Application of ANNs and MVLRA for Estimation of Specific Charge in Small Tunnel

A. Alipour¹; A. Jafari²; and S. M. F. Hossaini³

Abstract: Drilling and blasting method has been used for many years in underground excavations and still is very popular because of its many advantages. Blast performance is ordinarily measured by specific charge and by explosive consumption of broken rock. The empirical models are available for estimation of specific charge and different sets of parameters. This paper presents the possibility of applying artificial neural networks (ANNs) to estimate the specific charge in various conditions of tunnel blasting. Among available existing parameters in the literature, some of the most influencing parameters are selected. After running different models, P wave, rock-quality designation (RQD), tunnel area, maximum depth of the hole, and coupling ratio (charge-to-hole diameter) are selected to estimate specific charge of tunnel blasting under various conditions. Also, conventional multi variable linear regression analysis (MVLRA) is applied to estimate specific charge. The results show that the accuracy of ANN is more than the MVLRA-based models. DOI: 10.1061/(ASCE)GM.1943-5622.0000125. © 2012 American Society of Civil Engineers.

CE Database subject headings: Rocks; Blasting; Tunnels.

Author keywords: Rock blasting; Tunnel; Specific charge; ANN; MVLRA.

Introduction

Drilling and blasting method (D&B) is traditionally used in underground and surface excavations. Tunnels are widely used in mining and in many civil engineering applications (e.g., transport tunnels, water transfer tunnels, underground power plants) (Revey 2001; Rhyner 2004; Wang et al. 2007). Efficiency of any blasting operation is affected by the interaction between explosive materials and rock mass. Thus, knowledge of rock parameters can lead to optimization of blast results and, in particular, specific charge, which is defined as the consumed amount of explosive material per unit volume of excavated rock. Parameters affecting blast results may be categorized as explosive specifications, rock mass specifications, and geometry of drilling pattern (Jimeno and Jimeno 1995). Many models have been proposed for prediction of specific charge; most of these models are empirically developed by regression analysis of available data. Artificial neural networks (ANNs) have emerged as a powerful tool for solving engineering problems. Use of suitable input parameters could lead to reliable ANN models for accurate prediction of specific charge in tunneling. This paper presents application of ANNs as a pattern recognizer for nonlinear prediction of specific charge in underground excavations. Particular attention is given to small size tunnels, which are more common in mining practice.

Influencing Parameters

Type of explosive, rock mass characteristics, and geometry of blast pattern are considered as the main parameters affecting the specific charge. Different parameters have been incorporated in different models developed for both surface and underground blasting. Some of these models can be found in the following references: Langefors and Kihlstrom (1973), Pokrovsky (1980), Lilly (1986), Olofsson (1988), Ghose (1988), Hagan (1992), Chakraborty et al. (1998, 2004), and Kahriman et al. (2001). Determination of governing parameters for each model and the extent of their influence have to be judged by the experts who apply these models. An ideal model should employ the most important parameters. However, simplicity in obtaining these parameters should also be considered.

In this study, the data were analyzed to examine the effect of each parameter on specific charge. Fig. 1 shows the variation of 10 different parameters versus specific charge for 41 sets of data. However, Fig. 1 shows only a general trend and is not aimed to establishing any relationship. No definite correlations are shown in Fig. 1.

Specific Charge Estimation by Artificial Neural Networks

An ANN was employed to analyze 41 sets of available data to develop the model. From all data sets, 31 sets were used for the training phase, and 10 sets were left for the test phase. The matrix laboratory (MATLAB) package’s neural network toolbox was used for network development (Demuth and Beale 2003). Performance of the developed network was evaluated by using coefficient of determination ($R^2$), mean absolute error (MAE), and mean square error (MSE).

The number of input parameters is restricted by limitation in available data. Also, some parameters could not be incorporated in the model. According to the results of studies, the most influencing parameters can be considered to be $P$ wave, rock-quality
The model that incorporated these five parameters could best be trained and be able to predict the specific charge with minimum error when examined with new data sets. The investigation shows that incorporation of other parameters (e.g., $Q$ value, density, UCS of rock) did not improve the accuracy of the model. It is generally understood that adding these parameters could possibly improve the model if more data could be associated. Moreover, existence of more input parameters can decrease the error in the case of inaccuracy in some input data. Table 1 shows details of the variables that were used in the developed model. As shown in Table 1, the ANN model has five input layers, 10 hidden layers, and one output layer. The tangent sigmoid function was used as an activation function. Another important characteristic of the ANN model is the number of epochs that were used during training process.

