Evaluation and Comparison of Ground Vibration Predictors at Tourah Quarry–Egypt*

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The present paper mainly deals with the prediction of blast-induced ground vibration level at Tourah Mine in Egypt. The safe charge of explosive and peak particle velocity (PPV) were recorded for 79 blast events (79 blast data sets) at various distances by using single station seismograph of type REF TEK-130 SMA. These datasets were used and analyzed by the widely used vibration predictors. From the six predictors, vibration levels were calculated and compared with new monitored 15 blast data sets. Again, the same data sets were used to validate and test the three-layer feed-forward back-propagation neural network to predict the PPV. Different propagations equations were derived by using the shapes of the selected predictor's formulae. It is found that among all the predictors, ANN provides very near prediction with high degree of correlation.

KEY WORDS: Blasting, Ground Vibration, Damage Criteria, Particle Velocity, ANN Predictor

1. Introduction

Blasting is still an economical and viable method for rock excavation and displacement in mining as well as in civil construction works. The negative effect of blasting, i.e., ground vibration, air blast, fly rocks, back breaks, noises, etc are unavoidable and cannot be completely eliminated but certainly minimize up to permissible level to avoid damage to the surrounding environment with the existing structures. Among all negative effect, ground vibration is major concern to the planners, designers and environmentalists. The problem of ground vibration is alarming when blasting operations are going on near a historical site, like Tourah Caves as in this study.

A number of researchers have suggested various formulae to predict the ground vibration level during the blasting. The nature and intensity of blast induced ground vibration and frequency is largely dependent upon many factors. The most important influencing factors are shown in Fig. 1. All parameters are dependent upon each other and mostly interrelated. If a particular variable is changed, other parameters will also be changed¹⁾.

The quantity of explosive and distance from blast face to vibration monitoring point are of the most influencing controllable parameters and are considered the common

variables used in most predictors²⁾. In this study six predictors were evaluated and were compared to predict PPV. The collected predictors were Duvall and Fogelson through US Bureau of Mines (1962), Ambraseys-Hendron (1968), Davies et al, (1964), Langefors- Kihlstrom (1978), multiple variable regression analysis (MVRA), and Neural network (ANN). About 79 data points of PPV were measured from 79 blasts and were treated statistically by using programs Excel, Matlab, and SPSS to predict vibration level (PPV).

2. Field Measurement

The limestone quarry of Tora Cement Company (TCC) is opened at the south west foot slopes of Tourah Mountain, which forms the eastern high escarpments overlooking the Nile Mountain, and situated 23 km (14.3 miles) south of Cairo, on Maadi – Helwan road (Fig. 2). Geologically, this area belongs to Mokattam Formation (Middle Eocene)³⁾.

The quarry deposit is mainly composed of thick bedded limestone, mostly earthy white to faint yellow in the upper 60.0 m (196.8 feet) turning to greyish yellow and grey downwards. In the upper two segments of 4.0 m (13.1 feet) each, are composed of nodular limestone. The hardness of the limestone deposit is considerably varying from moderately hard to very hard.

Fissures are more frequent near the top and less frequent downwards. Most of these fissures are filled with iron oxides

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Fig.1 Factors affecting ground vibration (After Khandelwal, M., and Singh, T.N., 2006).

Fig.2 Location map for Tourah Area (Egypt map).

and siliceous sediments. The noticeable structures in the area are a group of step faults running east-west, and perpendicular to the investigated site³⁾.

The REF TEK-130 SMA seismograph was used for recording PPV during field investigation in this study. The REF TEK-130 is a Nitro Nobel accelerograph. This seismograph placed close to buildings towards the bench. In order to achieve the target of this research, the seismograph was stationed at the strategic location; near the important structure. Although the seismograph was set in one area, around the important structure, however the blasting source location was always different.

