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Development of a blast-induced vibration prediction model using an artificial neural network

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Synopsis

In an opencast mine explosives are used for fragmentation of rock. Inefficient use of explosive energy in an opencast operation produces excessive ground vibration, which is measured by peak particle velocity (PPV). To mitigate ground vibration, it is essential to develop a model to predict PPV. At present empirical models are used. These models are based on only a few input variables, hence they fail to take into account the effects of the myriad factors that cause ground vibration. Due to lack of explicit knowledge about the complex mine blasting system the scope of application of mathematical and statistical modeling techniques is limited. The artificial neural network (ANN) technique is a learning algorithm that can remove some of these limitations and can be applied to predict PPV. In this paper an ANN model is developed for prediction of blast vibration using 248 data records collected from three coal mines with diverse geomining conditions. The correlation coefficient between measured PPV and model output was found to be 0.96 and the average error percentage 11.85. The ANN model output was compared with the output of three empirical models that are widely used for prediction of PPV. The correlation coefficient between the PPV predicted by an empirical model and measured PPV data was 0.63 and the relative error percentage 38.47. This result demonstrates the superiority of the ANN model compared to empirical blast models. By using site-specific structural discontinuities as input the model performance can be further improved. Sensitivity analysis and 3D plotting were used to gain further knowledge about blast-induced ground vibration.

Keywords

artificial neural network, peak particle velocity, sensitivity analysis, 3D plot.

Introduction

In an opencast coal mine explosives are used for fragmentation of coal and overburden. If the explosive energy is not fully utilized it causes blast-induced ground vibration, which may damage nearby structures. Ground vibration is expressed as peak particle velocity (PPV). During different stages of mine planning and operation, it is necessary to use a ground vibration prediction model for blast-hole design. Selection of the modelling technique is crucial. Mathematical and statistical modelling techniques have limited application because of the lack of explicit knowledge about the complex mine blasting system. Vogiatzi (2002) highlighted the problem of multicollinearity in case of statistical modeling techniques. Mutalib *et al.* (2013) stated that mathematical models are unable to capture the nonlinear relationship between several blasting-related parameters due to the complexity of the model input data. However, the difficulty involved in modelling complex blast vibration problems can be removed by adopting an alternative soft computing modelling approach. One of the soft computing techniques is the artificial neural network (ANN). Ragam and Nimaje (2018) developed an ANN model for predicting PPV using six input variables. Kosti *et al.* (2013) stated that the conventional predictors fail to provide acceptable prediction accuracy. They showed that a neural network model with four mine blast parameters as input could make significantly more accurate on-site predictions. Sayadi *et al.*, (2013), using a database from Teheran Cement Company limestone mines, found that a neural network resulted in maximum accuracy and minimum error. Khandelwal and Singh (2009) developed an ANN model using 150 data records from an Indian coal mine with site-specific rock characteristics and geomining setting. Khandewal and Singh (2007) built a ground vibration prediction model for a magnesite mine using four prediction variables with 20 data records. Kamali and Ataei (2010) predicted PPV in the structure of the Karoun III power plant and dam using an ANN. El Hafiz *et al.* (2010) evaluated ground vibration predictors using data from a single-station seismograph at a limestone quarry in Egypt.

ANN prediction models have been built for one Indian coal mine and one limestone mine. Using the findings of these initial studies, it is essential to enhance the application of ANN in various mines in different Indian coal mining

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regions. In this investigation we collected 248 data records with 15 input variables from three mining regions. A combined database was built after randomization of the data. With the help of this database an ANN model was built and the final output obtained. The robustness of the model was tested by using data from other mines and using the model to predict PPV. Site-specific features, including fracture zones due to the presence of underground workings and fault planes, are expressed as a non-quantifiable variable by using an ordinal scale. Tests were carried out to establish whether the model prediction can be improved by using the non-quantifiable variable. Sensitivity analyses were performed by using input and output connection weights of the model. Also, 3D plotting was done to understand the interplay between two input variables, keeping the other variables equal to the mean values.

ANN model

Blast-induced ground vibration often damages structures near a mine site. The intensity of mine blast-induced vibration must be predicted prior to blasting operations near any important surface structure. PPV can be considered as the representative indicator of ground vibration. It is a significant factor in control of structural damage (Bureau of Indian Standards, 1973; Kahriman, 2002; Singh and Singh, 2005; Bakhshandeh, Mozdianfard, and Siamaki, 2010; Khandelwal and Singh 2009). Khandelwal, Kumar, and Yellishetty (2011) observed that the empirical equations do not include physicomechanical parameters of rock mass, blast design, and explosive type, which are relevant for the calculation of PPV.

The empirical method of PPV estimation is discussed here. The basic relationship between the variables is $V = KW^a D^b$, where W is the weight of explosive charge; D is the distance from the blast; V is the magnitude of vibration; and K, a, and b are constants whose values depend on the site-specific geomining conditions. V is expressed as PPV (mm/s). The prediction equation derived by the US Bureau of Mines is $V = K(D/Q^{0.5})^{-b}$. A plot of PPV as a function of scaled distance (D/Q.05) on a log-log scale gives a straight line for mine sites. To derive the values of K, a, and b for a particular site it is necessary to monitor test shots and plot PPV against scaled distance on a log-log scale. Ghasemi, Ataei, and Hashemolhosseini (2013) observed that since only a limited number of variables are considered for deriving empirical equations, the PPV predictions are not accurate enough for demarcation of a safe zone around a mine blast site. (Table I). The nature and intensity of blast-induced ground vibration is dependent on many factors, the most important of which are shown in Table II.

Artificial neural network (ANN) models can overcome some of the drawbacks of empirical models (Girish, 2007). ANN is a nonlinear self-adaptive approach without any prior assumptions about the interrelations between series of input variables. A back-propagation neural network (BPNN) is used as a learning algorithm for training a multilayer feed-forward neural network. It provides a computationally efficient method for changing the weights in a feed-forward network, with different activation function units. Dey *et al.* (2016) designed an ANN model that consists of number of inputs, a single output, and an intermediate hidden layer. Training of the network is the process of learning when the error is calculated as the difference between the predicted output and actual output (target). As the error reaches a user-defined error tolerance limit, the training is stopped; otherwise the weights are readjusted by back-propagation. All inputs to a node are weighted independently, summed with bias, and fed into logistic or other nonlinear functions. The output is then connected to all neurons of the next layer.

