Journal of Rock Mechanics and Geotechnical Engineering 6 (2014) 67–76

Journal of Rock Mechanics and Geotechnical Engineering

Journal of Rock Mechanics and Geotechnical Engineering

journal homepage: www.rockgeotech.org

An ANN-based approach to predict blast-induced ground vibration of Gol-E-Gohar iron ore mine, Iran

Mahdi Saadat [a], Manoj Khandelwal [b,*], M. Monjezi [c]

[a] Department of Mining Engineering, Shahid Bahonar University of Kerman, Kerman 76196-37147, Iran
[b] Department of Mining Engineering, College of Technology & Engineering, Maharana Pratap University of Agriculture & Technology, Udaipur 313001, India
[c] Faculty of Engineering, Tarbiat Modares University, Tehran, Iran

A R T I C L E I N F O

Article history:
Received 14 August 2013
Received in revised form
13 November 2013
Accepted 18 November 2013

Keywords:
Blast-induced ground vibration
Empirical predictors
Artificial neural network (ANN)
Multiple linear regression

A B S T R A C T

Blast-induced ground vibration is one of the inevitable outcomes of blasting in mining projects and may cause substantial damage to rock mass as well as nearby structures and human beings. In this paper, an attempt has been made to present an application of artificial neural network (ANN) to predict the blast-induced ground vibration of the Gol-E-Gohar (GEG) iron mine, Iran. A four-layer feed-forward back propagation multi-layer perceptron (MLP) was used and trained with Levenberg–Marquardt algorithm. To construct ANN models, the maximum charge per delay, distance from blasting face to monitoring point, stemming and hole depth were taken as inputs, whereas peak particle velocity (PPV) was considered as an output parameter. A database consisting of 69 data sets recorded at strategic and vulnerable locations of GEG iron mine was used to train and test the generalization capability of ANN models. Coefficient of determination (R^2) and mean square error (MSE) were chosen as the indicators of the performance of the networks. A network with architecture 4-11-5-1 and R^2 of 0.957 and MSE of 0.000722 was found to be optimum. To demonstrate the supremacy of ANN approach, the same 69 data sets were used for the prediction of PPV with four common empirical models as well as multiple linear regression (MLR) analysis. The results revealed that the proposed ANN approach performs better than empirical and MLR models.

1. Introduction

Blasting is one of the most pervasive excavation methods in mining and civil engineering projects. Since blast-induced ground vibration has an inevitable impact on rock mass as well as nearby structures and human beings, the prediction of blast-induced vibration and assessment of its effects must be performed prior to actual blasting activities. In order to control the harm of blasting vibration, vital consideration should be taken into the generation and propagation mechanism of blast-induced vibration. While any of three kinematic descriptors (displacement, velocity and acceleration) could be employed to describe ground motion, among these, peak particle velocity (PPV) is the most preferable (ISRM, 1992). All the empirical predictors are based on two parameters, i.e. the maximum charge per delay and the distance from the blasting face to the monitoring point. It is well-known that the intensity of PPV is closely associated with physico-mechanical parameters of rock mass, blast design as well as explosive (Khandelwal and Singh, 2009; Khandelwal et al., 2011), which are underestimated or overestimated while using available conventional predictors. It is important to understand the inter-relation among these parameters, to use appropriate blasting pattern, and to evaluate the detrimental impact of blasting. Moreover, empirical models are not well suitable for predicting any other important parameters such as frequency, air over pressure, fly rocks, etc., which are equally important and critical for safe, smooth and environmentally friendly excavation of rock mass for mining and civil engineering projects (Monjezi et al., 2006; Khandelwal and Singh, 2009).

To understand the complicated nature of ground vibration and to overcome limits of empirical models, artificial neural network (ANN) which has the ability to address the complicated problems can be implemented. ANN is a branch of the artificial intelligence science and has been developed rapidly since 1980s. This method

* Corresponding author. Tel.: +91 2942471379.
E-mail addresses: mkhandelwal1@gmail.com, mkhandelwal@mpuat.ac.in (M. Khandelwal).

Peer review under responsibility of Institute of Rock and Soil Mechanics, Chinese Academy of Sciences.

Production and hosting by Elsevier

1674-7755
http://dx.doi.org/10.1016/j.jrmge.2013.11.001

Table 1
Blasting parameters of GEG iron ore mine.

Explosive type	Blast hole pattern	Bench height (m)	Hole diameter (m)	Rows per blast	Holes per row
ANFO	Staggered	15	0.203	2–7	10–20

is capable of extracting the relation between inputs and outputs of a process, without the physics being explicitly provided to them. Similar to empirical models, this method is computationally inexpensive and easy to implement. Khandelwal and Singh (2007) used ANN to predict PPV at a magnesite mine in India. They considered two parameters, i.e. the distance from the blasting face to the monitoring point and explosive charge per delay, and compared their findings with commonly used predictors. In their other researches at an opencast mine, they studied blast vibration and frequency using rock, blast design and explosive parameters with the help of ANN and compared their results with multivariate regression analysis (Khandelwal and Singh, 2006). Mohammad (2009) used several ANN models on Assiut limestone and concluded that using more input data can improve the capability of ANN to predict PPV. Monjezi et al. (2011) developed an ANN model to predict PPV at Siahbisheh project in Iran, using the maximum charge per delay, the distance from the blasting face to the monitoring point, stemming and hole depth as input parameters and compared their results with empirical models and multivariate regression analysis. By sensitivity analysis, they found that the distance from the blasting face is the most effective and the stemming is the least effective parameter on the PPV. Dehghani and Ataee-pour (2011) developed a model to predict PPV using dimensional analysis. Monjezi et al. (2013) proposed an ANN-based solution for prediction of PPV at Shur River dam, Iran. Other researchers predicted PPV and/or frequency based on ANN models in different projects (Amnieh et al., 2010, 2012; Alvarez-Vigil et al., 2012; Mohamadnejad et al., 2012) and found very superior results compared to conventional methods. The idea of the present study is to predict blast-induced ground vibration in Gol-E-Gohar (GEG) iron ore mine based on the powerful function approximation tool, ANN. The results of both ANN and empirical models were compared with multiple linear regression (MLR) analysis to find the applicability of each method.

