Prediction of Rock Fragmentation in Open Pit Mines, using Neural Network Analysis

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Loading and transport costs constitute up to 50% of the total operational costs in open pit mines. Fragmentation of the rock after blasting is an important determinant of the cost associated with these two components of mine development. In this paper, fragmentation of the rock after blasting is estimated analytically by the use of neural network method. The results obtained here, are compared with those predicted by Kuz-Ram and image analysis methods. All these have then been tested using real data gathered from Gol Gohar iron ore mine of Iran. It is shown that neural network method can be used efficiently in such cases and the final results can be expected to have a high degree of accuracy. The results obtained in this study and the methodology introduced, can assist the mining design engineer to decide on a drilling and blasting pattern that produces the most suitable fragmentation of the blasted ore and hence minimize the total cost of the mining operations.

Key words: Neural network, Kuz-Ram, Rosin-Rammler , Blasting, Fragmentation, Open pit mine

1. Introduction

Mining operations include the five stages such as drilling, blasting, loading, haulage and crushing. Drilling and blasting costs constitute up to 30% of the total operational costs in open pit mines, which will be increased up to 50% by adding more oversize parts and the requirement of secondary blasting.

Hence, the specification of rock fragmentation after blasting such as shape and size is by far one of the most important parameters in product optimization in mineral industry. As the total cost of a mine can be reduced to the possible minimum and then the productivity is increased.

The case study in this paper is done on one of the largest iron ore mine of Iran, Gol-e-Gohar, which is located in the southwest of Sirjan-Kerman. Ore body of iron ore mine is settled at six anomalies in the area with 10 kilometers long and 4 kilometers width approximately.

The first anomaly ore body is now mining with extractable reserve 191.2 million tons (‘see table 1’). Drilling and blasting operations are accomplished in top magnetic, bottom

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magnetic, oxide magnetic, rock waste and soil waste in this mine. These operations are so important, because of the complex discontinuity system existence, the rock type variations and the water bearing beds. Therefore the case study of this paper is done on the first anomaly of the reserve.

Table 1 - Qualitative and quantitative specification of the first anomaly's [1]

Rock Type	Tonnage (Million Ton)	Ore Grade			
		Fe (%)	FeO (%)	P (%)	S (%)
Top Magnetite	19.4	58.6	17.1	0.056	0.053
Oxide	61	60.4	9.1	0.132	0.369
Bottom Magnetite	110.8	52.9	19.7	0.163	3.364
Total	191.2	55.9	16.1	0.142	2.072

2. Necessity of performing research

The first outcome of a good blasting is the simplification of performing next stages of mining, such as loading, haulage and crushing process. Good blasting not only reduces cost of secondary blasting, but also fragmentation size is the main factor in the stability of the waste dump and the face angle.

Blasting is also important from designing vision that the performance of the explosives and blasting patterns with size distribution determining of fragmented rock is analyzed and studied. Therefore regards to above items, suggesting model for dimension predicting of fragmented rock and estimating of fragmentation distribution are very important and results profitability for system.

Proper fragmentation is the main purpose of blasting. There are several methods for predicting fragmentation such as Larson, Kuz-Ram, Rosin-Rammler and etc. But regards to inconstant situations in practice such as existence of underground waters, sudden changing of geological structure, blasting pattern size, several blasting must be tested frequently, that is expensive and time consuming. Therefore operational and capital costs are increased then the system is leaded to no profitability.

According to the advantages of neural network such as ability to solve problem, express and solve broad range of problems, control mechanism to select operators for a situation, solving a problem with searching problem, deal with incompleteness, inexactness, uncertainty probabilistic reasoning and fuzzy reasoning, this method is used for presenting the mentioned model.

In this paper, it is attempted to predict the fragmented rock dimensions by neural network method regards to the existence situations and the practical data that collected from Gol-e-Gohar Iron Ore Mine.

3. Neural Network

Artificial Neural Networks are in fact the sets of mathematical models, which are similar to the some obvious specifications related to the nerve system of organisms. The pivotal element of artificial neural networks is the novel structure of its data processing system.

Artificial neural networks are compounded of legion processing alternatives with internal connections same as neurons. These alternatives are jointed and depended to each other by weight connections such as synapses.

Modification of Synapse connections between neurons is the way of training in the organic systems. The mentioned procedure happens in artificial neural networks. Net learning is implemented via samples training and weight connections between input and output data are modified frequently.

