OPTIMIZATION OF BLASTING DESIGN IN OPEN PIT LIMESTONE MINES WITH THE AIM OF REDUCING GROUND VIBRATION USING ROBUST TECHNIQUES

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Blasting operations create significant problems to residential and other structures located in the close proximity of the mines. Blast vibration is one of the most crucial nuisances of blasting, which should be accurately estimated to minimize its effect. In this paper, an attempt has been made to apply various models to predict ground vibrations due to mine blasting. To fulfill this aim, 112 blast operations were precisely measured and collected in one of the limestone mines of Iran. These blast operation data were utilized to construct the artificial neural network (ANN) model to predict the peak particle velocity (PPV). The input parameters used in this study were burden, spacing, maximum charge per delay, distance from blast face to monitoring point and rock quality designation and output parameter was the PPV. The conventional empirical predictors and multivariate regression analysis were also performed on the same data sets to study the PPV. Accordingly, it was observed that the ANN model is more accurate as compared to the other employed predictors. Moreover, it was also revealed that the most influential parameters on the ground vibration are distance from the blast and maximum charge per delay, whereas the least effective parameters are burden, spacing and rock quality designation (RQD). Finally, in order to minimize PPV, the developed ANN model was used as an objective function for imperialist competitive algorithm (ICA). Eventually, it was found that the ICA algorithm is able to decrease PPV up to 59% by considering burden of 2.9m, spacing of 4.4m and charge per delay of 627Kg.

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**Author Comments:** No comments

**Response to Reviewers:**
The paper now reads better. However I still find that authors have not done to improve the abstract except addition of some text at the end (it is too long). The abstract must be very clear and attractive to the readers. Please re-write it and length should be around 300 words.
Response: The abstract has been rewritten and now shortened to make around 300 words.
OPTIMIZATION OF BLASTING DESIGN IN OPEN PIT LIMESTONE MINES WITH THE AIM OF REDUCING GROUND VIBRATION USING ROBUST TECHNIQUES

COMPARISON OF EMPIRICAL AND ROBUST TECHNIQUES FOR PREDICTION OF GROUND VIBRATION DUE TO BLASTING IN OPEN PIT LIMESTONE MINES

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Abstract

Blasting operations create significant problems to residential and other structures located in the close proximity of the mines. Blast vibration is one of the most crucial nuisances of blasting, which should be accurately estimated to minimize its effect. In this paper, an attempt has been made to apply various models to predict ground vibrations due to mine blasting. To fulfill this aim, 112 blast operations were precisely measured and collected in one the limestone mines of Iran. These blast operation data were utilized to construct the artificial neural network (ANN) model to predict the peak particle velocity (PPV). The input parameters used in this study were burden, spacing, maximum charge per delay, distance from blast face to monitoring point and rock quality designation and output parameter was the PPV. The conventional empirical predictors and multivariate regression analysis were also performed on the same data sets to study the PPV. Accordingly, it was observed that the ANN model is more accurate as compared to the other employed predictors. Moreover, it was also revealed that the most influential parameters on the ground vibration are distance from the blast and maximum charge per delay, whereas the least effective parameters are burden, spacing and rock quality designation (RQD). Finally, in order to minimize PPV, the developed ANN model was used as an objective function for imperialist competitive algorithm (ICA). Eventually, it was found that the ICA algorithm is able to decrease PPV up to 59% by considering burden of 2.9m, spacing of 4.4m and charge per delay of 627Kg. Blasting operations creates significant environmental problems in the vicinity of residential areas and also can cause damage to the nearby residential and other structures. Blast vibrations are is
one of the most crucial nuisances of blasting which should be accurately estimated accurately and specifically to control and diminished the possible risk of damage to the surrounding structures. In this paper, an attempt has been in this paper to apply various models ground vibration prediction models to predict the blast ground vibrations due to mine blasting. To fulfill this, in one the limestone mines of Iran aim, relevant parameters of 112 blast operations were precisely measured 112 blast operations were precisely monitored and collected relevant blasting parameters were measured in one limestone open pit mine of Iran. Moreover, the most significant important ground vibration parameters, such as i.e. burden, spacing, rock quality designation (RQD), maximum explosive charge used per delay and the distance from the blast face to the blast vibration monitoring point were considered and utilized to construct the artificial neural network (ANN) model to predict the peak particle velocity (PPV). Also, the conventional empirical predictors and multivariate regression analysis were also performed to predict the peak particle velocity (PPV) on for the same purpose similar data sets, which were used with the ANN modeling. Accordingly, after considering different predictor models, it was found observed that the ANN model is more accurate as compared to the other employed conventional predictors and multivariate linear regression. Also, Moreover, it was revealed that the most influential parameters on the ground vibration are the distance from the blast face to the monitoring point and maximum explosive charge used per delay respectively. Whereas the least effective parameters ones are burden, spacing and rock quality designation (RQD) respectively. Finally, in order to minimize PPV, developed for up to by considering.

