Prediction of Flyrock in Boulder Blasting by Using Artificial Neural Network

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ABSTRACT

Rock mass is blasted to break it into smaller pieces such as in most surface mining, quarrying operation, dimensional stone mining and some civil engineering application. Flyrock is one of the most hazardous side effects of blasting operation in surface mining. This phenomenon can be considered as the main cause of casualties and damages. The aim of this study is to compare the actual distance of flyrock with the prediction suggested by empirical methods and by using Artificial Neural Network. In addition, this study is also aimed to investigate the most significant input parameters that affecting the flyrock. During this study, flyrock projections for 16 granitic boulders were monitored at Ulu Tiram-quarry site. Blasting parameters such as amount of explosive used, burden, stemming, hole depth, hole angle and hole diameter were carefully measured and recorded. By using these data and applying MATLAB (Matrix Laboratory) program (neural network toolbox), the flyrock distances were predicted for similar condition. The result shows that the coefficient of correlation between the actual and the predicted flyrock distance based on empirical methods is insignificant that is around 0.2. However the result revealed that the coefficient of correlation for overall analysis of flyrock distance is 0.92 based on ANN method. Based on Max-Min method powder factor, stemming and charge length are the most significant parameters in controlling the flyrock distance. This study found that ANN method produced a more accurate prediction than the empirical methods in assessing the actual flyrock projection.

KEYWORDS: Blasting, boulders, hazard, flyrock assessment, MATLAB, Artificial Neural Network.

INTRODUCTION

In civil engineering, rock is removed to create structures such as tunnels, hydraulic channels or caverns, or deep excavation at the ground surface for road cuts, foundation or basements (Bhandadari, 1997). Blasting—the controlled use of explosives to excavate rock—has been part of construction engineering for hundreds of years. Most primary blasting, whether on surface or underground, will leave some oversize boulders. Secondary blasting includes blasting carried out during bench toe leveling and bench sloping, oversize boulders breakage. Blasting has some environmental impact such as ground vibration, air blast, dust and fumes and flyrock. Flyrock, propelled rock fragments by explosive energy beyond the blast area, is one of the undesirable phenomena in the mining blasting operation (Stojadinovic et al. 2011), any mismatch between distribution of explosive energy, mechanical strength of rock mass and charge confinement can be cause of flyrock (Bajpayee et al. 2004).

The study will be included using blasting parameters data for flyrock distance that were measured at a granite quarry Ulu Tiram, Johor. In that site secondary blasting has occurred. During this study, flyrock projections for 16 boulders were monitored. Blasting parameters such as amount of explosive used, burden, stemming, hole depth, hole angle and hole diameter were carefully measured and recorded. The volume of boulders were approximately between 2.1 (m^3) to 4.2 (m^3). Maximum and minimum flyrock distance were 240 (m) and 160 (m).

Based on this study real data is going to be compared with experimental methods and also effect of different parameters on flyrock will be investigated which is done through the process of neural network. Aghajani-Bazzazi et al. (2007), Monjezi et al. (2009) and Rezaei et al. (2010) are those who worked on prediction of flyrock distance by using neural network before.

STUDY METHODOLOGY

This study is divided into three stages, the first stage involved the data collection, in this stage flyrock distances were measured by measuring tape. Second stage was calculation by empirical methods and the third stage deals with MATLAB software (neural network toolbox).

Analysis by Empirical Methods

In this study, empirical methods were obtained figure and formula. Lundborg et al. (1975) used a semi-empirical approach to estimate flyrock throw distance. Based on conservation of momentum and the scaling laws of spherical charges a relationship between charge diameter d and rock velocity V was obtained. Once V is known then the flyrock range (L_m) is calculated from the equation of ballistic trajectories. Lundborg et al. (1975) proposed $L_m = 260\ d^{2/3}$. Where L_m is in meters and d is hole diameter in inches. In another experimental study agreement between theory and experiment has been found to be reasonable. The diameters (ϕ) of these stones are $\phi = 0.1\ d^{2/3}$. Where ϕ is in meters and d is in inches.

