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Development of a model to predict peak particle velocity in a blasting operation

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ABSTRACT

Ground vibrations arising from rock blasting is one of the fundamental problems in the mining industry, and predicting it plays an important role in the minimization of environmental complaints. To evaluate and calculate the blast-induced ground vibration by incorporating blast design and rock strength, artificial neural networks (ANN) and dimensional analysis techniques were used. First a three-layer, feed-forward back-propagation neural network having nine input parameters, twenty-five hidden neurons and one output parameter was trained using 116 experimental and monitored blast records from one of the most important copper mines in Iran. Seventeen new blast datasets were used for the validation of the peak particle velocity (PPV) by ANN. In the second step, a new formula was developed applying dimensional analysis on results obtained from the sensitivity analysis of the ANN consequences. Results from the calculated formula were compared based on correlation coefficient and root mean square error (RMSE) between monitored and predicted values of PPV. In addition to providing the best prediction of vibration, the new formula has the greatest correlation coefficient and the lowest RMSE, 74.5% and 3.49, respectively.

1. Introduction

Ground vibrations consume explosive energy that could be applied instead to rock fracturing. The intensity of vibration plays a critical role in all types of adverse effects. High ground vibrations not only create problems to the nearby population, but also adversely affect the integrity of the structures in the mine area. Sometimes, it provokes the population and can lead to the mine's closure. High intensity vibration also damages the groundwater and harms the ecology of the nearby area. Blast-induced ground vibration has a detrimental effect on structures such as buildings, dams, roads, railroads, natural slopes, etc. If ground vibration is not controlled or minimized, it may be one of the main causes of deforestation in the future by changing the groundwater level, creating landslides, soil loss, etc [1]. Ground vibration may damage the free face and generate back breaks [2]. These back breaks create problems while drilling the next blast round and generate over-size boulders [3]. This adversely affects the mine's economics, hampers production and endangers the socio-economic development of the surrounding area. Therefore, it is important to control and measure the vibration with greater accuracy.

To prevent vibration problems, various parameters such as the physico-mechanical properties of rock mass, explosives specifications and geometrical and timing aspects of the blasting pattern should be considered when designing a blasting pattern. In the past, traditional methods were mostly used in the design of the blasting pattern. With regard to the fact that the number of effective parameters is too large and the interactions are too complicated, empirical blasting design methods may not be fully suitable for this purpose. Currently, new techniques such as artificial neural networks (ANN), genetic algorithms (GA), fuzzy expert systems (FES), techniques for order preference by similarity to ideal solution (TOPSIS), etc., are frequently applied [3–5].

The ANN technique is a relatively new branch of 'artificial intelligence' (AI) and has been developed since the 1980s. At the present time, the ANN technique is considered to be one of the most intelligent tools for simulating complex problems. This technique has the ability to generalize a solution from the patterns presented to it during training. Once the network is trained with a sufficient number of sample datasets, for a new input of relatively similar patterns, predictions can be made on the basis of previous learning [6]. Due to its multidisciplinary nature, ANNs are becoming popular among researchers, planners, designers and the like, as an effective tool [7–18]. In the ground vibration field, Mohamed applied ANN to predict and control the blast vibration in a limestone quarry [19]. Khandelwal and Singh [20] predicted the PPV by ANN, taking into consideration the distance from the blast face to monitoring point and explosive

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charge per delay. They compared their findings with the commonly used vibration predictors and found very good results by ANN prediction as compared to vibration predictor equations [1]. Khandelwal and Singh [21] also studied the blast vibration and frequency using rock, blast design and explosive parameters with the help of ANN and compared their results with multivariate regression analysis.

Since ground conditions vary from one mine to another, it is necessary to preset a specific formula for each mine in order to determine and decrease the vibration. Considering all the parameters affecting vibration in a single formula is a quite difficult task. On the other hand, for developing an efficient mathematical model, it is necessary to select and apply all the important factors. In this research, an attempt has been made to develop a rather more comprehensive relationship for calculating the peak particle velocity (PPV).

To determine PPV, dimensional analysis method was selected. The dimensional analysis technique is based on reducing complex physical problems to the simplest form prior to obtaining a quantitative answer. The principal use of dimensional analysis is to deduce certain limitations from a study of the dimensions of the variables in any physical system on the form of any possible relationship between those variables. The method is of great generality and mathematical simplicity [22].

With the help of dimensional analysis and having the results of ANN sensitivity analysis, a comprehensive mathematical model using the SPSS 17 software was developed.