Keywords: Blasting, Ground Vibration, Artificial Neural Networks, Multivariate Regression, Conventional Empirical Predictors.

1. Introduction

Blasting is the process, where explosives are used to fragment the rock mass, so that loading equipment can handle the fragmented rocks. The main objective of blasting is to fragment and displace the rock mass [Mehrdanesh et al, 2018]. Nevertheless, in these operations, a huge amount of explosive energy is not used in actual fragmentation and creates number of blast nuisances, such
as blast vibration, airblast, flyrock, backbreak, noise, etc, which can affect the surrounding area [Armaghani et al, 2018; Khandelwal and Singh, 2006; Khandelwal and Singh, 2007; Monjezi et al, 2011; Monjezi et al, 2013]. Among these environmental nuisances, ground vibration is considered as one of the most significant blasting effects [Monjezi et al, 2010; Hajihassani et al, 2015; Hasanipanah et al, 2015; Khandelwal and Ranjith, 2017]. High intensity ground vibrations generated due to blasting creates unwanted side effects on the structural integrity and groundwater of the adjacent area [Singh and Singh, 2005; Khandelwal and Singh, 2009]. Hence, precise and reliable estimation of ground vibration is need of the hour to alleviate the blasting environmental problems.

When explosive material is detonated in a blast-hole, a rapid chemical reaction takes places within a fraction of second and creates very high temperature and pressure. This generated gas pressure crushes the surrounding rock mass of the blast-hole and attenuates very rapidly. The remaining energy transmits to the ground and causes strains to the adjacent rocks [Duvall and Petkof, 1958]. The strain waves propagated in the rock medium as the elastic waves, when these stress wave intensity diminishes to the ground level [Dowding and Dowding, 1996; Dowding and Hryciw, 1986]. These stress waves are identified as blast induced ground vibration.

Typically, blast vibrations have two key parameters i.e. peak particle velocity (PPV) and frequency. Number of investigators [Nateghi, 2011; Khandelwal et al, 2011; Khandelwal et al 2010] have assumed that blast vibrations can be measured in terms of PPV. During a past few decades, number of different empirical vibration predictors have been proposed by various researchers in order to predict the PPV. However, it was found that these empirical vibration predictors are not proficient to predict the PPV in a precise and reliable manner. Some predictors overestimate the PPV values, and some underestimate, whereas high degree of accuracy is required to predict the PPV to determine blast-safety area. This may be due to consideration of only two affecting factors, i.e. maximum explosive charge used per delay and distance from the blast-face to the monitoring point in these predictors, whereas, it is well known fact that blast vibration is affected by many other controllable and non-controllable factors, like spacing, burden, powder factor and stemming [Monjezi et al, 2016; Armaghani et al, 2018]. Other than empirical vibration predictors, statistical techniques have also been widely applied to predict the PPV [Verma and
Singh, 2011; Hudaverdi, 2012]. However, implementation of these techniques are not trustworthy, if the new available data are different from the original ones [Khandelwal and Singh, 2009; Mohamed, 2011; Dyskin et al, 2018].

Nowadays, various soft computing practices have been comprehensively applied and developed to predict and assess the PPV. Khandelwal and Singh [2006] studied viability of empirical conventional predictors and artificial neural network (ANN) model to evaluate, predict and assess the PPV from 150 blasting events. They found that ANN results are very precise rather than the empirical predictors [Khandelwal and Singh, 2006]. Armaghani et al. [2015] and Iphar et al. [2008] applied the adaptive neuro-fuzzy inference system (ANFIS) to estimate the PPV. Fisne et al. [2011] proposed a fuzzy inference system (FIS) model to evaluate and predict the PPV values monitored at the Akdaglar quarry, Turkey. Hasanipanah et al. [2015] applied another soft computing tool, support vector machine (SVM) to evaluate the PPV values observed at Bakhtiar Dam, Iran. Hajihassani et al. [2015] applied hybrid intelligent soft computing techniques, i.e. particle swarm optimization (PSO)-ANN and imperialism competitive algorithm (ICA)-ANN respectively to study the blast induced ground vibration. Table 1 shows a summary of earlier research done by various researchers to predict the PPV based on input parameters, number of datasets and R² values.

In all these studies, it was tried to recognize the most influencing parameters related to ground vibration by using various approaches of conventional (regression analysis), empirical (USBM, Amberaseys and Indian) and machine learning (ANN) methods.