Sivaprasad *et al.* (2006) and Hornik, Stinchcombe, and White (1989) stated that an ANN could act as a universal approximation of nonlinear functions. Rahman *et al.* (2013) noted that an ANN can be trained to identify nonlinear patterns between input and output values of opencast blasting phenomena. Maqsood *et al.*, (2002) affirmed that ANNs do not require any prior knowledge of the system under consideration and are well suited for modellng dynamic systems on a real-time basis. Huang and Foo (2002) and Scardi (2001) observed that an ANN can be used either where no precise theoretical model is available, or when uncertainty in input parameters complicates deterministic modelling. García, Rodríguez, and Tenorio (2011) observed that the ANN technique can also perform tasks based on training or initial experience, and does not need an algorithm to solve a problem. This is because it can generate its own distribution of the weights of the links through learning.

Table II

Factors influencing ground vibration

Sl. No.	Factors
1	Rock types
2	Geological discontinuities
3	Distance
4	Explosive charge weight
5	Blast geometry
6	Rock mass properties
7	Explosive types

Table I

Empirical prediction models for prediction of ground vibration

Empirical models	Formula	Site constants
Empirical models	Empirical models	Site constants
USBM equation	$V = k(R/Q^{1/2})^{-b}$	k = 239.56 & b = 1.166
Ambraseys and Hendron equation	$V = k(R/Q^{1/3})^{-b}$	k = 1207.96 & b = 1.175
Langefors–Kihlstrom equation	$V=k(Q/(D^{2/3})^{b/2}$	k = 2.195 & b = 3.389
Indian Standard Predictor equation	$V=k(Q/(D^{2/3})^{b}$	k = 2.195 & b = 1.694

Mohamad (2009) used several ANN models in the Assiut limestone mine in Egypt and concluded that increasing the number of input variables can improve the capability of an ANN to predict PPV. Monjezi, Ghafurikalajahi, and Bahrami (2011) developed an ANN model to predict PPV at the Siahbisheh pumped storage 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. Using artificial intelligence approaches Khandelwal and Singh (2007), Mohamed (2011), Kamali and Ataei (2011), and Singh and Singh (2005) predicted PPV using hole depth and diameter, number of holes, burden, spacing, and the distance from the blast face as inputs. They concluded that the ANN is a more accurate approach compared to regression analysis. Other researchers predicted PPV based on ANN models in different projects. Amnieh, Mozdianfard, and Siamaki (2010), Amnieh, Siamaki, and Soltani (2012), and Alvarez *et al.* (2012) compared the results of both ANNs and empirical models with multiple linear regression (MLR) analysis to establish the applicability of each method. A discussion on superiority of ANN modeling techniqueas is included in Appendix A.

This subsection contains a brief discussion of the conceptual framework in ANN model-building. Based on the discussions so far an ANN model is built by training the network using input data from the study areas. Database development for model input is discussed in the next subsection. The training data constitutes 70% of the database. The network is trained in supervised manner with a back-propagation algorithm training a multilayered feed-forward network. Initially, training data is preprocessed by normalizing input and output data. A flow chart of the model-building process is shown in Figure 1.

Database

Mine blast-induced ground vibration (PPV) was recorded in three mechanized coal mines. Study area I is located in the Angul district in the state of Odisha. Study area II is located in the Raniganj coalfield, Burdwan District, in the state of West Bengal. Study area III is located in the North Karanpura coalfield, Chatra District in the state of Jharkhand.

PPV data was collected from 140 blasts: 50 blasts in study area I, 36 in study area II, and 54 in study area III. The blasting pattern is described in Table III. SME explosive and a Nonel initiation system were used. Ground vibration was recorded using BLASTMATE III, manufactured by Instantel, Canada. Two instruments were stationed at distances of 40 m to 320 m from the blast site. PPV was recorded at different distances for each blast. Only those values above 1 mm/s were included in the database. Two hundred and forty-eight data records were obtained from 140 blasts.

Input variables are presented in Table IV. These variables were selected based on the authors' experience as well as a study of the relevant literature in the section 'ANN model'. PPV data measured on the mine sites is described in Table V. The ANN technique can detect similarities between these

Table III

Blasting pattern in overburden

Number of blasting rounds	140
Number of observations	248
Diameter of drill-holes (mm)	150–160
Depth of holes(m)	3.50–6.50
Burden (m)	3.0–4.50
Spacing (m)	3.5–5.0
Explosive charge/hole (kg)	15.10–70.10
Maximum charge/delay (kg)	70.10
Maximum charge/round (kg)	7113.50

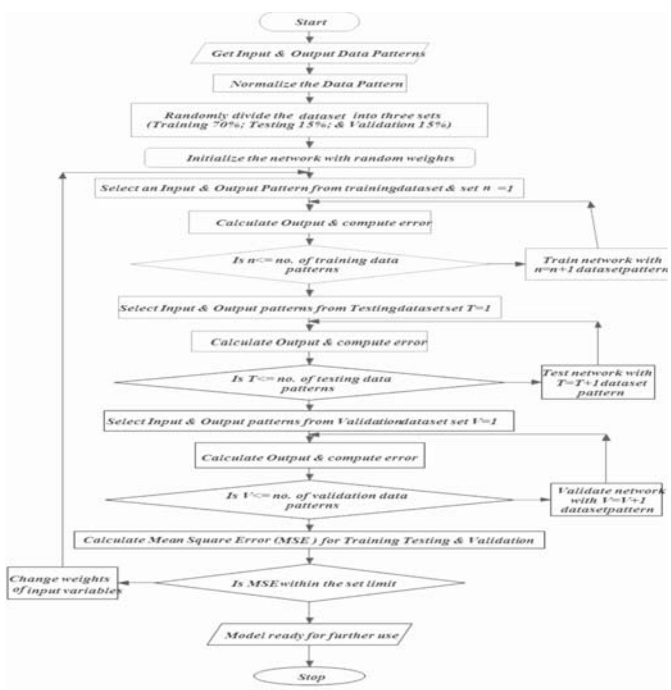

Figure 1—Model flow chart

Table IV

Descriptive statistics of input variables

No.	Input variables	Mean	Median	Mode	Standard deviation	Minimum	Maximum
1	Rock density (Rd) (gm/cc)	2.41	2.42	2.59	0.27	1.52	2.59
2	No. of holes (Nh)	61.60	57.00	60.00	36.73	1.00	142.00
3	Hole diameter (Hdia) (mm)	158.18	160.00	160.00	3.87	150.00	160.00
4	Hole depth (Hd) (m)	5.76	5.90	6.00	0.45	3.50	6.50
5	Burden (B) (m)	3.85	4.00	4.00	0.43	3.00	4.50
6	Spacing (S) (m)	4.45	4.50	5.00	0.55	3.50	5.00
7	Charge length (Cl) (m)	2.09	2.20	2.20	0.37	0.80	2.90
8	Stemming length (St) (m)	3.67	3.70	3.90	0.40	2.50	4.50
9	Max. explosive charge/delay (Ed) (kg)	52.34	55.10	60.10	9.45	15.10	70.10
10	Charge/round (Et) (kg)	3043.40	2813.50	2505.0	1923.38	45.10	7113.50
11	Monitoring point from face (DB) (m)	153.81	140.00	120.00	65.55	40.00	320.00
12	Young's modulus (E) (GPa)	14.40	15.25	15.25	3.31	2.21	15.65
13	Poisson's ratio (P)	0.24	0.23	0.23	0.03	0.20	0.35
14	P-wave velocity (Vp) (m/s)	5450.68	5800.00	5800.0	968.41	1804.20	5999.10
15	Density of explosive (De) (gm/cc)	1.11	1.12	1.11	0.02	1.06	1.18