2. Artificial neural network

The ANN technique is a branch of 'Artificial Intelligence' (AI). Other branches are Case Based Reasoning (CBR), Expert Systems (ES), Genetic Algorithms (GA) and fuzzy logic. The ANN method is an information processing system simulating the structures and functions of the human brain. It attempts to imitate the way in which a human brain works in processes such as studying, memorizing, reasoning and inducing with a complex network, which is performed by extensively connecting various processing units. It is a highly interconnected structure that consists of many simple processing elements or neurons capable of performing massive parallel computations for data processing and knowledge representation. The paradigms in this field are based on direct modeling of the human neuronal system [23]. A neural network can be considered as an intelligent hub that is able to predict an output pattern when it recognizes a given input pattern. The neural network is first trained by processing a large number of datasets. After completion of proper training, the neural network can detect similarities when presented a new pattern and accordingly, predict the output pattern. This property gives excellent interpolation capability to the technique, especially when the input data is noisy (not exact). Depending on computational capabilities, neural networks may be used as a direct substitute for auto-correlation, multivariable regression, linear regression and other statistical analysis techniques. When data are analyzed using a neural network, it is possible to detect important predictive patterns that were not previously apparent to a non-expert. Thus, the neural network can act like an expert. A particular network can be defined using three fundamental components; transfer function, network architecture and learning law [24]. One has to define these components according to the type of problem to be solved.

A network first needs to be trained before interpreting new information. Various algorithms are available for training neural networks. The back-propagation algorithm is the most versatile and robust technique and provides the most efficient learning procedure for multilayer perception neural networks. Also, the fact that the back-propagation algorithm is especially capable of solving predictive problems makes it so popular [25]. The feed-forward back-propagation neural network (BPNN) always consists of at least three layers; input layer, hidden layer and output layer [26]. Each layer consists of a number of elementary processing units, called neurons, which are connected to the next layer through weights, i.e. each neuron in the input layer will send its output (as input) for neurons in the hidden layer and similar is the connection between hidden and output layer. The number of hidden layers and the number of neurons in the hidden layers is changed according to the problem to be solved. The number of input and output neurons is the same as the number of input and output variables. For this research, multilayer network architecture with a hidden layer between input and output units is applied. To differentiate between the various processing units, bias values are introduced in the transfer functions. These biases are referred to as the temperature of a neuron. In the back-propagation neural network, with the exception of input layer neurons, all other neurons are associated with a bias neuron and a transfer function [27]. The bias is much like a weight, except that it has a constant input of 1, while the transfer function filters the summed signals received from this neuron. The transfer functions are designed to map a neuron or layers net output to its actual output. These transfer functions are either linear or nonlinear [27]. The type of these transfer functions depends on the purpose of the neural network. The output layer produces computed output vectors corresponding to the solution.

During network training, data is processed from the input layer to the hidden layer, until it reaches the output layer (forward pass). In this layer, the output is compared to the measured values (the "true" output) and the difference (error) is processed back through the network (backward pass) by updating the individual weights of the connections and biases of individual neurons. The input and output data are represented by vectors called training pairs. The process is repeated for all the training pairs in the dataset, until the network error converges to a threshold (minimum) defined by a corresponding cost function. The error can always be calculated using the root mean squared error (RMSE) or mean absolute error (MAE).

3. Dimensional analysis

Dimensional analysis is an engineering method for forming equations that simplifies the analysis of complex multivariable systems [28–30]. Dimensional analysis had its origin in the work of Maxwell who used the symbols $[F]$, $[M]$, $[L]$, $[T]$, $[Q]$ to denote force, mass, length, time, and charge, respectively. Lord Rayleigh used it extensively in his 'theory of sound', and called it 'the principle of similitude' or 'the method of dimensions' [30]. He was famous for writing the following statement testifying to the power of the method "It happens not infrequently that results in the form of laws are put forward as novelties on the basis of elaborate experiments, which might have been predicted a priori after a few minutes consideration". Applications of dimensional analysis to engineering problems have been conducted by well-known scholars such as Einstein and Reynolds. The method of dimensions developed over time to include many sub-techniques. First, it was used to derive dimensionless groups. Then, it was utilized for scale up purposes, so that small-scale models can be extrapolated to real-life models. This evolved to the point where dimensional analysis is used for appropriate scaling. Through scaling, it is possible to judge. Scaling leads to the useful concept of the order of magnitude. It is useful because it is possible to compare two phenomena and decide: relevant, comparable or irrelevant. This engineering judgment is critical in reducing the physical complexity of the problem to be solved [31]. For example, when a process involves a number of factors, the order of magnitude helps in finding which of these factors are dominant and which are irrelevant or negligible.

One of the best techniques or variations for carrying out a dimensional analysis is Buckingham π-theorem. The Buckingham π-theorem (also written as Pie-theorem) states that if n measurable quantities (or variables) form a complete functional relationship $\varphi(\alpha,\beta,\gamma,\ldots)=0$, then the solution has the form $f(\pi_1, \pi_2, \pi_3,\ldots)=0$ where the π's are then the n–m independent products of the arguments $\alpha,\beta,\gamma,\ldots$, etc., which are dimensionless in the fundamental units required to measure the quantities. It is called complete because the relationship consists of sufficient fundamental dimensions to describe the magnitude of the quantity of interest. So, the dimensionally homogeneous equation $\varphi(\alpha,\beta,\gamma,\ldots)=0$ is reduced to a relationship among a complete set of dimensionless products, referred to as the p terms, and the number of the members (terms) of the set is equal to the number n of measurable quantities/variables minus the number of fundamental units m involved in measuring the variables. The dimensional matrix has the variables as the column/row headings and the fundamental dimensions forming the rows/columns.