2. Site description and data set

The GEG iron ore mine is located in 60 km southwest of Sirjan in Kerman Province of Islamic Republic of Iran. The mine lies at a point approximately equidistant from the cities of Bandar Abas, Shiraz and Kerman, at an altitude of 1750 m above sea level. GEG has six anomalies out of which, the first one is under extraction by open-pit method. This mine is situated on the northeast margin of Sanandaj–Sirjan tectonic-metamorphic belt. Iron ores at GEG are classified in three types based on their chemical characterization, top, bottom, and oxide magnetic. The deposit is excavated by drill-and-blast method. Because of the complex discontinuity existence, the rock type variations and the water bearing beds, the evaluation of blast-induced ground vibration is critically important. The blasting design parameters of the GEG are listed in Table 1. A photograph of GEG mine is shown in Fig. 1.

3. Empirical methods for predicting PPV

In order to control the harm of blasting vibration, scaled distance (SD) laws are developed by various field investigators. SD laws are linear regression, in a log–log plane between PPVs recorded at various distances during a blast. Table 2 shows the empirical blast-induced ground vibration predictor equations proposed by various researchers. The values of site constants K and B are determined by plotting the graph between PPV and SD on log–log scale and are shown in Table 2. Fig. 2 shows the log–log plots between PPV and different SDs. Fig. 3 illustrates the relationship between measured and predicted PPVs by various SD laws. The higher coefficient of determination for Ambreseys–Henderson and USBM (The United States Bureau of Mines) predictors indicates the better prediction capability over Bureau of Indian Standard (BIS) and Langefors–Kihlstrom predictors.

4. Multiple linear regression analysis

Multiple linear regression (MLR) is a method used to model the linear relationship between a dependent variable and one or more independent variables. MLR is based on least squares, which means that the model is fit such that the sum of squares of differences of predicted and measured values are minimized. An MLR has been conducted for the prediction of PPV. MLR is given by the following equation (Scheaffer et al., 2011):

$$Y = \beta_0 + \beta_1 X_1 + \cdots + \beta_P X_P + e \tag{1}$$

where Y is the predicted variable, X_i ($i = 1, 2, \ldots, P$) are the predictors, β_0 is called intercept (coordinate at origin), β_i ($i = 1, 2, \ldots, P$) is the coefficient on the ith predictor and e is the error associated with the predictor. MLR model was developed based on the same input-independent variables and output-dependent variables as used in ANN model. This resulted in the following equation:

$$PPV = -133.8090 - 0.0002Q_{\max} - 0.1103D + 11.7270H + 4.3550S \tag{2}$$

where H is the hole depth and S is the stemming.

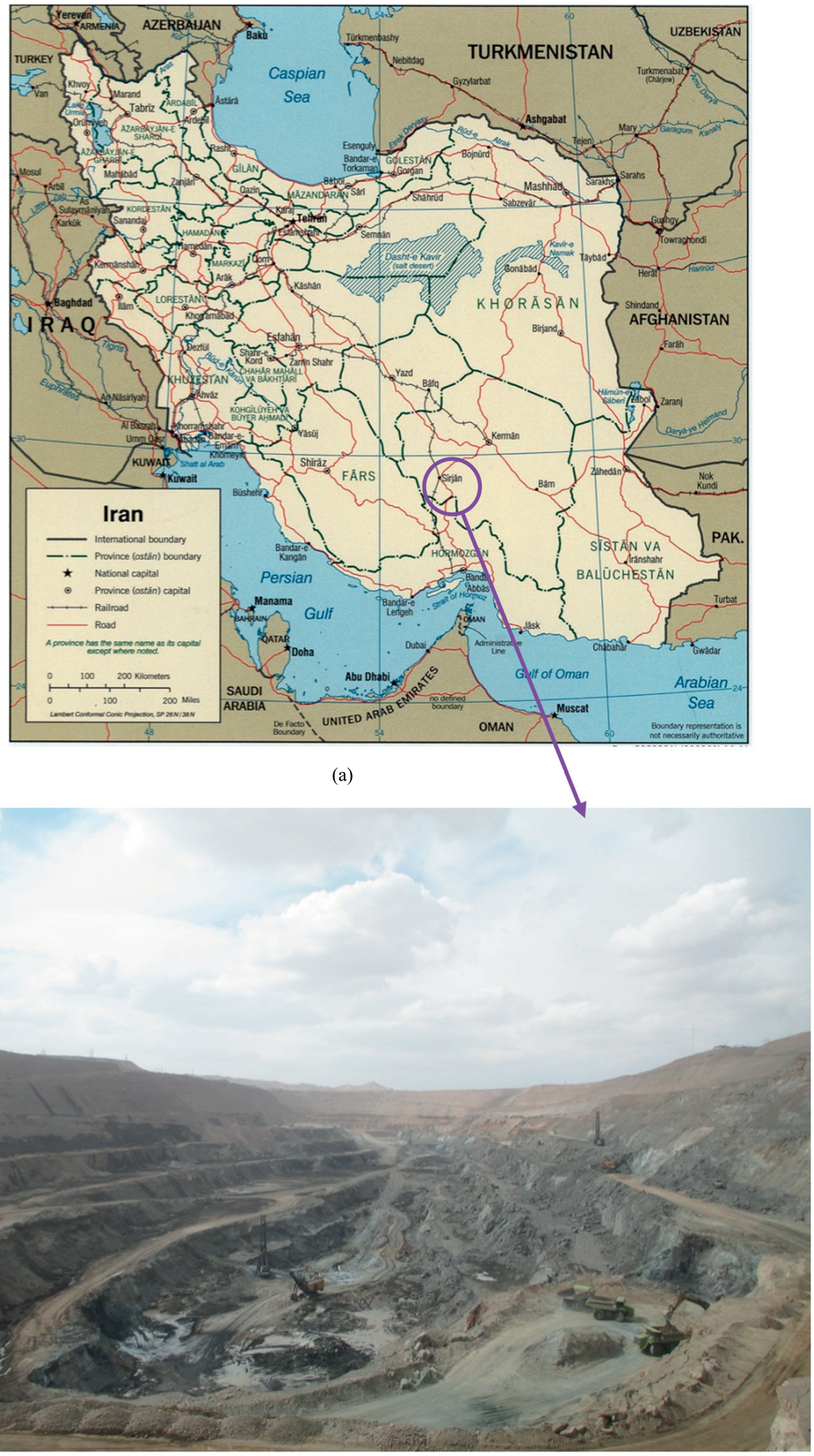
The coefficient of determination for predicted and measured values of PPV is 0.276. Fig. 4 shows the plot of measured and predicted PPVs by MLR model.