The blasting practice involves the use of ANFO, NONEL and dynamite primer. The blast timing patterns are designed to have 25 ms delay between rows and 42 ms delay between holes within a row. During investigation, 79 data had been obtained. Table 1 introduces sample from these measurements.^{1, 2)}

3. Different vibration predictor's equations

The most common form of the propagation equations which selected in this research are:

$$\bar{v} = k \left(\frac{R}{\sqrt{Q_{\max}}} \right)^{-n} \quad (1)$$

$$\bar{v} = k \left(\frac{R}{\sqrt[3]{Q_{\max}}} \right)^{-n} \quad (2)$$

$$\bar{v} = k \left(\frac{\sqrt{Q_{\max}}}{R^{2/3}} \right)^n \quad (3)$$

$$\bar{v} = k R^m Q_{\max}^n \quad (4)$$

where, $Q_{\max}$ (kg) is the maximum charge weight/delay, R (m) is the distance between the source and the observation point, and v (mm/s) is the peak particle velocity of ground vibration. K , m , and n are constants and greatly influenced by the physical properties of the transmitting medium.

4. Multivariate Regression Analysis (MVRA)

The purpose of multiple regressions is to learn more about the relationship between several independent or predictor variables and a dependent or criterion variable. The goal of regression analysis is to determine the values of parameters for a function that cause the function to best-fit as set of data

Table 1 Sample of measuring data.

Blast No.	Max. charge Per delay (kg)	Distance to blast (m)	Peak particle velocity (mm/sec)	Burden (m)	Spacing (m)	Subdrill (m)	Stemming (m)	Total charge (kg)	Bench Height (m)	Total holes No.
1	230	1214.54	0.51	5.75	8	1.5	2.5	2670	28.9	7
2	231	1185.1	0.66	5.5	8	1.5	2.5	3995	40.4	6
3	221	1175.26	1.24	6	8	1.5	2.5	2565	40.9	5
4	252	1205.04	0.48	5.5	8	1.5	2.5	2720	33.5	7
5	189	1166.07	0.82	6	8	1.5	2.5	2500	39.4	6
6	458	1235.68	0.72	6	8	1	2.5	3000	33.1	8
7	400	1228	0.69	5.5	8	1	2.5	2995	28.3	10
8	460	1200.16	0.6	6	8	1	2.5	2640	31.8	7
9	402	1220.43	0.46	5	8	1	2.5	2800	30.5	7
10	335	1147.13	0.86	6	8	1.5	2.5	2820	39.3	6

observations provided. In linear regression, the function is a linear (straight-line) equation. When there is more than one independent variable, the multivariate regression analysis (MVRA) is used to get best-fit equation. Multiple regressions analyze the datasets by performing least squares fit. It constructs and solves the simultaneous equations by forming the regression matrix and solving for the coefficient using the backslash operator. The form of MVRA equation including the variables in this study is as follow⁽¹⁾:

$$v = k - k_1(R) + k_2(S/B) + k_3(J/B) - k_4(N) + k_5(Q_t) + k_6(d/D) + k_7(Q_{\max}) - k_8(T/B) \quad (5)$$

where, R is distance from blast point to measuring point (m), S/B is spacing/burden, J/B is sub drilling/burden, N is total number of bore holes, Q_t is total charge of explosive (Kg), d/D is total length of charge/Total length of b.h, $Q_{\max}$ is max charge/delay (Kg), and T/B is Stemming/Burden.

5. Artificial Neural Network

ANN is a systematic method for training multiple layers which at least consists of three layers: input layer, hidden layer and output layer. The multilayer feed-forward back-propagation neural network was adopted in this research.

The processing elements in each layer are called nodes or neurons. Each of the nodes is connected to the nodes of neighbouring layers. This processing element consists of two parts. The first part simply aggregates (sums) the weighted inputs resulting in a quantity: $I = (\sum w_{ji} x_i)$. The second part is effectively a nonlinear filter, usually called the activation function. Activation functions for the hidden units are needed to introduce nonlinearity into the network. Without nonlinearity, hidden units would not make nets more powerful than just plain perceptions.

For back-propagation learning, the activation function must be differentiable, and it helps if the function is bounded. For hidden units, sigmoid activation functions are easier to train than threshold units. With sigmoid units, a small change in the weights will usually produce a change in the outputs.

The parameters associated with each of the connection of nodes are called weights. To determine the set of weights, a corrective-repetitive called learning or training is performed. During the training, a network predicts output and compares it with the actual one. The difference or error between both is processed back through the network updating the individual weights of the connections and the biases of the individual

Fig.3 Back propagation neural network.

neurons. The process will be repeated until the network error converged to a threshold minimum defined by a corresponding cost function; usually the mean square error (MSE).