The application of dimensional analysis goes through several steps. First, all variables involved in the phenomenon are listed. Because dimensional analysis finds the minimum number of groups based on primary dimensions, close attention needs to be paid to make sure that only relevant quantities are included and physical irrelevant independent variables are discarded. A physically irrelevant variable has a sufficiently small influence on the dependent variable (the target variable).We can also recognize a physically irrelevant variable through physical insight of the problem at hand or through experimental investigations. At this stage, one has to be careful about the linear dependency among parameters. After which the dimensional matrix is assembled (sometimes called the constitutive matrix). Once the matrix is assembled a number of techniques and conditions help one proceed and these depend on the number of dimensions involved with respect to the number of variables. When equations governing the process are provided, then the dimensionless groups can be set to 1 for scale factors, and to zero for reference factors. This usually leads to the minimum parametric representation. The π's include dimensionless groups which are made from combining geometric and physical quantities and other dimensionless independent variables.

4. Model development

Blast vibration was studied in one of the most important and largest copper mines in Iran. The Sarcheshmeh copper ore mine is situated 160 km southwest of Kerman and 50 km south of Rafsanjan city, Kerman province, in 55°52′13″ longitude and 29°57′0″ latitude. This mine is at 2500 m above sea level (Fig. 1). The area belongs to central part of an elongated NW–SE mountain belt, which is principally composed of folded volcano-sedimentary rocks. The geology of Sarcheshmeh porphyry deposit is very complicated and various rock types can be found. Other minerals such as molybdenum, gold and silver are seen in the deposit. Mineralization in this deposit is associated with a Late Tertiary. The main minerals of the deposit are Chalcocite, Chalcopyrite, Pyrite, Covellite, Bornite and Molybdenite. The oxide zone of deposit consists mainly of Cuprite, Tenorite, Malachite and Azurite. The proved reserve of the deposit is approximately 826 Mt with an average grade of 0.7%. The mine is exploited by open pit mining. The height and slope of working benches are 14 m and 62.5°, respectively. The angle of overall slope ranges from 32° to 34°. The distance of crusher to mine is 3 km. The annual capacity of the mill plant is 51 000 tons concentrated with an average grade of 30% and a recovery of 65%.

The diameter and depth of blast holes are mostly 0.200 and 15 m, respectively. The explosive used is ANFO. The average powder factor is 0.2 kg/ton. Pattern geometry is staggered. Drilling cuttings are used as stemming material. The range of the other blasting design parameters is listed in Table 1.

4.1. ANN model

Table 1 indicates the input and output parameters, considered for developing the neural network, their respective symbols and possible ranges. The previous blasting operations helped in collecting data during the present study. The distance of the monitoring point from blasting face was measured in the field

Fig. 1. Sarcheshmeh copper mine.

prior to blast. The term of delay in charge per delay was calculated from the delay time in each row. To maintain statistical consistency, the data were grouped into training and testing sets. From a total of 116 datasets, only 99 datasets were selected randomly for training the model. The rest of datasets, i.e. 17 datasets, were used for testing the ANN model.

To reach an appropriate architecture, MLP networks with one and two hidden layers were examined. As errors of the two-hidden-layer networks were high, one-hidden-layer network was selected for simulation (Table 2). To determine the optimum network topology, the following indexes, i.e. root mean squared error (*RMSE*), mean absolute error (E_a) and mean relative error (E_r) were used [2]:

$$RMSE = \sqrt{\frac{(O_i - T_i)^2}{N}} \tag{1}$$

Table 1
Input and output parameters used for developing neural network.

Parameter	Symbol	Range	Unit
Input			
Burden	B	2–7.5	m
Spacing	S	2.5–11	m
Delay between rows	D_e	15–70	ms
Powder factor	q	0.1–0.24	kg/m^3
Number of rows in each blast	n	2–7	–
Distance of monitoring point from blasting face	μ	133.02–2845.02	m
Maximum hole per delay	θ	6–32	–
Charge per delay	ch	1332–10985	kg
Point load index	σ	6.51–8.9	MPa
Output			
Peak particle velocity	*PPV*	0.49–77.3	mm/s

Table 2
Results of a comparison between some of ANN.