5. Overview of artificial neural network

ANN is a form of artificial intelligence which is based on the human neuronal system. ANN can be used to learn and compute functions for which the analytical relationships between inputs and outputs are unknown. An ANN is a computing system consisting of highly interconnected set of simple information processing elements called neurons or perceptrons. The arrangement of these neurons determines the ANN architecture. One of the most commonly implemented ANNs is multi-layer perceptron (MLP) technique.

5.1. Multi-layer perceptron network

MLP networks are feed-forward networks having several layers of simple computing elements, called neurons or perceptrons. A particular network could contain one or more layers in which two or more perceptrons can be combined. The layers of MLP have different roles. The interfacing layer at the input side of the network is called sensory layer (or input layer in common); the one at output side is referred as output layer. All intermediate layers are called hidden layers (Sethi and Jain, 1991). Based on the configuration of the connections between neurons of different layers, the



(a)

(b)

Fig. 1. (a) Location of GEG mine in Iran map and (b) the picture of GEG mine.

number of ANN architectures can be obtained (Rafiai and Moosavi, 2012). Feed-forward neural networks (FFNNs) are a special kind of ANNs, in which the inputs are received and simply forwarded through all the next layers to obtain the outputs (Engelbrecht, 2007). MLP employs an iterative gradient-based optimization routine called back-propagation (BP) learning technique, a kind of FFNN model (Rumelhart et al., 1986; Leondes, 1998). The advantage of BP is that it is simple and easy to understand, but the disadvantage is that convergent speed is slow and BP is not so robust (Lin and Hoft, 1994). The mathematical functions implemented by MLP are continuous and differentiable, which significantly simplifies training and error analysis. The perceptron is the basic structural

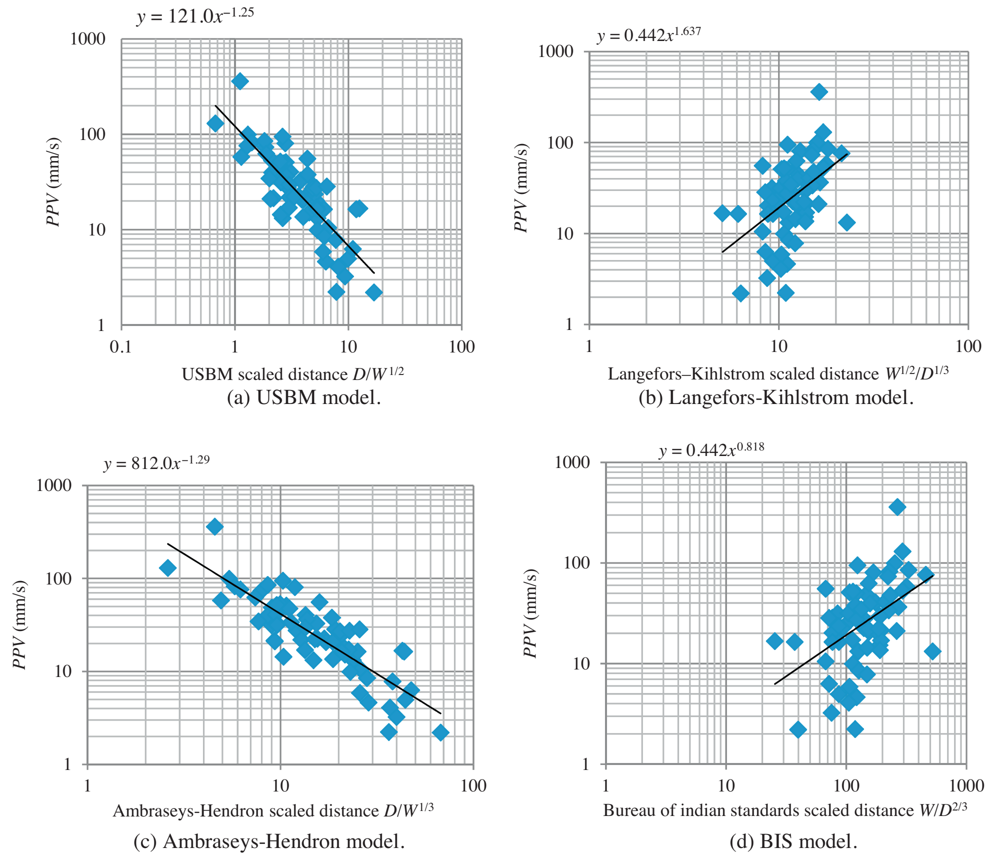


Fig. 2. Log–log plots between PPV and scaled distance for various models (W is the charge per delay, kg; D is the distance between blasting face to vibration monitoring point, m).