In Fig. 3 of the architecture of typical neurons, each neuron j receives incoming signals from every neurons i in the previous layer. The j^{th} neuron is connected with a number of inputs $x_i = (x_1, x_2, x_3 \dots x_n)$. Associated with each incoming signal (x_i) is a weight (w_{ji}) and bias (θ_j). The net input values in the hidden layer will be ^{2,4},

$$Net_j = \sum_{i=1}^n x_i w_{ji} + \theta_j \quad (6)$$

where x_i is the input units, w_{ji} is the weight on the connection of i^{th} input and j^{th} neuron, θ_j is the bias neuron (optional), and n is the number of input units. The effective incoming signal, I_j , is passed through an activation function to produce the outgoing (O_j) of node j . In this study, the net output from hidden layer is calculated using a tansig function:

$$O_j = f(Net_j) = 2 / \left(1 + e^{-2(Net_j + \theta_j)} \right) - 1 \quad (7)$$

The total input to the k^{th} unit is,

$$Net_k = \sum_{j=1}^n w_{kj} O_j + \theta_k \quad (8)$$

where θ_k is bias neuron, w_{kj} is the weight between j^{th} neuron and k^{th} output. So, the total output from k^{th} unit will be,

$$O_k = f(Net_k) \quad (9)$$

In the learning process, the network is presented with a pair of patterns, an input pattern and a corresponding desired output pattern. The network computes its own output pattern using its weights and threshold. Now, the actual output is compared with the desired output. Hence, the error at any output in layer k is defined as:

$$e_l = t_k - O_k \quad (10)$$

where t_k is the desired output, and O_k is the actual output. The total error function is given by,

Fig.4 Graph between PPV and square root-scaled distance.

$$E = \frac{1}{n} \sum_{k=1}^n (t_k - O_k)^2 \quad (11)$$

Training of the network is basically a process of arriving at an optimum weight space of the network. The descent down error surface is made using the rule,

$$\nabla W_{kj} = -\eta (\delta E / \delta W_{kj}) \quad (12)$$

where η is the learning rate parameter, the update of weights for the $(n+1)^{\text{th}}$ pattern is given as,

$$W_{kj}(n+1) = W_{kj}(n) + \nabla W_{kj}(n) \quad (13)$$

This procedure is repeated with each pattern pair of training exemplar assigned for training the network. Each pass through the training patterns is called a cycle or epoch. The process is then repeated as many epochs as needed until the error within the user specified goal is reached successfully. This quantity is the measure of how the network has learned ^{2, 4}.

6. Results and Discussions

6 • 1 Prediction by USBM equation (Duvall and Fogelson)

The USBM equation for PPV is $v = k(R / \sqrt{Q_{\max}})^{-n}$, the site constant k and n can be determined by plotting the graph between the square-root-scaling $[R/Q^{1/2}]$ and PPV as shown in Fig. 4.

The value of k is 31.0012 and the value of n is 0.9133. Now the USBM equation for the particular site became,

$$v = 31.0012 \left(\frac{R}{\sqrt{Q_{\max}}} \right)^{-0.9133} \quad [r = 0.54] \quad (14)$$

where, r is correlation coefficient

6 • 2 Prediction by Ambrassey-Hendron equation

The Ambrassey-Hendron equation for PPV is $v = k(R / 3\sqrt{Q_{\max}})^{-n}$, the site constant k and n can be determined by plotting the graph between the cube-root-scaling $[R/Q^{1/3}]$ and PPV as shown in Fig. 5.

The value of k is 950 and the value of n is 1.4. Now the Ambrassey-Hendron equation for the particular site became.

Fig.5 Graph between PPV and $(R/Q_{\max}^{1/3})^n$ cube root scaled distance. Fig.6 Graph between PPV and $(R/Q_{\max}^{2/3})^{1/2}$ -scaled distance.

$$v = 950 \left(\frac{R}{\sqrt[3]{Q_{\max}}} \right)^{-1.4}, [r = 0.57] \quad (15)$$

6 • 3 Prediction by Langefors-Kihlstrom equation

The Langefors-Kihlstrom equation for PPV is $v = k(\sqrt{Q_{\max}/R^{2/3}})^n$, the site constant k and n can be determined by plotting the graph between the $(Q_{\max}/R^{2/3})^{1/2}$ and PPV as shown in Fig. 6.