Model	Transfer Function	E_a	E_r	*RMSE*
9-25-1	Logsig-Logsig-Poslin (LLP)	0.012	1.345	0.0245
9-35-1	Logsig-Logsig-Poslin (LLP)	0.014	1.446	0.0280
9-15-1	Logsig-Tansig-Poslin (LTP)	0.017	1.864	0.0319
9-20-1	Logsig-Logsig-Poslin (LLP)	0.015	1.692	0.0262
9-10-20-1	Logsig-Tansig-Tansig-Poslin (LTTP)	0.137	15.099	0.1551
9-15-10-1	Logsig-Logsig-Logsig-Poslin (LLLP)	0.036	4.022	0.0776
9-12-35-1	Tansig-Tansig-Logsig-Poslin (TTLP)	0.122	13.426	0.1417

$$E_a = |T_i - O_i| \tag{2}$$

$$E_r = \left(\frac{|T_i - O_i|}{T_i}\right) \times 100 \tag{3}$$

Here, T_i, O_i and N represent the actual historical output, the predicted output and the number of input–output data pairs, respectively. The network with architecture 9–25–1, which has the minimum *RMSE*, E_a and E_r is considered as the optimum model (Fig. 2). Some of the simulated ANNs were shown in Table 2. The first and second columns of this table refer to the architecture of simulated ANNs and their transfer functions, respectively. As shown in row 1, the *RMSE*, E_a and E_r for the selected network are equal to 0.0245, 0.0123% and 1.3445%, respectively.

A graphic comparison of measured and predicted PPV is shown in Fig. 3. As seen in this figure, a very high conformity exists between the measured PPV for different types of patterns and the ones predicted by the ANN method.

Sensitivity analysis is a method for extracting the cause and effect relationship between the inputs and outputs of the network. To make sure of the influence of the input variables on output variables, sensitivity analysis was also carried out. This testing process provides a measure of the relative importance among the inputs of the neural model and illustrates how the model output varies in response to variations of an input.

A sensitivity analysis was carried out for all nine input parameters to understand the relative significance of each parameter on PPV (Fig. 4). The sensitivity analysis was executed by keeping all input parameters constant except one and then finds the effect of that input parameter on PPV. For example, the burden was deleted from the input parameters and then the ANN was run by eight input parameters. So, the effect of burden on the PPV can be understood by comparing the new result of the simulation and previous results. This procedure must be done for the other input parameters, too.

Parameters including distance of monitoring point from blasting face (μ), powder factor (q), charge per delay (ch), maximum hole per delay (θ) and delay between rows (D_e) are the most influential factors on PPV.

4.2. Dimensional analysis model

The relationships among concerned parameters with each other and with PPV were defined in the form of dimensionless

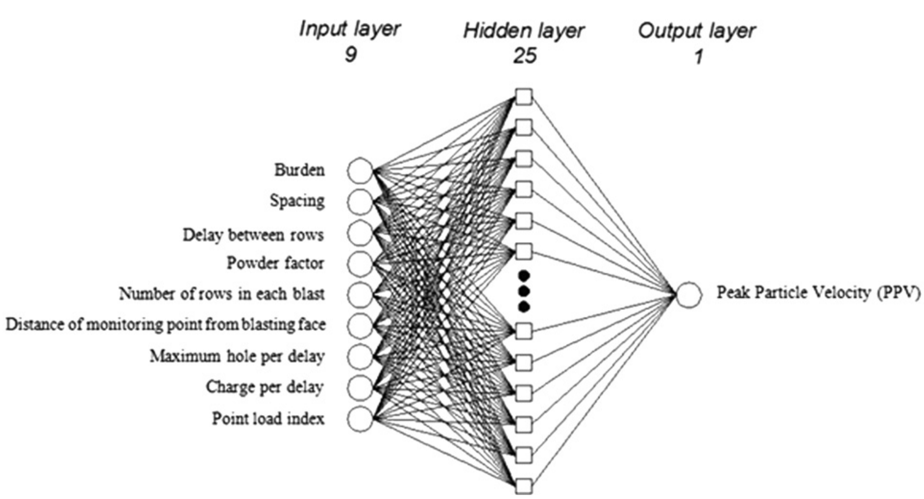

Fig. 2. Suggested ANN used for the case study.

