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Prediction of blast induced ground vibrations and frequency in opencast mine: A neural network approach

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Abstract

This paper presents the application of neural network for the prediction of ground vibration and frequency by all possible influencing parameters of rock mass, explosive characteristics and blast design. To investigate the appropriateness of this approach, the predictions by ANN is also compared with conventional statistical relation. Network is trained by 150 dataset with 458 epochs and tested it by 20 dataset. The correlation coefficient determined by ANN is 0.9994 and 0.9868 for peak particle velocity (PPV) and frequency while correlation coefficient by statistical analysis is 0.4971 and 0.0356.

1. Introduction

The increasing development of opencast mines due to the enhanced demand for coal, and other minerals has lead to usage of huge amounts of explosives for blasting particularly in India. Till now, explosives are the efficient source of energy required for breakage and excavation of rocks. When an explosive detonates in a blast hole, instantaneously huge amount of energy in forms of pressure and temperature liberates. Although significant developments have taken place in explosive technology, the explosive energy utilization has not made much progress due to complexity of various rock parameters [1–3]. Only a small proportion of this total energy is utilized for actual breakage and displacement of rock mass and the rest of the

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energy is spent in undesirable side effects like ground vibrations, air blasts, noises, back breaks, etc. [4].

The ground vibration is literally a wave motion, spreading outward from the blast like ripples spreading outwards due to impact of a stone dropped into a pond of water. As the vibration passes through the surface structures, it induces vibrations in those structures also. These vibrations induce a resonance in the structures if the frequency of ground vibration matches with the frequency of the structure and due to this, amplitude of the vibration may exceed the amplitude of the initial ground vibrations [3]. Frequency and peak particle velocity (PPV) are most commonly used parameters for assessment of ground vibrations. Dowding [5] underlies the importance of frequency because structural responses depend on the frequency of ground vibrations. Ground vibration is influenced by a number of parameters such as physico-mechanical properties of rock mass, explosive characteristics and blast design. It is essential to know the effect of these parameters on blasting for efficient utilization of explosive energy in a given rock mass vis-à-vis minimization of blast induced side effects. The design parameters like maximum charge per delay, delay time, burden, spacing, charge length, initiation sequence and decoupling charges considerably alter dispersion of the seismic energy. Rock characteristics also often vary greatly from place to place in a mine or even from one end to another of a single face. Hence, blast design parameters and explosives characteristics need to be optimized based on rock mass properties, e.g. strength, density, porosity, longitudinal wave velocity, impedance, stress–strain response and presence of structural discontinuities [6].

The artificial neural network (ANN) is a new branch of intelligence science and has developed rapidly since 1980s. Nowadays, ANN is considered to be one of the intelligent tools to understand the complex problems. Neural network has the ability to learn from the pattern acquainted before. Once the network has been trained, with sufficient number of sample datasets, it can make predictions, on the basis of its previous learning, about the output related to new input dataset of similar pattern [7]. Due to its multidisciplinary nature, ANN is becoming popular among the researchers, planners, designers, etc., as an effective tool for the accomplishment of their work. Therefore, ANN is being successfully used in many industrial areas as well as in research area also. Maulenkamp and Grima [8] developed a model by which uniaxial compressive strength can be predicted from Equotip hardness. It has been reported that the prediction of uniaxial compressive strength by ANN is closer from the measured values. It is indicated by the consistency of the correlation coefficient for the different test set. Yang and Zhang [9] investigated the point load testing with ANN. Cai and Zhao [10] used ANN for tunnel design and optimal selection of the rock support measure and to ensure the stability of the tunnel. Singh et al. [11] predicted the strength property of schistose rocks by neural network. The stability of waste dump from dump slope angle and dump height is investigated by Khandelwal and Singh [12]. They found very realistic results as compared to the other analytical approach. Maity and Saha [13] assessed the damage in structures from changes in static parameters by neural network. Singh et al. [14] predicted the P-wave velocity and anisotropic properties of rocks by neural network. These applications demonstrate that neural network model have superiority in solving problems in which many complex parameters influence the process and results, when process and results are not fully understood and where historical or experimental data are available. The prediction of blast induced ground vibrations is also of this type.

In the present investigation, an attempt has been made to predict the PPV and its corresponding frequency with the help of ANN by using relevant parameters of rock mass, explosive characteristics and blast design.

2. Geology of the area

The study was conducted at Northern Coalfields Limited (NCL), which is a subsidiary company of Coal India Limited and it is located at Singrauli, Dist. Sidhi (M.P.). It is one of the biggest coal producing company at about 2202 km^2. The area of NCL lies geographically between latitudes of 24°0′–24°12′ and longitudes 82°30′–82°45′ and comprises Gondwana rocks.

