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Prediction of ground vibrations and frequency in opencast mine using neuro-fuzzy technique

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Present work proposes a methodology to predict ground vibrations induced by blast in opencast mine. Proposed methodology showed substantial improvement over artificial neural networks and multiple linear regression.

Keywords: Ground vibrations, Neuro-fuzzy technique, Opencast mine

Introduction

Explosives are used as a source of energy to break and excavate rocks. A majority of energy from explosives is lost by ground vibrations, noise, air blasts, etc[1-3]. Ground vibrations are influenced by a number of parameters (rock mass, explosive characteristics, blast design etc), monitoring of which via regression analysis shows a poor performance (R^2 0.5), whereas artificial neural network (ANN) turns out to be a better alternative[4]. Maulenkamp & Grima[5] model can predict uniaxial compressive strength from equotip hardness. Stability of waste dump[6] from dump slope angle and dump height has been investigated. Yang & Zhang[7] investigated point load testing with ANN. Cai & Zhao[8] used ANN for tunnel design and optimal selection of rock support measure and to ensure tunnel stability. ANN predicted P-wave velocity and anisotropic properties of rocks are reported[9].

Present work used neuro-fuzzy technique (NFT)[11-14] to predict ground vibrations and frequency in opencast mine.

Methodology

The data (Table 1) was collected from Northern Coalfields Limited, Singurali, M P, India. Inputs used were fuzzy grades of input[4] (hole diameter, depth, spacing, burden, charge length, explosive per hole, distance, blastibility index, Young's Modulus, Poisson's ratio, P-wave velocity, VOD and density of explosive). To compare effectiveness of proposed and existing methodologies, same inputs[4] were considered. Further, t-test was carried out to determine suitability of inputs.

Results and Discussion

Neuro-fuzzy technique(NFT) was implemented and t-test was carried out to check significance of inputs[15]. Selection of optimal network architecture forms a key ingredient to the success of network implementation. Input and output layers contain 39 and 6 neurons respectively. Initially, number of iterations was taken at 30,000 and number of neurons was varied for 1 and 2 hidden layers (Fig. 1). Hidden layer showed consistently better results compared to two hidden layers, which is an optimal choice. Beyond 7 hidden layer neurons, not much improvement was seen. Hence to minimise processor time, 7 hidden layer neurons were selected. Keeping hidden layer parameters, network was tested to find optimal number of iterations (Fig. 2). Results show 25,000 iterations to be the optimal choice as no further improvement was observed beyond that.

With chosen network parameters, network was trained with a part of the data; remaining data was used for testing. Results obtained were compared with ANN results (Figs 3 & 4). In almost all cases, results from NFT were found closer to measured values than that from ANN, possibly due to the ability of fuzzy logic to deal with uncertainties invariably associated with measurements.

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Table 1—Fuzzy grades of inputs[4]

S No.	Hole diam cm	Depth cm	Burden m	Spacing m	Charge length m	Explosive per hole kg	Distance km	Blastibility Index	Young's Modulus GPa	Poisson's ratio	P-wave velocity km/s	VOD of explosive km/s	Density of explosive t/m^3	PPV mm/s	Frequency Hz
1	15	4.8	3	4	1.3	175	0.5	6.6	7.54	0.23	2.7	3.54	1.15	0.95	5
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	12
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	15.3
4	16.5	7	3	4	4	93	0.25	8.75	6.81	0.24	3.42	5.04	1.05	15.45	39
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	8
6	25	35	7	9	28	2025	5	6.2	6.46	0.28	3.25	4.98	1.2	1.64	7.5
7	25	39	9	11	32.75	2300	0.6	9.75	7.38	0.22	4.2	4.72	1.2	43.8	18.4
8	25	39	9	11	32.75	2300	0.4	8.1	6.44	0.35	2.26	4.12	1.3	62.4	8.5
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	8
10	26.9	39	9	11	32.75	2300	0.35	8.7	5.51	0.2	2.87	3.83	1.2	69.8	6.2
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	6.7
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	22.7
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	18.9
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	11.2
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	7.3
16	31.1	39	9	11	33	2441	1.8	9.1	8.11	0.21	2.28	3.79	1.2	9.37	9.8
17	31.1	43	10.5	12.5	37.5	3420	1.08	8.23	5.19	0.3	1.89	5.23	1.3	27.4	13.4
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	15.8
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	18.5
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	8