Table V

Descriptive statistics of the output variables

Sl. no.	Target variables	Mean	Median	Mode	Standard deviation	Minimum	Maximum
1	PPV (mm/s)	10.38	8.11	26.36	7.20	1.249	33.84

Table VI

Testing of retraining performance of the ANN with 15 input-4 Hidden Nodes-1 output

No of run	Training / testing algorithm	Overall correlation coefficient, R-value
1	Tansig/ Trainlm	0.966
	Tansig/ Trainscg	0.924
2	Tansig/ Trainlm	0.968
	Tansig/ Trainscg	0.957
3	Tansig/ Trainlm	0.975
	Tansig/ Trainscg	0.940
4	Tansig/ Trainlm	0.943
5	Tansig/ Trainlm	0.959

input variables. This property gives it excellent interpolation capability, especially when the input data is noisy (not exact). An ANN is capable of calculating arithematic and logical functions, generalizing and transforming independent variables to dependent variables, parallel computations, nonlinear processing, handling of noisy data, function approximation, and pattern recognition (Sayadi *et al*., 2013).

ANN can be applied to combat the problem of multicollinearity in the data (Hermosilla and Carpio, 2005). The correlation coefficient is widely used in statistics but correlation is a measure of the linear association between variables. If two variables are related in a nonlinear manner the correlation coefficient will not be able to do justice to the strength of relationship (Makridakis, Wheelwright, and Hyndman, 2005). The neural network is capable of capturing the interactions between the inputs, because of the hidden units are able to handle extreme nonlinearity. The nature of these interactions is implicit in the values of the weights. Therefore multicollinearity in the input data is not an issue for training a neural network. Further discussion of this aspect is presented in the review paper by Bhadesjia (1999).

Results and discussion

The neural network toolbox of MATLAB 2015 was used to build an ANN blast-induced vibration model. The ANN architecture (Table VIII) has fifteen input variables, one hidden layer, and four nodes. Four nodes were selected since this gives a high R value (Table VII). The network was trained up to maximum epoch of 1000 and the error goal was set at 1e-7. In Figure 2 and Table IX the association between the PPV predicted by the model and the actual PPV measured in the field is 0.968, and the average relative error is 11.85. Therefore, the prediction capability of the model was deemed to be good and the model ready for use. An attempt was made to improve the model prediction by including non-quantifiable variables. Diverse structural features were observed during inspection of different mine sites. Some of the quantifiable rock parameters are included in Table III as input to ANN models. Site-specific structural features are mostly non-quantifiable variables, therefore an ordinal scale of 1 to 3 is used. To cite an example, if the site has minimum structural discontinuities then a value 1 is assigned, while 3 represents highly fractured and faulted strata (Table XI). However, further research on use of non-quantifiable variables as model input is essential. By including the above variable a marginal increase in R value from 0.968 to 0.975 was obtained. The model performance was also compared

Table VII

ANN model performance by varying number of nodes

Hidden nodes	Transfer/ training function	R Training	R Testing	R Validation	R Overall
1	Tansig/ Trainlm	0.95	0.92	0.92	0.94
	Tansig/ Trainscg	0.89	0.86	0.85	0.87
2	Tansig/ Trainlm	0.97	0.94	0.93	0.95
	Tansig/ Trainscg	0.92	0.90	0.89	0.90
3	Tansig/ Trainlm	0.97	0.94	0.94	0.95
	Tansig/ Trainscg	0.94	0.91	0.92	0.92
4	Tansig/ Trainlm	0.97	0.96	0.97	0.97
	Tansig/ Trainscg	0.96	0.94	0.95	0.95
5	Tansig/ Trainlm	0.97	0.94	0.94	0.95
	Tansig/ Trainscg	0.94	0.91	0.92	0.92

Table VIII

Network architecture

Number of input variables	15
Number of nodes in hidden layer	4
Number of hidden layers	1
Transfer function	Hyperbolic tangent sigmoid transfer function (tansig) for hidden layer and Purelin for output layer

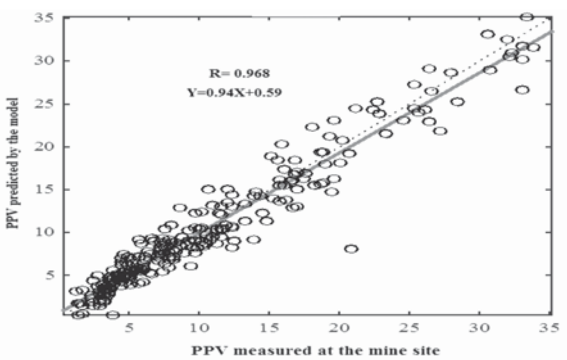

Figure 2—Graphical representation of actual and predicted values of PPV

Table IX

Performance of ANN model

Type of model	ANN	Multivariate linear regression
No. of observations	248	248
Correlation coefficient	0.97	0.80
Av. relative error (%)*	11.85	16.01

*The absolute error is the difference between the measured value and the true value. The relative error is defined as the absolute error relative to the size of the measurement.

with the multivariate linear regression model (Table IX) and results show the benefits of an ANN for enhancing accuracy in model prediction.

The robustness of the training was tested with different initialized states of the network parameters for the given architecture while holding other training parameters and algorithms constant. Typical results for the 15-4-1 architecture with the sigmodal transfer function and Levenberg-Marquardt training function retrained for five runs are presented in Table VI. The result shows significantly good convergence under repeated training with different initialized states, leading to a close variation in prediction performance.

Twenty-eight new data records were used to examine the prediction performance of the ANN model. The output is compared with measured PPV in Table X. Also, the same database was used for predicting PPV by four empirical models (Table I). The reasons for selection of four out of several available empirical models are stated below. Scaled distance (maximum charge weight divided by the cube root or square root of actual distance) is used for deriving empirical formulae for Indian mines. The correlation coefficients between the predicted and measured PPVs in case of the ANN and empirical model are 0.96 and 0.67 respectively (Table X). Other formulae, which are not included in Table II, are based on inelastic effects, which cause energy losses during blast wave propagation. Inelastic attenuation of elastic waves is dependent on the geotechnical properties of the rocks. In case of other formulae, empirical constants are derived for specific geomining features and therefore they were not considered.