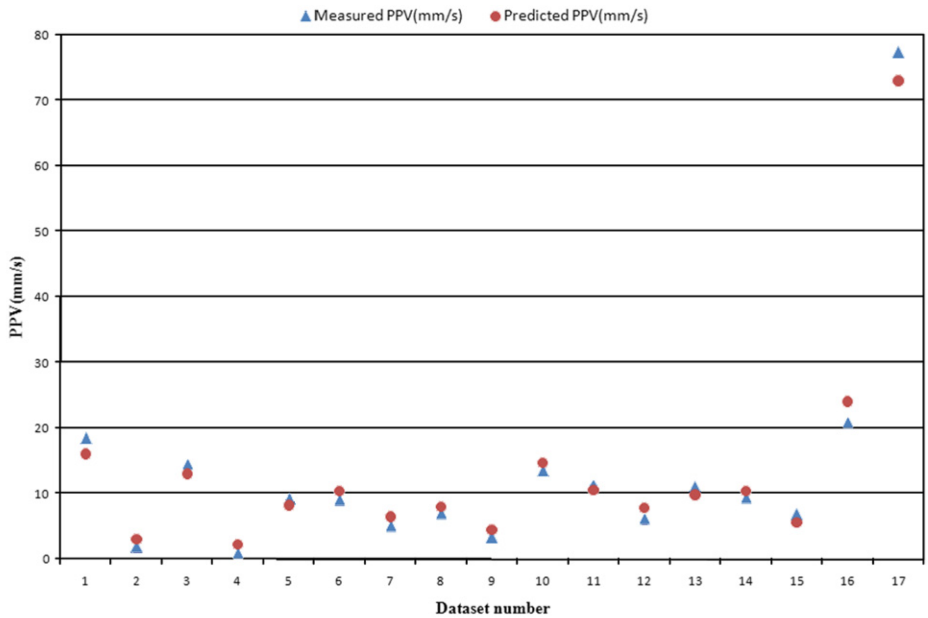

Fig. 3. Comparison of measured and predicted peak particle velocity for different type of patterns.

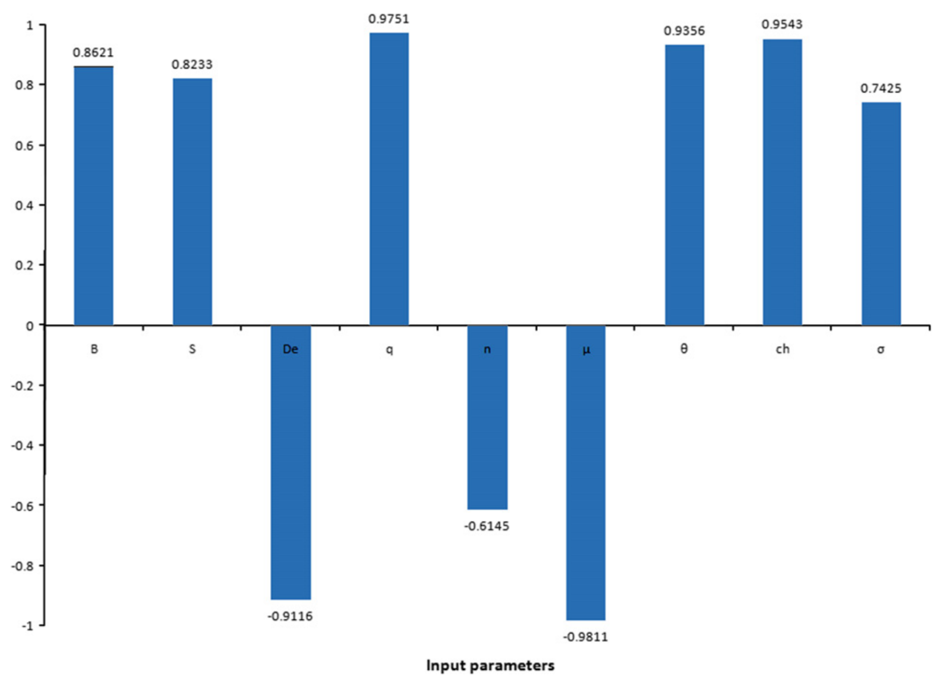

Fig. 4. Sensitivity analysis between the peak particle velocity and each input parameters.

terms. As a result of ANN sensitivity analysis, it is assumed that PPV is a function of the important input variables the score of which was at least 80%. Therefore, a formula can be written as follows:

$$PPV = f(B,S,D_e,ch,q,\theta,\mu) \tag{4}$$

Eq. (4) can be converted as follows:

$$f(PPV,B,S,D_e,ch,q,\theta,\mu) = 0 \tag{5}$$

In dimensional analysis, it is necessary to select a unit system, i.e. mass or force. Here, the force system has been chosen. Accordingly, dimension of each variable can be defined as follows: $[PPV]=LT^{-1}$, $[B]=L$, $[S]=L$, $[D_e]=T$, $[q]=FL^{-4}T^2$, $[\mu]=L$, $[\theta]=1$, $[ch]=FL^{-1}T^2$, where F, T and L represent force, time and length, respectively.

With the available variables, a lot of dimensionless combinations of complete sets can be constructed. But as a first step, to make dimensional matrix, variables should be arranged correctly. Dimensional matrix for PPV may be considered as follows:

	PPV	B	S	θ	μ	D_e	Q	ch
F	0	0	0	0	0	0	1	1
L	1	1	1	0	1	0	−4	−1
T	−1	0	0	0	0	1	2	2

To determine the rank of the matrix, the determinant of the right side is calculated.

$$\begin{vmatrix} 0 & 1 & 1 \\ 0 & -4 & -1 \\ 1 & 2 & 2 \end{vmatrix} = 3$$

The determinant is not equal to zero. Therefore, it can be concluded that the variables are selected correctly and the rows of matrix are not linearly dependent.