Weight connections are saved as essential data for solving particular cases. Nowadays, artificial neural networks are used to solve virtual problems of world.

Neural networks are combined of simple elements, which work parallel with each other. These elements are gotten from organic neural systems. Network function is determined by the connections between elements.

Neural network training can be accomplished by moderating the values of element connections (weights) for specific case. Neural networks are built in various types and models such as Kohenin, Hopfield Net, multi layer networks and etc. [2]

3.1. Multi-layer neural networks

The suggested method in this paper is the utilization of multi-layer neural network by back propagation training algorithm. The multi-layer networks with supervised training are used for various cases successfully. Multi-layer network training is performed by a popular algorithm, which is called back propagation that works based on error correction learning rule. Substantially, back propagation process consists of two transitions among networks layers (forward and backward transition). In the forward transition a pattern is enforced as an input vector to the input neurons of network and its effect will be disseminated layer by layer.

Eventually, output sets are created as real response of the network. Neural weights are constant during forward transition but based on error correction rules, in backward transition weights are produced by subtraction of real response from desired output (target).

The back propagation error is called BP or simple briefly [3]. Overall, learning method of BP algorithm has two stages: forward and backward stage

- In forward transition, inputs are transmitting in network layer by layer and eventually sets of outputs are obtained as actual response of net. In this stage connection weights are constant.
- During backward transition, connection weights are changed based on error correction rule. ERROR signal (Subtraction of actual and desired response of network) is transmitted at inverse direction in the network. Weights are changed in the way that the actual and desired response approaches to each other.

In mentioned network, logarithmic sigmoid, tangent sigmoid and linear functions are used as transmission functions. Network variables are the numbers of neurons in hidden layers, network error rate and trainer algorithm parameters of network. [3]

3.2. Research method

In this research more than 50 patterns is evaluated and studied. All of the blasting pattern specifications are gathered and saved in a database such as rock mass description, blasting pattern size, drilling pattern, explosive weight, explosive type, water situation in blast holes, stemming length, bench height, specific factor and detonator. Then, image analysis method was used to determine the fragmented rock distribution after blasting. Hence, the photographs of faces were analysis and the results were illustrated by one of the image analysis software (Gold Size 2.0) and size distributions graphs of ore are obtained based on it.

In this method, there is no need to do the sampling in wide range for distributing. It is possible to obtain the fragmented distribution resulted from blasting just by imaging the fragmented rock, more precisely and less costly.

In the research, 30-60 photographs were taken after each blasting during loading. Then the fragmented rock distribution is illustrated via Goldsize image analysis software ('see figure 1'). Illustrating the fragmentations surroundings in each photo, is very boring and time consuming as sometimes there are more than 1700 fragmentations in each photo[4].

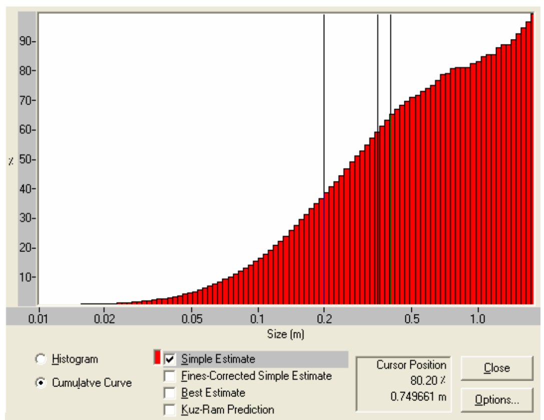

Figure 1 - The result of image processing

Three types of rock such as oxide, top magnetite and bottom magnetite are extracted in Gol-e-Gohar Iron Ore Mine. During the rock dimensions study, it is attempted to select 50 patterns until the fragmentation of all three rock types are being evaluated. Also waste and soil fragmented distribution are measured during shovel loading.

Ultimately, a model has been made by MATLAB software neural network. The mentioned model can predict fragmented rock dimensions without requiring particle size distribution.

3.3. Input and output parameters of model

Input layer consists of three sections of rock mass, specifications of the blasting pattern size and the way of charging which have the most effect on fragmentation. Input layer parameters are the followings ('see table 2'): - The specifications of blasting pattern size, Burden, Spacing and blasting holes height.

- The specifications of rock mass including rock type, specific gravity, water situation and water depth in blast holes.
- The blasting specifications including explosive type, specific factor, height of charge, stemming and booster.

