Applicability of a Neural Network Model for Forecasting Ground Vibrations in Opencast Mining

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Abstract

Ground vibration and air-blast over pressure are two significant undesirables, among many environmental risks, in open-pit mining. Gaining control over the ground vibrations generated by rock blasts had been difficult mainly due to the complexities involved with local geology and properties of the blast. Accordingly, existing empirical equations are only capable of making vague approximations on the vibration frequencies based on site-specific parameters and attenuation factor. Therefore, the available models cannot be generalized to different geo-mining environments to obtain sufficiently reliable forecasts for ground vibration and air-blast overpressure. Hence, this study attempts to employ an Artificial Neural Network (ANN) based feed-forward back-propagation algorithm to train a model, using a supervised learning technique to forecast possible ground vibration frequencies. The main input parameters included in the model are noise level, number of boreholes per single blast, depth and diameter of a borehole, charge per hole, number of delays of the Electric Detonators (ED) in a single blast, burden and spacing. Air blast overpressure and the ground vibration levels will be the output by ANN model. The model was validated using 50 datasets, which were obtained from a quarry site. After adequate training, the model can determine Peak Particle Velocity (PPV) and frequency of Ground Vibrations (GV) for new input parameters with a statistically significant confidence level.

Keywords: ANN, PPV, Rock blasting, Surface mining

1. Introduction

Blasting operations in opencast mining have been preferred as an economically feasible mining method. These operations are carried out either as controlled blasting or as production blasting. Controlled blasts are primarily employed to generate cracks for the blast propagation or at the latter stages to trim off the benches. Production blasts are used to expand the initially developed cracks and span the damage thereby increasing the yield of the aggregates. Increasing demand for aggregates outweighs the environmental concerns, such as the ground vibrations, noise and air pollution, that emerge from these blasting operations. However, due to the property damages and safety reasons, the effects of ground vibrations on the surrounding environment have been closely monitored by relevant authorities.

The ground vibration (GV) can be measured in terms of the peak particle velocity (PPV), which is considered as a vibration index that defines the structural damage [1]. Available empirical relationships suggest that the maximum charge used per delay and the distance from the free face mainly govern the PPV [2]. Other parameters such as blast geometry, rock strength, and discontinuity conditions are not included in these empirical equations; however, PPV value seems to be affected by the variability of these parameters. On the other hand, four important sources can cause air pressure waves in blasting operations: the air pressure pulse, which results from displacement of the rock at the bench face as the blast progresses; the rock pressure pulse, which is induced by ground vibration; the gas release pulse, which results from the escape of gases through rock fractures; and the stemming release pulse, which results from the escape of gases from the blast hole when the stemming is ejected [3]. These air pressure waves are generally defined as air blast overpressure (ABOP), which is quantified in terms of sound and measured in decibels (dB) or Pascals (Pa). Blast geometry, explosive charge weight per delay, the distance between the free face and the monitoring point, geological discontinuities, blasting direction, surface topography, and vegetation predominantly govern the magnitude of ABOP [4].

In the recent years, there has been a growing interest in the mining industry to employ robust computational models to redefine the classical empirical relationships such as the ones used to predict PPV and ABOP. In this regard, artificial neural network (ANN) techniques show more compliance. In mining and geotechnical industry, ANN has been used for optimizing the tunnel design [5], predicting anisotropic properties of rock [6], and evaluating the strength characteristics of rocks [7]. ANN has also been applied to predict PPV [8,9,10] and ABOP [11]; however, the optimum network architecture that maximizes the accuracy level has not been fully understood. This paper attempts to develop different ANN based forecasting models for GV and ABOP employing blast-design parameters, and the distance of the monitoring locations from the blast as input parameters. The prediction accuracy of each model is compared to identify the best practice.

2. Methodology

2.1 Data collection

The data was acquired for the study from an operational quarry site approximately located 1.5 km away from Padukka town in the Western Province, Sri Lanka. Dominant rock type of the quarry is identified as Chanokitic Gneisses comprising Garnet and Quartz. The data had been acquired for two months of operation time from January to February 2018. The mine site has two locations to record the vibration data. The distance from the blast hole to the observation point (L m), number of delays of the electric detonator in a single blast (EDn), Water Gel (w), ANFO weight (wa), charge per hole (c) were recorded as the input data. Maximum depth of the borehole, the hole diameter, average spacing, and the average burden were observed to be constant values of 3 m, 38 mm, 1.30 m and 1.10 m respectively. ABOP and

GV were recorded using a computerized seismic and sound recording instrument (Blastmate digital seismograph, made in Canada). The mean (μ) and the standard deviation (σ) 500 records are given in Table 1.

