al. [21] proposed an ANN model for estimating rock fragmentation. A four-layer neural network was found to be optimum in predicting rock fragmentation. Sensitivity analysis from the same study revealed that blastability index, charge per delay, burden, and powder factor are the most effective parameters for fragmentation. Shams et al. [12] offered a fuzzy inference system (FIS) and MVRA model for predicting rock fragmentation. The results showed that the FIS model was more accurate in predicting fragmentation than MVRA, with an RMSE of 2.423 and a variance account (VAF) of 92.195%. sShi et al. [22] predicted the mean particle size of rock fragmentation due to

ISSN: 2521-2293

bench blasting using support vector machine (SVM), MVRA, and the Kuznetsov empirical model. The prediction accuracy of SVM was more acceptable than the other methods.

Hasanipanah et al. [23] offered ANFIS combined with particle swarm optimization (PSO) model to predict rock fragmentation. In their study, SVM and nonlinear multiple regression (NLMR) methods were used. About 72 blasts were investigated, and the results showed that ANFIS-PSO is more accurate in predicting fragmentation than SVM and NLMR.

This study presents three data-driven models for predicting rock fragmentation. We used three methods, namely, ANN with gradient descend, ANN with PSO, and ANN with GA. The contributions of this paper are:

- A blast dataset consisting of 8 blast design parameters were collected from Orapa Diamond Mine, in Botswana for training and testing the models. The data sample size is 50.
- ANN is optimised by using GA and PSO to predict rock fragmentation, instead of the usual gradient descend method.
- Sensitivity analysis is conducted to determine the most effective parameters on rock fragmentation.

II. *DATA SETS*

In this study, a database consisting of 50 blasts has been collected from the Orapa Diamond Mine, in Botswana, to construct and verify the proposed PSO-ANN, GA-ANN, and ANN models. The parameters considered in this study are burden, spacing, hole depth, hole diameter, maximum charge per delay, stemming length, powder factor, and distance from the monitoring point as inputs and fragmentation as the output. The blast geometry parameters are shown in Fig. 1. Split desktop software was used to analyse the images obtained using a digital camera. Before implementing the modelling process, the data was first pre-processed which included cleaning and normalisation. It was then divided into train and test sets, 80% and 20%, respectively. Table 1 shows the range of parameters used in this study.

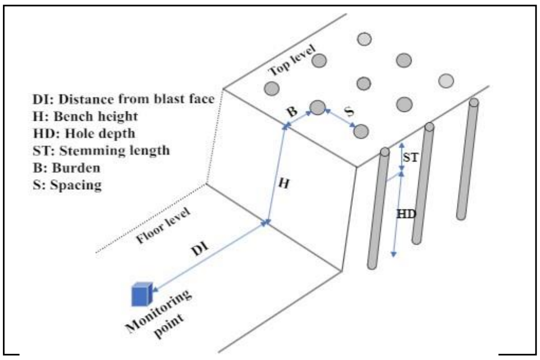


Fig. 1. Schematic Diagram of Blast Geometry

I. *METHODS*

Hybrid algorithms are used that combine the search properties of ANN with that of PSO and GA algorithms as a way of optimizing its performance in solving the given problem.

TABLE I. THE RANGE OF THE INPUT AND OUTPUT PARAMETERS

Parameter	Type	Unit	Symbol	Min	Max
Burden	input	m	B	4	8
Spacing	input	m	S	4	7
Stemming length	input	m	St	4	8
Hole depth	input	m	HD	12.28	16.29
Hole diameter	input	mm	D	127	250
Distance - blast face	input	m	DI	438	1500
Charge per delay	input	kg	MC	27	61.4
Powder factor	input	kg/m^3	Pf	0.3	1
Fragmentation	output	%	F	70	81

A. *ARTIFICIAL NEURAL NETWORKS*

The machine learning algorithm ANN was initially introduced by McCulloch and Pitts in 1943 and it has gained popularity due to the rise in computing capacity [24]. ANNs are inspired by the way neurons in the human brain process information. Three main constituents make up a typical ANN, namely, the network architecture, the transfer function, and the learning rule [25]. A simple neural network architecture consists of neurons in three layers (input, hidden, and output), connected by weights. The weighted total of the inputs and the bias is computed using a transfer function. After the transfer function computes the sum, the activation function gets the outcome and provides threshold values over which the neurons of the network will fire. The most applied learning rule for training ANNs is the backpropagation (BP) algorithm [26]. In the BP-ANN, input data is first forward propagated in the input layer, through the hidden layer, to the output layer. The error is computed in the output layer by taking the difference between the actual and predicted output as shown in (1)

$$E_n = \frac{1}{2}\sum_{n=1}^{n}\sum_{i=1}^{i}(A_{ni} - P_{ni})^2 \quad (1)$$

where A_{ni} and P_{ni} are actual and predicted values of the ith neuron, i is the total number of neurons, and n is the dataset number.