Output layer is formed from three parameters, d50, d63.5, d80.

Table 2 - Neural network input data

Rock Type	Specific Gravity	Spacing	Stemming	Explosive length	Height	explosive weight	Explosive Type	Detonation	Water Depth	Specific Factor
1	4.17	7	4	8.3	12.3	365	0	0.14	0	0.63
1	4.17	7	4	9.5	13.5	418	0	0.14	0	0.72
1	4.17	7	5	10.1	15.1	475	0	0.14	0	0.82
2	1.85	6.5	5	11.2	16.2	493	0	0.08	2.5	0.92
2	1.85	6.5	5	11.6	16.6	510	0	0.08	2.3	0.95
3	4.33	7	8.7	8.8	17.5	600	1	0.06	2.2	1.04
3	4.33	7	5	12.7	17.7	559	0	0.06	1.0	0.97
3	4.33	7	8.4	8.8	17.2	600	1	0.06	3.7	1.04
4	2.65	7	9.7	9.1	18.8	620	1	0.11	3.3	1.07
4	2.65	7	5	11	16	484	0	0.11	1.0	0.84
3	4.33	7	5	13.2	18.2	581	0	0.11	1.0	1.01
3	4.33	7	5	12.8	17.8	563	0	0.11	0.8	0.97
1	4.17	6.5	6.1	9.7	15.8	660	1	0.21	3.0	1.23
1	4.17	6.5	8.4	8.8	17.2	600	1	0.21	8.0	1.12
5	4.3	6.5	6.5	7.7	14.2	339	0	0.11	0	0.63
5	4.3	6.5	9	7.4	16.4	500	1	0.11	4.0	0.93

The model inputs effect on each other because of having different dimension. Therefore the system would not be trained well. In order to be able to compare the inputs, they must be made dimensionless. In this model utility function is used to normalize inputs. This utility function uses maximum of each series inputs for making dimensionless as all data be between zero and one value.

3.4. Model Architecture

This section presents the architecture of the network model that is used with the back propagation algorithm-the multilayer feed forward network. Details of the error back propagation algorithm can be found in Rumelhart et al. [5] and any recent textbook, such as Haykin [6].

This model is structured by one input layer, two hidden layers and one output layer. An elementary neuron with R inputs (50 in this model) is shown in figure 2. Each input is weighted with an appropriate w. The sum of the weighted inputs and the bias forms the input to the transfer function f. Neurons may use any differentiable transfer function f to generate their outputs.

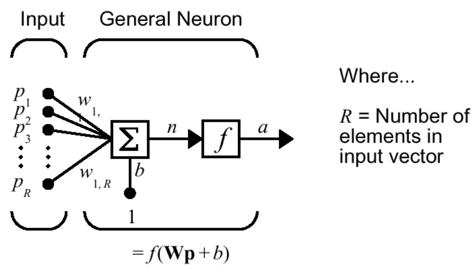

Figure 2 – An elementary neuron

In this multilayer network model, the tan-sigmoid transfer function is used in first and second. This function generates outputs between -1 and 1 as the neuron's net input goes from negative to positive infinity. ('See figure 3')

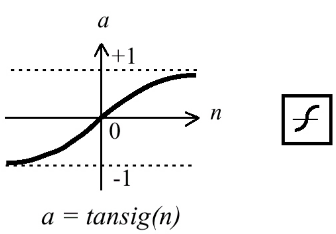

Figure 3 – Tan-Sigmoid transfer function

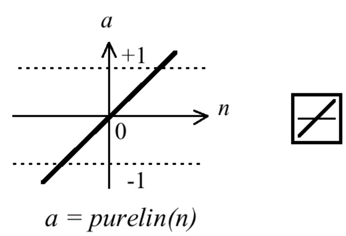

Figure 4 – Linear transfer function

The linear transfer function, purelin is used in the third layer of back propagation network ('see figure 4'). If the last layer of a multilayer network has sigmoid neurons, then the outputs of the network are limited to a small range. If linear output neurons are used, the network outputs can take on any value. In back propagation it is important to be able to calculate the derivatives of any transfer functions used.

3.5. Feed forward Network

This Feedforward network has two hidden layers of tan sigmoid neurons followed by an output layer of linear neurons ('see figure 5'). Multiple layers of neurons with nonlinear transfer functions allow the network to learn nonlinear and linear relationships between input and output vectors. The linear output layer lets the network produce values outside the range –1 to +1.