The dimensional matrix included eight variables and the rank of this matrix is 3. According to the π theorem, in a complete set there should exist five dimensionless terms [30,32]. Π and homogeneous algebraic equations can be written by the dimensional matrix as follows:

$$\pi_1 = \pi_2 = \pi_3 = (T)^{k1}(FL^{-4}T^2)^{k2}(FL^{-1}T^2)^{k3}(L) \tag{6}$$

$$\pi_4 = \theta \tag{7}$$

$$\pi_5 = (T)^{k4}(FL^{-4}T^2)^{k5}(FL^{-1}T^2)^{k6}(LT^{-1}) \tag{8}$$

The summation of the powers in Eqs. (6)–(8) must be equal to zero. The summations of the powers of each parameter of Eq. (6) are as follows:

For $T: k_1 + 2k_2 + 2k_3 = 0$
For $F: k_2 + k_3 = 0$
For $L: -4k_2 - k_3 + 1 = 0$

By solving the above equations, the powers are found to be $k_1=0$, $k_2=1/3$, and $k_3=-1/3$.

The summations of power of each parameter of Eq. (8) are as follow:

For $T: k_4 + 2k_5 + 2k_6 - 1 = 0$
For $F: k_5 + k_6 = 0$
For $L: -4k_5 - k_6 + 1 = 0$

By solving the above equations, the powers are found to be $k_4=1$, $k_5=1/3$, and $k_6=-1/3$.

The complete set consists of the following dimensionless terms: $\pi_1 = (PPV)(D_e)(q/ch)^{1/3}$, $\pi_3 = S(q/ch)^{1/3}$, $\pi_2 = B(q/ch)^{1/3}$, $\pi_4 = \mu(q/ch)^{1/3}$, $\pi_5 = \theta$.

These formulas show that the powder factor and charge per delay as presented in the sensitivity analysis played a very important role in *PPV*. In the next stage, it should be considered whether the relationship is linear or nonlinear. With the help of multivariable regression analysis from the collected data, unknown coefficients can be determined. With a comparison between correlation coefficient (R^2) of the linear and nonlinear equations, it was concluded that the nonlinear equation is more suitable:

$$\ln[PPV * D_e * (q/ch)^{1/3}] = k + a\ln[(B(q/ch)^{1/3}] + b\ln[S(q/ch)^{1/3}] + c\ln[\mu(q/ch)^{1/3}] + d\ln\theta \tag{9}$$

The unknown coefficients were calculated by SPSS 17 to be $a=-5.642$, $b=3.426$, $c=-1.225$, $d=-1.181$, and $k=5.129$. After some manipulation, the model can be expressed as

$$PPV = \frac{168.85}{D_e}(q/ch)^{-1.48}B^{-5.64}S^{3.43}\mu^{-1.22}\theta^{-1.18} \tag{10}$$

The correlation coefficient (R^2) of this formula is 77.5%. It should be mentioned that by this method, specific information of each case should be applied for using the model, and therefore, accuracy and reliability of the calculation of the coefficients, depends on the accuracy of recorded information of real blasting operations. In Fig. 5 the measured *PPV* and calculated *PPV* using the obtained formula is compared.

Table 3
Different conventional predictors.

Name	Equation
USBM (1959)	$PPV = a_1(\mu/\sqrt{Q_{max}})^{-\alpha_2}$
Langefors–Kihlstrom (1963)	$PPV = a_1(\mu/\sqrt{Q_{max}/\mu^{2/3}})^{\alpha_2}$
General predictor (1964)	$PPV = a_1\mu^{-\alpha_2}(Q_{max})^{\alpha_3}$
Ambraseys–Hendron (1968)	$PPV = a_1(\mu/\sqrt[3]{Q_{max}})^{-\alpha_2}$
Bureau of Indian Standard (1973)	$PPV = a_1(Q_{max}/\mu^{2/3})^{\alpha_2}$
Ghosh–Daemen predictor (1983)	$PPV = a_1(\mu/\sqrt{Q_{max}})^{-\alpha_2}e^{-\alpha 4\mu}$
CMRI predictor (1993)	$PPV = a_5 + a_1(\mu/\sqrt{Q_{max}})^{-1}$