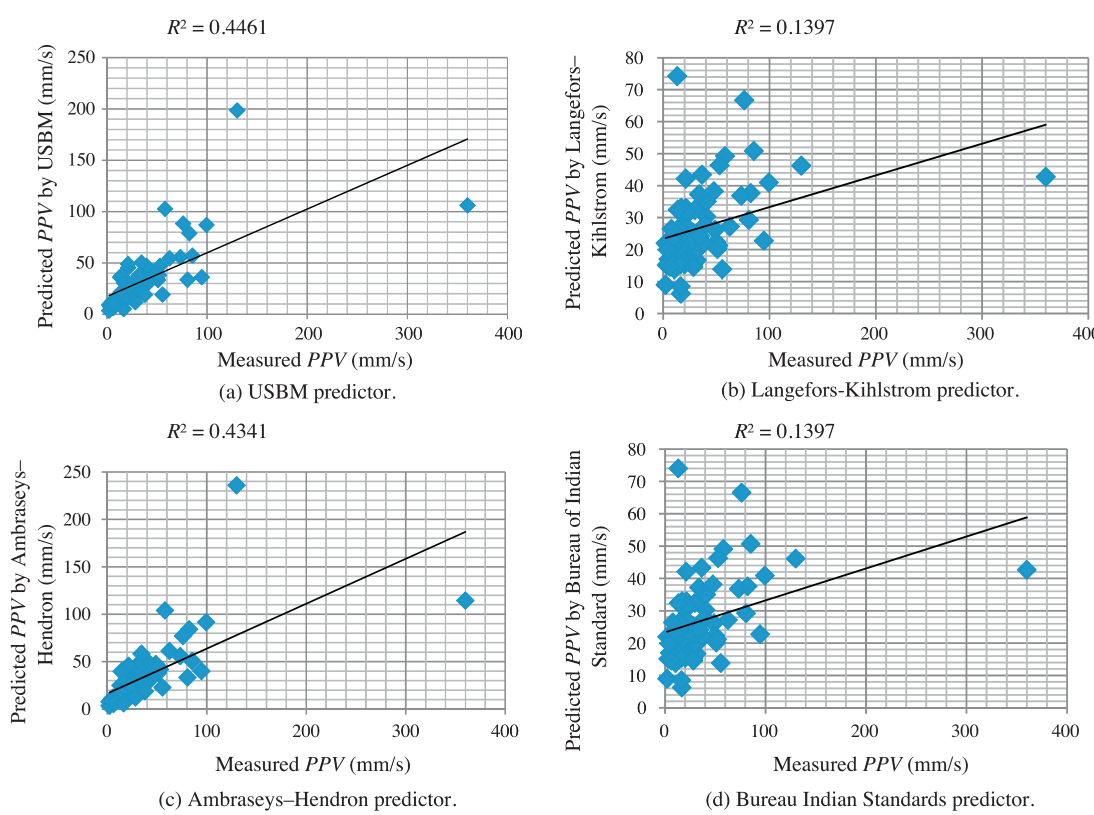


Fig. 3. Graphs between measured and predicted PPVs by various predictors.

Table 2
Different empirical predictors.

Name	Equation	K	B
USBM (Duvall and Fogleson, 1962)	$v = K(D/\sqrt{Q_{max}})^{-B}$	121.0	1.25
Langefors–Kihlstrom (Langefors and Kihlstrom, 1963)	$v = K(\sqrt{Q_{max}/D^{2/3}})^{B}$	0.442	1.637
Ambraseys–Hendron (Ambraseys and Hendron, 1968)	$v = K(D/Q_{max}{}^{1/3})^{-B}$	812.0	1.29
Bureau of Indian Standard (Indian Standard Institute, 1973)	$v = K(Q_{max}/D^{2/3})^{B}$	0.442	0.818

Note: v is the PPV (mm/s) and Q_{max} is the maximum charge per delay (kg).

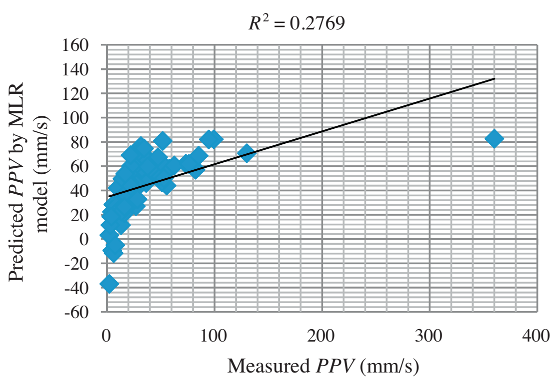


Fig. 4. Graph between measured and predicted PPVs by MLR model.

element of feed-forward multi-layer perceptron (FFMLP) networks. The perceptron with n inputs is shown in Fig. 5. The inputs to a perceptron are weighted with an appropriate weight (w). The sum of weighted inputs and the bias (b) form the input for transfer function f (Blackwell and Chen, 2009). Transfer function can be written as follows:

$$y = f\left(\sum_{i=1}^{N} w_i x_i + b\right) \tag{3}$$

where x_i is the ith input, w_i is the weight associated with the ith input, b is the bias and f is the transfer function of the perceptron.

5.2. Network training

Network training is essential before interpreting new results. The training algorithm of back propagation (BP) involves four stages (Sumathi and Paneerselvam, 2010):

(1) initialization of weights,
(2) feed-forward,
(3) back-propagation of errors, and
(4) updating of weights and biases.

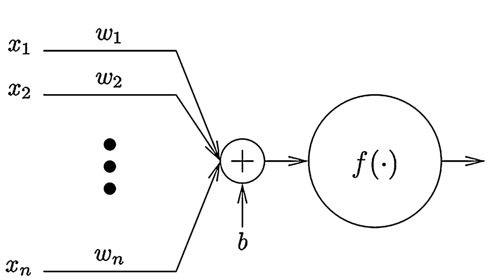


Fig. 5. Structure of an elementary perceptron (Blackwell and Chen, 2009).

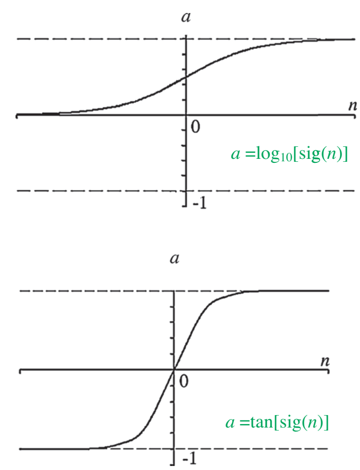


Fig. 6. Sigmoid transfer functions used for hidden layers (MathWorks Inc., 2009).

Various training algorithms have been developed for function approximation problems. Levenberg–Marquardt appears to be the fastest method for training moderate-sized FFNNs (up to several hundred weights). This algorithm has high accuracy and convergence speed. It also has an efficient implementation in MATLAB software, because that the solution of the matrix equation is a built-in function and that its attribute becomes even more pronounced in MATLAB environment (MathWorks Inc., 2009). Thus, in the present study, this algorithm is used for training the network.