For multiple-layer networks we used the number of the layers to determine the superscript on the weight matrices. The appropriate notation is used in the two-layer tansig / network shown next.

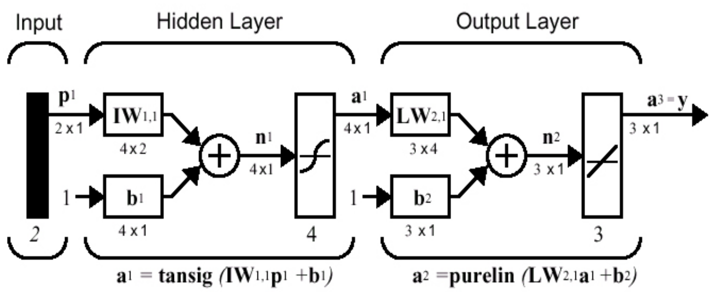

Figure 5 – Feed forward network

3.6. Training Network

The first step in training a feedforward network is to create the network object. The function newff creates a feedforward network in MATLAB software. It requires four inputs and returns the network object. The first input is 13 by 2 matrix of minimum and maximum values for each of the 13 elements of the inputs vector. The second input is an array containing the sizes of each layer. In our case it is [5 5 3].

The third input is a cell array containing the names of the transfer functions to be used in each layer. The final input contains the name of the training function to be used. {'tansig','tansig','purelin'}

The following command creates a three-layer network. There are 50 input vectors with 13 elements. The values for the all elements of the input vector range between 0 and 1. There are five neurons in the first and second layers and 3 neurons in the last layer. The transfer functions in the first and second layers are tan-sigmoid, and the output layer transfer function is linear. The training function is trained.

net=newff([-1 2;0 5],[3,1],{'tansig','purelin'},'traingd');

Neural network structure is shown in figure 6.

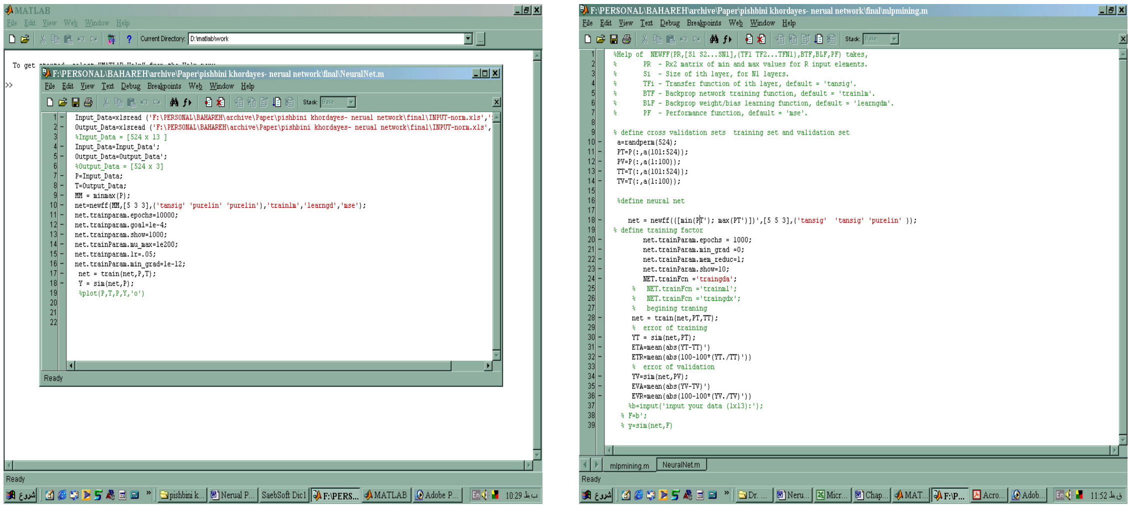

Figure 6 – Neural Network structure in Matlabsoftware

3.7. Network Error

The training process requires a set of examples of proper network behavior - network inputs PT and target outputs TT. During training, the weights and biases of the network are iteratively adjusted to minimize the network performance function. The default performance function for feedforward networks is mean square error MSE -the average squared error between the network outputs YT and the target outputs TT. In this model the goal of mean square error is considered zero (‘see figure 7’).