Table 1 - The input parameters obtained from the quarry site

Input parameter	μ	σ
EDn	18	2.9
Water Gel (kg)	2	2.0
ANFO (kg)	17	3.3
L (m)	300	30.8
D (m)	52	9.3
Charge per Blast Hole (kg)	1	0.2
GV (mm/s)	1	1.0
ABOP (dB)	100	8.9

2.2 ANN approach

Artificial Neural Networks comprise a collection of code blocks that contain instructions mimicking the mathematical functionality of a biological neuron. A single code block often referred to as a neuron, can only perform a single defined mathematical operation on given input variables to yield a single or multiple output variables. The neurons can statistically optimize the weights that quantify the influence of each input on calculating the given output variables (eq. 1) by minimizing the standard error.

$$X = \sum x_i w_i - \theta \qquad \text{Eq.(1)}$$

where n is the number of inputs, and x_i and w_i denote the values of the ith input and weight, respectively. θ represents the allowable biases (quantified as the standard error) in the model.

The input parameters and the output parameters were selected as represented in Figure 1. The collected data were normalized (X_{norm}) to obtain a positive distribution in the range of 0 to 1 to increase the converging accuracy, and hence the learning speed of the ANN model (Eq. 2). In Eq.(2), x_{min} and x_{max} are the minimum and maximum values of the input data respectively. 70% of the data samples (350 nos.) were used to train the ANN model while 15% was used to validate the model. Separated 15% of the total data were used as random test inputs after the model calibration to ensure that the neural network would predict the outputs at the optimum accuracy. Six neurons were used in the input layer; each input was connected to a neuron. The network architecture is given in Figure 1.

$$X_{norm} = \frac{x_i - x_{min}}{x_{max} - x_{min}} \qquad \text{Eq.(2)}$$

The components of a neural network fall into three main categories: the activation function, the network architecture, and the learning law [7]. The activation function and the learning law govern the mathematical optimization of a given neuron. Typical activation functions include a linear function, sigmoid, or hyperbolic tangent. Employing an appropriate activation function can significantly improve the quality of the ANN model in information processing operation. The learning law is defined to minimize the standard error of the model [12].

The network architecture defines the accuracy of an ANN in identifying the complex correlations between the input and output variables. The ANN network has three categories of neuron layers: input, output and hidden layers. The activation function projects the data from the input layer to the hidden layer (or layers), while the final hidden layer projects the information to the output neurons.

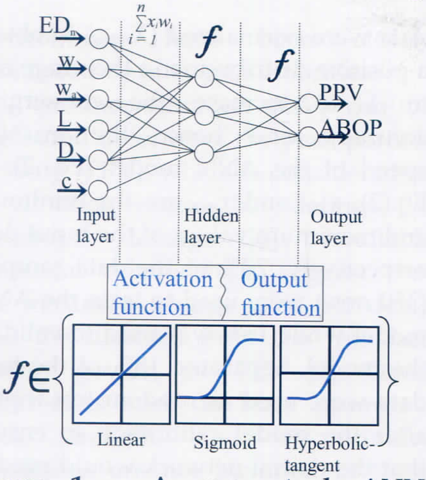


Figure 1 - A conceptual ANN architecture with the layers and activation functions

The predictive capability of an ANN model (learning) comes from the training method that is used to statistically match the relationship between the given outputs and the input variables. The training method in which both the input data and output data are fed to the model is called the supervised training. Among many distinct algorithms, feed forward backpropagation (BP) stands out as the most efficient, general, and simple algorithm used for supervised training of multilayered ANNs (e.g.,[5, 6]).

This study employed the BP training method available in MATLAB neural network toolbox. The normalized input data were fed to the input layer. Each of the six neurons determined its net weighted input (eq. 1). Weighted inputs were then presented to the hidden layer to compute the actual outputs, its weights, and the optimum value of the mathematical function. The difference between the predicted values and the actual data value was quantified using the mean squared error (MSE). ANN would minimize this error using the learning algorithm [12] by feeding the adjusted weights backward, and then forward, for 1000 epochs until the optimum model value was achieved.

3. Results

In this study, four combinations of sigmoid and hyperbolic-tangent learning algorithms were used in the hidden layer and the output layer to evaluate the optimum combination. These algorithm combinations would adjust the weights of the hidden layer and the output layer to account for the minimum error.

Classical regression analysis methods performed on the collected data yielded significant root mean squared errors. From the four regression types, linear regression showed the minimum error (Table 2); however, this method excluded the variables with minimum correlation. When the least correlated variables are excluded from the analysis, two truncated empirical relationships (Eq. 3 and 4) between two input variables (Y1: PPV, Y2: ABOP) could be established.

Table 2 - The accuracy comparison of the three different regression analyses

Regression type	RMSE (Y1)	RMSE (Y2)
Linear	0.84	8.94
Quadratic	1.56	10.51
Cubic	11.77	70.65

$$ABOP(dB)=0.044\times DB+0.284\times ED+82.007 \quad \text{Eq.(3)}$$

$$PPV = -0.015\times DB \quad \text{Eq.(4)}$$

Figure 2 shows the convergence of the MSE to the minimum value for training, validation and test data used in this study. The validated ANN model predicts the output at a nominal MSE value of <6%. The predicted output values and the input values follow a linear regression (Figure 3) with 93% of the input data governing the standard deviation of the normalized output (i.e., $R^2 = 0.93$). The strength of the correlation identified by the ANN exceeds the empirical linear regression relationship.