The behavior of ANN mainly depends on both transfer functions and weights. The output of transfer function is passed to the output layer, where it is multiplied by the connection weights between the output layer and hidden layer, and again a number of products are taken to generate the output for the network. Log–sigmoid, tan–sigmoid and linear transfer functions are the most commonly used in BP (Figs. 6 and 7). The logarithmic sigmoid function (logsig) is defined as (MathWorks Inc., 2009)

$$f = \frac{1}{1 + e^{e_x}} \tag{4}$$

where e_x is the weighted sum of the inputs for a processing unit.

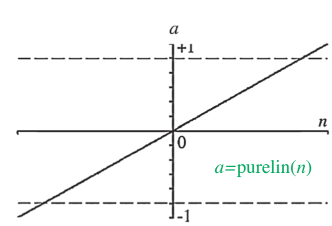


Fig. 7. Linear transfer functions used for output layer (MathWorks Inc., 2009).

Table 3
The range of variables used to train the network.

Input				Output
Charge weight per delay equivalent to ANFO *Q* (kg)	Distant from the blast point *D* (m)	Stemming *S* (m)	Hole depth *H* (m)	Peak particle velocity *PPV* (mm/s)
1606–31,573	40–1092	3–7	14–18	2.2–360

The tangent sigmoid function (tansig) is defined as follows (MathWorks Inc., 2009):

$$f = \frac{e^{e_x} - e^{-e_x}}{e^{e_x} + e^{-e_x}} \tag{5}$$

5.3. Monitoring the validation and performance of ANN

Typically neural networks adapt satisfactorily to training usually the data but the test performance does not provide significant results. The unfavorable generalizing property is caused by the overfitting of neural network parameters to the training data. Overfitting occurs when the neural network begins to memorize the training set instead of learning them, and consequently loses the ability to generalize (Rafiai and Moosavi, 2012). As the training process continues, the error on the training set decreases while on the validation set, it decreases initially and subsequently increases after some training period. Early stopping is an effective remedy for resolving this issue. In early stopping, weights are initialized to very small values. Part of the data sets is used for training the network and the other part is used for monitoring the validation error. Training is stopped when the validation error begins to increase.

Early stopping in its basic form is rather inefficient, as it is very sensitive to the initial condition of the network and only part of the data is used for training the model. These problems can easily be alleviated by using committee of early stopping networks, with different partitioning of the data to training, test and validation sets for each network. MATLAB random selection of data sets is also

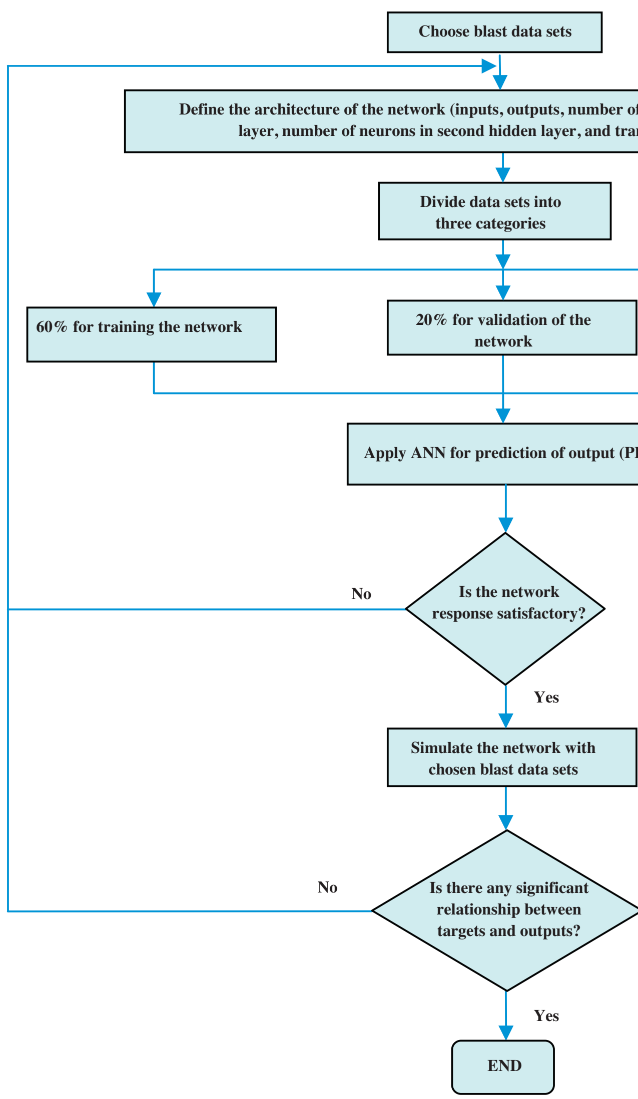


Fig. 8. Flow chart for ANN method.

Table 4
Results of different examined ANN models with one hidden layer.

Number of neurons	Transfer function	R				R^2	MSE
		Training	Validation	Test	Overall		
25	tansig	0.99	0.72	0.82	0.93	0.77	0.004
	logsig	0.99	0.69	0.88	0.88	0.65	0.011
23	tansig	0.9	0.75	0.93	0.82	0.42	0.0163
	logsig	0.97	0.62	0.9	0.92	0.45	0.0158
20	tansig	0.99	0.94	0.88	0.93	0.89	0.00199
	logsig	0.99	0.61	0.97	0.85	0.135	0.0359
18	tansig	0.99	0.83	0.82	0.96	0.48	0.0158
	logsig	0.97	0.67	0.99	0.96	0.86	0.00347
15	tansig	0.99	0.65	0.93	0.96	0.86	0.00354
	logsig	0.97	0.83	0.94	0.96	0.45	0.0155
12	tansig	0.99	0.83	0.8	0.97	0.58	0.022
	logsig	0.99	0.58	0.95	0.97	0.64	0.0143

Table 5
Results of different examined ANN models with two hidden layers.