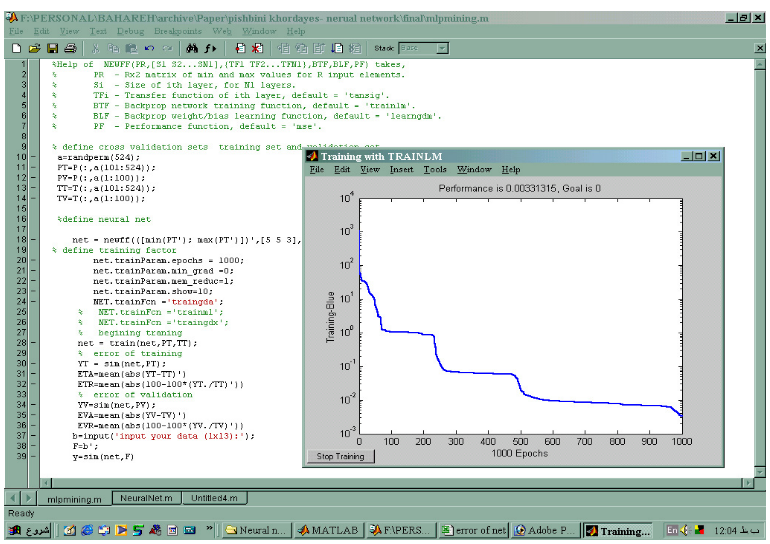

Figure 7 – MSE error in Neural Network model

3.8. Training Error, Cross-Validation

The following cross-validation procedure was performed for training the network as a way to control the over-fitting of training data. 80% of the data sets were selected randomly for training the network and 20% of the data for validation [7]. The error of the network on the validation data was calculated after every pass, or epoch, through the training data. All networks were trained for 1000 epochs. At the conclusion of training, the network's weight values at the epoch for which the validation error was the smallest was chosen as the weight values for which the network would most likely perform the best on novel data. This best network was then applied to the remaining 20% of the data, referred to as the test set. All representations were classified 15 times using different random selections of training, validation, and test sets and initial weight values.

After training the network, the net will be tested by 20% remained data and the Absolute error and Relative error value were calculated. Table 4 presents the absolute and relative errors of both training error and cross-validation between real and predicted values d80. The calculated error rates are all less than one percent in all the examinations and it is acceptable. This represents that this model is applicable in Gol-e-Gohar Iron Ore Mine and other similar mines.

Table 4 - Absolute and relative errors of both training error and cross-validation

Experience No.	Training Error		Cross-Validation	
	Relative	Absolute	Relative	Absolute
1	0.0537	0.0257	0.0705	0.0351
2	0.1140	0.0534	0.1407	0.0674
3	0.0968	0.0473	0.8550	0.7593
4	0.1267	0.0617	1.0396	0.4376
5	0.0238	0.0122	0.1612	0.2966
6	0.1029	0.0507	0.0813	0.0813
7	0.0882	0.0440	0.1985	0.1056
8	0.1117	0.0541	0.1759	0.0871
9	0.0729	0.0352	0.4295	0.1941
10	0.0134	0.0064	0.0507	0.0424
11	0.0254	0.0123	0.0359	0.0173
12	0.1348	0.0653	1.0660	1.2447
13	0.1127	0.0544	0.1756	0.0866
14	0.0712	0.0344	0.1948	0.0869
15	0.0583	0.0288	0.1623	0.0640

4. Sensitivity Analysis

In this section, the effect of variety the fragmented rock parameters were obtained by making one parameter variable but all the other ones constant. Spacing and Specific factor are the most sensitive parameters as Graphs resulted from the sensitivity analysis represent. By increasing the specific factor, the fragmented rock dimensions will be reduced considerably as it is shown in figure 1. With regards to figure 1 with specific factor equal to 1.15 kg/m3, the d80 (the 80% passing size) of rock is become 40cm. in other words, 80 percents of the fragmented rock dimensions is 40cm after blasting ('see figure 8').