One of the most extensive study of the distance that flyrock is thrown was conducted by Lundborg (1981). His work was based on the observations that the flyrock distance and exit velocity were proportional to be specific charge or powder factor. The results of Lundborg's work is shown in below (Figure 1). The maximum throw distance, L is shown to be a function of hole diameter d and flyrock diameter, ϕ, in meters.

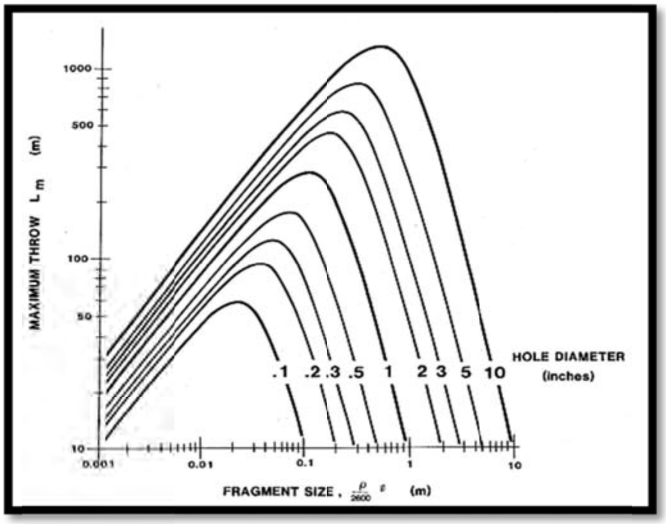

Figure 1: Relationship Between Fragment Size and Maximum Throw

Artificial Neural Network Method

An artificial neural network (ANN), usually called neural network (NN), is a mathematical model. Every neural network is formed in three layers, called the input layer, hidden layer, and output layer. Each layer consists of one or more nodes. The lines between the nodes indicate the flow of information from one node to the next. Input layer is actually shows different features of data base and output is the target of the each study. Hidden layer makes an equation that can be calculated output layer from input layer. Input layer includes 8 parameters and feed-forward network was designed which had two hidden layers with Different neurons in the first and second layer, and then the output layer is flyrock distance in one layer. The structure of neural network system is shown in below (Figure 2).

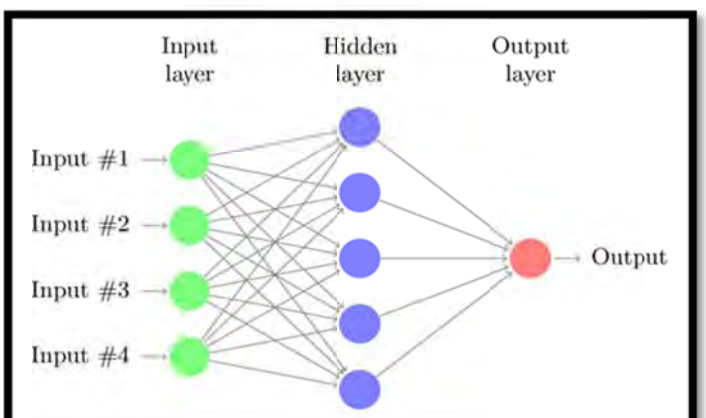

Figure 2: Structure of Neural Network

RESULTS OF GEOSTRUCTURAL CHARACTERIZATION

Using Empirical Formula

By using fragment size from the site and also using empirical formula the flyrock distances will be calculated (Table 1).

Table 1: Comparison Between Actual Flyrock and Estimated by Empirical Formula in (km)

Dataset Number	Fragment Size (cm)	Actual Flyrock Distance (km)	Flyrock Distance by Empirical Formula (km)
1	5.1	0.195	0.134
2	4.8	0.210	0.126
3	4	0.18	0.106
4	4.3	0.2	0.113
5	3.5	0.21	0.092
6	3.3	0.175	0.086
7	3	0.24	0.08
8	5.8	0.16	0.153
9	4.5	0.22	0.119
10	5.5	0.205	0.143
11	4	0.185	0.106
12	3.5	0.17	0.092
13	3.1	0.225	0.083
14	3	0.225	0.08
15	6	0.175	0.157
16	5.6	0.19	0.146

According to Table 1, the values of actual flyrock distance are much more than the values of flyrock distance by formula. For better understanding the values of actual flyrock distance and flyrock by formula and also correlation between them are shown in Figure 3 and Figure 4. From Figure 4, it is seen that the coefficient of correlation is very low.