The coalfield can be divided into two basins, viz. Moher sub-basin (312 km^2) and Singrauli Main basin (1890 km^2). It is divided into 11 mining blocks namely Kakri, Bina, Marrack, Khadia, Dhudhichua, Jayant, Nighahi, Amlohri, Moher, Gorbi and Jhingurdah [15].

The overburden rocks in this area are mostly medium to coarse-grained sandstone, carbonaceous shale and shaly sandstone.

3. Factors affecting ground vibrations and frequency

The nature and intensity of blast induced ground vibrations and frequency is largely dependent upon many factors [16]. The most important influencing factors are shown in Fig. 1.

All the above-mentioned parameters are dependent upon each other and mostly interrelated. If a particular variable is changed, others parameters will also be changed.

The surrounding rock types have moderate influence on ground vibration behavior [17]. While designing any blast, geo-physical properties should be considered to get an optimum blast with less vibration.

Geological discontinuity also plays a very imperative role in the transmission of ground vibration [6].

The distance from blast face to vibration monitoring point is one of the most influencing parameter. If distance is more, then vibration will be less due to dissipation and dispersion of waves.

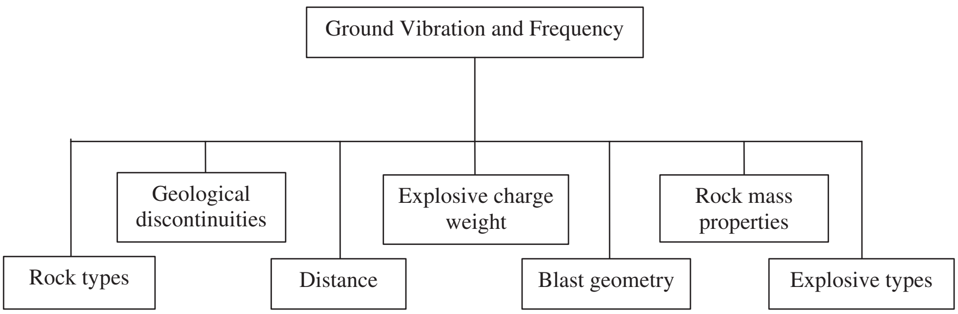

Fig. 1. Factors affecting ground vibration.

Blast geometry plays a very crucial role for control of ground vibration. Burden, spacing, charge length, stemming, sub-drilling, hole diameter, length of hole, etc. are specific parameters, by which ground vibration can be minimized under control level.

Explosives do have influence on the magnitude and frequency of ground vibration. High velocity of detonation explosive generates high intensity ground vibration, and low velocity of detonation explosive generates low intensity ground vibration.

4. Artificial neural network

ANN is a branch of the 'Artificial Intelligence', other than, Case Based Reasoning, Expert Systems, and Genetic Algorithms. The Classical statistics, Fuzzy logic and Chaos theory are also considered to be related fields. The ANN is an information processing system simulating the structure 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 (called neurons) capable of performing massively parallel computation for data processing and knowledge representation. The paradigms in this field are based on direct modeling of the human neuronal system [18]. 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 input patterns and showing what output resulted from each input pattern. The neural network is able to recognize similarities when presented with a new input pattern after proper training and results a predicted output pattern.

Neural networks are able to detect similarities in inputs, even though a particular input may never have been known previously. This property allows its excellent interpolation capabilities, especially when the input data is noisy (not exact). Neural networks may be used as a direct substitute for auto-correlation, multivariable regression, linear regression, trigonometric 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. Particular network can be defined using three fundamental components: transfer function, network architecture and learning law [19]. One has to define these components, depending upon the problem to be solved.

5. Network training

A network first needs to be trained before interpreting new information. Several different algorithms are available for training of neural networks but the back-propagation algorithm is the most versatile and robust technique, which provides the most efficient learning procedure for multilayer neural networks. Also, the fact that back-propagation algorithms are especially capable to solve predictive problems which make them so popular. The feed forward back propagation neural network (BPNN) always consists of at least three layers: input layer, hidden layer and output layer. Each layer consists of a number of elementary processing units, called neurons, and each neuron is connected to the next layer through weights, i.e. neurons 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. Number of hidden layer and number of neurons in the hidden layer changes according to the problem to be solved. The number of input and output neuron is the same as the number of input and output variables.

To differentiate between the different processing units, values called biases are introduced in the transfer functions. These biases are referred to as the temperature of a neuron. Except for the input layer, all neurons in the back-propagation network are associated with a bias neuron and a transfer function. 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. These transfer functions are designed to map a neuron or layers net output to its actual output and they are simple step functions either linear or nonlinear functions. The application of these transfer functions depends on the purpose of the neural network. The output layer produces the computed output vectors corresponding to the solution.