The value of k is 0.4206 and the value of n is 0.8441. Now the Ambrasseys-Hendron equation for the particular site became.

$$v = 0.4206 \left(\sqrt{\frac{Q_{\max}}{R^{2/3}}} \right)^{0.8441} \quad [r = 0.47] \quad (16)$$

6 • 4 Prediction by Davies equation

The Davies equation for PPV is $v = kR^m Q^n$, the site constant k, n and m can be determined by regression analyses. Fig. 7 shows the relation between the $Q_{\max}/\text{delay}$, PPV and distance.

The value of k is 1.61×10^7 , the value of m is -2.7092 and the value of n is 0.3819. Now the Ambrasseys-Hendron equation for the particular site became:

$$v = 1.61 \times 10^7 R^{-2.7092} Q_{\max}^{0.3819}, [r = 0.607] \quad (17)$$

6 • 5 Prediction by Multiple Regressions MVRA

By taking into account many blasting variables such as $R, S/B, J/B, N, Q_t, d/D, Q_{\max}$, and T/B and by applying the program of SPSS (Statistical Package for the Social Sciences), it can be determined the multivariable equation as it follows:

$$V = 1.319239 - 0.001731(R) + 0.216301(S/B) + 0.132923(J/B) - 0.007109N + 0.000061(Q_t) + 1.078372(d/D) + 0.000553(Q_{\max}) - 0.209375(T/B), [r = 0.702] \quad (18)$$

Also, it is found that, the blasting variables which have a greater impact on PPV are the distance to the blast (R) with impact of 20.4%, $Q_{\max}$ with impact 13.9%, Q_t with impact 6.3% and d/D with impact 5.6%.

6 • 6 Prediction by ANN

Feed forward network is adopted here as this architecture is

Fig.7 Graph between PPV and $Q_{\max}$ for different values of distance R (ranged from 1000 to 1300 m).

reported to be suitable for our problem based on problem identification. Pattern matching is basically an input/output mapping problem, the closer the mapping, and the better performance of the network.

There are many parameters affecting ground vibration (PPV) as discussed before. It is difficult to determine all the relevant parameters which have influence on the prediction of ground vibration. However, the objective of the present investigation was to predict PPV from some parameters. All the influencing parameters are not independent and some of them are strongly correlated. Hence, it was not important to use all the variables as input parameters.

Thus, taking the above discussion and objective of the investigation under consideration, one network was designed to predict the PPV (ground vibration). The suggested ANN architecture for this model is one hidden layers, one input and one output layer. To select the optimum architecture of the network, we try many network configurations by changing the number of hidden neurons in the second layer as shown in Table 2. The network with 8 hidden neurons gives the smallest mean square error. Therefore we choose this network as a model to fit our experimental data.

Table 2 Various neural network design sessions.

Session	# of Input Neuron	# of neuron 2 nd hidden layer	# of neurons output layer	Learning rate	# of training data	# of Epochs	MSE	# of Test Data
1	8	3	1	0.05	79	100	0.04025	15
2	8	4	1	0.05	79	100	0.031721	15
3	8	5	1	0.05	79	100	0.0127401	15
4	8	6	1	0.05	79	100	0.0084494	15
5	8	7	1	0.05	79	100	0.0044766	15
6	8	8	1	0.05	79	100	0.0019207	15

Table 3 Comparison between recorded and predicted values of peak particle velocity for different predictors.