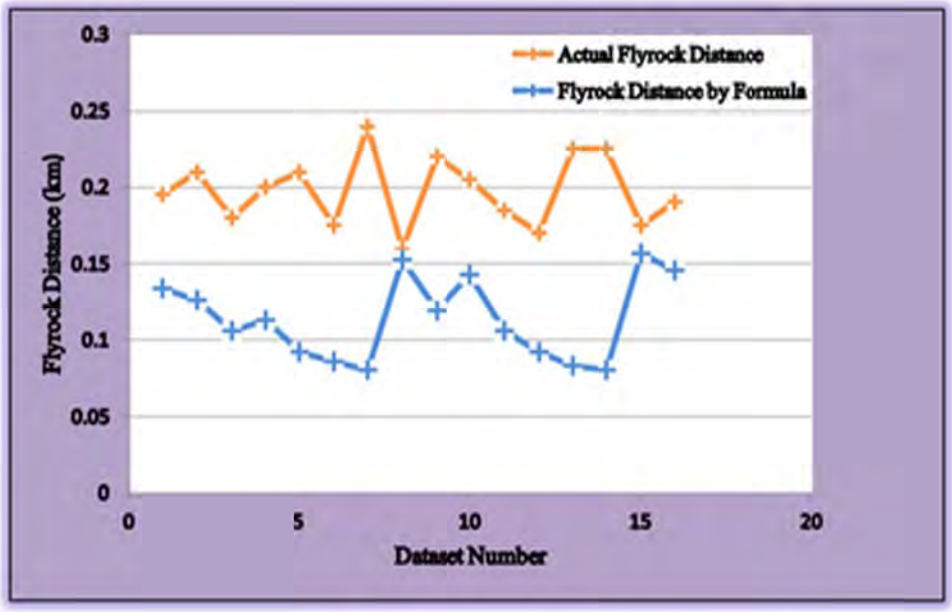

Figure 3: Actual Flyrock Distance and Flyrock Distance by Formula

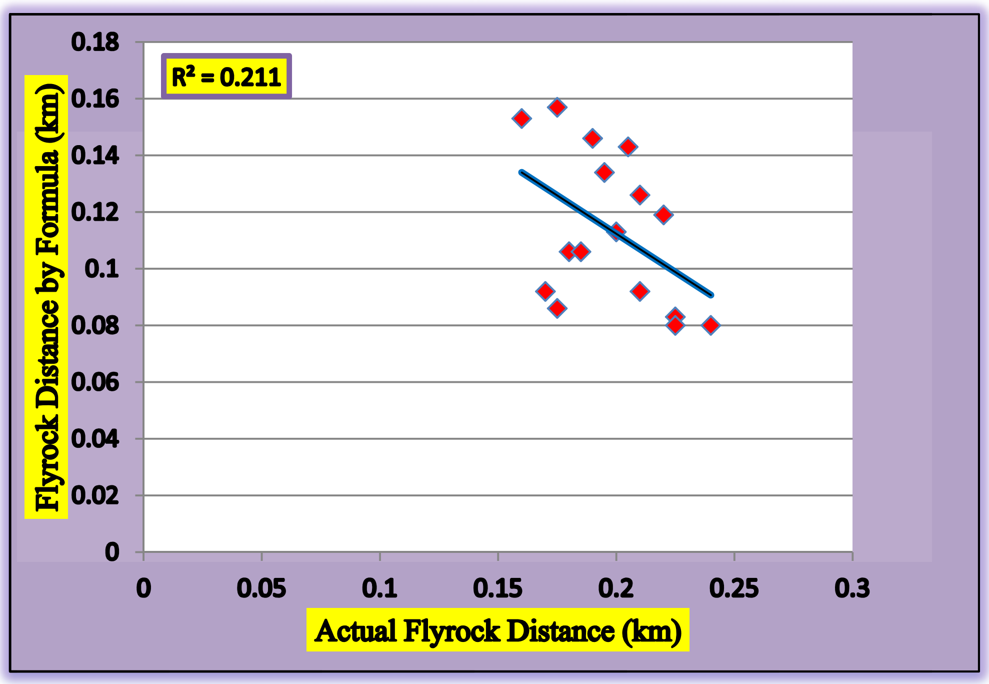

Figure 4: Correlation Between Actual and Formula Flyrock Distance

Using Empirical Figure

By using fragment size, hole diameter (8.9 cm ≈ 3.5 inches) and Figure 1 maximum throw can be found and shown in Table 2 which will be compared with actual flyrock distance.

