A Novel Approach for Blast-Induced Flyrock Prediction Based on Particle Swarm Optimization and Artificial Neural Network

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Abstract*- Fly-rocks are the excessive rock fragments. There random throw from a blast can travel a large distances which may be beyond the blast safety area. This process of the blasting operation results in human injuries, fatalities, and structural damage. There are various empirical relationships which have been established to predict fly-rock resulted from blasting. These practical methods only studypartial numbers of activefactors such as fly-rock distance. But, the blasting also affected by other parameters such as blast geometry and geological conditions. Due to this disadvantage, the empirical methods lacks in accuracy, even in accuracy of the fly-rock distance. In this research work, a method is proposed to predict the fly-rocks. These rocks are made by blasting over a freshmethod. This approach is built on the mixture of Particle Swarm Optimization and Artificial Neural Network. Here ANN used to predict fly-rock distance. Generally ANN used as one of the forceful areas of research in advanced and varied applications of science. ANN has the ability to right to map the input to output patterns. Also, it utilizes all influential parameters in case of prediction of fly-rock distance. But, there are still some limitations concern to ANN i.e. the rateof slow learning and getting stuck in local minima. PSO can be used to overcome these shortcomings. PSO is generally utilized in the various optimization engineering problems. This research work offerings a mix PSO-ANN predictive model for fly-rock prediction. The results of the developed model are compared to the results of ICA-ANN, BP-ANN, empirical equation and multivariate regression analysis (MRA). The parameters for comparison are (Root Mean Square Error), Coefficient of Determination (R^2) and Least Cost. These parameters are firstly calculated by comparing testing and trained data from ANN. These parameters are than compared with that of existing methods i.e. ICA-ANN, BP-ANN, empirical equation and multivariate regression analysis (MRA). MATLAB R2013a is used as an implementation platform using general MATLAB toolbox and Artificial Neural Network toolbox.

Keywords: Artificial neural network, Imperialist competitive alg orithm, flyrock, Blasting etc.

I.INTRODUCTION

One of the crucial components of the surface mining is blasting. It serves as the most important role in dividing [6] burden and disclosing coal and inother mineral deposits [1].The boundaries of the blast areaare determined by the blaster and the flyrock is not probable to travel outside the blast zone. For the period of blasting, all employees must be detached from the blast part. Also all entries to the blast area must be guarded. If someone is essential to visitclassified the blast area, a proper blasting safetyshould be taken. [11].

II. FLYROCK AND ITS PARAMETERS

Flyrock is unnecessary rock garbage thrown during bench blasting in mines [1]. It is driven rock fragments by energy of explosive away from the blast zone. It is objectionable environmental effects of blasting operations. In this there is an affective relationship among explosive energy sharing, rock mass automatic strength, and charge limitation.

III. IMPERIALIST COMPETITION ALGORITHM

It isnewoverall search [9] experiential that uses colonization [2] and imperialistic competition process and used expansively to solve different types of optimization problems [4]. This algorithm starts with some early countries. It is new evolutionary algorithm that is moved by the human's socio-political progress [8]. Each singular of the population is called country. Population is divided in two parts, colonies and imperialist state. The competition between imperialists to take ownership of the colonies of each other forms this algorithm. In this competition the weak empires collapse slowly and finally one imperialist and other country is its colony [3].After dividing all colonies among imperialists and creating the initial empires, these colonies move to their important imperialist. This movement is simple
model of assimilation policy that was assumed.

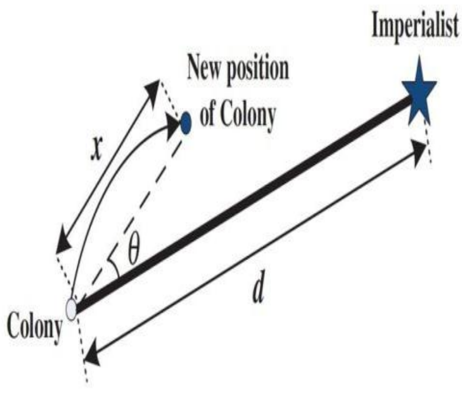

Figure 1 Movement of colonies to their related imperialist [3].

In ICA the optimization process starts with producing the population. This algorithm, each unit of the population called a country. The countries are distributed in two sections; the finest countries are considered to be imperialists and the rest of the countries form the colonies. All colonies are distributed between the remaining imperialists on the basis power. Combination of each imperialist organized with its colonies makes an empire. After the initial empires, the colonies move to relevant imperialists and keep the assimilation of imperialist states. The following steps ICA optimization procedure is [1].