Sensitivity analysis

Explicit knowledge about the interplay between different variables responsible for blast-induced ground vibration is largely lacking. To extract knowledge from the ANN model,

Table X

Performance of ANN and empirical models

Model performance	ANN	USBM	Ambraseys and Hendron	Langefors–Kihlstrom	Indian Standards predictor equation
No. of observations	28	28	28	28	28
Correlation coefficient	0.96	0.67	0.63	0.68	0.74
Av. relative error (%)	11.8	37.3	38.47	37.89	35.19

Table XI

Site-specific structural features of the case study areas

Features	Case study area I	Case study area II	Case study area III
Presence of fractures	Minor fracture planes	Highly fractured due to presence of underground working below opencast	Prominent fractures not found
Faults	Minor faults	Three major faults of throw 80–240 m	No major faults
Structural discontinuities expressed in ordinal scale	1	3	2

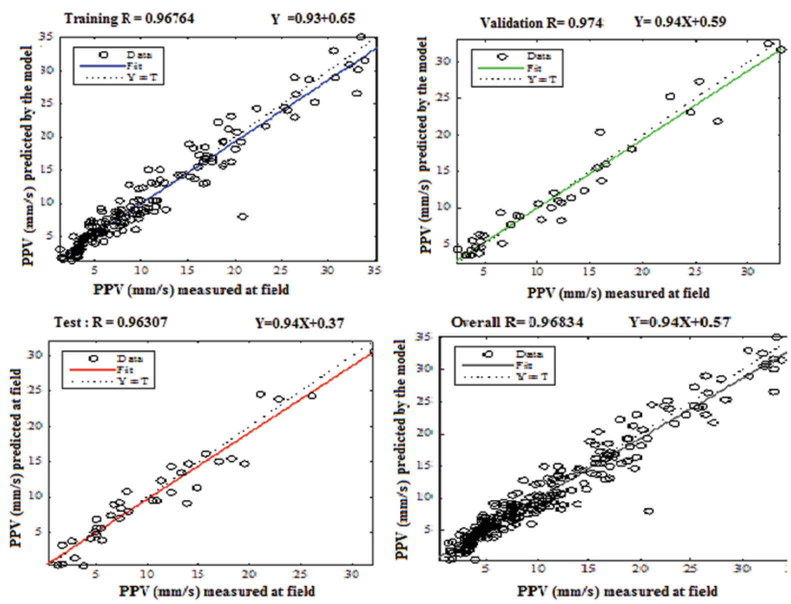

Figure 3—Actual *versus* predicted values of PPV using training, test, validation, and all data

output sensitivity analysis was carried out. Sensitivity analysis is the method of studying a model by assessing the significance of each input variable on the model output. By this means it is possible to identify how different input variables influence the model output. A connection weight approach was adopted. Calculation of the product of the raw input-hidden and hidden-output will assign weights between each input neuron and output neuron. Summation of the products across all hidden neurons is done for finding out connection weights. Olden and Jackson, (2002) observed that the sensitivity analysis approach can determine the significance of the variables in the neural network. Negative connection weights represent inhibitory effects on neurons and decrease the value of the predicted response, whereas positive connection weights represent excitatory effects on neurons and increase the value of the predicted response. The sensitivity of the network is given by connection weights used in the network architecture by means of the following calculations.

(i) Input-hidden-output connection weights: the product of input-hidden and hidden-output connection weights for each input and hidden neuron(Table XII);
For Input I = 1 to j where j = no. of variables, hidden neurons h= 1 to i, where i = no. of hidden neurons
and For Output O = 1 to o, where o = no. of outputs
Weight of input variable j and hidden neuron i = W_{ji}
Weight of output o and hidden neuron i = W_{oi}
Contribution of each input neuron to the output via each hidden neuron is given by (Table XIII):

$$C_{ji} = |W_{oi}| \times |W_{ji}| \quad [1]$$

ii. Overall connection weight: the sum of the input-hidden-output connection weights for each input variable

iii. Relative importance (%) for each input variable based on Garson's algorithm

Garson, 1991 gave the procedure for partitioning the connection weights to determine the relative importance of various inputs. The method essentially involves partitioning the hidden-output connection weights of each hidden neuron into components associated with each input neuron.

i. For each hidden neuron h, multiplying the absolute value of the hidden-output layer connection weight by the absolute value of the hidden input layer connection weight. This is donefor each input variable j. The following product P_{ji} is obtained Table XIV:

$$\text{The product } P_{ji} = |W_{oi}| \times |W_{ji}| \quad [2]$$

Table XII

Matrix containing input-hidden and output-hidden connection weights

	Hidden 1	Hidden 2	Hidden i-1	Hidden i
Input 1	$W_{(1,1)}$	$W_{(1,2)}$	$W_{(1,i-1)}$	$W_{(1,i)}$
Input 2	$W_{(2,1)}$	$W_{(2,2)}$	$W_{(21,i-1)}$	$W_{(2,i)}$
Input 3	$W_{(3,1)}$	$W_{(3,2)}$	$W_{(3,i-1)}$	$W_{(3,i)}$
Input 4	$W_{(4,1)}$	$W_{(4,2)}$	$W_{(4,i-1)}$	$W_{(4,i)}$
Input j-1	$W_{(j-1,1)}$	$W_{(j-1,2)}$	$W_{(j-1,i-1)}$	$W_{(j-1,i)}$
Input j	$W_{(j,1)}$	$W_{(j,2)}$	$W_{(j-1,i-1)}$	$W_{(j,i)}$
Output	$W_{(0,1)}$	$W_{(0,2)}$	$W_{(0,i-1)}$	$W_{(o,i)}$

Table XIII

Contribution of each input neuron to the output *via* each hidden neuron

	Hidden 1	Hidden 2	Hidden i-1.	Hidden i
Input 1	$C_{(1,1)}$	$C_{(1,2)}$	$C_{(1,i-1)}$	$C_{(1,i)}$
Input 2	$C_{(2,1)}$	$C_{(2,2)}$	$C_{(2,i-1)}$	$C_{(2,i)}$
Input 3	$C_{(3,1)}$	$C_{(3,2)}$	$C_{(3,i-1)}$	$C_{(3,i)}$
Input 4	$C_{(4,1)}$	$C_{(4,2)}$	$C_{(4,i-1)}$	$C_{(4,i)}$
Input j-1	$C_{(j-1,1)}$	$C_{(j-1,2)}$	$C_{(j-1,i-1)}$	$C_{(j-1,i)}$
Input j	$C_{(j,1)}$	$C_{(j,2)}$	$C_{(j-1,i-1)}$	$C_{(j,i)}$

