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2008

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Publication Details

This conference paper was originally published as Hossaini, SMF, Alipour, A and Jafari, A, Neural Network or Empirical Criteria? A Comparative Approach in Evaluating Ground Vibration in Karoue - 3 Underground Cavern-SW Iran in Aziz, N (ed), Coal 2008: Coal Operators' Conference, University of Wollongong & the Australasian Institute of Mining and Metallurgy, 2008, 245-250.

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NEURAL NETWORK OR EMPIRICAL CRITERIA? A COMPARATIVE APPROACH IN EVALUATING GROUND VIBRATION IN KAROUE - 3 UNDERGROUND CAVERN-SW IRAN

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ABSTRACT: In this study results of an investigation into ground vibrations of an underground excavation in south-west Iran has been discussed. Recorded experimental blast data have been analyzed employing two different methods of analysis. A comparison between the two ways of investigation, namely empirical equations and neural network, is presented. It has been shown that the applicability of neural network method is, by far, more promising than any of three selected empirical equations. It was also found that, in spite of releasing high correlation of determination (R^2), empirical equations face discrepancies with real data in high range of vibration intensity whereas neural network fit the data of all ranges with a consistent accuracy.

INTRODUCTION

The hydroelectric project of Karoune-3 requires 3.3 and 1.9 million cubic meter of surface and underground excavation respectively. Drilling and blasting is the technique selected for excavation in this site. Therefore, optimization of the blast operation is of the most importance.

In a large power plant project such as Karoune -3, in most occasions, blasting is performed in the vicinity of underground spaces, structural foundations, monitoring equipments and site machinery like turbines and electrical generators. Therefore, restrictions have to be imposed on ground vibration intensity to avoid any damages to the surrounding facilities.

To come out with proper amounts of maximum instantaneous charge which produces limited ground vibration, several empirical equations are available in literature (Jimeno, C L and Jimeno, E L, 1995 and Dowding, C H, 1996). These empirical equations are normally used for estimating peak particle velocity (ppv) of ground vibration by blasting.

In recent decades artificial neural networks (ANN's) has emerged as a powerful tool for rock engineering analysis. As a branch of artificial intelligence, ANN's have got the ability of calculating some logical functions in forms of non-linear analyzers. In this paper, both conventional empirical criteria and ANN's method have been used in predicting ground vibration. A comparison between the applicability of the two methods has been demonstrated.

SITE DESCRIPTION

Karoune-3 dam and power plant is located in east of the town of Izeh in Khouzestan province south west of Iran. This project is the largest amongst many of its kinds constructed or under constructions nationwide. Underground excavations of this site including power plant spaces, tunnels, water passages and drifts are located adjacent to the main body of the dam. Geologically, the project site consisted of limestone, marne-limestone, marlstone and shale. Table 1 summarizes the main mechanical properties of the site. The outline of drilling and blasting pattern at Karoune -3 was as appears in Table2.

Table 1 - Mechanical properties of the site.

Rock type	Specific gravity t/m^3	Yong modulus (GPa)	UCS (MPa)	RMR
limestone	2.5	20	98	75
marne limestone	2.4	20	98	65
marlstone	2.3	17	50	55
shale	2.3	17	50	50

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Table 2 - Drilling and blasting outlines.

Parameter	Floor blasting	Tunnels	Drifts
hole diameter(mm)	64	45&51	32
hole length(m)	3-3.6	2-4	1.2-3
dynamite cartridge diameter(mm)	30	22&30	22
powder factor(kg/m ³)	0.25	0.8-2	2

VIBRATION ESTIMATION BY EMPIRICAL EQUATIONS

To modify and improve drilling and blasting pattern of underground excavations, ground vibration was monitored during the operations. Using three selected empirical equations (Hossaini and Sen, 2004) the data then were analyzed. These three equations are versions of the following general form of all of these types being used by investigators (Hossaini and Sen, 2006):

$$PPV = v = k R^a Q^b$$

Where v is peak particle velocity in mm/s, R is distance in meter, Q is the maximum instantaneous amount of explosive charge in kg and k , a and b are normally called site specific parameters.

Table 3 and Figure 1 represent the results of applying the equations to the ground vibration data where comparison between the applicability of the criteria is available. As seen in Table 3 that equation 3 is the best fit to the data, with greater coefficient of determination (R^2).