A. Initial Empires optimization procedure

Starts with initializing the entities section which are called countries. In this problem, a country have 1*N variables range. This array is defined as follows:
Country = [A1 , A2 , A3 , . . . , AN variable]
In thisthe particle which need to best solution. In a country, each parameter can be considered as a human related characteristic such as culture and Language, in which this makes an attempt to find the best combination of thesecharacteristics. Cost function country is as follows:
F (Country) = [A1, A2, A3, . . . , AN variable]
The technique of ICA optimization starts with size of countries, Ncountry and select a powerful countries as the (N imperialist), remaining of the countries are measured as a colonies (N colony). The colonies are distributed into imperialists based on power to makingoriginal empires. Therefore the normalized cost of each imperialist is defined as follows:

$$c_{n=}c_n - \max(c_i)$$

Inthis c_n is cost of nth imperialist and $c_n$is its normalized cost. The normalized power of each imperialist is as follows:

$$\rho_n = \frac{C_n}{\sum_{i=1}^{Nimp} C_i}$$

The number of initial colonies for each empire is as follow:
N.Cn= round $\{p_n \cdot N\text{colony}\}$
In which N.Cn is the initial colonies of $n$thEmpire and Ncolony is the total number of initial colonies.
To distribute the colonies within imperialists, N.C.n of the colonies is accidentally selected and making to the nth imperialist and therefore produce the nth empire.

A.Assimilation, Revolution, and Uniting

In this step, assimilation and revolution are the process. Assimilation is movement of colonies toward the imperialists where imperialists attempt to accept their colonies and makes part of them. This process is simulated by affecting all colonies to the imperialist along different axis.
Revolution is defined as changes in the power and structure that happen quickly. In optimization process, revolution makes sudden changes in sociopolitical things of a country. This action increases the optimal part of algorithm and makes quick result of countries to local minima.
Unitealike empires when distance between two imperialist becomes minus than the threshold distance. In this scenario these imperialists are united and a new empire will be formed.

B. Imperialistic Competition

In ICA optimization procedure, all empires make an attempt the colonies of other empires. In this terminology this action is called “imperialistic competition” which is the final optimization step…..
The imperialistic competition is shown in Figure 2

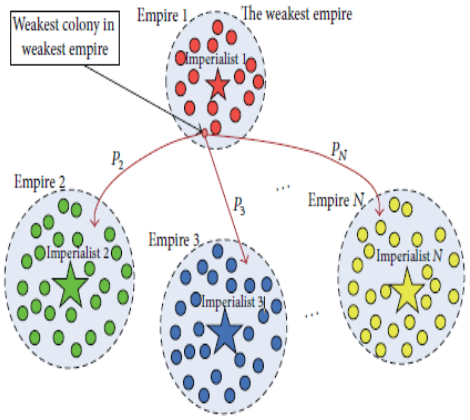

Figure 2: Imperialistic competition [1].

The virtual code of Imperialist competitive algorithm includes following steps.
1) Selection of unplanned points on the function and initialization of the empires.
2) Move the colonies to relevant imperialist. It is called Assimilation.
3) Unplanned change in position of colonies called revolution.
4) If there is colony in empire which has fewer cost than the imperialist, exchange the places of that colony and the imperialist and unites the alike empires.
5) Add the total cost of all empires.
6) Chose the weakest colony from weakest empires and provide it to one of the powerful empires and this is called Imperialistic competition.
7) Remove lowest weak empires, if break conditions fulfilled stop, if not go to 2.

IV. ARTIFICIAL NEURAL NETWORK

It is a mathematical model that works on the basis of simulating the human brain. In other words, an ANN is nonlinear function approximation which comprehends a relationship between desired input data and output data. ANNs require training to learn and accordingly map a relationship from the data. The capability of ANNs that learn the samples and increase performance over. Learning is the property that makes ANN dissimilarto other networks. This ability comes from training algorithm [1].
ANNmethod to calculate blast-induced fly rock the pattern of the result is projected by ANN on the basis of preceding learning. Once the neural network has been trained, any similarities in the new pattern will be detected and the

result will change accordingly, thus providing the technique interpolation capability. ANN trained using back propagation algorithm. The feed forward BPNN back propagation comprises 3 layers, i.e. input layer visible, hidden layer not visible and output layer that gives result. Layers are made up by neurons i.e. the basic processing units. These neurons connect the layer using appropriate weight.