The result is then backpropagated to update the individual weights as shown in (2) and (3). The process is iterated until the error is minimised [27]

$$\Delta W_{jk} = \mu \frac{\delta E_n}{\delta W_{jk}} Out_k \quad (2)$$

$$W_{jk}^{new} = W_{jk}^{old} + \Delta W_{jk} \quad (3)$$

where Out_k is the output of the kth neuron, u is the learning rate, and E_n is the mean square error (MSE) of the ANN.

B. PARTICLE SWARM OPTIMISATION

Kennedy and Eberhart et al. [28] are credited with developing PSO, which was first designed to simulate social behaviour by mimicking the movement of a flock of birds or a fish school. A population of potential solutions, called particles are used to solve the problem, and these particles are moved across the search space over the particle's position and velocity ~~shown~~ expressed in equations (4) and (5)

$$V_{new} = \mathrm{wV} + \mathrm{r}_1\mathrm{C}_1 * (\mathrm{P}_{best} - \mathrm{X}) + \mathrm{r}_2\mathrm{C}_2 * (\mathrm{G}_{best} - \mathrm{X}) \quad (4)$$

$$X_{new} = \mathrm{X} + \mathrm{V}_{new} \quad (5)$$

where Vnew, X, and V are the new velocity, current position, and current velocity of particles, respectively. The symbol w is the inertial weight coefficient, and r_1 and r_2 are random values in the range (1,0). The symbols C_1 and C_2 are predefined acceleration coefficients, P_{best} is the particle's personal best position, and G_{best} is the global best position among all particles.

In addition to being led toward the best-known positions in the search space, which are updated as other particles find better positions, each particle's movement is also influenced by its local best-known position. The swarm migrates toward a better solution as a result of this [29]. PSO is a metaheuristic because it can search very huge areas of potential solutions and makes little to no assumptions about the problem being optimised.

1) Implementation of PSO-based ANN:

According to Jadav and Panchal [30], ANN has the drawback of getting stuck in local minima. PSO can search a much wider space and find global minima. Therefore weights and biases of the neural network are updated using the best positions found by the PSO algorithm.

C. *GENETIC ALGORITHM*

Holland [31] introduced a genetic algorithm that is normally employed as a method for optimisation and stochastic search. GA was influenced by Charles Darwin's theory of natural selection. The selection of the fittest individuals in a population is the first step in the process of natural selection. They give birth to offspring who carry on their parent's traits and will be added to the following generation. Parents who are more physically fit will produce offsprings who will outperform the offspring from parents who are not as fit and have a higher chance of surviving [32]. The fittest generation will eventually emerge because of this process' continual iterations. The algorithm terminates when the population has converged (does not produce offspring which are significantly different from the previous generation) [33]. Five phases are considered in a genetic algorithm. These are:

- Initial population - The process begins with a set of individuals which are known as a population. These individuals are a potential solution to the problem. Genes are a set of parameters (variables) that define an individual. A chromosome (solution) is made up of a string of genes.
- Fitness function - The fitness function gauges an individual's level of fitness which is the ability of an individual to compete with other individuals. Based on its fitness score, an individual's likelihood of being chosen for reproduction is determined.
- Selection - The purpose of the selection phase is to choose the fittest individuals based on their fitness ratings and allow them to pass on their genes to the following generation.
- Crossover - A crossover point is picked at random from the genes for each set of parents to mate. A crossover can be a single point or double point. Parents' genes are exchanged among one another until the crossover point is achieved, at which time the offsprings are produced.
- Mutation - Some of the newly produced offspring's genes are subjected to a low-probability random mutation. When using binary values, mutation entails changing string 1 to 0 and string 0 to 1. To preserve variety throughout the population and avoid early convergence as mutation takes place.

2) Implementation of GA-based ANN

ISSN: 2521-2293

The algorithm GA has the significant advantage of being able to perform a multidirectional search and avoid being trapped in local optima [34-35]. Therefore, the weights and biases are updated using GA.