Table XIV

Product of hidden input-output connection weights

	Hidden 1	Hidden 2	Hidden i-1	Hidden i
IInput 1	$P_{(1,1)}$	$P_{(1,2)}$	$P_{(1,i-1)}$	$P_{(1,i)}$
Input 2	$P_{(2,1)}$	$P_{(2,2)}$	$P_{(2,i-1)}$	$P^{(2,i)}$
Input 3	$P_{(3,1)}$	$P^{(3,2)}$	$P_{(3,i-1)}$	$P_{(3,i)}$
Input 4	$P_{(4,1)}$	$P_{(4,2)}$	$P_{(4,i-1)}$	$P_{(4,i)}$
Input j-1	$P_{(j-1,1)}$	$P_{(j-1,2)}$	$P_{(j-1,i-1)}$	$P_{(j-1,i)}$
Input j	$P_{(j,1)}$	$P_{(j,2)}$	$P_{(j,i-1)}$	$P_{(j,i)}$

Table XV

Relative contribution of each neuron to the outgoing signal of each hidden neuron

	Hidden 1	Hidden 2	Hidden i-1	Hidden i
Input 1	$Q_{(1,1)}$	$Q_{(1,2)}$	$Q_{(1,i-1)}$	$Q_{(1,i)}$
Input 2	$Q_{(2,1)}$	$Q_{(2,2)}$	$Q_{(2,i-1)}$	$Q_{(2,i)}$
Input 3	$Q_{(3,1)}$	$Q_{(3,2)}$	$Q_{(3,i-1)}$	$Q_{(3,i)}$
Input 4	$Q_{(4,1)}$	$Q_{(4,2)}$	$Q_{(4,i-1)}$	$Q_{(4,i)}$
Input j-1	$Q_{(j-1,1)}$	$Q_{(j-1,2)}$	$Q_{(j-1,i-1)}$	$Q_{(j-1,i)}$
Input j	$Q_{(j,1)}$	$Q_{(j,2)}$	$Q_{(j,i-1)}$	$Q_{(j,i)}$

Table XVI

Sum of input neuron relative contribution of each hidden neuron

	Hidden 1	Hidden 2	Hidden i-1	Hidden i	Sum Sj
Input 1	$Q_{(1,1)}$	$Q_{(1,2)}$	$Q_{(1,i-1)}$	$Q_{(1,i)}$	$S_1 = (Q_{(1,1)} + Q_{(1,2)} +..+ Q_{(1,i)}$
Input 2	$Q_{(2,1)}$	$Q_{(2,2)}$	$Q_{(2,i-1)}$	$Q_{(2,i)}$	$S_2 = (Q_{(2,1)} + Q_{(2,2)} +..+ Q_{(2,i)}$
Input 3	$Q_{(3,1)}$	$Q_{(3,2)}$	$Q_{(3,i-1)}$	$Q_{(3,i)}$	$S_3 = (Q_{(3,1)} + Q_{(3,2)} +..+ Q_{(3,i)}$
Input 4	$Q_{(4,1)}$	$Q_{(4,2)}$	$Q_{(4,i-1)}$	$Q_{(4,i)}$	$S_4 = (Q_{(4,1)} + Q_{(4,2)} +..+ Q_{(4,i)}$
Input j-1	$Q_{(j-1,1)}$	$Q_{(j-1,2)}$	$Q_{(j-1,i-1)}$	$Q_{(j-1,i)}$	$S_j = (Q_{(j-1,1)} + Q_{(j-1,2)} +..+ Q_{(j-1,i)}$
Input j	$Q_{(j,1)}$	$Q_{(j,2)}$	$Q_{(j,i-1)}$	$Q_{(j,i)}$	$Sj = (Q_{(j,1)} + Q_{(j,2)} +..+ Q_{(j,i)}$

ii. For each hidden neuron,Pjiis divided by sum for all the input variables to obtain Q_{ji} (Table XV). For example for Hidden neuron1,

$$Q_{(1,1)}= P_{(1,1)}/ (P_{(1,1)} + P_{(2,1)}+........+ P_{(j,1)})$$

$$i.e.\ Q_{ji} = \frac{P_{ji}}{\sum P_{ji}} \qquad [3]$$

(iii) For each input neuron sum the product Sj formed from the previous computation Q_{ji} (Table XVI).

$$S_j = \sum Q_{ji} \qquad [4]$$

iv. S_j is divided by the sum for all the input variables and expressed in terms of percentage, which gives the relative importance or distribution of all output weights attributable to the given input variable.

$$\text{Relative Importance Percentage} = S_j/ \sum S_j \qquad [5]$$

Knowledge gain by sensitivity analysis

Weights are plotted on the y axis (Figure 4), which gives a measure of sensitivity from least to highest sensitivity. The graph shows that the maximum charge per delay and distance from the face have the highest sensitivity. This implies that blast-induced ground vibration (PPV) is highly sensitive to the above variables. A negative sign indicates an inverse relationship with blast-induced ground vibration. Other variables with moderate sensitivity are the blast design parameters like spacing, burden, and depth. It is common

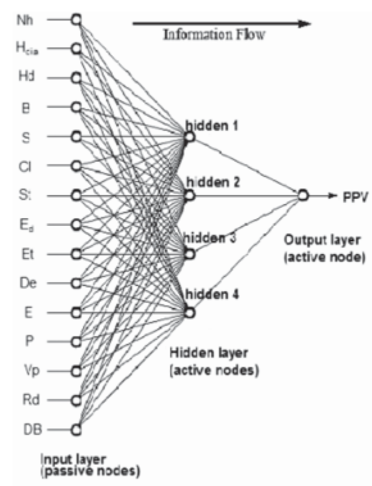

Figure 4—Architecture of ANN network

knowledge that some of the variables are related to blast-induced ground vibration but the degree of sensitivity of these variables is definitely knowledge gained from the model output. The details of sensitivity analysis are given in Table XVII and graphically represented in Figures 4 and 5.

3D plotting

Three-dimensional shaded graphs were drawn to study the responses of blast-induced ground vibration to the changes in various input variables. Out of the fifteen variables, only values of two variables were changed at a time, and the remaining variables were kept constant at their mean values. In this manner a two-way interaction of variables or sensitivity is created. The purpose is to study how ground vibration is sensitive to the changes of these input variables.

A database was prepared with the input variables varying at regular intervals within the range of values collected from the mines. For one value of a variable there will be ten values of the other variable. Keeping the remaining variables at their mean values, the selected variables were varied at regular intervals.

A 3D plot (Figure 7) was constructed using area to represent two input variables, distance of the monitoring station and charge per delay, and showing the model output PPV. The following conclusions can be drawn from the plot.

(a) PPV is more sensitive to changes in distance between the blast site and the monitoring station at distances greater than 150 m.

(b) PPV is more sensitive to charge per delay when distance between the blast site and the monitoring station is less than 150 m.