During training of the network, data is processed through the input layer to hidden layer, until it reaches the output layer (forward pass). In this layer, the output is compared to the measured values (the "true" output). The difference or error between both is processed back through the network (backward pass) updating the individual weights of the connections and the biases of the individual neurons. The input and output data are mostly represented as vectors called training pairs. The process as mentioned above is repeated for all the training pairs in the dataset, until the network error converged to a threshold minimum defined by a corresponding cost function; usually the root mean squared error (RMS) or summed squared error (SSE).

In Fig. 2 the jth neuron is connected with a number of inputs

$$x_i = (x_1, x_2, x_3, \ldots, x_n).$$

The net input values in the hidden layer will be:

$$\mathrm{Net}_j = \sum_{i=1}^{n} x_i w_{ij} + \theta_j,$$

where x_i is the input units, w_{ij} the weight on the connection of ith input and jth neuron, θ_j the bias neuron (Optional), and n the number of input units.

So, the net output from hidden layer is calculated using a logarithmic sigmoid function

$$O_j = f(\mathrm{Net}_j) = 1/1 + \mathrm{e}^{-(\mathrm{Net}_j + \theta_j)}.$$

The total input to the kth unit is

$$\mathrm{Net}_k = \sum_{j=1}^{n} w_{jk} O_j + \theta_k,$$

where θ_k is the bias neuron, w_{jk} the weight between jth neuron and kth output.

So, the total output from kth unit will be

$$O_k = f(\mathrm{Net}_k).$$

In the learning process, the network is presented with a pair of patterns, an input pattern and a corresponding desired output pattern. The network computes its own output pattern using its

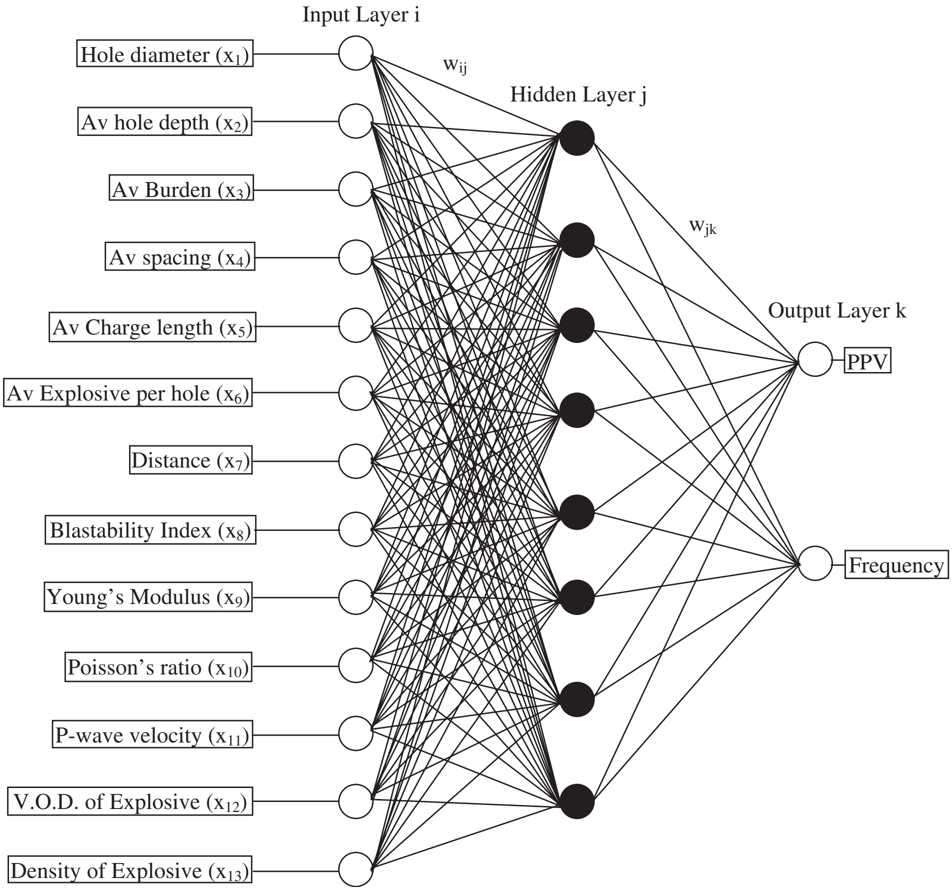

Fig. 2. Back propagation neural network.

(mostly incorrect) weights and thresholds. Now, the actual output is compared with the desired output. Hence, the error at any output in layer k is

$$e_l = t_k - O_k,$$

where t_k is the desired output, and O_k the actual output.