The output of the neurons in the input layer becomes input for the neurons in the hidden layer and the same scenario applies to connection between hidden and output layers. The problem defines the number of hidden layers which is not visible and the neurons in them. In the present case, algorithm and 'log-sigmoid' transfer function has been undertaken. After trial of a number of different and same combinations, two hidden layer between input output and ten neurons in each hidden layer have been found as the best model for the case under the study.

Here below the full steps for implementations:

1. Reading and inputting of data
2. Extraction of Last column (Y) and rest of the data (X) separately
3. Calculation of number of Rows and columns of extracted data
4. Normalization of extracted data
5. Finding of minimum and maximum value from the extracted matrix X
6. Finding minimum and maximum value from the extracted matrix Y
7. Declaration of a loop according to number of column of X
8. Normalization of X matrix column wise
9. Normalization of X matrix column wise
10. Generation of feed-forward back-propagation network using number of rows of X-matrix
11. Training of network using PSO method
    - Extraction of all the elements of network one by one
    - Computation of total number of elements in the network
    - Creation of one's matrix according to total number of elements
    - Inputting of PSO Algorithm's Parameters i.e. Size of swarm and maximum number of iterations, Cognition Coefficient Social Coefficient
    - Generation of Initial Population according to size of swarm and computation of best position and best cost of particle using ANN
    - Optimization of cost and position of the particles at each iteration
    - Updation of particle Velocity using Cognition Coefficient and Social Coefficient
    - Updation of position using updated velocity of particle
    - Updation of the cost using updated position of the particle and ANN
    - Final updation of the Position and cost of particle
    - Display and accumulation of best cost at each iteration
    - Plotting of all the best cost
12. Simulation of Trained Network using Testing and Training data matrix and getting of Testing and Training simulated optimized object
13. Calculation of Mean Square Error by comparison of optimized object matrix with initial Y matrix Testing and Training objects
14. Display of initial and final optimized training data
15. Display of initial and final optimized testing data
16. Display of Coefficient of determination (R^2) for Training data
17. Display of Coefficient of determination (R^2) for Testing data

V. EXPERIMENTAL RESULTS

platform using general MATLAB toolbox and Artificial Neural Network toolbox. In this research work, a method is proposed to predict the fly-rocks. These rocks are made by blasting complete a newmethod. This approach is based on the combination of Particle Swarm Optimization (PSO) and Artificial Neural Network (ANN). Here ANN is used to predict fly-rock distance. Generally ANN is used as one of the most forceful areas of research in advanced applications of engineering. ANN has the ability to right map input to output patterns. Also, it utilizes all influential parameters in case of prediction of fly-rock distance. But, there are still some limitations concern to ANN i.e. the measuredspeed of learning and getting stuck in limitedjots. PSO can be used to overcome these shortcomings. PSO is generally utilized in the various optimization engineering problems. This research work presents a hybrid PSO-ANN predictive model for fly-rock prediction. The results of the developed model are compared to the results of ICA-ANN, BP-ANN, empirical equation and multivariate regression analysis (MRA). The parameters for comparison i.e. Root Mean Square Error, Coefficient of Determination and Minimum Cost. These parameters are firstly calculated by comparing testing and trained data from ANN. These parameters are than compared with that of existing methods i.e. ICA-ANN, BP-ANN, empirical equation and multivariate regression analysis (MRA). The value of these parameters has been given in Table 1. Table 1 Comparison of RMSE and Minimum Cost.

Method/Parameters	RMSE (Root Mean Square Error)	Coefficient of Determination (R^2)	Minimum Cost
PSO-ANN (Proposed)	0.0393	0.9927	0.0030
ICA-ANN	6.582	0.981	0.067
BP-ANN	13.478	0.919	NA
MRA	23.877	0.743	NA
Empirical	109.064	0.118	NA

We have also given snapshots of some graphs and bar chart for showing the performance of proposed predictive model. Figure 3 is the snapshot of cost value w.r.t. number of repetitions. Its clearly showing that cost is exponentially decreasing w.r.t. number of iterations. Figure 4 is the snapshot of comparison of ANN output and actual input of training data w.r.t.