Number of neurons	Transfer functions	R				R^2	MSE
		Training	Validation	Test	Overall		
10–5	tansig–tansig	0.99	0.89	0.95	0.98	0.77	0.00825
11–5	tansig–tansig	0.99	0.97	0.89	0.97	0.93	0.00139
11–5	tansig–logsig	0.99	0.92	0.96	0.93	0.95	0.000722
12–5	logsig–logsig	0.99	0.94	0.95	0.96	0.94	0.00647
12–5	tansig–logsig	0.97	0.94	0.99	0.98	0.94	0.00125
12–6	tansig–tansig	0.98	0.97	0.98	0.93	0.9	0.000563
12–6	logsig–tansig	0.99	0.85	0.98	0.97	0.94	0.00138
12–7	tansig–tansig	0.99	0.91	0.95	0.94	0.69	0.00829

helpful in this remedy. This random selection might stop training procedure so that the trained ANNs with different validation sets might have different generalization errors even if ANNs would be trained on the same training set (Chen and Wang, 2007). Finally, the most appropriate model based on its correlation of determination (R^2) and mean square error (MSE) will be chosen as the ANN model. The performance function, MSE, can be calculated as follows:

$$MSE = \frac{1}{N}\sum_{i=1}^{N}(T_i - O_i) \tag{6}$$

where T_i, O_i and N represent the measured output, the predicted output and the number of input-output data sets, respectively.

6. Development of the ANN-based prediction

6.1. Preparation of data for ANN models

Feed-forward back propagation artificial neural network with sigmoid functions in the hidden layers and linear transfer function in the output layer are appropriate structures for function approximation. In this study, ANN was used as a function approximation tool for prediction of PPV from four variables, which are the most effective parameters in predicting PPV (Monjezi et al., 2011). These parameters are listed in Table 3. Levenberg–Marquardt back propagation algorithm gives the most convincing performance when inputs and targets are scaled. In order to meet this requirement, pre-process of the data is needed. The performance of this

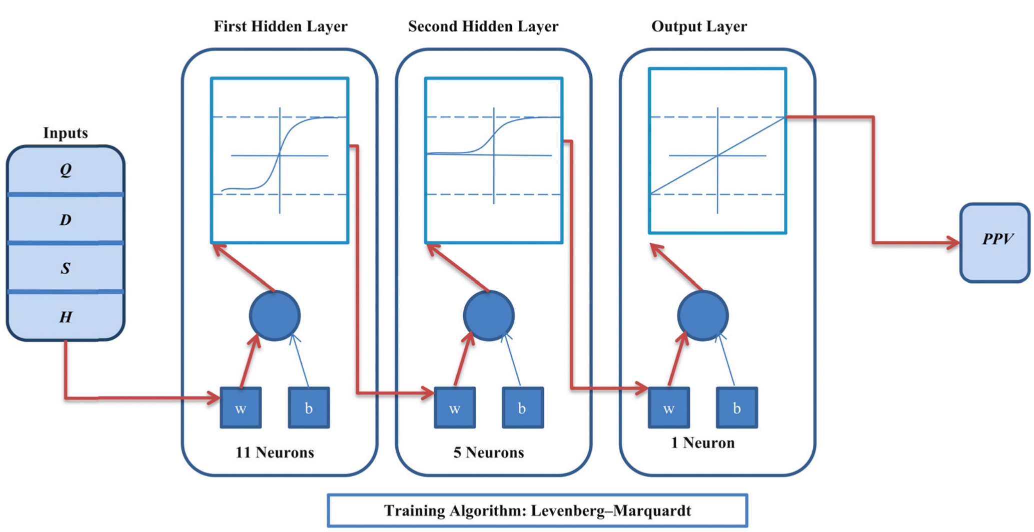


Fig. 9. Proposed ANN architecture.

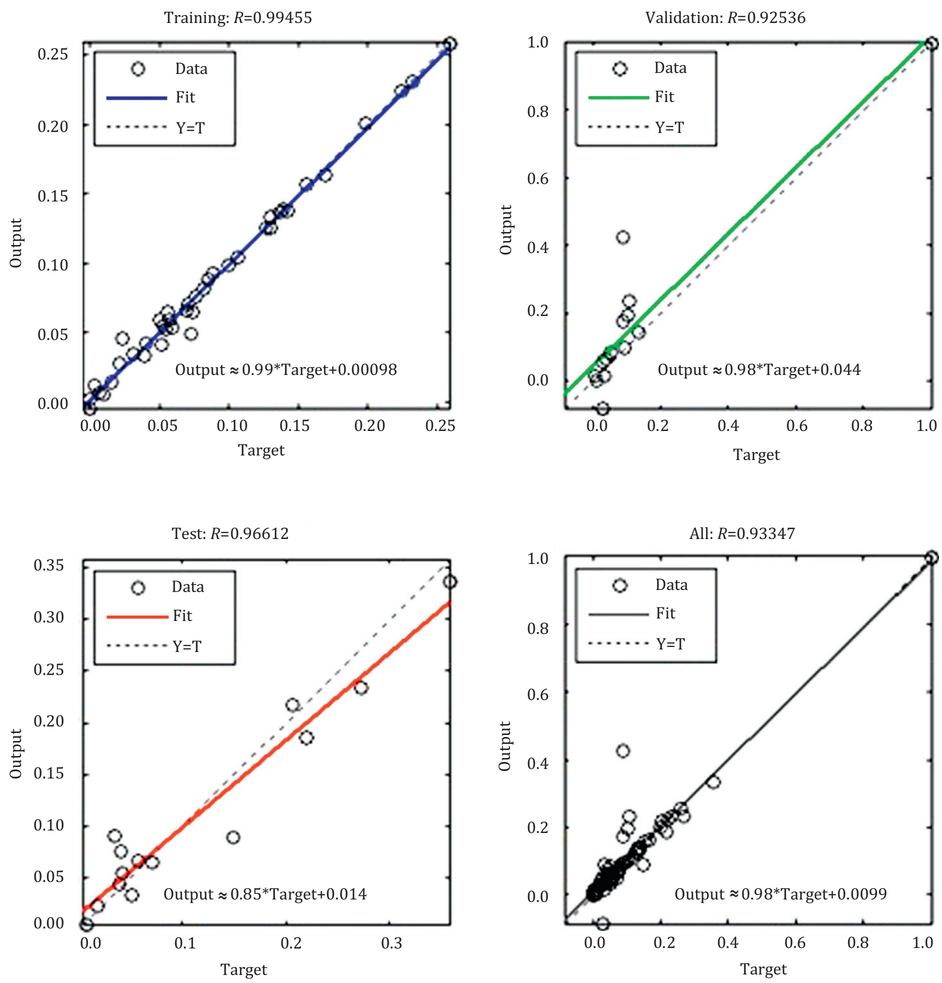


Fig. 10. Coefficient of correlation for the training, testing, validation and overall data sets.

algorithm will be high when the input and target are normalized so that they fall approximately in the range [0, 1]. The following relationship is implemented for normalizing the input and target parameters (Sivanandam et al., 2006):

$$X_{\text{new}} = \frac{X - X_{\min}}{X_{\max} - X_{\min}} \tag{7}$$

where X_{new} is the normalized value, X is the original value, $X_{\max}$ is the maximum value for all data and $X_{\min}$ is the minimum value for all data. The normalized values are used as input and targeted data in the network.