Table XVII

Connection weights and relative importance for the neural network modelling

Name of variables *		Connection weights	Relative importance (%)
No. of holes	Nh	0.5	6.08
Hole diameter (m)	Hdia	-0.5	6.15
Hole depth (m)	Hd	0.4	4.85
Burden (m)	B	0.3	3.45
Spacing (m)	S	0.5	5.97
Charge length (m)	Cl	0	0.04
Stemming length (m)	St	-0.1	1.4
Max. explosive charge/hole (kg)	Ed	2.4	29.25
Charge per round (kg)	Et	-0.05	0.88
Density of explosive (g/cm^2)	De	0.05	0.45
Young's modulus (GPa)	E	0.4	4.63
Poisson's ratio	P	-0.3	3.53
P-wave velocity (m/s)	Vp	-0.2	2.33
Rock density (g/ cm^2)	Rd	0.05	0.64
Distance of monitoring point from face (m)	DB	-2.5	30.33

* Variables shown in Figure 4

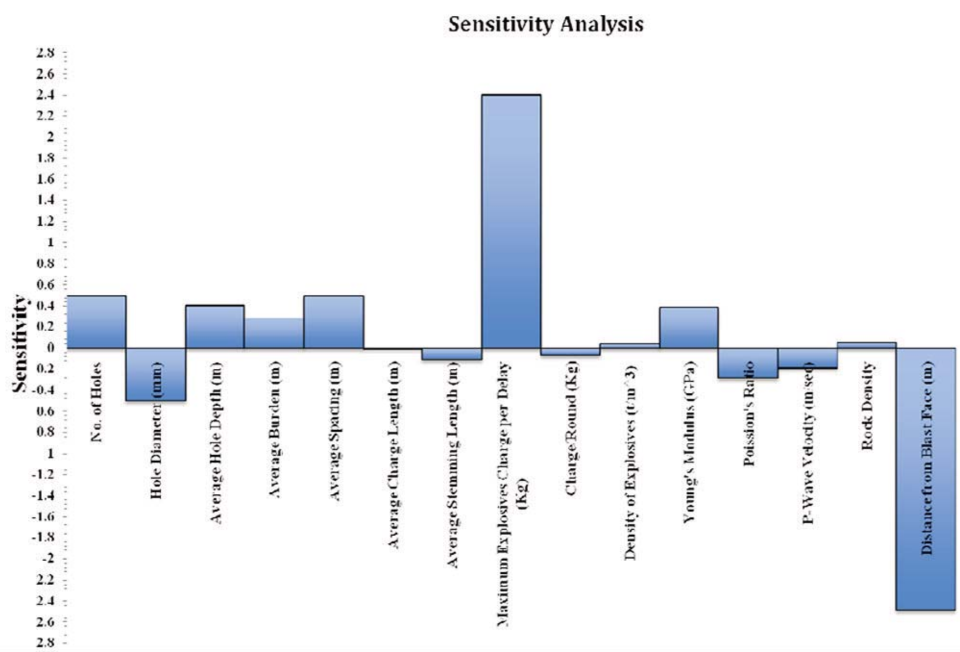

Figure 5—Sensitivity analysis of distributions of input-hidden-output connection weights

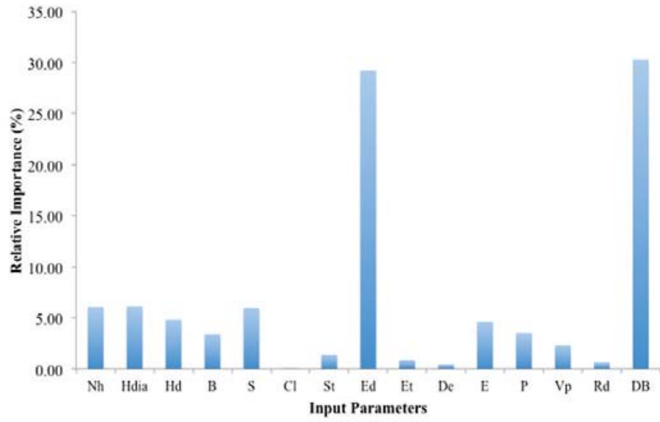

Figure 6—Relative importance of model input parameters on output (PPV)

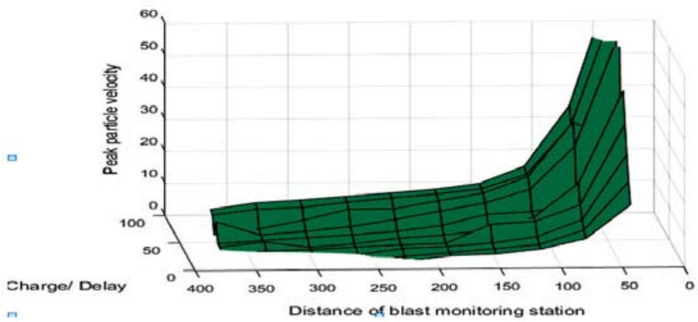

Figure 7—3D plot: distance of monitoring station, charge per delay, and PPV

Conclusion

An ANN model was developed using fifteen variables covering blast design, rock characteristics, and the distance between the blast site and monitoring station as input variables. The ANN model was found to perform better than the conventional models. Thus far, application of the ANN modelling technique to predict blast-induced ground vibration is limited and the number of input variables taken into consideration is small. In this research an attempt was made to train the model at three coal mining sites across India, which are being operated under highly diverse geological and mining conditions. The predictive capability of the model was further tested with a new set of data. An attempt was made to gain knowledge about ground vibration by analysis of the model output. The findings will help engineers to design optimum blasting patterns for their mines. The paper provides a basis for future research on identification of some significant variables that can further enhance the performance of the prediction model. Also, the applicability of the model can be further expanded by extensively training the model using data from different opencast coal mining sites.

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Appendix A

Review of available literature on the superiority of ANNs over other modelling techniques in predicting mine blast-induced ground vibration

The empirical method for prediction of blast-induced vibration has been adopted by many researchers in the form of predictor equations. Predictor equations are site-specific and indirectly related to the physical, mechanical, and geological properties of the rock mass as blast-induced ground vibration is a function of various controllable and uncontrollable parameters. Rock parameters for the blasting face and propagation media for blast vibration waves are uncontrollable parameters, whereas blast design parameters like hole diameter, hole depth, column length of explosive charge, total number of blast-holes, burden, spacing, explosive charge per delay, total explosive charge in a blasting round, and initiation system are controllable parameters. For a blasting engineer it is essential to gain knowledge, which is otherwise very limited, about the interplay between the several blast variables, since a blasting engineer will have to design, by trial and error, an optimum blast-hole pattern to achieve a high powder factor and optimum fragmentation. In commonly used empirical models this knowledge base is not available as it is primarily based on two variables. ANN models are claimed to be better than empirical models. Also, in the case of empirical models it is not possible to predict PPV for new blast sites unless test shot are fired and the results are used for deriving two site constants. Some of the empirical predictors are highlighted in Table A.1