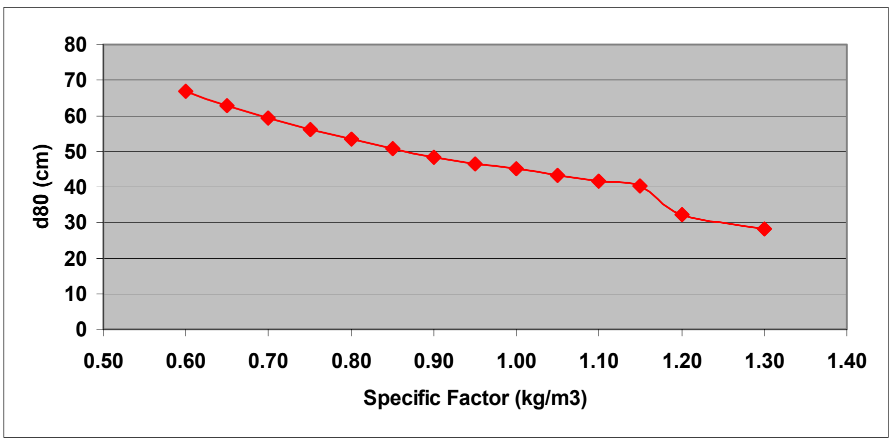

Figure 8- d80 measurement with different specific factor

Results obtained from changing the spacing also shows ('see figure 9') that while the spacing is between 4.5 and 5.8 meters, according to the constant value of other parameters, 80 percents of the fragmented rock dimensions will be between 28 and 40 cm. This is the best result and if the spacing is less than the 4.5 meters then the fragmented rock dimensions have lots of undersized rocks which causes the increasing in drilling and blasting costs and also making the mineral processing more complex. However when the spacing is more than 5.8 meters, the boulder and the oversized rocks are increased that will requires secondary blasting which increase blasting costs subsequently.

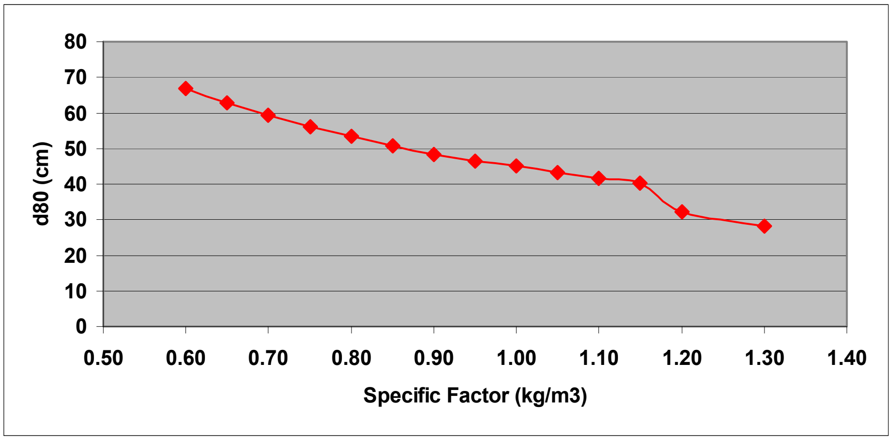

Figure 9- d80 measurement with different spacing

5- Model Analysis

The predicting model for estimation of the Fragmented rock dimensions was tested several times with real data from Gol-e-Gohar Iron Ore Mine via Artificial Neural Network. In this section, by using the Kozentsof and Kuz-Ram prediction methods and also image analyzing, Particle size distribution curve were studied and drawn at four blasting patterns in order to analyze the results obtained via neural network model.

Adaptation of curves obtained from Kuz-Ram approach, image analyzing and the neural network outcomes are representing that using neural network model has a very little difference with image analyzing in most of the cases. Also, Kuz-Ram fragmentation predicting approach can be used in Gol-e-Gohar Mine with a few modifications ('see figure 10'). The effect of rock mass specifications is not evaluated (studied) comprehensively in Kuz-Ram model and therefore it can not be reliable in all the conditions (situations). Hence Kuz-Ram model can not be adapted absolutely with neural network and image analyzing.

The results of rock size distribution are shown at four blasting patterns in Gol-e-Gohar Mine. ('See table 5').