### Table 1 A summary of earlier research done by various researchers to predict the PPV.

<table>
<thead>
<tr>
<th>Reference</th>
<th>Technique</th>
<th>Input variables</th>
<th>No. of dataset</th>
<th>R²</th>
</tr>
</thead>
<tbody>
<tr>
<td>Iphar et al. (2008)</td>
<td>ANFIS</td>
<td>DI, MC</td>
<td>44</td>
<td>0.98</td>
</tr>
<tr>
<td>Monjezi et al. (2011)</td>
<td>ANN</td>
<td>HD, ST, DI, MC</td>
<td>182</td>
<td>0.95</td>
</tr>
<tr>
<td>Khandelwal et al. (2011)</td>
<td>ANN</td>
<td>DI, MC</td>
<td>130</td>
<td>0.92</td>
</tr>
<tr>
<td>Mohamed (2011)</td>
<td>ANN, FIS</td>
<td>DI, MC</td>
<td>162</td>
<td>ANN = 0.94, FIS = 0.90</td>
</tr>
<tr>
<td>Fisne et al. (2011)</td>
<td>FIS</td>
<td>DI, MC</td>
<td>33</td>
<td>0.92</td>
</tr>
<tr>
<td>Li et al. (2012)</td>
<td>SVM</td>
<td>DI, MC</td>
<td>32</td>
<td>0.89</td>
</tr>
<tr>
<td>Mohamadnejad et al. (2012)</td>
<td>SVM, ANN</td>
<td>DI, MC</td>
<td>37</td>
<td>SVM = 0.89, ANN = 0.85</td>
</tr>
<tr>
<td>Ghasemi et al. (2013)</td>
<td>FIS</td>
<td>B, S, ST, N, MC, DI</td>
<td>120</td>
<td>0.95</td>
</tr>
<tr>
<td>Monjezi et al. (2013)</td>
<td>ANN</td>
<td>MC, DI, TC</td>
<td>20</td>
<td>0.93</td>
</tr>
<tr>
<td>Jahed Armaghani et al. (2014)</td>
<td>PSO-ANN</td>
<td>S, B, ST, PF, MC, D, N, RD, SD</td>
<td>44</td>
<td>0.94</td>
</tr>
<tr>
<td>Study</td>
<td>Method</td>
<td>Features</td>
<td>RMSE</td>
<td>VAF</td>
</tr>
<tr>
<td>------------------------------</td>
<td>---------</td>
<td>---------------------------------------------------------------------------</td>
<td>------</td>
<td>------</td>
</tr>
<tr>
<td>Hajihassani et al. (2015)</td>
<td>ICA-ANN</td>
<td>BS, ST, PF, MC, DI, Vp, E</td>
<td>95</td>
<td>0.98</td>
</tr>
<tr>
<td>Hasanipanah et al. (2015)</td>
<td>SVM</td>
<td>DI, MC</td>
<td>80</td>
<td>0.96</td>
</tr>
<tr>
<td>Dindarloo (2015)</td>
<td>SVM</td>
<td>RD, E, UCS, TS, Js, B, S, HD/B, SC, ST, DPR, DI</td>
<td>100</td>
<td>0.99</td>
</tr>
<tr>
<td>Hajihassani et al. (2015)</td>
<td>PSO-ANN</td>
<td>BS, MC, HD, ST, SD, DI, PF, RQD</td>
<td>88</td>
<td>0.89</td>
</tr>
<tr>
<td>Jahed Armaghani et al. (2015)</td>
<td>ANFIS</td>
<td>DI, MC</td>
<td>109</td>
<td>0.97</td>
</tr>
<tr>
<td>Monjezi et al. (2016)</td>
<td>GEP</td>
<td>DI, MC</td>
<td>35</td>
<td>0.878</td>
</tr>
<tr>
<td>Hasanipanah et al. (2017)</td>
<td>CART</td>
<td>DI, MC</td>
<td>86</td>
<td>0.95</td>
</tr>
<tr>
<td>Shirani Faradonbeh et al. (2017)</td>
<td>GEP</td>
<td>B, S, ST, D, HD, PF, MC, DI</td>
<td>115</td>
<td>GEP=0.876</td>
</tr>
<tr>
<td>Khandelwal et al. (2017)</td>
<td>CART</td>
<td>DI, MC</td>
<td>51</td>
<td>0.92</td>
</tr>
</tbody>
</table>

**Burden (B); Spacing (S); hole length (HL); stemming (ST); powder factor (PF); blastability index (B); support vector machine (SVM); maximum charge per delay (MC); rock density (RD); hole diameter (D); hole depth (HD); burden to spacing (BS); number of row (N); particle swarm optimization (PSO); sub-drilling (SD); distance from the blast face (DI); total charge (TC); rock quality designation (RQD); Young’s modulus (E); imperialist competitive algorithm (ICA); p-wave velocity (Vp); adaptive neuro-fuzzy inference system (ANFIS); fuzzy inference system (FIS); coefficient of determination (R²); uniaxial compression strength (UCS); tensile strength (TS); joint spacing (Js); hole depth-to-burden ratio (HD/B); specific charge (SC); delay per row (DPR), gene expression programming (GEP)**

### 2. Artificial neural networks (ANN)

ANN is basically resembles the human brain [Trippi and Turban, 1992] and comprises numerous interconnected layers. A computational components known as neurons is existed in each layer. ANN has the capacity to solve non-linear problems very easily. ANN is a robust tool and work on function approximation and feature selection [Simpson, 1990; Kosko, 1992]. Initially training of the ANN network is required from input and corresponding output datasets. There are numerous strategies can be applied to train the neurons, nevertheless feed forward back propagation algorithm has added advantages compared to the other existing methods. Back propagation networks encompasses an input, intermediate and an output layers. Number of neurons in the intermediate layer is based on the problem complexity. A connection weight is principally specified between the existing nodes in each layer, while training. This initial weight would be changed to observe the competence of the model [Neaupane and Achet, 2004; Rahul et al, 2015; Verma and Sirvaiya, 2016].