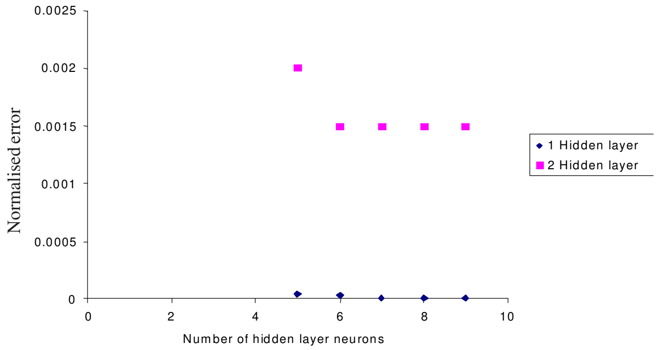

Fig. 1—Variation of error with change in hidden layer neurons

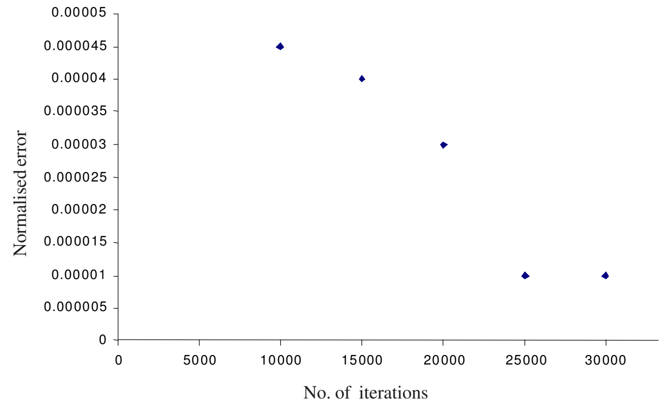

Fig. 2—Variation of error with number of iterations

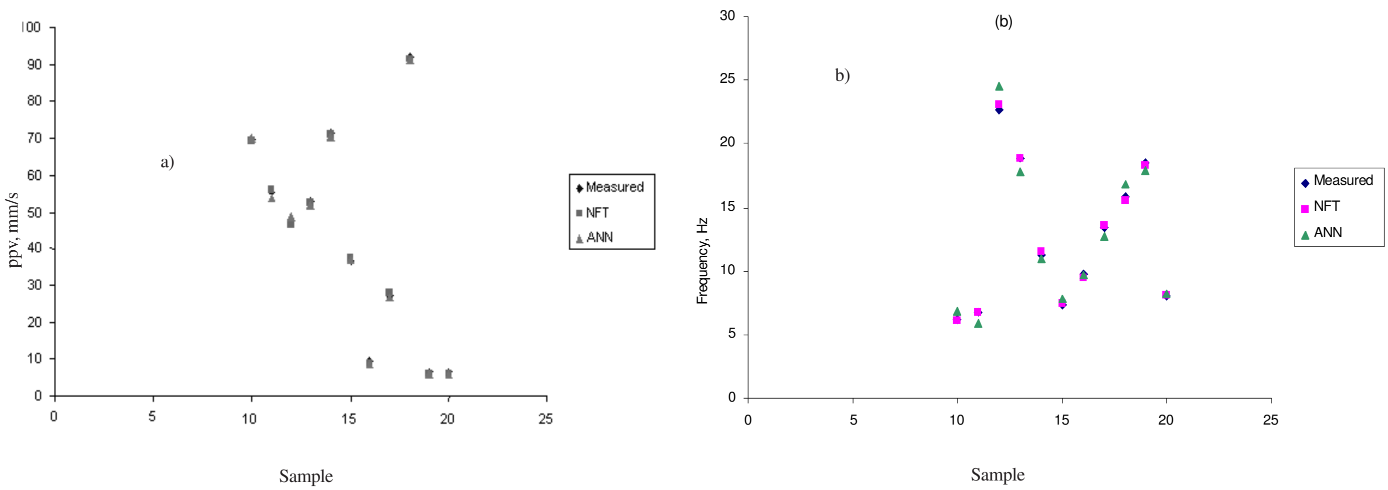

Fig. 3—Predictions with NFT and ANN of: a) PPV; and b) Frequency

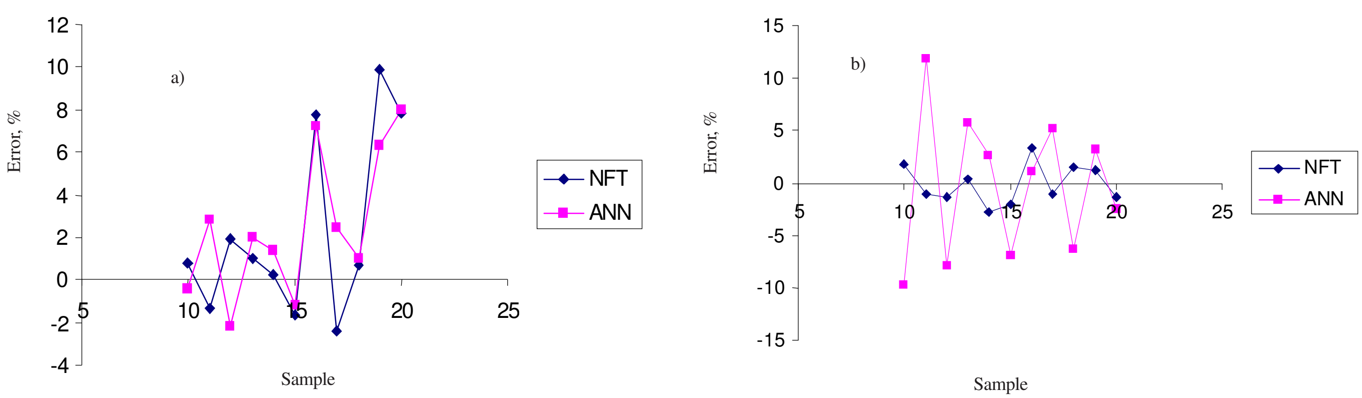

Fig. 4—Percent errors in predictions of: a) PPV; and b) Frequency

Conclusions

NFT to predict ground vibrations and frequency in an opencast mine is found superior compared to ANN and regression model etc. In prediction of PPV, results obtained from NFT are nearer to measured values compared to results from ANN prediction. Thus, NFT is a better alternative to existing methods for prediction of ground vibrations in opencast mines. However, results need to be generalized, as present work is valid only for the considered data.

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