Blast No.	PPV mm/sec Measured	Predicted PPV USBM (Duvall and Fogelson, 1962) mm/s	Error of estimation	Predicted PPV Ambrasseys-Hendron (1968) mm/s	Error of estimation	Predicted PPV Langefors-Kihlstrom/ Lankhui(1978)mm/s	Error of estimation	Predicted PPV Davies et al. (1964) mm/s	Error of estimation	Predicted PPV Multiple Regression (MVRA) mm/s	Error of estimation	Predicted PPV Neural Net Work mm/s	Error of estimation
1	0.88	0.54973	0.33027	0.55109	0.32891	0.54498	0.33502	0.53664	0.34336	0.49650	0.38350	0.91610	-0.03610
2	0.74	0.51969	0.22031	0.51924	0.22076	0.51848	0.22152	0.50790	0.23210	0.42500	0.31500	0.93870	-0.19870
3	0.68	0.51549	0.16451	0.51216	0.16784	0.51795	0.16205	0.49322	0.18678	0.49880	0.18120	0.51050	0.16950
4	0.50	0.67872	-0.17872	0.67593	-0.17593	0.67231	-0.17231	0.60929	-0.10929	0.60730	-0.10730	0.42960	0.07040
5	0.42	0.71905	-0.29905	0.72001	-0.30001	0.70591	-0.28591	0.65019	-0.23019	0.73670	-0.31670	0.39000	0.03000
6	0.96	0.57539	0.38461	0.57648	0.38352	0.56973	0.39027	0.55356	0.40644	0.53480	0.42520	0.93910	0.02090
7	0.65	0.46725	0.18275	0.46471	0.18529	0.47082	0.17918	0.46093	0.18907	0.47700	0.17300	0.39010	0.25990
8	0.66	0.46111	0.19889	0.45678	0.20322	0.46713	0.19287	0.44896	0.21104	0.48740	0.17260	0.39000	0.27000
9	0.48	0.60531	-0.12531	0.60029	-0.12029	0.60552	-0.12552	0.55052	-0.07052	0.60530	-0.12530	0.39010	0.08990
10	0.41	0.60154	-0.19154	0.60842	-0.19842	0.58776	-0.17776	0.59494	-0.18494	0.57490	-0.16490	0.39000	0.02000
11	0.67	0.51381	0.15619	0.50834	0.16166	0.51896	0.15104	0.48347	0.18653	0.64320	0.02680	0.94000	-0.27000
12	0.94	0.58561	0.35439	0.60805	0.33195	0.55499	0.38501	0.65077	0.28923	0.70730	0.23270	0.94000	0.00000
13	0.90	0.55109	0.34891	0.55258	0.34742	0.54612	0.35388	0.53813	0.36187	0.55890	0.34110	0.93950	-0.03950
14	0.64	0.44123	0.19877	0.44074	0.19926	0.44333	0.19667	0.45005	0.18995	0.38900	0.25100	0.93940	-0.29940
15	0.88	0.57258	0.30742	0.57215	0.30785	0.56887	0.31113	0.54554	0.33446	0.58290	0.29710	0.39160	0.48840
Standard error of estimate			0.2753		0.2737		0.2773		0.2708		0.2769		0.2197

Fig.8 Comparison of predicted PPV with measured for new 15 datasets.

7. Comparison among all prediction

By comparison of the predictors through 15 new datasets as indicated in Table 3 and according to the standard error of estimate, 0.2197, it is found that the suitability of application of the ANN for prediction of PPV is over the widely used vibration predictors.

All above equations have been used for the prediction of PPV of 15 datasets. Fig. 8 shows the comparison of all predictors with new measured data (15 datasets).

8. Conclusion

Based on 79 vibration datasets and by statistical and programming treatment, six predictors were determined. It was

found that, statistical models of five predictors have weak to medium intensity correlation coefficient, while ANN has high intensity correlation coefficient with vibration data.

If an unusual noise or scattering exists in the measured data of vibrations, statistical models have difficulty in making accurate prediction. Therefore, the use of neural network (ANN) is very important to predict the vibration level (PPV) precisely.

It was found that, the distance (R), max charge /delay (Q_{max}), total charge of explosive (Qt), and total length of charge / total length of b.h (d/D) have more effect on PPV, where their correlation coefficient is 68%. But geometrical parameters such as spacing/burden (S/B), sub drilling/ burden (J/B), total number of bore holes (N), and stemming/ burden (T/B) have less effect on PPV, where their correlation coefficient is only 2.2 % with PPV.

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エジプト・Tourah 鉱山における発破振動予測式の比較及び検討

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この論文では、エジプト Tourah 鉱山における発破振動予測について述べる。すなわち、振動計 REF TEK-130 SMA を用いて適切な装薬量と最大粒子速度 (PPV) の関係について発破孔からの距離が異なる 79 箇所の発破観測データをもとに種々の検討を行い、一般的に利用される振動予測式を用いて解析を行うとともに、6 つの異なる予測式から PPV を算出し、前述の計測とは異なる 15 箇所の PPV 結果と比較検討を行った。また、現場に適した PPV 予測式を選定するために、同データを 3 層構造のニューラルネットワーク解析に適用した。その結果、本鉱山において、ニューラルネットワーク解析により得られた予測式は、一般的に利用されている振動予測式よりも高い精度で PPV を予測できることが分かった。

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