Table 2: Comparison Between Actual Flyrock and Estimated by Empirical Figure in (km)

Dataset Number	Actual Flyrock Distance (km)	Flyrock Distance by Using Figure (km)
1	0.195	0.32
2	0.210	0.314
3	0.18	0.29
4	0.2	0.3
5	0.21	0.27
6	0.175	0.26
7	0.24	0.25
8	0.16	0.336
9	0.22	0.306
10	0.205	0.325
11	0.185	0.29
12	0.17	0.27
13	0.225	0.254
14	0.225	0.25
15	0.175	0.34
16	0.19	0.332

As shown above, it is clear that maximum throws by using figure are much more than the actual flyrock distance. For better understanding the values of actual flyrock distance and flyrock by using figure and also correlation between them are shown in Figure 5 and Figure 6. From Figure 6, it is seen that the coefficient of correlation is very low.

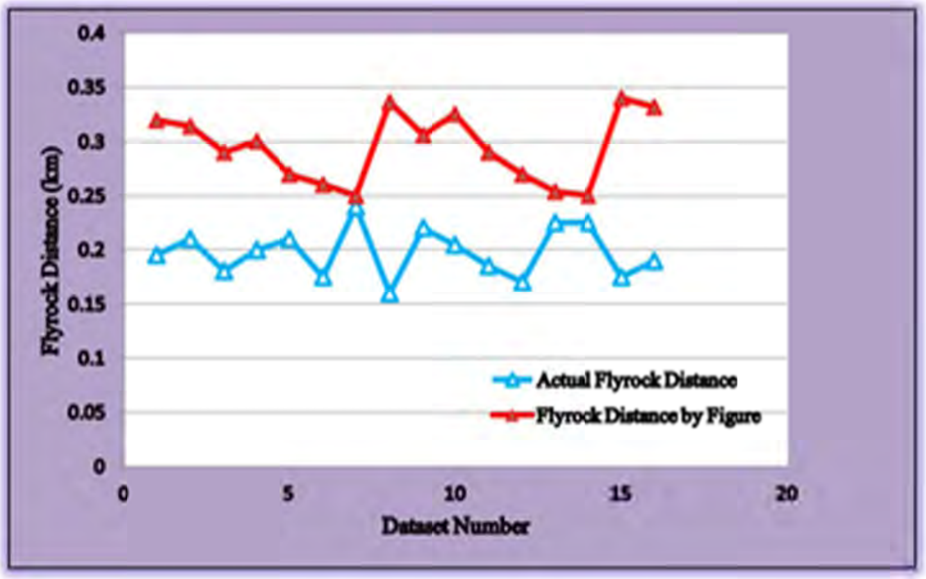

Figure 5: Actual Flyrock Distance and Flyrock Distance by Figure

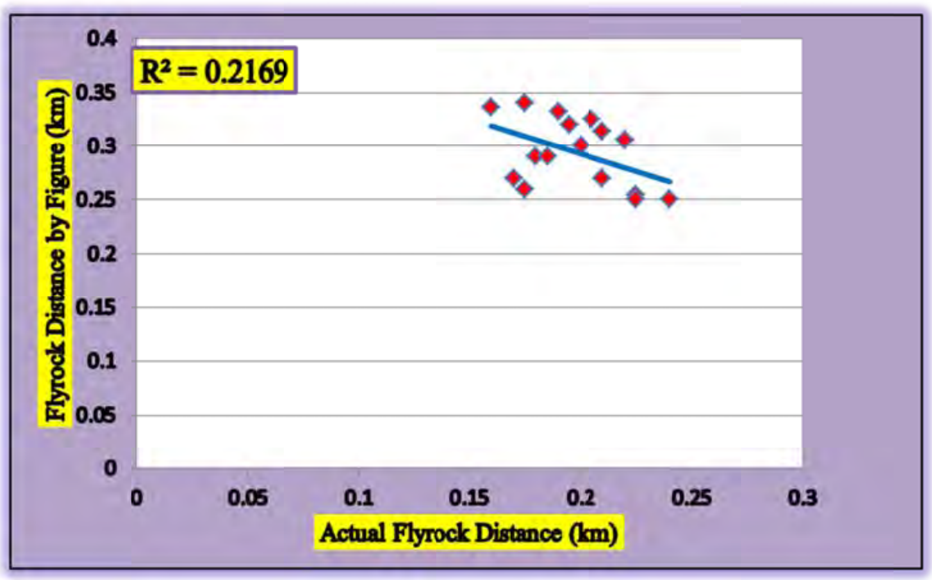