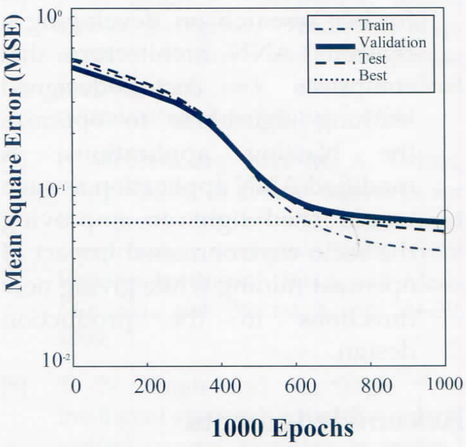


Figure 2 - A performance graph of an ANN model containing sigmoid learning algorithm in both hidden and output layers

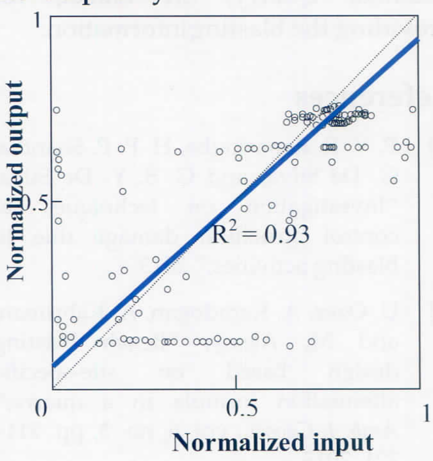
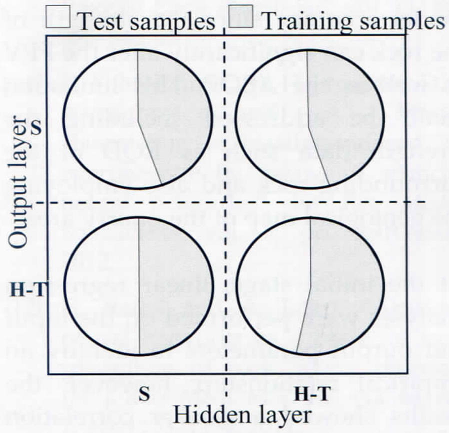


Figure 3 - The correlation of the input and output parameters predicted by the optimum ANN model

The success of an ANN can be defined as the percentage of statistically significant predictions generated by the model. Four different learning algorithm combinations investigated in the analysis yielded different success values (Figure 4). When the output layer was assigned with a sigmoid learning function, a comparatively better accuracy could be obtained. Hyperbolic-tangent functions seem to predict the outputs with lesser accuracy.



S: Sigmoid **H-T**: Hyperbolic tangent

Figure 4 - The success percentage in predicting a random pool of test data and validation data ("S" denotes sigmoid function and "H-T" denotes Hyperbolic-tangent function)

4. Discussion

The scope of this study was to develop an insight into the applicability of ANN techniques on forecasting the PPV and ABOP. This was accomplished with a comparison of the prediction accuracy of commonly used learning algorithms. When a sigmoid function is employed in the output layer, a higher number of predictions lie near the observed values. None of the typically used statistical techniques could yield empirical equations that show statistically significant accuracy. The ANN techniques can update the weights, and hence update predictions dynamically. The accuracy of the ANN models incorporated in this study could be further investigated using a larger pool of data.

The underlying geology between the two monitoring locations was assumed to be identical to minimize the variability of the model. However, this assumption could influence the model accuracy since the strength of the rock can significantly alter the PPV as well as the ABOP. This limitation could be addressed including the strength data such as RQD of the surrounding rock and also employing the geological map of the quarry area.

At the initial stage, linear regression analyses were performed on the input and output parameters to identify an empirical relationship; however, the results showed a weaker correlation between the input and output variables. This ill-correlation shown by the regression analysis additionally supported employing ANN techniques in this study. Hence, the ANN models were trained to identify the relationship between the input and output variables.

5. Conclusions

- The study reveals applicability of ANN learning algorithms in predicting the PPV and ABOP for the selected quarry site, which produce metal aggregates, while presenting a comparison between four combinations of hidden layer-output layer function arrangements.
- The dynamic capability warranted by ANNs further endorses their applicability in mining-related activities, which suffer from high variability in the underlying geology. Hence, the robust computational power facilitated by the ANN techniques can be successfully integrated to accurately predict the nuisance aftermaths of rock blasting (PPV and ABOP) while continuously updating the prediction model with new observations.
- It is recommended to conduct further research on developing a rigorous ANN architecture that comprises custom-designed learning algorithms to optimize the blasting applications. A modified ANN application as such would shed light on improving the socio-environmental impact of opencast mining while giving new directions to the production design.

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