Table 3-Drilling and blast outlines

Equations	K	B	R^2
(1) $PPV = K \left[\frac{R}{\sqrt[3]{Q}} \right]^{-B}$	1825.1	2.435	0.81
(2) $PPV = K \left[\frac{R}{\sqrt[3]{Q}} \right]^{-B}$	7671.6	2.415	0.77
(3) $PPV = K \left[\sqrt{\frac{Q}{\sqrt[2]{R^3}}} \right]^B$	400.86	2.232	0.84

NEURAL NETWORK

Artificial neural networks (ANN's), are massively parallel, distributed and adaptive systems, modeled on the general features of biological networks with the potential for ever improving performance through a dynamical learning process. Neural networks are made up of a great number of individual processing elements, the neurons, which perform simple tasks. A neuron is the basic building block of neural network technology which performs a nonlinear transformation of the weighted sum of the incoming inputs to produce the output of the neuron. The input to a neuron can come from other neurons or from outside the network. The nonlinear transfer function can be a threshold, a sigmoid, a sine or a hyperbolic tangent function (Samui, P and Kumar, B, 2006).

Neural networks are comprised of a great number of interconnected neurons. There exists a wide range of network architectures. The choice of the architecture depends upon the task to be performed. For the modeling of physical systems, a feed forward layered is usually used. It consists of a layer of input neurons, a layer of output neurons and one or more hidden layers. In the present work, a three-layer feed forward network was used.