The model accurateness is considered based on the predicted outputs and the actual measured outputs. Various performance indicators (coefficient of determination (R²), root mean square error (RMSE) and variance account for (VAF) (eqs. 1-3)), are typically use to observe the model performance [Monjezi et al, 2013]:

\[
R^2 = 1 - \frac{\sum_{i=1}^{N}(y - y')^2}{\sum_{i=1}^{N}(y - \bar{y})^2}
\] (1)
\[ VAF = \left[ 1 - \frac{VAR(y - y')}{VAR(y)} \right] \times 100 \]  
\[ \text{RMSE} = \sqrt{\frac{1}{N} \sum_{i=1}^{N} (y - y')^2} \]  

Where

1. \( y \) – Measured values
2. \( y' \) - Predicted values
3. \( \bar{y} \) – Mean of the \( y \) values, and
4. \( N \) – Total number of data.

3. Case Study and Input Selection

A detailed blast vibration study was performed at Alvand Qoly quarry (Figure 1) of Kurdestan Cement Company. The quarry site is situated close to the Bijar city in western Iran. Limestone deposit of pliocene age is the main deposit of the quarry. The quarry consists of horizontal bedding planes in nature. The limestone is medium-hard and has uniaxial compressive strength of nearly 80 MPa and a density of 2450 kg/m³.

![Fig 1. Geographical location of Alvand Qoly mine](image)

The quarry is having vertical blast holes with 76 mm diameter in all the benches. The average depth of blast holes are 13.5 m in length with a 1 m sub-drilling and 3.5 m of stemming. Ammonium nitrate and Fuel Oil (ANFO) and emulsion explosive were used in blasting operations to blast the limestone. Non-electric system (detonating cord) was used to detonate the explosive.
4. Collection of data sets

Table 2 depicts the inputs (burden, spacing, rock quality designation (RQD), maximum explosive charge used per delay and the distance from blast-face to the monitoring point) and output parameter (peak particle velocity). The collected data was sorted into training and testing data.

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Symbol</th>
<th>Mean</th>
<th>Min</th>
<th>Max</th>
<th>Std. Dev</th>
</tr>
</thead>
<tbody>
<tr>
<td>Burden (m)</td>
<td>B</td>
<td>3.034</td>
<td>2.500</td>
<td>3.500</td>
<td>0.3534</td>
</tr>
<tr>
<td>Spacing (m)</td>
<td>S</td>
<td>4.145</td>
<td>3.500</td>
<td>4.900</td>
<td>0.4485</td>
</tr>
<tr>
<td>Charge Per Delay (Kg)</td>
<td>CPD</td>
<td>1464.760</td>
<td>225.000</td>
<td>3000.000</td>
<td>805.31</td>
</tr>
<tr>
<td>Rock Quality Designation</td>
<td>RQD</td>
<td>66.312</td>
<td>55.000</td>
<td>75.000</td>
<td>5.9255</td>
</tr>
<tr>
<td>distance from the blast face</td>
<td>DI</td>
<td>850.182</td>
<td>256.000</td>
<td>1500.000</td>
<td>332.8471</td>
</tr>
<tr>
<td>Output</td>
<td>PPV</td>
<td>1.021</td>
<td>0.030</td>
<td>5.810</td>
<td>1.1215</td>
</tr>
</tbody>
</table>

5. ANN architecture

In this study, a total 112 datasets was used to develop the models. The datasets were sorted into training and testing datasets. Back propagation neural network were used to train the model using 87 datasets. Normalization of input and out data sets were done in the range of -1 to 1 and the network elements (number of layers, neurons, transfer function, etc.) were computed. Training of the network was done until the user specified error is not reached. Among the various models, a back propagation network with an architecture 5-16-1 (No.6), as shown in Fig. 2 was showing the best performance. Fig. 3 illustrates the scatter plot between the predicted and monitored PPV for the training datasets with a $R^2$ values of 0.9003. From the figure, it can be easily said that the ANN method is capable to predict PPV with the least error.
Table 3 demonstrates the RMSE, VAF and $R^2$ values for the various network structures. The best model was chosen based on minimum RMSE and maximum VAF and $R^2$ among all the models.