Number of nodes in unseen layer. Figure 5 is the snapshot of ANN output and actual input of testing data w.r.t. Number of nodes in hidden layer. Figure 6 is the snapshot of measured fly-rock distance vs. Predicted fly-rock distance in meters according to ANN testing data. Figure 7 is the snapshot of measured fly-rock distance vs. Predicted fly-rock distance in meters according to ANN training data. Figure 8 is the snapshot of Bar chart showing comparison of RMSE for ICA-ANN and PSO-ANN. Figure 9 is the snapshot of Bar chart showing comparison of Coefficient of determination (R^2) for Testing data for ICA-ANN and PSO-ANN. Figure 10 is the snapshot of Bar chart showing comparison of minimum cost value for ICA-ANN and PSO-ANN.

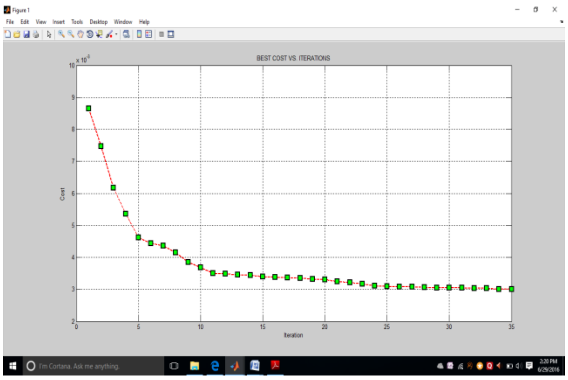

Figure 3 snapshot of cost value w.r.t. number of iterations. Its clearly showing that cost is exponentially decreasing w.r.t. number of repetitions

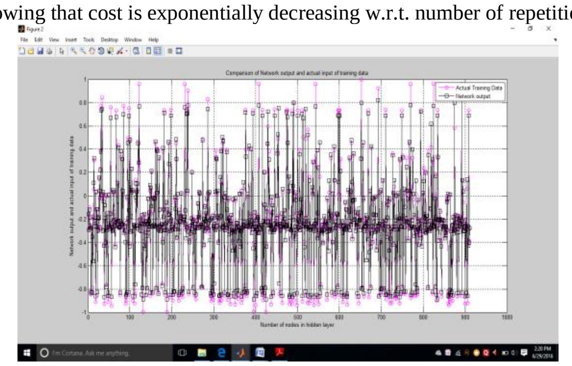

Figure 4 snapshot of comparison of ANNoutputand actual input of training data w.r.t. Number of nodes in hidden layer

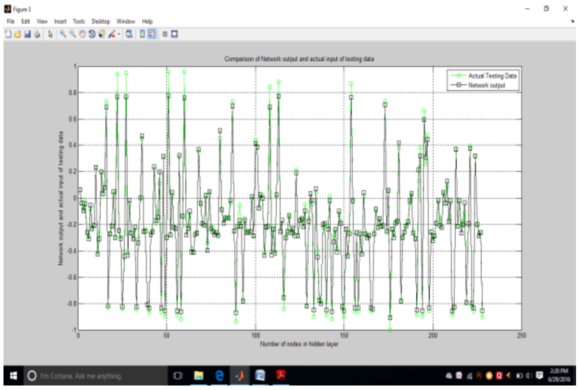

Figure 5 snapshot of ANN output and actual input of testing data w.r.t. Number of nodes in unseen layer

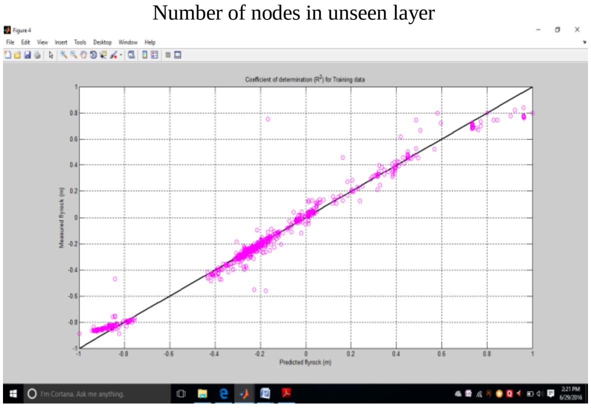

Figure 6 snapshot of measured fly-rock distance vs. Predicted fly-rock distance in meters according to ANN testing data