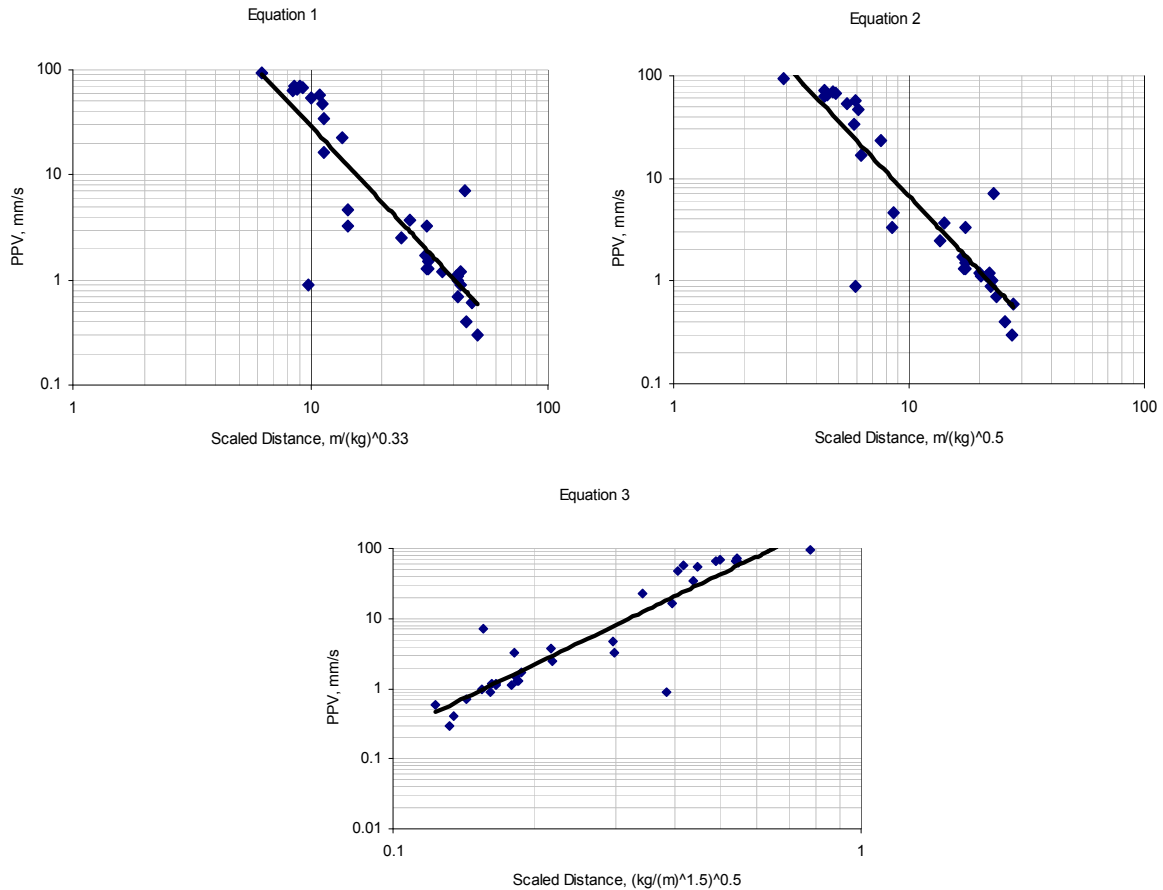


Figure 1 - Peak particle velocity versus scaled distance for the three equations

To establish an optimal network, one needs to begin with training and testing the artificial neural networks using a subset of all data sets. This process is referred to as a pilot experiment. This experiment is based on a certain number of samples; a sample being a set of input data and observed/measured information. In the pilot experiment data set, the samples are divided into a training set and a validation set. Networks with different numbers of hidden nodes will be trained all the way to the convergence of the training samples, measuring their performance with the validation set, and choosing the network that yields the best performance of the validation set. Finally, this selected network model will be used for the whole data set.

Performance of the developed network was tested with the help of:

- (i) drawing a scatter diagram of estimated versus target values.
- (ii) Computing mean absolute error (MAE) using:

$$MAE = \frac{1}{Q} \sum_1 |y - x| \tag{4}$$

Where;

- x is target
- y is network output
- Q is number of test patterns.

- (iv) Computing mean square error (MSE) using:
- (v)

$$MSE = \frac{1}{Q} \sum_1 (y - x)^2 \tag{5}$$

Where;

x is target

y is network output

Q is number of test patterns

VIBRATION ESTIMATION BY NEURAL NETWORK

When supplied with adequate vibration data neural networks are capable of drawing a relationship between peak particle velocity from one hand and distance and maximum instantaneous charge from the other hand. Distance and maximum instantaneous charge are introduced as inputs of the neural network as appears in Figure 2 for the data of Karoune-3. An optimized model of neural network built after several executions in MATLAB environment is detailed in Table 4. Coefficient of determination (R^2) between real and estimated values of ppv for training and testing groups are 0.98 and .94 respectively.

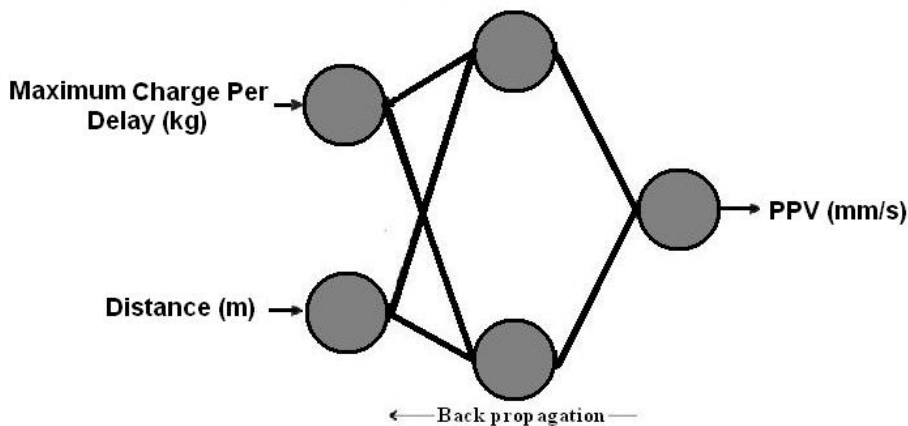


Figure 2 - Neural network model used for analyzing Karoune-3 data

COMPARISON BETWEEN APPLICABILITY OF THE TWO METHODS

As far as the comparison between the applicability of the empirical equations is concerned Different results can be achieved by applying the same empirical criterion to different cases. An empirical criterion which offers an outstanding correlation with a group of data may lead to discrepancy in another case of the same nature. Therefore, specific equations have to be found for specific cases. The results of applying the three empirical equations and neural network are compared in Table 5. As seen in this Table, the applicability of neural network is by far better than any of the equations.

Figure 3 visualizes the degree of agreement of the equations as well as neural network model with the data. In this figure, the data are sorted and numbered in ascending order of ppv.

As far as the comparison between the applicability of the empirical equations is concerned, Equation 3 provides better R^2 (Table 3) while Equation 1 is better in MSE and MAE factors (Table 5). Discrepancy of the three equations with data of higher range of ppv (over 20 mm/s) is observed in Figure 3 whereas neural network is quite promising in that data range too. These discrepancies are the reason for getting different outputs when different statistical methods are employed. This implies that coefficient of correlation(R) or coefficient of determination (R^2) are not lonely capable of being a proper tool of judgment over the whole range of a data groups.

Table 4 - Details of optimized neural networks model built for Karoune 3.