**Table 1. Characteristics of Artificial Neural Network Model**

<table>
<thead>
<tr>
<th>Characteristic</th>
<th>Value/description</th>
</tr>
</thead>
<tbody>
<tr>
<td>Number of training data</td>
<td>31</td>
</tr>
<tr>
<td>Number of test data</td>
<td>10</td>
</tr>
<tr>
<td>Number of optimum neurons in hidden layer</td>
<td>10</td>
</tr>
<tr>
<td>Global error function</td>
<td>Mean square error</td>
</tr>
<tr>
<td>Activation function hidden layer</td>
<td>Tan-Sig</td>
</tr>
<tr>
<td>Activation function output layer</td>
<td>Linear</td>
</tr>
<tr>
<td>Training algorithm</td>
<td>Levenberg-Marquardt</td>
</tr>
<tr>
<td>Number of optimum epochs</td>
<td>10</td>
</tr>
<tr>
<td>Mean absolute error for training stage</td>
<td>0.10</td>
</tr>
<tr>
<td>Mean absolute error for test stage</td>
<td>0.11</td>
</tr>
<tr>
<td>Mean absolute error for training stage</td>
<td>0.019</td>
</tr>
<tr>
<td>Mean absolute error for test stage</td>
<td>0.033</td>
</tr>
</tbody>
</table>

**Fig. 1.** Variation of specific charge versus different parameters, including hole diameter, maximum depth of hole, cut angle degree, intact rock specific gravity, Barton’s rock mass rating ($Q$), coupling ratio, tunnel area, rock-quality designation, UCS, and $P$ wave velocity of rock.

**Fig. 2.** Measured values of specific charge versus predicted values by artificial neural networks for test and training data.
Fig. 2 shows the predicted specific charge versus the measured values for training and test data. The results show that the model has a very good ability in prediction of specific charge for the test data. The MSEs of the model are 0.019 and 0.033 for training and test data sets, respectively.

Multi variable Linear Regression Analysis

The purpose of multivariable regression is to establish a relationship between several independent variables and a dependent variable. Multi variable linear regression analysis (MVLRA) was done on the same data sets and same input parameters, which are used in the ANN model. The formula can be simplified for all 31 training sets of data as follows:

\[
SC = 0.03 + 0.0136RQD + 0.0698V - 0.0235S \\
+ 0.140H + 0.82C
\]  

in which \(SC\) = specific charge in kg/m\(^3\); \(V\) = \(P\)-wave velocity in km/s; \(S\) = tunnel area in m\(^2\); \(H\) = maximum depth of the hole in m; and \(C\) = coupling ratio.

Fig. 3 shows the predicted values versus the measured values. A relatively good agreement is shown between these values.

Comparison of Two Models

Fig. 4 shows the measured specific charge used for the 10 cases of test data and the predicted values by both models. It’s clearly shown that the ANN model is more accurate in predicting the specific charge. The MAE values for ANNs and MVLRA methods are 0.11 and 0.24, respectively. Also, MSE values for ANNs and MVLRA methods are 0.033 and 0.085, respectively. It is shown that the MSE value for the MVLRA method is 2.5 times more than for the ANN model.

The coefficient of determination for both models was applied to the fresh test data. The ANN model shows better correlation (\(R^2 = 0.97\)) in comparison with the MVLRA model (\(R^2 = 0.83\)). It should be reminded that both methods are compared using same data for training and test stages.

Conclusions

This paper presents estimation of the specific charge in the blasting method for tunneling purpose. Data collected from three projects were used to develop an ANN model for prediction of specific charge in tunnel blasting. Different models were tested, and five parameters, including \(P\) wave velocity, RQD, tunnel area, maximum depth of the hole, and coupling ratio, which are found to be the most influencing parameters in an estimation’s accuracy, were selected as input parameters for the final model. An ANN is shown to be a powerful tool for defining the relationship between rock and tunnel specifications with specific charge. The same inputs were used to estimate the specific charge by MVLRA, which is a traditional method for such problems. Comparison between two methods showed that the MSE would be 60% less when the ANN model is used.

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References