II. *RESULTS AND DISCUSSIONS*

To assess the performance of all the models, the determination coefficient (R^2) and the root mean square error (RMSE) were utilised as the performance indices. These are expressed by equations (6) and (7):

$$R^2 = \left[\frac{\sum_{i=1}^{N}(y-\tilde{y})(y'-\tilde{y}')}{\sum_{i=1}^{N}(y-\tilde{y})^2 \sum_{i=1}^{N}(y'-\tilde{y}')^2}\right]^2 \quad (6)$$

$$\text{RMSE} = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(y-y')^2} \quad (7)$$

where y and y' are measured and predicted values, respectively; ỹ and ỹ' are mean measured and mean predicted values, respectively and N is the dataset number.

A good RMSE is a value close to or equal to 0 while a good R^2 is a value close to or equal to 1. Table 2 summarises the performance indices for all the models with their hyper-parameters. It is observed that the PSO-ANN model with 30 particles and 10 neurons in the hidden layer gives the highest R^2 value of 0.88 and the lowest RMSE of 1.97 compared to other models. It is therefore considered the optimum model for predicting rock fragmentation. A comparison is shown between the measured and predicted fragmentation by all models in Fig. 2.

The predicted results of the PSO-ANN model are in close agreement with the actual rock fragmentation, proving the capability of this model in forecasting blast-induced rock fragmentation compared to other models. Figs. 3 to 5 show the correlations between the measured and predicted fragmentation by all the models. Most of the data points are close to the line of best fit for the PSO-ANN model compared to other models indicating that it gives the highest correlation and highest accuracy than other models. Fig. 3 shows that the ANN model data points are the farthest from the line of best fit showing that the ANN model gives the lowest correlation and accuracy. Hence the performance of the ANN is significantly improved by being optimised by PSO.

TABLE II. PERFORMANCE INDICES FOR ALL THE MODELS

GD-ANN			GA-ANN			PSO-ANN		
Neurons	*R^2*	*RMSE*	*Population*	*R^2*	*RMSE*	*Particles*	*R^2*	*RMSE*
10	0.81	2.56	10	0.63	1.54	10	0.78	2.90
	0.77	2.81	20	0.52	2.30	30	0.88	1.97
	0.52	2.92	40	0.84	2.45	60	0.73	2.88
	0.61	3.67	60	0.61	4.89	90	0.65	3.61
12	0.75	2.78	10	0.65	3.66	10	0.79	2.63
	0.68	3.05	20	0.59	3.90	30	0.62	2.99
	0.63	3.97	40	0.40	4.11	60	0.54	3.43
	0.54	4.21	60	0.47	4.26	90	0.56	3.73
14	0.63	4.16	10	0.46	2.29	10	0.63	3.41
	0.66	4.23	20	0.48	3.45	30	0.59	3.66
	0.51	4.66	40	0.40	3.98	60	0.65	4.05
	0.44	3.54	60	0.39	3.67	90	0.60	4.11
16	0.61	4.27	10	0.43	4.24	10	0.55	4.72
	0.55	4.39	20	0.50	4.55	30	0.48	4.23
	0.43	4.51	40	0.55	4.73	60	0.45	4.56
	0.38	5.67	60	0.41	4.12	90	0.52	4.79

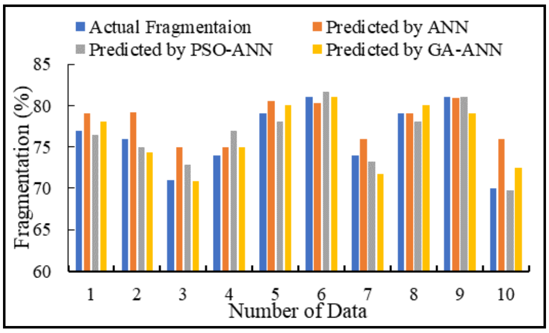
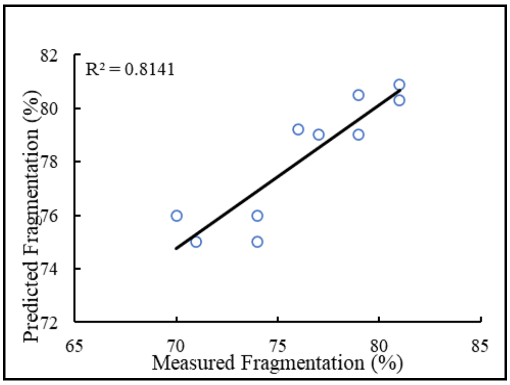