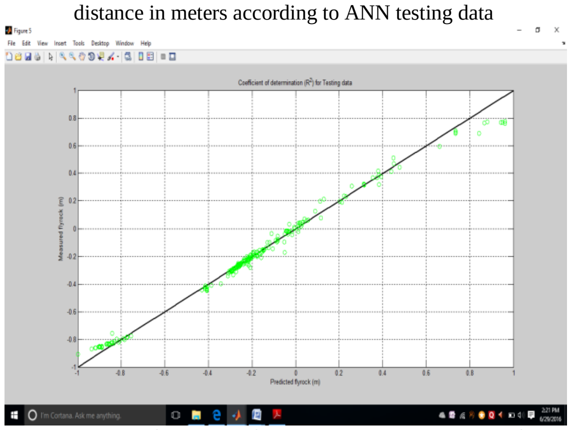

Figure 7 snapshot of measured fly-rock distance vs. Predicted fly-rock distance in meters according to ANN training data

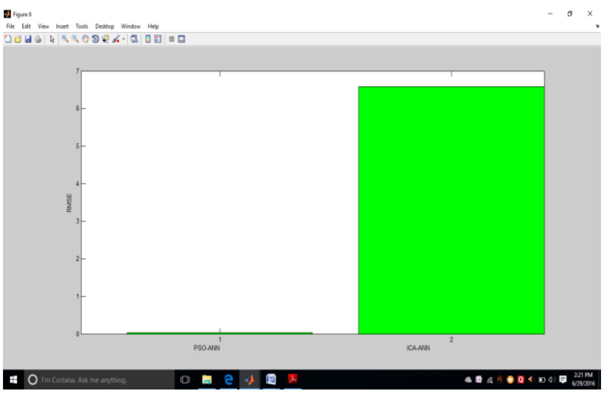

Figure 8 snapshot of Bar chart showing comparison of RMSE for ICA-ANN and PSO-ANN

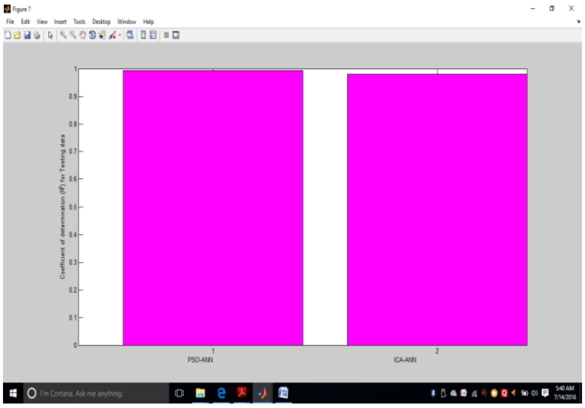

Figure 9 snapshot of Bar chart showing comparison ofCoefficient of determination (R^2) for Testing data for ICA-ANN and PSO-ANN

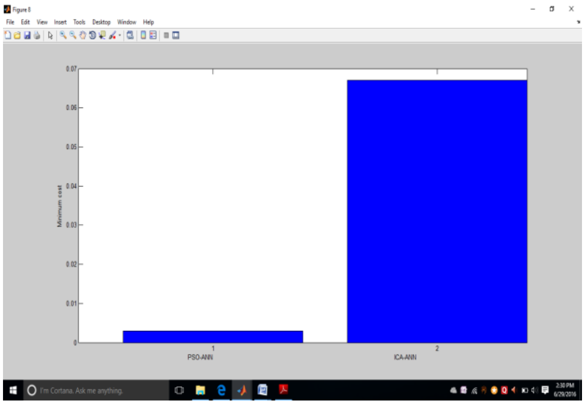

Figure 10 snapshot of Bar chart showing comparison of minimum cost value for ICA-ANN and PSO-ANN

VI. CONCLUSION

A predictive model based on the arrangement of PSO and ANN is developed to predict fly-rock which is made by blasting. An exactly recorded and collected data is utilized to train the PSO-ANN predictive model. Hole depth, load to spacing ratio, reducing length, burden per delay, powder factor, rock density considered as input limitations. Fly-rock distances are assigned as the output parameter. It can be concluded from the experimental results that the proposed model is well able to expect fly-rock distance with high mark of correctness. The proof of previous statement is the snapshots of measured fly-rocks for testing and training data in last chapter. Measured fly-rocks are very much closer to that of predictive fly-rocks. Also, for comparison purpose, the results of proposed method are compared with existing methods such as ICA-ANN, BP-ANN, empirical equation and multivariate regression analysis (MRA). Also, it is surveyed that the existing predictors provide very quick and simple prediction, whereas the proposed PSO-ANN model exhibited higher prediction performance model compared to other methods.

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