The total error function is given by

$$E = 0.5 \sum_{k=1}^{n} (t_k - O_k)^2.$$

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

$$\nabla W_{jk} = -\eta(\delta E/\delta W_{jk}),$$

where η is the learning rate parameter, and E the error function.

The update of weights for the $(n+1)$th pattern is given as

$$W_{jk}(n+1) = W_{jk}(n) + \nabla W_{jk}(n).$$

Similar logic applies to the connections between the hidden and output layers [20]. This procedure is repeated with each pattern pair of training exemplar assigned for training the network. Each pass through all the training patterns is called a cycle or epoch. The process is then repeated as many epochs as needed until the error within the user specified goal is reached successfully. This quantity is the measure of how the network has learned.

6. Dataset

The range of values of different input parameters has been decided by the detailed field investigations by the authors as well as from the published literatures by the various researchers [6,21–24] (Table 1).

Rock density is also a critical parameter for prediction of PPV and frequency of ground vibration. The range of rock density of Singrauli area lies between 2.05 and 2.97 t/m^3. The variation of rock density is not so high, that is why it has not taken as an input parameter for training of neural network (Table 2).

All the input and output parameters were scaled between 0 and 1. This was done to utilize the most sensitive part of neuron and since output neuron being sigmoid can only give output between 0 and 1, the scaling of output parameter was necessary.

$$\text{Scaled value} = (\text{max. value} - \text{unscaled value})/(\text{max. value} - \text{min. value}).$$

Table 1
Input parameters for network and their range

S. No.	Input parameter	Range
1	Hole diameter (mm)	150–311
2	Average hole depth (m)	6–43
3	Average burden (m)	3–10.5
4	Average spacing (m)	4–13
5	Average charge length (m)	4–38
6	Average explosive per hole (kg)	75–3526
7	Distance of monitoring point from blasting face (m)	85–8500
8	Blastability Index	5.6–14.8
9	Young's modulus (GPa)	3.2–12.15
10	Poisson's ratio	0.16–0.38
11	P-wave velocity (km/s)	1659–4837
12	Velocity of detonation of explosive (km/s)	3.14–5.8
13	Density of explosive (t/m^3)	0.95–1.4

Table 2
Output parameters for network and their range

S. No.	Output parameter	Range
1	Peak particle velocity (mm/s)	0.73–98.34
2	Frequency (Hz)	3.3–48.7

7. Network architecture

Feed forward network is adopted here as this architecture is reported to be suitable for problem based on problem identification. Pattern matching is basically an input/output mapping problem. Closer the mapping, better performance of the network.

The objective of the present investigation was to predict PPV and its corresponding frequency from relevant parameters like physico-mechanical properties of the rock mass, explosive properties and blast design. It is difficult to determine all the relevant parameters which have influence on the prediction of ground vibration and frequency. However, all the influencing parameters are not independent and some of them are strongly correlated. Hence, it was not important to use all the variables as input parameters.

Thus, taking the above discussion and objective of the investigation under consideration, one network was designed to predict the two outputs.

The architecture of the network is tabulated below:

1. No. of input neurons: 13
2. No. of output neurons: 2
3. No. of hidden layers: 1
4. No. of hidden neurons: 8
5. No. of training epochs: 458
6. No. of training datasets: 150
7. No. of testing datasets: 20
8. Error goal: 0.005

8. Testing and validation of ANN model

To test and validate the ANN model, the new datasets have been chosen. These data are not used while training the network. It will validate the use of ANN in a more versatile way. However, all available vibration predictors proposed by different researchers have site-specific equations [25–29]. They are not able to use any equation for even other similar geo-mining conditions. The constants which are called site-specific constants and attenuation factor varied once the ground condition changed. Moreover, they are derived based on only two main parameters, i.e. maximum charge per delay and distance from monitoring point to blast face. These are the limitations of various parameters. These predictors are based on linear relation between scaled distance and PPV and not able to evaluate frequency.

The results are presented in this section to demonstrate the performance of the networks. The mean absolute percentage error (MAPE) and coefficient of correlation between the predicted and observed values are taken as the performance measures. The prediction was based on the input datasets discussed above.

Training of the network was done using 1 hidden layer with 8 hidden neurons. As we have used Bayesian regulation [30], there was no danger of over-fitting problems, hence, the network was trained with 458 training epochs. The training performance and error elimination by sum squared error (SSE) method for datasets is shown in Fig. 3. Observed and predicted values of PPV and frequency have been given in Table 3. The correlation coefficients for the predicted and observed values are as high as 0.9994 and 0.9868 for the PPV and frequency, respectively (Figs. 4 and 5). The MAPE were calculated by subtracting measured value from the corresponding predicted value and then divided it by measured value expressed in percentage. The MAPE for PPV and frequency are 4.76 and 6.99, respectively.