Among the various models, a back-propagation network with an architecture 5-16-1 (No.6), as shown in Fig. 2 was showing the best performance. Fig. 3 illustrates the scatter plot between the predicted and monitored PPV for the training datasets with a $R^2$ values of 0.9003. From the figure, it can be easily said that the ANN method is capable to predict PPV with the least error.
Fig. 4 shows the comparison chart for the training datasets between measured and predicted PPV values. The figure reveals that the predicted PPV is very closer with the monitored PPV, which clearly establish the ANN capability in anticipating these parameters.

Table 3. RMSE, VAF and $R^2$ for some of the models

<table>
<thead>
<tr>
<th>No</th>
<th>Architecture</th>
<th>Hidden activation</th>
<th>Output activation</th>
<th>$R^2$</th>
<th>RMSE</th>
<th>VAF</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>5-22-1</td>
<td>Logistic</td>
<td>Poslin</td>
<td>0.84</td>
<td>0.45</td>
<td>85</td>
</tr>
<tr>
<td>2</td>
<td>5-9-1</td>
<td>Poslin</td>
<td>Tanh</td>
<td>0.71</td>
<td>0.63</td>
<td>72</td>
</tr>
<tr>
<td>3</td>
<td>5-3-1</td>
<td>Tanh</td>
<td>Poslin</td>
<td>0.81</td>
<td>0.51</td>
<td>82</td>
</tr>
<tr>
<td>4</td>
<td>5-28-1</td>
<td>Exponential</td>
<td>Sine</td>
<td>0.80</td>
<td>0.51</td>
<td>79</td>
</tr>
<tr>
<td>5</td>
<td>5-10-1</td>
<td>Sine</td>
<td>Logistic</td>
<td>0.89</td>
<td>0.38</td>
<td>90</td>
</tr>
<tr>
<td>6</td>
<td>5-16-1</td>
<td>Tanh</td>
<td>Logistic</td>
<td>0.9003</td>
<td>0.35</td>
<td>93</td>
</tr>
<tr>
<td>7</td>
<td>5-10-1</td>
<td>Tanh</td>
<td>Poslin</td>
<td>0.82</td>
<td>0.47</td>
<td>82</td>
</tr>
<tr>
<td>8</td>
<td>5-7-1</td>
<td>Exponential</td>
<td>Logistic</td>
<td>0.87</td>
<td>0.39</td>
<td>88</td>
</tr>
<tr>
<td>9</td>
<td>5-23-1</td>
<td>Sine</td>
<td>Sine</td>
<td>0.72</td>
<td>0.62</td>
<td>73</td>
</tr>
<tr>
<td>10</td>
<td>5-15-1</td>
<td>Sine</td>
<td>Exponential</td>
<td>0.83</td>
<td>0.48</td>
<td>83</td>
</tr>
<tr>
<td>11</td>
<td>5-5-1</td>
<td>Poslin</td>
<td>Sine</td>
<td>0.72</td>
<td>0.63</td>
<td>71</td>
</tr>
<tr>
<td>12</td>
<td>5-30-1</td>
<td>Tanh</td>
<td>Tanh</td>
<td>0.79</td>
<td>0.52</td>
<td>80</td>
</tr>
<tr>
<td>13</td>
<td>5-3-1</td>
<td>Tanh</td>
<td>Poslin</td>
<td>0.81</td>
<td>0.51</td>
<td>82</td>
</tr>
<tr>
<td>14</td>
<td>5-22-1</td>
<td>Poslin</td>
<td>Poslin</td>
<td>0.73</td>
<td>0.62</td>
<td>74</td>
</tr>
<tr>
<td>15</td>
<td>5-17-1</td>
<td>Logistic</td>
<td>Sine</td>
<td>0.78</td>
<td>0.52</td>
<td>77</td>
</tr>
</tbody>
</table>

Fig. 2 Architecture of ANN model
Fig. 3 Correlation between measured and predicted PPV in ANN model (Training accuracy)

Fig. 4 shows the comparison chart for the training datasets between measured and predicted PPV values. The figure reveals that the predicted PPV is very closer with the monitored PPV, which clearly establish the ANN capability in anticipating these parameters.

![Graph showing correlation between measured and predicted PPV](image)

**Predicted by ANN**

\[ y = 0.8849x + 0.0871 \]

\[ R^2 = 0.9003 \]

Fig. 4 Comparison of predicted and measured PPV in ANN model (Training accuracy)

6. Multivariate Linear Regression (MLR)

Multivariable regression analysis is a subdivision of statistics applying to get the mapping between the input and output parameters. MLR technique is widely used in various branches of engineering and sciences [Gokceoglu and Zorlu, 2004; Grima and Verhoef, 1999]. The Statistica software was used to get the governing relationship between the input and output parameters (Eqs. 4). Fig. 5 shows the graphs between predicted and monitored PPV using the MLR technique.
PPV = 0.0005(CPD) – 0.0023(D) +0.01(RQD) +0.1242(B) +0.1881(S)+0.4182  \hspace{3em}(4)

Where,

PPV – Peak particle velocity (mm/s),
CPD – Explosive charge used per delay (kg),
D – Distance between blast face to the monitoring point (m),
RQD – Rock quality designation
B – Burden (m), and
S – Spacing (m).