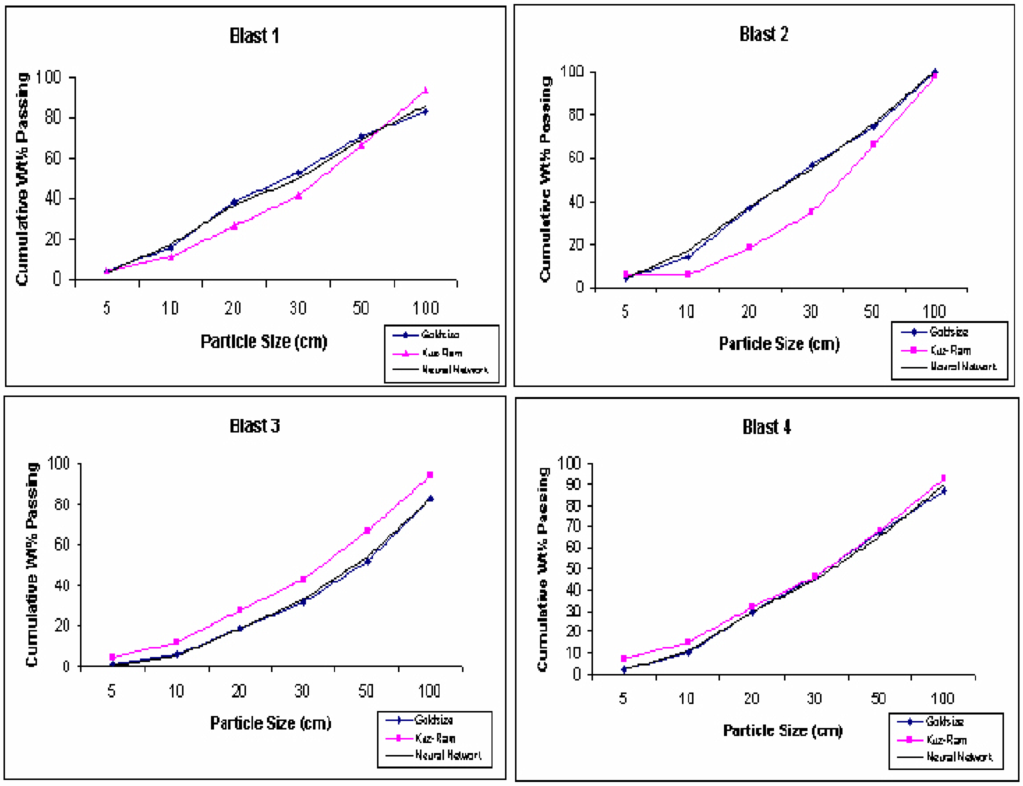

Figure 10- Comparison of size distribution with Neural Net work, Gold size and Kaz-Ram method in Gol-e-gohar Iron Ore Mine

Table 5- comparison of obtaining results between neural network model and fragmentation prediction models

Blast No.	Blasted Volume (m^3)	d50 (Kuz-Ram)	d50 (Koznetsof)	d50 (Goldsize)	d50 (Neural Network)
1	634	39.15	47.88	26	26.85
2	473.94	35.76	46.74	27	27.91
3	579.86	35.42	46.60	48	47.36
4	664.4	32.93	44.65	33	32.2

6. Conclusion

It is more than 40 years of presenting the fragmentation prediction models. But the type of input data makes the usage of the fragmentation prediction models difficult. On the other hand, with regards to this point that each mentioned models were obtained under the specific circumstances, their accuracy will be reduced via situation changing. Therefore several methods were studied and presented in order to determine distribution.

In this paper, a model has been presented via neural network theory that the dimensions of fragmented rock can be predicted with very scarcely error.

In order to predict the dimensions of the fragmented rock an artificial multi-layer neural network is used with back propagation learning algorithm. The network is best trained by 13 input parameters and 3 output parameters with one input layer, 2 hidden layers and one output layer. Purlin tan-sigmoid functions are used as transfer functions in the net. One of the model ability towards the other fragmentation prediction models is its unlimited numbers of input parameters.

By examining the represented model in Gol-e-Gohar mine, the accuracy of model is confirmed by comparison between the size of real fragmented rocks and the predicted ones. The relative error of the model is less than 3% at all the examinations. The model carries out in the way that the dimensions of fragmented rock after blasting can be measured by inputting the blasting pattern specifications.

Eventually, the study on adaptation of Particle size distribution curves obtained from artificial neural network, image analyzing methods (Goldsize software) and Kuz-Ram model show that the results from neural network and image analyzing methods are nearly the same. Also comparison of these two methods with Kuz-Ram model shows the considerable error. This is because of not considering the rock type and its mechanical specifications. Despite of all above, Kuz-Ram model can be used as the fragmentation prediction model in the Gol-e-Gohar mine with few corrections. The study shows that because Kuz-Ram model considers more important factors, thus more suitable results for prediction of fragments dimentions will be obtained by this model.

7. References

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