Table A.1

Empirical models

Sl no.	Reference	Empirical model	Sl no.	Reference	Empirical model
1	Duvall and Petkof (1959)	$v = k(R/Q^{1/2})^{-b}$	12	Kahriman *et al.* (2006)	$v = 0.561D^{-1.432}$
2	Langefors and Kihlstrom (1963)	$v = k(Q/R^{2/3})^{b/2}$	13	Rai and Singh (2004)	$v = kR–^{b}Q_{max}e^{-\alpha}$
3	Ambraseys and Hendron (1968)	$v = k(R/Q^{1/3})^{-b}$	14	Nicholson (2005)	$v = 0.438D^{-1.52}$
4	Nicholls *et al.* (1971)	$v = 0.362D^{-1.63}$	15	Rai *et al.* (2005)	$Q_{max} = k(vD^{2})^{b}$
5	IS 6922 (1973)	$v = k(Q^{2/3}/R)^{1.25}$	16	Ozer (2008) (sandstone)	$v = 0.257D^{-1.03}$
6	Siskind *et al.* (1980)	$v = 0.828D^{-1.32}$	17	Ozer (2008) (shale)	$v = 6.31D^{-1.9}$
7	Ghosh and Daemen (1983)	$v = k(R/Q^{1/2})–^{b}e–^{\alpha R}$	18	Ozer (2008) (limestone)	$v = 3.02D^{-1.69}$
8	Pal Roy (1991)	$v = n + k(R/Q^{1/2})^{-1}$	19	Ak *et al.* (2009)	$v = 1.367D^{-1.59}$
9	CMRI (1993)	$v = n + k(R/Q^{1/2})^{-1}$	20	Badal (2010)	$v = 0.29D^{-1.296}$
10	Kahriman (2002)	$v = 1.91D^{-1.13}$	21	Mesec *et al.* (2010)	$v = 0.508D^{-1.37}$
11	Kahriman (2004)	$v = 0.34D^{-1.79}$			

v is the PPV (m/s); D is the scaled distance (m/kg$^{1/2}$), which is defined as the distance R (m) divided by the square root of explosive charge mass Q (kg) net equivalent charge weight, *i.e.* $D = R/Q^{1/2}$; k and b are site-specific constants. Generally, site constants k and b are determined by regression analysis of blasting results.

Peak particle velocity (PPV) is a function of the borehole pressure, confinement, charge weight, distance from blast area, manner of decay of compressive waves through the rock mass, and the firing sequence of adjacent holes. In the case of empirical predictors there is no uniformity in the predicted result since different predictors give different values of PPV for various amounts of allowable charge per delay in the same operating area. (Dowding, 1985; Khandelwal and Singh, 2007; Monjezi *et al.*, 2011). Moreover, empirical methods are unable to incorporate the numerous factors that affect the PPV and their complex interrelationships, hence the need for other techniques, including artificial neural networks (Khandelwal, 2010). Table A.2 highlights some of the applications of the ANN technique for modelling some of the detrimental effects of blasting.

Table A.2

ANN models

Reference	Technique	Input	Output	No. of data-set	R^2
Iphar, Yavuz, and Ak (2008)	ANFIS	DI, C	PPV	44	R^2 = 0.98
Bakhshandeh, Mozdianfard, and Siamaki (2010)	ANN	ST, DI ,C ,N	PPV	29	R^2 = 0.99
Monjezi *et al.* (2011a)	ANN	HD, ST, DI, C	PPV	182	R^2 = 0.95
Khandelwal, Kumar, and Yellishetty (2011)	ANN	DI, C	PPV	130	R^2 = 0.92
Mohamed (2011)	ANN, FIS	DI, C	PPV	162	R^2_{ANN}=0.94; R^2_{FIS}=0.90
Fisne, Kuju, and Hudaverdi (2011)	FIS	DI, C	PPV	33	R^2 = 0.92
Li, Yan, and Zhang (2012)	SVM	DI, C	PPV	37	R^2 = 0.89
Mohamadnejad *et al.* (2012)	SVM, ANN	DI, C	PPV	37	R^2_{SVM}=0.89; R^2_{ANN}=0.85
Ghasemi, Ataei, and Hashemolhosseini (2013)	FIS	B, S, ST, N, C, DI	PPV	120	R^2 = 0.95
Monjezi *et al.* (2013a)	ANN	C, DI, TC	PPV	20	R^2 = 0.93
Armaghani *et al.* (2013)	ANN-PSO	S, B, ST, PF, C, D, N, RD, SD	PPV	44	R^2 = 0.94
Hajihassani *et al.* (2014b)	ANN-ICA	BS, ST, PF, C, DI, Vp, E	PPV	95	R^2 = 0.98
Ghoraba *et al.* (2015)	ANN	BS, DI, C, ST, HL	PPV	115	R^2 = 0.98
Khandelwal and Singh (2005)	ANN	DI, C	AOp	56	R2 = 0.96
Mohamed (2011)	ANN, FIS	DI, C	AOp	162	R^2_{FIS}=0.92; R^2_{ANN}=0.86
Khandelwal and Kankar (2011)	SVM	DI, C	AOp	75	R2 = 0.85
Bakhshandeh, Siamaki, and Mohamadi (2012)	ANN	HD, S, B, N, D, ST, PF	AOp	38	R^2 = 0.93
Hajihassani *et al.* (2015)	ANN-PSO	HD, S, B, ST, PF, N, DI, C, RQD	AOp	62	R^2 = 0.86
Monjezi *et al.* (2010)	ANN	HD, BS, ST, PF, SD, N, C, RD	Flyrock	250	R^2 = 0.98
Rezaei *et al.* (2011)	FIS	HD, S, B, ST, PF, SD, RD, C	Flyrock	490	R^2 = 0.98
Monjezi *et al.* (2011)	ANN	HD, BS, ST, PF, D, SD, C, B	Flyrock	192	R^2 = 0.97
Monjezi *et al.* (2012)	ANN-GA	HD, S, B, ST, PF, SD, D, C, RMR	Flyrock	195	R^2 = 0.89
Ghasemi *et al.* (2012)	SVM, ANN	HL, S, B, ST, PF, SD, D	Flyrock	245	R^2_{SVM}=0.97; R^2_{ANN}=0.92
Mohamad *et al.* (2013)	ANN	HD, BS, ST, PF, C, D, N, RD, SD	Flyrock	39	R^2 = 0.97
Armaghani *et al.* (2013)	ANN-PSO	S, B, ST, PF, C, D, N, RD, SD	Flyrock	44	R^2 = 0.94
Monjezi *et al.* (2013b)	ANN	HD, S, B, D, C	Flyrock	310	R^2 = 0.98
Khandelwal and Monjezi (2013)	SVM	HL, S, B, ST, PF, SD	Flyrock	187	R^2 = 0.95
Marto *et al.* (2014)	ANN-ICA	RD, HD, BS, ST, PF, C, Rn	Flyrock	113	R^2 = 0.98
Trivedi, Singh, and Raina, (2014)	ANN	B, ST, ql, q, σc, RQD	Flyrock	95	R^2 = 0.98
Ghasemi *et al.* (2014)	ANN, FIS	HL, S, B, ST, PF, C	Flyrock	230	R^2_{FIS}=0.94; R^2_{ANN}=0.96
Armaghani *et al.* (2015)	ANN, ANFIS	BS, ST, PF, C, DI	PPV, Aop, Flyrock	166	R^2_{ANFIS}=0.77; R^2_{ANN}=0.94 R^2_{ANFIS}=0.86; R^2_{ANN}=0.95 R^2_{ANFIS}=0.83; R^2_{ANN}=0.96