6.2. Network architecture and validation of ANN-based prediction

A committee of early stopping networks was built by employing a set of 69 data points recorded in vulnerable part of GEG iron ore mine. These data sets are randomly divided into three categories, about 60% for training the network (41 data sets), 20% for test of the network (14 data sets) and 20% for validation of training procedure (14 data sets). The flow chart for ANN method is illustrated in Fig. 8.

MATLAB software was used for implementation of ANN. Training data were used to obtain the weight matrix and bias vector; while test and validation data were chosen to monitor the accuracy and validation of the network. After stopping, the training procedure and measurement of the accuracy of the network performance, 69 data sets, were simulated in order to reach the final outputs and to test the accuracy of the ANN model. Validation check is carried out to show that ANN models perform the nonlinear regression analysis properly. Coefficient of determination (R^2) (between predicted and measured PPVs) and MSE were used to compare the performance of each ANN model. The results for different ANN models with one and two hidden layers are shown in Tables 4 and 5. These results revealed that an

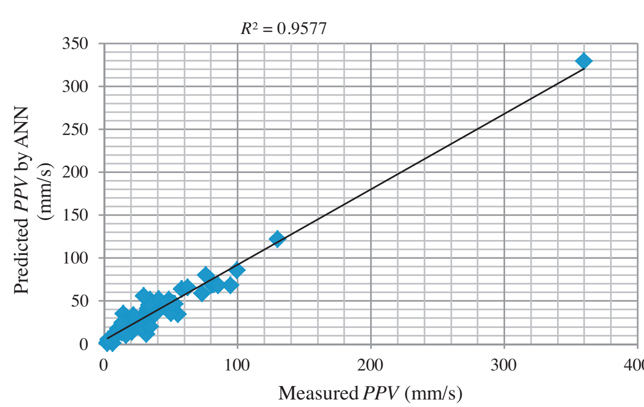


Fig. 11. Graph between measured and predicted PPVs by ANN model.

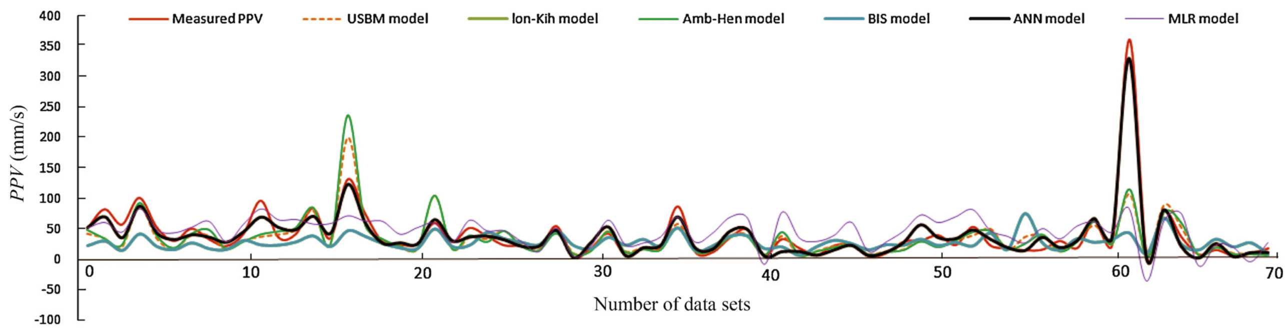


Fig. 12. Comparison of measured and predicted PPVs by various models.

Table 6
R^2 and RMSE of PPV by various models.

Model	R^2	RMSE
ANN	0.957	8.796
Ambraseys–Hendron	0.434	25.74
Langefors–Kihlstrom	0.139	11.7
Bureau of Indian Standard	0.139	11.66
USBM	0.446	22.61
MLR	0.276	20.85

Note: RMSE is roots of mean square error.

ANN with architecture 4-11-5-1, tansig transfer function in its first hidden layer, logsig transfer function in its second hidden layer and purelin transfer function in its output layer, can be selected as the most fitting predictor of PPV (Fig. 9). Fig. 10 illustrates the correlation coefficient (R) for the proposed ANN model including training, test, validation and overall data.

Fig. 11 shows the graph between measured and predicted PPVs by ANN model. The graph demonstrates that the value of R^2 is 0.95 between measured and predicted PPVs. It is clearly shown that the proposed model has the capability to predict the PPV very close to measured PPV values, and that the accuracy between measured and predicted PPVs is acceptable.

7. Results and discussion

Fig. 12 shows a comparison between measured and predicted PPVs by ANN, MLR and different predictor equations. Considering four input parameters, ANN model predicted PPV is very close to the measured data. Prediction by empirical equations underestimates or overestimates the value of PPV. Therefore, any prediction based on empirical equations requires more consideration and prudence. MLR results show that the relationships between PPV and the maximum charge per delay, distance from the blasting face to the monitoring point, stemming, and hole depth cannot be linear. Table 6 shows R^2 and RMSE for all models. The authenticity of ANN can be easily established in comparison with other predictors.

8. Conclusions

Using back propagation ANN model with an optimum number of hidden layer neurons and Levenberg–Marquardt training algorithm, MSE and R^2 for prediction of PPV were 0.000722 and 0.95, respectively. For building ANN models, a committee of early stopping networks was trained by 69 data sets recorded at vulnerable parts of GEG iron ore mine in Iran. Optimum ANN architecture has been found to have four neurons in the input layer, two hidden layer with 11 and 5 neurons, respectively, and one neuron in the output layer. Considering the complexity between inputs and output parameters, the application of ANN technique in the ground vibration is proven to be promising. To ascertain the authenticity of ANN model, the results were compared with empirical models and MLR analysis.