Fig. 2. Comparison of the Measured and Predicted Fragmentation by all the models



ISSN: 2521-2293

Fig. 3. ANN Model Performance

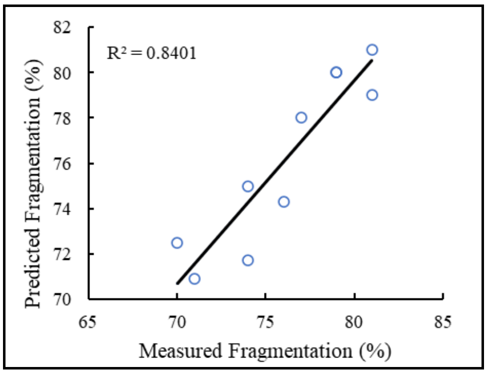


Fig. 4. GA-ANN Model Performance

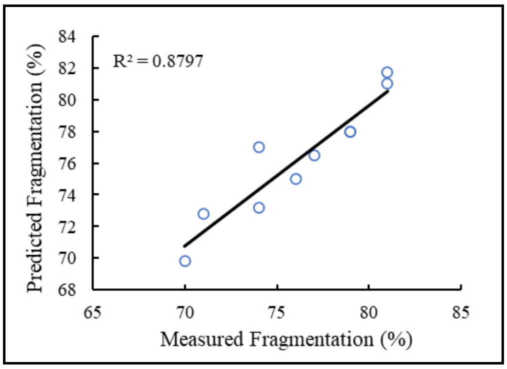


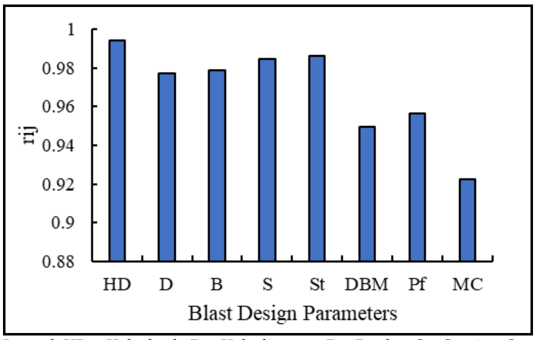
Fig. 5. PSO-ANN Model Performance

III. SENSITIVITY ANALYSIS

Sensitivity analysis is conducted using the cosine amplitude method [36]. It is used to determine the relative influence of the input parameters on the output. This can be calculated using equation (8) and the calculated results are plotted in Fig. 6

$$R_{ij} = \frac{\sum_{k=1}^{m} x_{ik} x_{jk}}{\sqrt{\sum_{k=1}^{m} x_{ik}^2 \sum_{k=1}^{m} x_{jk}^2}} \quad (8)$$

where X_i and X_j are the input and output parameters respectively, and m represents the number of data samples.



Legend: HD = Hole depth, D = Hole diameter, B = Burden, S = Spacing, St = Stemming, DBM = Distance from blast point, Pf = Powder factor and MC = Maximum charge per delay.

Fig. 6. Strength of Relation Between Input and Output Parameters

From Fig. 6, it can be inferred that hole depth is the most effective parameter on fragmentation while maximum charge per delay is the least influential parameter on fragmentation.

IV. CONCLUSIONS

In this paper, a PSO-ANN model was developed for forecasting blast-induced rock fragmentation at Orapa Diamond Mine in Botswana. In this regard, blast design parameters as well as rock fragmentation of 50 blasting operations were used. For comparison purposes, ANN and GA-ANN models were also developed using the same dataset. The blast design parameters considered in this study for predicting rock fragmentation are burden, spacing, hole depth, hole diameter, the maximum charge per delay, powder factor, stemming length, and distance from the blast point to the monitoring point. It was observed that the PSO-ANN model is more efficient in predicting fragmentation than ANN and GA-ANN. The R^2 and RMSE values obtained for the PSO-ANN model are 0.88 and 1.97 respectively, while the values for the least performed ANN model were computed as 0.38 and 5.67 respectively. The results of sensitivity analysis indicated that maximum charge per delay is the most influential parameter on rock fragmentation while hole depth is the least effective parameter on fragmentation.

ACKNOWLEDGMENT

The authors wish to extend their appreciation to the Debswana Diamond Company, Project No. P00064 for making this research possible. The authors would also like to thank Orapa Diamond Mine for providing the required data for this research.

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