Figure 6: Correlation Between Actual and Figure Flyrock Distance

Artificial Neural Network Analysis

Neural network has analyzed the flyrock distance by input and output layers. Input layer includes 8 parameters (hole diameter, hole depth, burden, stemming height, hole angle, charge length, explosive per hole and powder factor) and feed-forward network was designed which had two hidden layers with 15 and 15 neurons in first and second layer, then the output layer is flyrock distance in one layer.

Figure 7 demonstrates the regression analysis carried out between the network response and their corresponding actual data that yielded the correlation coefficients 1, 0.47521 and 0.9994 for training, validate and test subsets respectively and 0.95864 for the overall analysis.

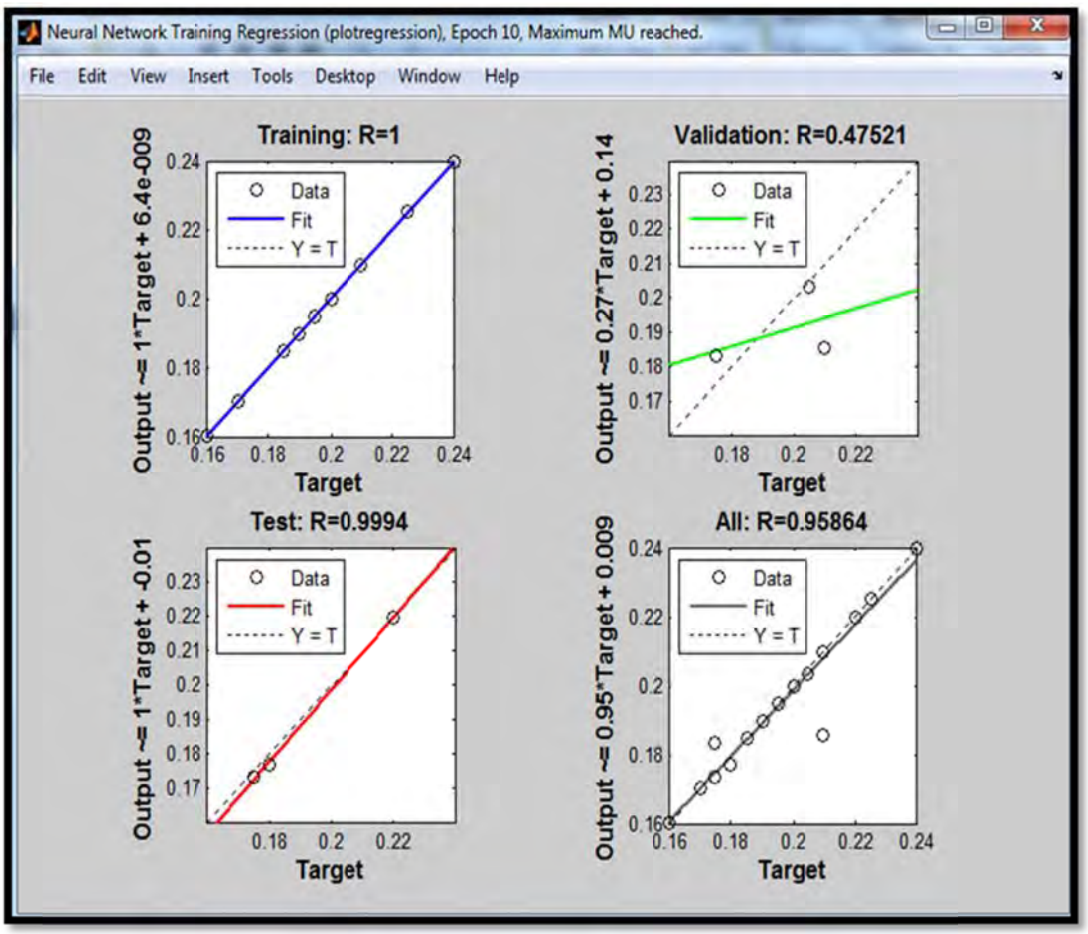

Figure 7: The results of the regression analysis carried out on the Training, Validation, Test and overall sets