**Fig. 5 shows the graphs between predicted and monitored PPV with \( R^2 = 0.5429 \) using the MLR technique.** The graph reveals that predicted PPV by MLR is showing wide scattering compared to the measured PPV.

**Table 4. Different Empirical Formula for prediction PPV**
Where $\alpha$ and $\beta$ the site constants, which can be calculated by multiple regression. The calculated site constants values for the various conventional predictor equations are presented in Table 5.

<table>
<thead>
<tr>
<th>Model</th>
<th>Result</th>
<th>$R^2$</th>
</tr>
</thead>
<tbody>
<tr>
<td>USBM [Duvall and Fogelson, 1962]</td>
<td>$PPV = \alpha \left( \frac{D}{\sqrt{CPD}} \right)^{-\beta}$</td>
<td>0.6872</td>
</tr>
<tr>
<td>Ambraseys-Hendron [1968]</td>
<td>$PPV = \alpha \left( \frac{D}{\sqrt{CPD}} \right)^{-\beta}$</td>
<td>0.6568</td>
</tr>
<tr>
<td>Indian Standard [1973]</td>
<td>$PPV = \alpha \left( \frac{D}{\sqrt{CPD^2}} \right)^{-\beta}$</td>
<td>0.6991</td>
</tr>
</tbody>
</table>

Figs 6-8 shown the relationship between measured and predicted PPV by different empirical formula. Here, $R^2$ values are ranging from 0.6568 to 0.6991, where Indian model is showing highest $R^2$ and Ambraseys model is showing lowest $R^2$. All the three conventional models have higher $R^2$ compared to the MLR model.
8. **Models validation Results and Discussion**

Evaluation and assessment of the ANN, empirical and regression models was accomplished using 25 new datasets. These new 25 datasets were not used in the models development. Various performance indices RMSE, VAF and $R^2$ were pursued to validate the models. Table 6 illustrates the calculated values of RMSE, $R^2$ and VAF for all three different models. Table 6 shows that the ANN model has the best performance capability in the prediction of PPV compared to MLR, USBM, Amberaseys and Indian models. Figs. 9-18 depicts the scatter plot and comparison chart between predicted and monitored PPV. The $R^2$, VAF and RMSE between measured and predicted PPV by MLR is 0.7725, 77.244 and 0.542 respectively. The $R^2$, VAF and RMSE measured and predicted PPV by conventional predictors are ranging from 0.865 – 0.881, 82.803 – 87.500 and
The $R^2$, VAF and RMSE between measured and predicted PPV by ANN is 0.9788, 97.833 and 0.174 respectively.

### Table 6. Calculated validation indices for the ANN, MLR, USBM, Amberaseys and Indian models

<table>
<thead>
<tr>
<th>Model</th>
<th>RMSE (mm/s)</th>
<th>VAF (%)</th>
<th>$R^2$</th>
<th>RMSE (mm/s)</th>
<th>VAF (%)</th>
<th>$R^2$</th>
</tr>
</thead>
<tbody>
<tr>
<td>Train</td>
<td>Test</td>
<td></td>
<td></td>
<td>Train</td>
<td>Test</td>
<td></td>
</tr>
<tr>
<td>ANN</td>
<td>0.300576</td>
<td>89.99882</td>
<td>0.900251</td>
<td>0.174926</td>
<td>97.88303</td>
<td>0.97883</td>
</tr>
<tr>
<td>MLR</td>
<td>0.639994</td>
<td>54.19502</td>
<td>0.542933</td>
<td>0.570465</td>
<td>77.2441</td>
<td>0.772452</td>
</tr>
<tr>
<td>USBM</td>
<td>0.967458</td>
<td>68.5668</td>
<td>0.687166</td>
<td>0.946589</td>
<td>86.89025</td>
<td>0.978972</td>
</tr>
<tr>
<td>Amberaseys</td>
<td>1.405504</td>
<td>65.04171</td>
<td>0.656203</td>
<td>1.572548</td>
<td>82.80335</td>
<td>0.865553</td>
</tr>
<tr>
<td>Indian</td>
<td>1.001381</td>
<td>69.99199</td>
<td>0.699064</td>
<td>0.900209</td>
<td>87.50064</td>
<td>0.881789</td>
</tr>
</tbody>
</table>

Fig. 9 Correlation between measured and predicted PPV with MLR model

$y = 0.7695x + 0.1054$

$R^2 = 0.7725$
**Fig. 10** A comparison chart between predicted and measured PPV with MLR model.