The maximum charge per delay and the distance from the blasting face to the monitoring point are the major parameters for empirical models. Whereas in MLR and ANN models, two more parameters, i.e. stemming and hole depth, are taken into consideration as effective variables to predict PPV. The poor results obtained from MLR model revealed that the relationship between predictor parameters and PPV must not be linear. The capability of ANN solution to find nonlinear relationships is a testament to this fact. The MLR analysis could possibly be improved if other techniques like potential or even exponential non-linear multiple regression were used. The results obtained from traditional empirical models revealed that the Bureau of Indian Standard overestimates but Longforce–Kihlstrom underestimates predicted PPV values. This considerable fluctuation in prediction of PPV shows that any use of empirical predictors without validation causes damage to the nearby structures and imposes financial penalties for hindrance to the mine smooth working.

Conflict of interest

The authors declare no conflict of interest.

References

Alvarez-Vigil AE, Gonzales-Nicieza C, Lopez Gayarre F, Alvarez-Fernandez MI. Predicting blasting propagation velocity and vibration frequency using artificial neural network. International Journal of Rock Mechanics and Mining Sciences 2012;55:108–16.

Ambraseys NR, Hendron AJ. Dynamic behavior of rock masses. In: Rock mechanics in engineering practices. London: Wiley; 1968. p. 203–7.

Amnieh HB, Mozdianfard MR, Siamaki A. Predicting of blasting vibration in Sarcheshmeh copper mine by neural network. Safety Science 2010;48(3):319–25.

Amnieh HB, Siamaki A, Soltani S. Design of blasting pattern in proportion to the peak particle velocity (PPV): artificial neural networks approach. Safety Science 2012;50(9):1913–6.

Blackwell WJ, Chen FW. Neural networks in atmospheric remote sensing. MA, USA: Massachusetts Institute of Technology; 2009. p. 78–80.

Bureau of Indian Standard (BIS). Criteria for safety and design of structures subjected to underground blast. ISI Bull; IS-6922; 1973.

Chen K, Wang L. Trends in neural computation. Rotterdam: Springer; 2007. p. 234.

Dehghani H, Ataee-pour M. Development of a model to predict peak particle velocity in a blasting operation. International Journal of Rock Mechanics and Mining Sciences 2011;48(1):51–8.

Duvall WI, Fogleson DE. Review of criteria for estimating damage to residences from blasting vibration. USBM-RI, 5968; 1962.

Engelbrecht AP. Computational intelligence. Chichester, England: John Wiley & Sons, Inc; 2007. p. 27.

ISRM. Suggested method for blast vibration monitoring. International Journal of Rock Mechanics and Mining & Geomechanics Abstracts 1992;29(2):145–6.

Khandelwal M, Kumar DL, Yellishetty M. Application of soft computing to predict blast-induced ground vibration. Engineering with Computers 2011;27(2):117–25.

Khandelwal M, Singh TN. Evaluation of blast-induced ground vibration predictors. Soil Mechanics and Earthquake Engineering 2007;27(2):116–25.

Khandelwal M, Singh TN. Prediction of blast induced ground vibrations and frequency in opencast mine: a neural network approach. Journal of Sound and Vibration 2006;289(4/5):711–25.

Khandelwal M, Singh TN. Prediction of blast-induced ground vibration using artificial neural network. International Journal of Rock Mechanics and Mining Sciences 2009;46(7):1214–22.

Langefors U, Kihlstrom B. The modern technique of rock blasting. New York: Wiley; 1963.

Leondes CT. Neural network systems techniques and applications. Salt Lake City, USA: Academic Press; 1998. p. 87.

Lin BR, Hoft RG. Neural networks and fuzzy logic in power electronics. Control Engineering Practice 1994;2(1):113–21.

MathWorks Inc. Neural networks toolbox for use with MATLAB, User's Guide Version 7.8. MA, USA: The MathWorks Inc; 2009.

Mohamadnejad M, Gholami R, Ataei M. Comparison of intelligence science techniques and empirical methods for prediction of blasting vibrations. Tunnelling and Underground Space Technology 2012;28:238–44.

Mohammad MT. Artificial neural network for prediction and control of blasting vibration in Assiut (Egypt) limestone quarry. International Journal of Rock Mechanics and Mining Sciences 2009;46(2):426–31.

Monjezi M, Ghafurikalajahi M, Bahrami A. Prediction of blast-induced ground vibration using artificial neural networks. Tunnelling and Underground Space Technology 2011;26:46–50.

Monjezi M, Hasanipanah M, Khandelwal M. Evaluation and prediction of blast-induced ground vibration at Shur River Dam, Iran, by artificial neural network. Neural Computing and Applications 2013;22(7/8): 1637–43.

Monjezi M, Singh TN, Khandelwal M, Sinha S, Singh V, Hosseini I. Prediction and analysis of blast parameters using artificial neural network. Noise & Vibration Worldwide 2006;37(5):8–16.

Rafiai H, Moosavi M. An approximate ANN-based solution for convergence of lined circular tunnels in elasto-plastic rock masses with anisotropic stresses. Tunnelling and Underground Space Technology 2012;27(1):52–9.

Rumelhart DE, Hinton GE, Williams RJ. Learning internal representations by error propagation. In: Rumelhart DE, McClelland JL, editors. Parallel distributed processing: explorations in the microstructure of cognition, foundation. Cambridge: MIT Press; 1986. p. 318–62.

Scheaffer R, Mulekar M, McClav J. Probability and statistics for engineers. 5th ed. Boston, USA: Brooks/Cole; 2011. p. 599.

Sethi IK, Jain AK. Artificial neural network and statistical pattern recognition. USA: Elsevier; 1991. p. 77.

Sivanandam S, Sumathi S, Deepa SN. Introduction to neural network using Matlab 6.0. New Delhi: Tata McGraw-Hill; 2006. p. 533.

Sumathi S, Paneerselvam S. Computational intelligence paradigms: theory & applications using MATLAB. 1st ed. Boca Raton, FL, USA: CRC Press; 2010. p. 85–6.