Figure 8 shows differences between actual flyrock distance and predicted flyrock distance by ANN in phase Train-Validate-Test. These two lines are almost similar during the dataset numbers. Also a correlation between actual flyrock distance and predicted flyrock distance by ANN in phase Train-Validate-Test is indicated in Figure 9. From Figure 9, it is seen that the coefficient of correlation is very high.

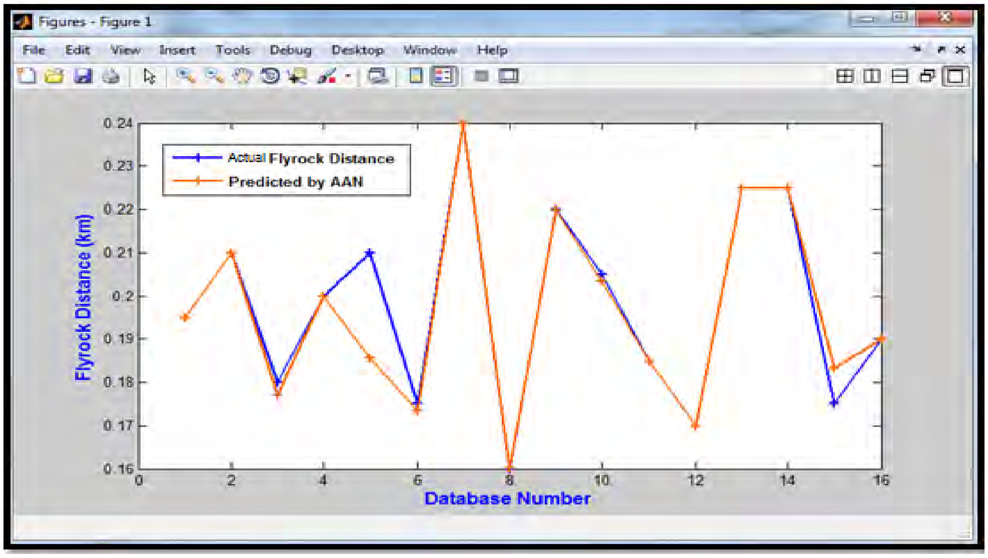

Figure 8: Differences between actual flyrock distance and predicted flyrock distance by ANN in phase Train-Validate-Test

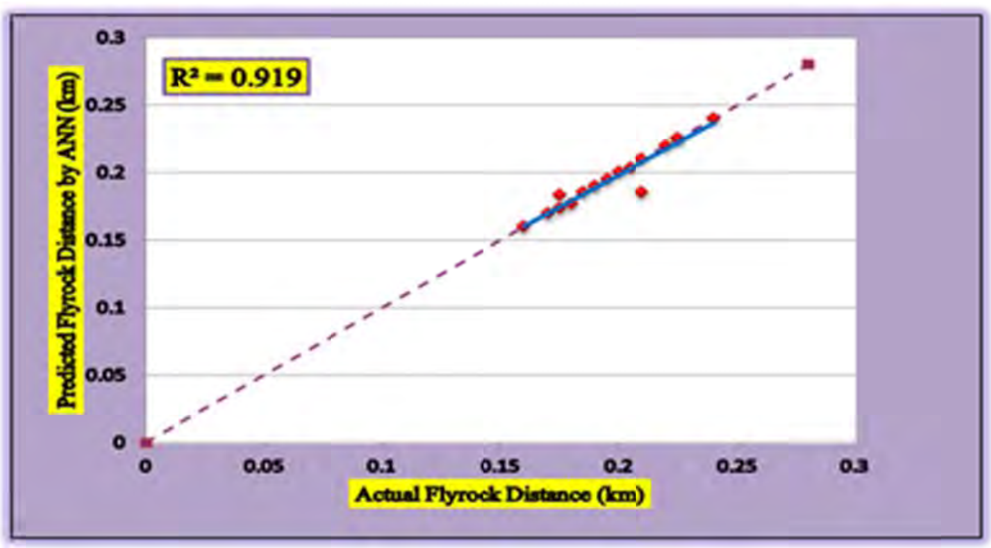

Figure 9: Correlation between actual flyrock distance and predicted flyrock distance by ANN in phase Train-Validate-Test