**Fig. 11** Correlation between measured and predicted PPV with USBM model.
Fig. 12 Correlation between measured and predicted PPV with Ambraseys model

\[ y = 2.0766x - 0.9885 \]
\[ R^2 = 0.8656 \]

Fig. 13 Correlation between measured and predicted PPV with Indian model

\[ y = 1.5502x - 0.626 \]
\[ R^2 = 0.8818 \]
Fig. 14 A comparison chart between measured and predicted PPV with USBM model

Fig. 15 A comparison chart between predicted and measured PPV with Ambraseys model
Fig. 16 A comparison chart between predicted and measured PPV with Indian model.

Predicted by ANN

\[ y = 0.9788x - 0.0309 \]

\[ R^2 = 0.9788 \]

Fig. 17 Correlation between measured and predicted PPV in ANN model.
**9. Optimization Section Using ICA**

Imperialist competitive algorithm (ICA), developed by Atashpaz-Gargari and Lucas (2007) has been used as a global search population-based algorithm in optimization problems. ICA gets started with a set of random initial generated solutions which call countries. In the second step, the best countries are selected as imperialist countries and the rest form the imperialist colonies. This algorithm has three main processes, namely assimilation, revolution, and competition. In the phase of assimilation, colonies are attracted towards the imperialists by the power of cultural, political and social criteria. During revolution, some sudden changes occurred in the countries’ positions. The positions of countries are suddenly changing. Assimilation and revolution, create the potential for the colonies to attain a better position compared to that of their respective imperialist and take over the empire. In the competition phase, the imperialists are striving to develop their colony and all empires try to seize the colonies of other empires. It is possible that relying on their power, all imperialists seizes a minimum of one colony of the weakest empire. Consequently, through the competition process, weak empires fall gently and stronger empires increase their power. Triple
mentioned processes iteratively continues until only the strongest empire retain the power and the others fall. Figure 19 shows the flowchart of the imperialist competitive algorithm.

ICA has been extensively used as optimization algorithm to optimize the complex problems (Hosseini and Khaled, 2014). In the Alvand Qoly quarry, ICA can determine the blasting pattern parameters through the optimization process. Different ICA-based models were created with the use of various modifiable parameters. Following the accomplishment of several analyses, the most appropriate ICA parameters were achieved and recorded in Table 6.

<table>
<thead>
<tr>
<th>number of decade</th>
<th>number of country</th>
<th>number of imperialism</th>
</tr>
</thead>
<tbody>
<tr>
<td>78</td>
<td>112</td>
<td>30</td>
</tr>
</tbody>
</table>

ICA algorithm requires an objective functions which in this study is the developed ANN model obtained from the previous section. In fact, the ANN model has the task of simulating the objective function.
Eventually, the optimal pattern parameters (the improved version compared to the initial pattern) in order to reduce ground vibration, were obtained by ICA as shown in Table 7. In addition, the 

![Imperialist competitive algorithm flowchart](image)

**Fig. 19** Imperialist competitive algorithm flowchart.
difference percentages of the parameters compared to their mean values are calculated in Table 7. According to the table, the ground vibration was reduced 59% if there are 3% reduction of burden, 6% increment of spacing, 57% reduction of charge per delay. All of the differences percentage were calculated based on mean values of original database. The results of optimization section confirmed that ICA is a powerful optimization technique which is able to minimize ground vibration up to 59% based on the used database. In fact, this technique, due to its powerful, can be used in other optimization problems in engineering fields.

**Table 7. The optimal pattern parameters obtained by ICA to reduce ground vibration**

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Original mean value</th>
<th>Obtained by ICA</th>
<th>Difference (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>B (m)</td>
<td>3</td>
<td>2.9</td>
<td>3, reduction</td>
</tr>
<tr>
<td>S (m)</td>
<td>4.14</td>
<td>4.4</td>
<td>6, increment</td>
</tr>
<tr>
<td>CPD (Kg)</td>
<td>1464</td>
<td>627</td>
<td>57, reduction</td>
</tr>
<tr>
<td>PPV</td>
<td>1</td>
<td>0.41</td>
<td>59, reduction</td>
</tr>
</tbody>
</table>

10. Results and Discussion

Figs. 9-18 show a comparison between predicted PPV by ANN, MLR and conventional predictor equations. Here, prediction by ANN is closer to the measured PPV whereas, prediction by conventional predictors and MLR has wide variation.

The figures revealed that ANN predicted PPV is just overlapping the measured PPV line, whereas widely used vibration predictors show very high level of error. This is due to the fact that they do not take into consideration all the influencing parameters of blast vibration. All the conventional predictors have site specific constants and these are not able to predict the safe charge for even other similar mining conditions. The value of site and attenuation constants also varied as the ground conditions changed. Moreover, these are derived based on only two parameters i.e.
maximum charge per delay and the distance from monitoring point to blast face. These empirical
predictors are based on linear relation between scaled distance \((D/\sqrt{CPD})\) and PPV.