9. Multivariate regression analysis (MVRA)

The purpose of multiple regressions is to learn more about the relationship between several independent or predictor variables and a dependent or criterion variable. The goal of regression analysis is to determine the values of parameters for a function that cause the function to best fit a set of data observations provided. In linear regression, the function is a linear (straight-line) equation. When there is more than one independent variable, then multivariate regression analysis (MVRA) is used to get best-fit equation. Multiple regressions solve the datasets by performing least squares fit. It constructs and solves the simultaneous equations by forming the regression matrix and solving for the coefficient using the backslash operator. The MVRA has been done by same datasets and same input parameters which have been used for the predictions by ANN.

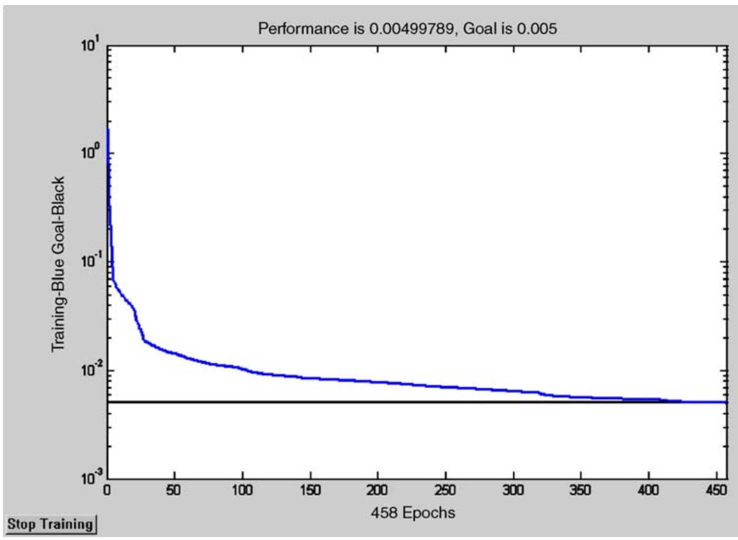

Fig. 3. Performance of ANN while training.

Table 3
Predicted PPV and corresponding frequency with % error

S. No.	Hole Dia (cm)	Average					Distance (km)	Blastability index	Young's modulus (GPa)	Poisson's ratio	P-wave velocity (km/s)	V.O.D. of Explosive (km/s)	Density of Exp(t/m^3)	PPV (mm/s)			Frequency (Hz)		
		Hole depth (m)	Burden (m)	Spacing (m)	Charge length (m)	Explosive per hole (kg)								Measured	Predicted (ANN)	Predicted (MVRA)	Measured	Predicted (ANN)	Predicted (MVRA)
1	15.0	4.8	3	4	1.3	175	0.5	6.6	7.54	0.23	2.70	3.54	1.15	0.95	0.78	19.23	5	5.4	28.50
2	16.5	15	6	7.5	8	150	0.2	10.3	3.88	0.22	2.55	4.36	1.1	4.47	4.20	17.97	12	14.5	11.67
3	16.5	12.5	5	7	7.4	512	0.35	10.2	6.81	0.34	1.85	3.67	1.15	4.62	4.75	37.30	15.3	15.1	24.77
4	16.5	7	3	4	4	93	0.25	8.75	6.81	0.24	3.42	5.04	1.05	15.45	15.63	23.70	39	40.3	26.29
5	16.5	8.5	3.8	3.8	5.3	375	0.55	7.3	7.54	0.18	2.74	4.17	1.2	1.38	1.32	17.07	8	9.2	23.31
6	25.0	35	7	9	28	2025	5.0	6.2	6.46	0.28	3.25	4.98	1.2	1.64	1.97	14.24	7.5	8.5	24.27
7	25.0	39	9	11	32.75	2300	0.6	9.75	7.38	0.22	4.20	4.72	1.2	43.8	45.26	51.46	18.4	18.5	25.04
8	25.0	39	9	11	32.75	2300	0.4	8.1	6.44	0.35	2.26	4.12	1.3	62.4	62.54	48.68	8.5	7.6	22.97
9	26.9	34.5	9	11	28.5	2100	2.8	8.5	4.15	0.27	2.74	4.8	1.3	6.38	6.65	-20.68	8	7.7	21.54
10	26.9	39	9	11	32.75	2300	0.35	8.7	5.51	0.20	2.87	3.83	1.2	69.8	70.08	54.63	6.2	6.8	23.83
11	26.9	39	9	11	32.75	2300	0.45	7.68	6.2	0.28	3.12	3.38	1.25	55.4	53.83	54.08	6.7	5.9	24.95
12	26.9	39	9	11	32.75	2300	0.55	8.75	8.11	0.25	3.65	4.37	1.1	47.5	48.52	53.83	22.7	24.5	26.89
13	26.9	39	9	11	32.75	2300	0.5	8.75	9.67	0.21	3.37	3.96	1.15	52.9	51.84	39.49	18.9	17.8	27.14
14	31.1	43	10.5	12.5	37.5	3420	0.4	11.6	6.81	0.34	3.81	5.1	1.15	71.3	70.29	57.37	11.2	10.9	20.89
15	31.1	43	10.5	12.5	37.5	3377	1.2	8.4	7.54	0.27	3.27	4.88	1.3	36.8	37.24	55.77	7.3	7.8	25.81
16	31.1	39	9	11	33	2441	1.8	9.1	8.11	0.21	2.28	3.79	1.2	9.37	8.69	56.74	9.8	9.7	29.45
17	31.1	43	10.5	12.5	37.5	3420	1.08	8.23	5.19	0.30	1.89	5.23	1.3	27.4	26.74	49.05	13.4	12.7	20.50
18	31.1	43	10.5	12.5	37.5	3370	0.35	8.31	7.54	0.26	2.45	3.92	1.2	92.3	91.35	60.92	15.8	16.8	24.06
19	31.1	40.5	9	11	33.5	2535	2.1	7.56	7.54	0.23	3.05	4.24	1.2	6.37	5.97	34.66	18.5	17.9	25.45
20	31.1	32	9	10	24.5	2000	1.79	12.9	5.26	0.26	2.08	4.83	1.2	6.4	5.89	27.34	8	8.2	19.83