Significant Parameters

A useful concept has been proposed to identify the significance of each cause factor (input) on the effect factors (outputs) using a trained neural network. This enables us to hierarchically recognize the most sensitive factors affecting on flyrock distance. There are some methods such as cosine amplitude method (CAM), relative strength of effects (RSE) and Max-Min method for sensitivity analysis of input parameters.

Figure 10 shows the relation between Max – Min method and input parameters. Based on the acquired rij values, it is observed that powder factor (H), stemming (G) and charge length (E) are the most effective parameters on flyrock distance. On the other hand, hole diameter (A), hole depth (B), burden (C), hole angle (D) and explosive per hole (F) are the least important parameters in this regard.

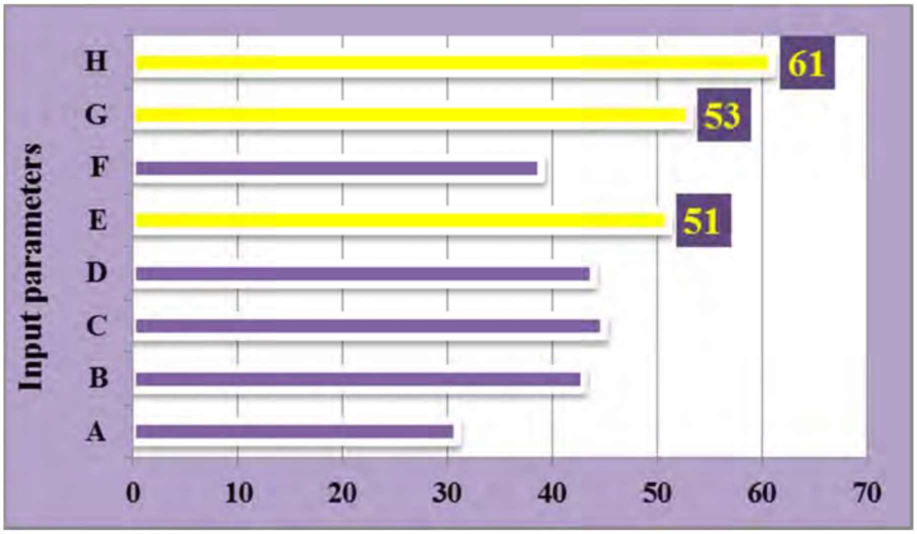

Figure 10: Significant parameters

CONCLUSIONS

This study found that the range of actual flyrock distance was between 160 m to 240 m and dependant on fragmentation size. Prediction based on empirical methods was carried out by two methods that are figure and formula. Lundborg et al.'s Formula (1975) was found to under estimated projection (80 m to 157 m)(Actual flyrock distance 160 m to 240). The difference between two results was 42%. Lundborg's Figure (1981) was found to over estimate projection (250 m to 340 m)(Actual flyrock distance 160 m to 240). The difference between two results was 48%. Coefficients of correlation in empirical methods were very low (around 0.2)

An ANN with 8 input parameters, 2 hidden layers and one output layer was found to be optimum for concurrent prediction of flyrock distance. Input layer includes 8 parameters and feed-forward network was designed which had two hidden layers with 15 and 15 neurons in first and second layer. Train-Validate-Test system was used in this study with low error system (around 0.04%). Coefficient of correlation in ANN method was very high (around 0.92).

Max-Min method is used for finding important parameters on flyrock distance. According to this method, powder factor (H), stemming (G) and charge length (E) are the most effective parameters on flyrock distance. On the other hand, hole diameter (A), hole depth (B), burden (C), hole angle (D) and explosive per hole (F) are the least important parameters in this regard.

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