Table 6 illustrates the calculated values of RMSE, \(R^2\) and VAF for all three different models. The
Table 6 shows that the ANN model has the best performance capability in the prediction of PPV
compared to MLR, USBM, Amberaseys and Indian models. The ANN model is showing highest
\(R^2\) and VAF compared to the MLR and other conventional models with less RMSE for training
and testing data. From the Figs. 9-18 and Table 8, it can be said that prediction capability of ANN
is quite remarkable and compares well to the field observations.

<table>
<thead>
<tr>
<th>Model</th>
<th>RMSE</th>
<th>VAF (%)</th>
<th>(R^2)</th>
<th>RMSE</th>
<th>VAF (%)</th>
<th>(R^2)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Train</td>
<td></td>
<td></td>
<td>Test</td>
<td></td>
<td></td>
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<td>ANN</td>
<td>0.300576</td>
<td>89.99882</td>
<td>0.900251</td>
<td>0.174926</td>
<td>97.88303</td>
<td>0.97883</td>
</tr>
<tr>
<td>MLR</td>
<td>0.639791</td>
<td>54.19502</td>
<td>0.542933</td>
<td>0.570465</td>
<td>77.2441</td>
<td>0.772452</td>
</tr>
<tr>
<td>USBM</td>
<td>0.967458</td>
<td>68.5668</td>
<td>0.687166</td>
<td>0.946589</td>
<td>86.89025</td>
<td>0.877972</td>
</tr>
<tr>
<td>Amberaseys</td>
<td>1.405504</td>
<td>65.01171</td>
<td>0.656792</td>
<td>1.572548</td>
<td>82.89375</td>
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<td>1.001381</td>
<td>69.99199</td>
<td>0.699064</td>
<td>0.900209</td>
<td>87.50964</td>
<td>0.881789</td>
</tr>
</tbody>
</table>

11. Sensitivity analysis

A sensitivity analysis was performed to assess the effects of each input parameters on the PPV. In
this study, the relevancy factor (RF) was used to evaluate the degree of influence of each input
parameters on PPV [Chen et al, 2014]. Here, it should be noted that higher the absolute value of
RF of any input and output variables, the more significant influence of that input in predicting the
output’s value. The RF values can be calculated as followed:

\[
RF = \frac{\sum_{i=1}^{n}(x_{il} - \bar{x}_l)(y_i - \bar{y})}{\sqrt{\sum_{i=1}^{n}(x_{il} - \bar{x}_l)^2 \sum_{i=1}^{n}(y_i - \bar{y})^2}}
\]  

(6)

Where
\( x_{l,i} \) – \( i \)th value of the \( l \)th input variable,
\( \bar{x}_l \) – Average value of the \( l \)th input variable,
\( y_i \) – \( i \)th value of the predicted output, and
\( \bar{y} \) – Average value of the predicted output.

Fig. 19-20 shows the RF values of each input parameters against the PPV prediction. From the figure, it can be observed that the DI and CPD are the most effective parameters on the PPV prediction, whereas B, S and RQD are the least effective parameters, respectively in this regard.

<table>
<thead>
<tr>
<th>Series1</th>
<th>RF</th>
</tr>
</thead>
<tbody>
<tr>
<td>D</td>
<td>0.37</td>
</tr>
<tr>
<td>CPD</td>
<td>0.19</td>
</tr>
<tr>
<td>S</td>
<td>0.15</td>
</tr>
<tr>
<td>RQD</td>
<td>0.15</td>
</tr>
<tr>
<td>B</td>
<td>0.14</td>
</tr>
</tbody>
</table>

**Fig. 19** Sensitivity analysis of the input parameters

12. Conclusions

In the present paper, ANN, empirical models and regression analysis were performed to evaluate and predict the PPV as well as to find the effect of various blast design parameters on the ground vibration. For this study, a database was developed from Alvand-Qoly quarry of northwest Iran. Initially, superiority of different models were investigated from which competence of the neural network modeling was explored. According to outcomes of the application of the network modeling, it is concluded that the most influential parameters on ground vibration are the distance from blast-face to the monitoring point and maximum explosive charge used per delay, respectively and the least effective ones are burden, spacing and rock quality designation (RQD).
respectively. In the last phase of this paper with name of optimization, ICA technique was used to minimize PPV where the developed ANN model was considered as the objective function. Various effective parameters of ICA were identified and utilized in optimizing process. The results of ICA showed that this optimization approach is able to minimize PPV till 59% compared to its mean value. This can be occurred when burden is 2.9m (3% reduction), spacing is 4.4m (6% increment), and charge per delay is 627 Kg (57% reduction). The results of this study can be used for similar conditions and the same model inputs and their ranges.

References:


Comments for the Author:

The paper now reads better. However I still find that authors have not done to improve the abstract except addition of some text at the end (it is too long). The abstract must be very clear and attractive to the readers. Please re-write it and length should be around 300 words.

Response: The abstract has been rewritten and now shortened to make around 300 words.