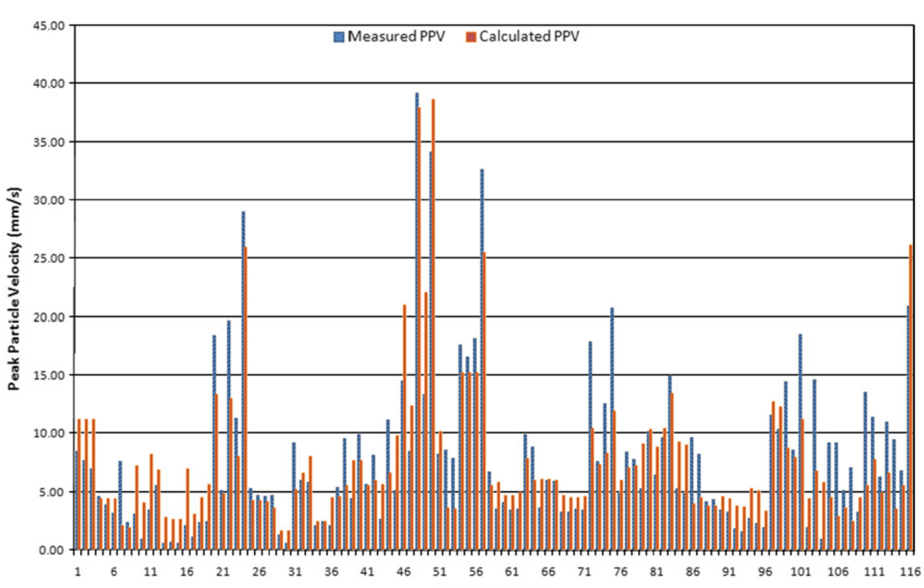

Fig. 5. Comparison between measured and calculated *PPV*.

Table 4
Calculated values of site constants, correlation coefficient and RMSE.

Name	a_1	a_2	a_3	a_4	a_5	R^2	RMSE
USBM (1959)	118.8	1.22	0.693			58.8%	4.75
Langefors–Kihlstrom (1963)	0.049	2.34				41.2%	4.97
General predictor (1964)	19.505	1.034				67.6%	4.63
Ambraseys–Hendron (1968)	596.3	1.19				56.1%	4.78
Bureau of Indian Standard (1973)	0.049	1.17				41.2%	4.97
Ghosh–Daemen predictor (1983)	83.048	0.996		0.00002		66.8%	4.40
CMRI predictor (1993)	84.89		3.426		−0.358	66.8%	4.49
New formula (2009)	5.129	−5.642		−1.225	−1.181	74.5%	3.49

5. Discussion

Table 3 illustrates various conventional vibration predictor equations proposed by different researchers [33–39]. The determined formula was compared with these formulas. The result of comparison is shown in Table 4.

Where *PPV* is the peak particle velocity in mm/s, Q_{max} is the maximum charge per delay in kg, μ is the distance between blast face and vibration monitoring point, in metres and $\{a_1, a_2, a_3, a_4, a_5\}$ are site constants.

Here, RMSE is varying between 3.49 and 4.97 and the correlation coefficient of the new formula is the greatest.

6. Conclusion

On the basis of the acquired results, the present study concludes that ANN is a robust and versatile technique to improve the efficiency of blasting in open pit mines by controlling the undesirable phenomenon.

The back-propagation algorithm was realized as the most efficient learning procedure. An ANN 9-25-1 topology was found to be optimum for prediction of *PPV* in blasting operation at the Sarcheshmeh copper mine located in Iran.

Dimensional analysis can be considered as an important tool for solving most scientific problems. The contemporary effect of several parameters on blasting results can be studied with the help of dimensional analysis. According to the developed mathematical model, vibration is a function of most important parameters such as powder factor, charge per delay and burden.

The proposed mathematical model has been compared by available conventional *PPV* predictors and yields excellent blast results.

The new formula with coefficient correlation 77.5% and RMSE 3.49 can estimate *PPV* better than other empirical formulae.

References

[1] Khandelwal M, Singh TN. Prediction of blast-induced ground vibration using artificial neural network. Int J Rock Mech Min Sci 2009;46: 1214–22.

[2] Duvall WI, Johnson CF, AVC Meyer. Vibrations from blasting at Iowa limestone quarries. USBM Rep Invest 1963;6270:28.

[3] Monjezi M, Dehghani H. Evaluation of effect of blasting pattern parameters on back break using neural networks. Int J Rock Mech Min Sci 2008;45: 1446–53.

[4] Monjezi M, Dehghan H, Samimi Namin F. Application of TOPSIS method in controlling fly rock in blasting operations. In: Proceedings of the seventh international multidisciplinary scientific geoconference & expo (SGEM). Sofia, Bulgaria, 2007, p. 41–50.

[5] Monjezi M, Dehghani H, Singh TN, Sayadi AR, Gholinejad A. Application of TOPSIS method for selecting the most appropriate blast design. Arab J Geosci, in press, doi:10.1007/s12517-010-0133.

[6] Khandelwal M, Roy MP, Singh PK. Application of artificial neural network in mining industry. Indian Min Eng J 2004;43:19–23.

[7] Maulenkamp F, Grima MA. Application of neural networks for the prediction of the unconfined compressive strength (UCS) from Equotip hardness. Int J Rock Mech Min Sci 1999;36:29–39.

[8] Yang Y, Zhang Q. Analysis for the results of point load testing with artificial neural network. In: Proceedings of the International conference on computing methods and advances in geomechanics (IACMAG), China, 1997, p. 607–19.