Parameter	Related information	Parameter	Related information
No. of train data	26	Global error function	MSE
No. of test data	7	No. of optimum neurons in hidden layer	30
ANNs Structure	2-30-1	No. of optimum epochs	35
Activation function of hidden layer	Log_Sig	MAE for train and test data	20.06, 1.93
Activation function of output layer	Linear	MSE for train and test data	8.77, 13.02
Train algorithm	Levenberg_Marquardt	–	–

Table 5 - Comparison of error values in various approaches.

Model	MAE	MSE
Equation 1	8.97	213.80
Equation 2	9.38	221.82
Equation 3	9.33	361.53
Neural network	3.31	27.43

The problem of different applicability in different ranges of data does not happen in the case of neural network method. As Figure 3 explains, this method is in very good agreement with the data in all ranges. This can be regarded as a prime advantage of this method.

CONCLUSIONS

- Empirical criteria for ground vibration evaluation may submit different results in different cases or even in different ranges of data of the same case.
- Although having lower rate of agreement with real data comparing to neural network method, empirical criteria, due to their simplicity in usage, can be regarded as a useful tool provided that specific equations are searched for specific range of any specific case.
- Neural network is a powerful, precise and reliable tool of predicting ground vibration having excellent results in different data ranges yielding much better results than any empirical equations.

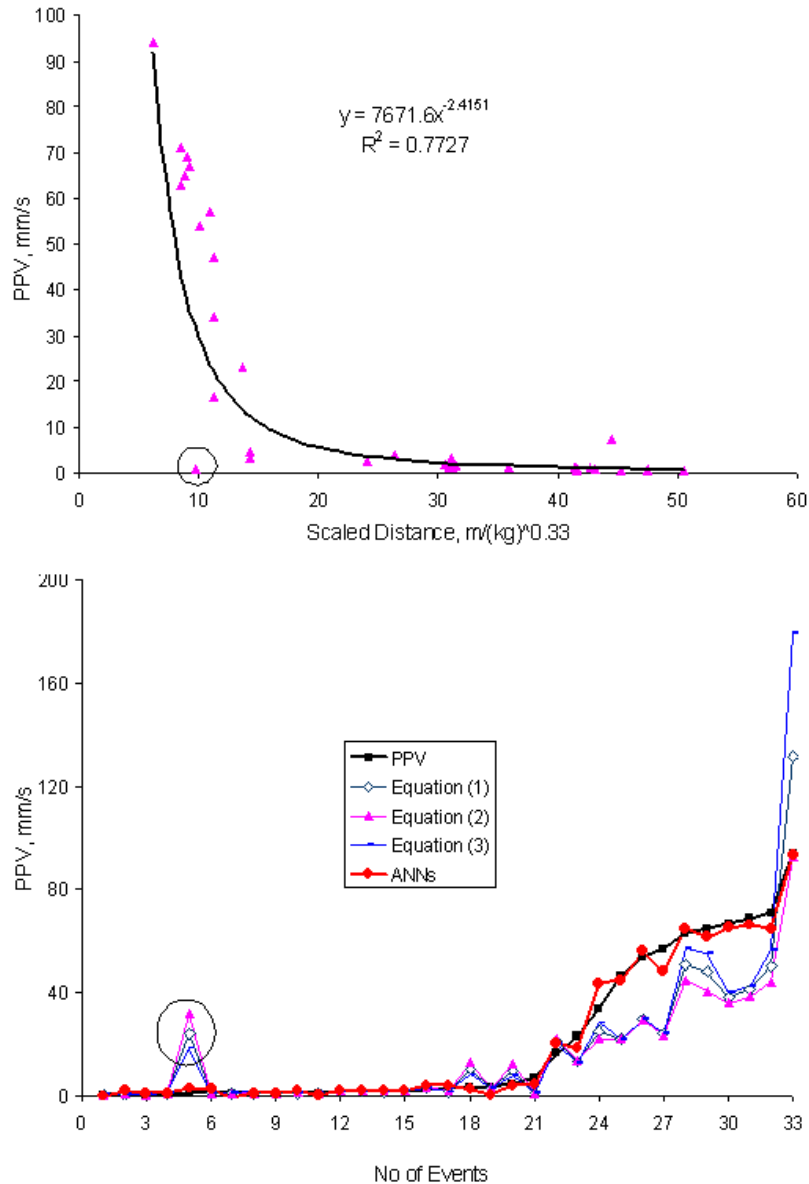


Figure 3 - Scatter diagram of estimated versus target values.

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