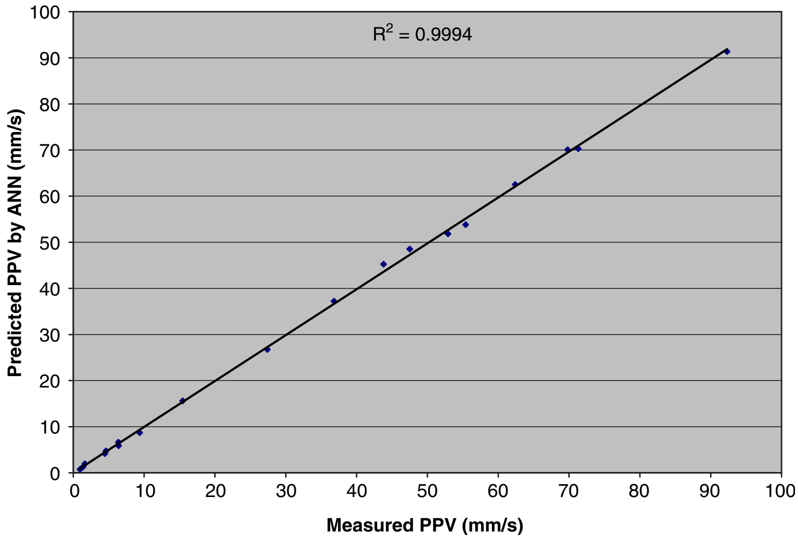

Fig. 4. Measured vs. predicted PPV by ANN.

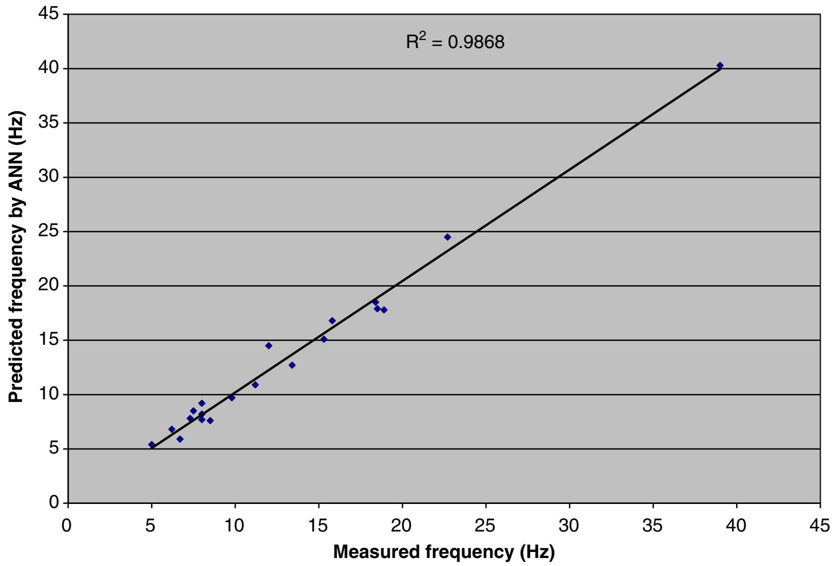

Fig. 5. Measured vs. predicted frequency by ANN.