[9] Cai JG, Zhao J. Use of neural networks in rock tunneling. In: Proceedings of computing methods and advances in geomechanics (IACMAG), China, 1997, p. 613–31.

[10] Singh VK, Singh D, Singh TN. Prediction of strength properties of some schistose rock. Int J Rock Mech Min Sci 2001;38:269–84.

[11] Khandelwal M, Singh TN. Prediction of waste dump stability by an intelligent approach. In: Proceedings of national symposium on new equipment—new technology, management and safety, ENTMS, Bhubaneshwar, 2002, p. 38–45.

[12] Maity D, Saha A. Damage assessment in structure from changes in static parameters using neural networks. Sadhana 2004;29:315–327.

[13] Singh TN, Kanchan R, Saigal K, Verma AK. Prediction of P-wave velocity and anisotropic properties of rock using artificial neural networks technique. J Sci Indust Res 2004;63:32–8.

[14] Dysart PS, Pulli JJ. Regional seismic event classification at the noress array: seismological measurements and the use of trained neural networks. Bull Seismol Soc Amer 1990;80:1910–33.

[15] Finnie GJ. Using neural networks to discriminate between genuine and spurious seismic events in mines. Pure Appl Geophys 1999;154: 41–56.

[16] Musil M, Plesinger A. Discrimination between local micro earthquakes and quarry blasts by multi-layer perceptrons and Kohonen maps. Bull Seismol Soc Amer 1996;86:1077–90.

[17] Rudajev V, Ciz R. Estimation of mining tremor occurrence by using neural networks. Pure Appl Geophys 1999;154:57–72.

[18] Monjezi M, Singh TN, Khandelwal M, Sinha S, Singh V, Hosseini I. Prediction and analysis of blast parameters using artificial neural network. Noise Vibr Worldwide 2006;37:8–16.

[19] Mohamed MT. Artificial neural network for prediction and control of blasting vibrations in Assiut (Egypt) limestone quarry. Int J Rock Mech Min Sci 2009;46:426–31.

[20] Khandelwal M, Singh TN. Evaluation of blast induced ground vibration predictors. Soil Dynam Earthq Eng 2007;27:116–125.

[21] Khandelwal M, Singh TN. Prediction of blast induced air overpressure in opencast mine. Noise Vibr Worldwide 2005;36:7–16.

[22] Bridgman PW. Dimensional analysis. In: Haley W, editor. Encyclopaedia Britannica. vol. 7. Chicago, 1969, p. 439–49.

[23] Kosko B. Neural networks and fuzzy systems: a dynamical systems approach to machine intelligence. New Delhi: Prentice-Hall; 1994 p. 12–7.

[24] Simpson PK. Artificial neural system—foundation, paradigm, application and implementations. New York: Pergamon; 1990.

[25] Tawadrous AS, Katsabanis PD. Prediction of surface crown pillar stability using artificial neural networks. Int J Numer Anal Meth Geomech 2006;31:917–31.

[26] Neaupane KM, Adhikari NR. Prediction of tunneling-induced ground movement with the multi-layer perceptron. Int J Tunnel Underg Space Technol 2006;21:151–9.

[27] Demuth H, Beal M, Hagan M. Neural network toolbox 5 user's guide. Natick, MA: The Math Works, Inc; 1996.

[28] Langhaar H. Dimensional analysis and theory of models. 1st ed.. New York: Wiley; 1951.

[29] JWS Rayleigh. The theory of sound. London: Macmillan; 1878.

[30] Bellamine FH, Elkamel A. Numerical characterization of distributed dynamic systems using tools of intelligent computing and generalized dimensional analysis. Appl Math Comp 2006;182:021–1039.

[31] Bridgman P. Dimensional analysis. New Haven: Yale University Press; 1922.

[32] Murphy G. Similitude in engineering. New York: Ronold Press; 1950.

[33] Duvall WI, Petkof B. Spherical propagation of explosion generated strain pulses in rock. USBM Rep Invest 1959;5483:21.

[34] Langefors U, Kihlstrom B. The modern technique of rock blasting. New York: Wiley; 1963.
[35] Davies B, Farmer IW, Attewell PB. Ground vibrations from shallow subsurface blasts. The Engineer, London 1964:553–559.
[36] Ambraseys NN, Hendron AJ. Dynamic behaviour of rock masses. In: Stagg KG, Zienkiewiez OC, editors. Rock Mechanics in engineering practice. London: Wiley; 1968. p. 203–36.
[37] Bureau of Indian Standards. Criteria for safety and design of structures subjected to underground blast. India. ISI Bull IS-6922; 1973.
[38] Ghosh A, Daemen JK. A simple new blast vibration predictor. In: Proceedings of the 24th US rock mechanics symposium, Texas A&M, 1983, p. 151–161.
[39] Pal Roy P. Putting ground vibration predictors into practice. Colliery Guard 1993;241:63–70.