B Blastability index
B Burden
BS Burden to spacing
C Maximum charge per delay
D Hole diameter
DI Distance from the blasting face
E Young's modulus
GA Genetic algorithm
HD Hole depth
HL Hole length
ICA Imperialist competitive algorithm
N Number of row
PF Powder factor
PSO Particle swarm optimization
q Specific charge
ql Linear charge concentration
RD Rock density
RMR Rock mass rating
RQD Rock quality designation
S Spacing
Sb Subdrilling
SD Specific drilling
ST Stemming
SVM Support vector machine
TC Total charge
Vp P-wave velocity
σc Unconfined compressive strength

Khandelwal and Singh (2006) applied an ANN for predicting ground vibration by including relevant parameters for rock mass, explosive characteristics, and blast design. The ANN was trained by 150 data-sets with 458 epochs and 20 testing data-sets. The ANN was found to be superior to a conventional statistical relationship. The correlation coefficient determined by ANN for PPV was higher than that determined by statistical analysis. Khandelwal and Singh (2007) investigated the prediction of PPV at a magnesite mine in a tectonically active hilly terrain in the Himalayan region in India. This study established that the feed-forward back-propagation neural network approach seems to be the better option for predicting PPV in order to protect surrounding environment and structures. Khandelwal and Singh (2009) predicted PPV in a coal mine in India based on ten input parameters using an ANN technique. The network architecture was a three-layer, feed-forward back-propagation neural network with 15 hidden neurons. Input parameters were trained using 154 experimental and monitored blast records. Comparison of the results by using correlation and mean absolute error (MAE) for monitored and predicted values of PPV showed that that ANN results for the PPV were very close to the field data-sets compared to the conventional predictors and MVRA predictions. Monjezi *et al.* (2010) predicted blast-induced ground vibration using various types of neural networks such as multi-layer perceptron neural network (MLPNN), radial-basis function neural network (RBFNN), and general regression neural network (GRNN) at Sarcheshmeh copper mine, Iran. MLPNN gave the best results, with a root mean square error and correlation coefficient of 0.03 and 0.954 respectively. ANN, multivariate regression analysis (MVRA), and empirical, analysis were used by Kamali and Ataei (2010) to predict the blast-induced PPV at the Karoun III power plant and dam.

Table A.2

ANN models (continued)

The best model was the ANN, since its outputs were highly correlated to the measured and observed data. Tang *et al.* (2007) developed a back-propagation neural network model to predict the peak velocity of blast vibration. They considered the charge hole diameter, distance, depth, column distance between charge holes, line of least resistance, maximum charge of single hole, maximum charge weight per delay, stemming length, total charge, magnitude of relative altitude and explosive distance as input parameters and found the predicted results from the ANN closer to the measured values than those from empirical predictors. Singh and Singh (1995) studied the blast-induced ground vibration at Dharapani magnesite mine, Pitthoragarh Himalaya in India and predicted PPV using neural networks.

The artificial intelligence method of simulating and predicting ground vibration due to blasting is accurate, reliable, practical, user-oriented, and easy to operate as well as useful for engineers (Lianjon, Guojian, and Yingxian, 2002). Neural network models provide descriptive and predictive capabilities and, for this reason, have been applied through the range of rock parameter identification and engineering activities (Hudson and Hudson, 1997). A number of conventional statistical, empirical equations and ANN systems have been employed by various researchers to predict rock fragmentation, ground vibration and air blast prior to blasting operations. However, the ANN is preferred over the other predictive techniques due to its ability to incorporate the numerous factors affecting the outcome of a blast among other advantages. The ANN model generated is site specific, the input parameters can be expanded to include mechanical and geotechnical rock parameters such as rock strength, RQD, rock hardness, number of joints etc. to provide the ANN model a wider application.

The artificial intelligence method of simulating and predicting blasting is accurate, reliable, practical, user-oriented, and easy to operate as well as useful for engineers (Lianjon, Guojian, and Yingxian, 2002). Cai and Zhao (1997) discussed ANN applications and incorporated the numerous factors that affect the PPV and their complex interrelationships. Chakraborty *et al.* (2004) underlined the effectiveness of multilayer perceptron (MLP) networks for estimation of blasting vibration and proposed a fusion network that combines several MLPs and on-line feature selection technique to obtain more reliable and accurate estimations compared with the empirical predictors. Mohamed (2009) used three different variations of ANN for prediction of PPV due to blast-induced ground vibrations and observed that the ANN using a large number of inputs parameters gave better prediction of PPV than an ANN using one or two inputs parameters. Also, the ANN model with two input parameters provided better results than the model with one input parameter. That is to say, increasing the number of input variables improves the ability of the ANN to learn and to predict more precisely. Singh (2005) attempted to predict the ground vibration in Indian coal measure rocks using ANN and confirmed that the network provided better results than a conventional multivariate regression method. PPV is generally used to assess potential blast vibration damage to structures on surface, but this parameter cannot fully explain the effect on structures situated far from the point of blasting and which can be damaged even at very low PPVs. (Ramchandar and Singh, 2001; Singh, Singh and Singh, 1994). The longer wavelength and smaller amplitude of these vibrations damage structures more severely than higher amplitude, shorter wavelength vibrations (Perrson, 1997). Maity and Saha (2004) used a neural network to assess damage in structures due to variation of static parameters. Using ANN, P-wave velocity and anisotropic property of rocks were investigated by Singh *et al.* (2004a). Lu (2005) studied the blast-induced ground shocks using an ANN at underground mines. Singh and Singh (2005) studied the dynamic constants of rock mass with a neural network and neuro-fuzzy system.

This literature review provides a broad overview of the wide application of the ANN modelling technique. The observations quoted by several researchers, as discussed above, establish the superiority of ANN as modelling technique in predicting blast-induced ground vibration .