The equation for prediction of PPV by MVRA is:

$$\begin{aligned}\text{PPV} = {} & 3.6223 + 0.012\,[\text{Hole Dia., mm}] + 0.6636\,[\text{Hole depth, m}] \\ & - 3.5373\,[\text{Burden, m}] + 5.5001\,[\text{Spacing, m}] - 0.0021\,[\text{Charge Length, m}] \\ & - 0.0025\,[\text{Explosive per hole, kg}] - 0.0131\,[\text{Distance, m}]\end{aligned}$$

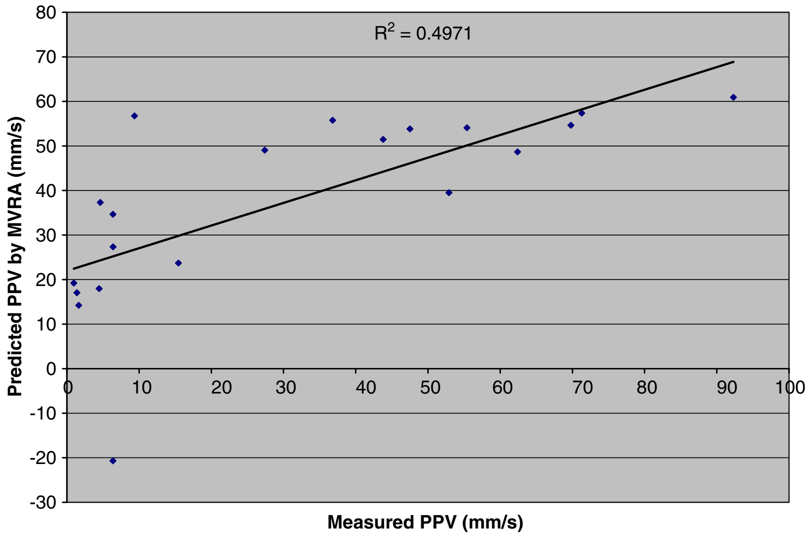

Fig. 6. Measured and predicted PPV by MVRA.

$$
\begin{aligned}
&- 0.0053\,[\text{Blastability Index}] + 1.1451\,[\text{Young's Modulus, GPa}] \\
&+ 1.024\,[\text{Poisson's Ratio}] - 0.0012\,[\text{P-wave, m/s}] \\
&- 0.2547\,[\text{V.O.D. of Explosive, km/s}] + 1.3263\,[\text{Density, t/m}^3].
\end{aligned}
$$

The equation for prediction of frequency by MVRA is:

$$
\begin{aligned}
\text{Freq} = {} & 14.0641 + 0.0024\,[\text{Hole Dia., mm}] + 0.0007\,[\text{Hole depth, m}] \\
&- 4.2033\,[\text{Burden, m}] + 5.125\,[\text{Spacing, m}] - 0.1269\,[\text{Charge Length, m}] \\
&- 0.0038\,[\text{Explosive per hole, kg}] - 0.0003\,[\text{Distance, m}] \\
&- 0.2086\,[\text{Blastability Index}] + 1.4647\,[\text{Young's Modulus, GPa}] \\
&+ 0.6896\,[\text{Poisson's Ratio}] - 0.0008\,[\text{P-wave, m/s}] \\
&- 0.1575\,[\text{V.O.D. of Explosive, km/s}] + 0.0454\,[\text{Density, t/m}^3].
\end{aligned}
$$

The predicted values of PPV and frequency by MVRA have been given in Table 3. The correlation coefficient for PPV and frequency are 0.4971 and 0.0356, respectively (Figs. 6 and 7). The MAPE for PPV and frequency are 343.98 and 140.40, respectively.

10. Results and discussion

Figs. 4 and 5 show that predictions of PPV and frequency by ANN are very nearer to measured PPV in field but predictions by MVRA have shown very high errors (Figs. 6 and 7), even though, most of the researchers used simply regression analysis or conventional method for prediction of

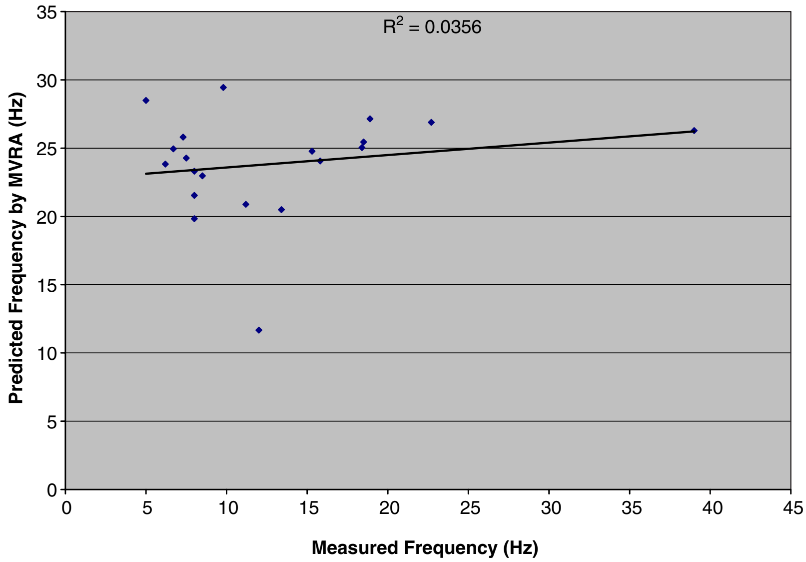

Fig. 7. Measured and predicted frequency by MVRA.

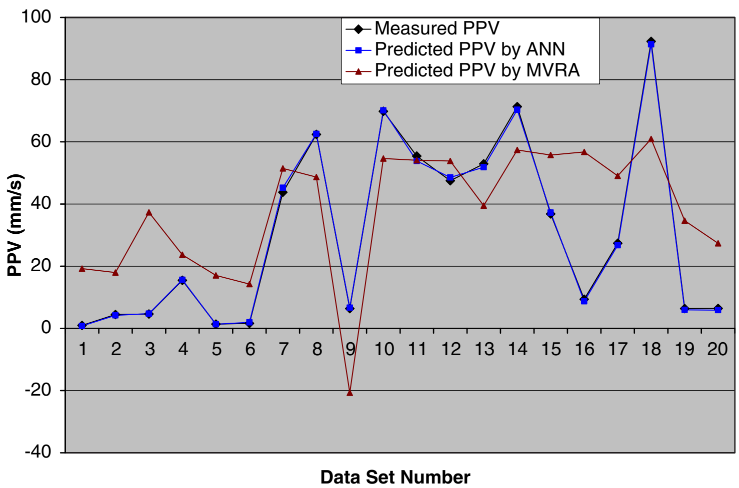

Fig. 8. Comparison of measured PPV with predicted PPV by ANN and MVRA.

blast induced ground vibration. MVRA is not able to predict the PPV and frequency upto an acceptable limit. ANN demonstrates the superiority over MVRA technique particularly when variables are more. After observing MAPE, coefficient of correlation and number of predicted parameters, on which output is depending for the network, it can be said that prediction made by ANN for PPV and frequency is accurate and impressive. Figs. 8 and 9 illustrate the comparison of measured PPV and frequency with predicted PPV and frequency by ANN and MVRA.

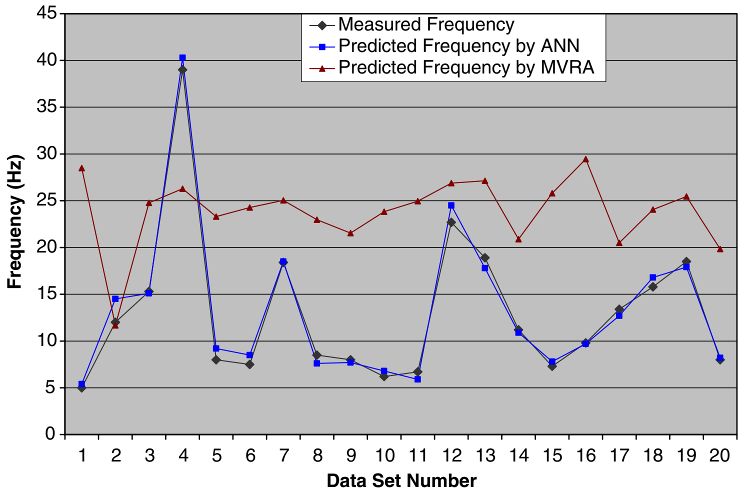

Fig. 9. Comparison of measured frequency with predicted frequency by ANN and MVRA.

11. Conclusions

Using Bayesian regulation and optimum number of neurons in the hidden layer, the MAPE for PPV and frequency are 4.76 and 6.99, respectively, by ANN. The corresponding coefficients of correlation are 0.9994 and 0.9868, respectively. The prediction by MVRA has very high error. The coefficient of correlation for PPV and frequency by MVRA are 0.4971 and 0.0356, respectively, and MAPE is 343.98 and 140.40. Considering the complexity of the relationship among the inputs and outputs, the results obtained are highly encouraging and satisfactory. Since neural network can learn new patterns that are not previously available on the training datasets, and as they can update knowledge over time as long as more training datasets are presented, and process information in parallel way, they result in a greater degree of accuracy, robust and fault tolerance than any other analysis techniques. Hence, the technique proves to be economical and easier in comparison to hectic and expensive experimental work and can be successfully used as a substitute for that.

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