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Optimizing Blasting’s Air Overpressure Prediction Model using Swarm Intelligence

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Abstract. Air overpressure (AOp) resulting from blasting can cause damage and nuisance to nearby civilians. Thus, it is important to be able to predict AOp accurately. In this study, 8 different Artificial Neural Network (ANN) were developed for the purpose of prediction of AOp. The ANN models were trained using different variants of Particle Swarm Optimization (PSO) algorithm. AOp predictions were also made using an empirical equation, as suggested by United States Bureau of Mines (USBM), to serve as a benchmark. In order to develop the models, 76 blasting operations in Hulu Langat were investigated. All the ANN models were found to outperform the USBM equation in three performance metrics; root mean square error (RMSE), mean absolute percentage error (MAPE) and coefficient of determination (R²). Using a performance ranking method, MSO-Rand-Mut was determined to be the best prediction model for AOp with a performance metric of RMSE=2.18, MAPE=1.73% and R²=0.97. The result shows that ANN models trained using PSO are capable of predicting AOp with great accuracy.

1. Introduction

Construction blasting refers to the controlled use of explosives for construction projects. It plays an important role in mining operations, road constructions and tunneling projects. It is cheaper and more economical compared to alternative means of rock excavation, such as ripping and mechanical breaking.

Blasting releases powerful energy in the form of pressure and heat. A fraction of it fragments and displaces rock mass, the rest are converted into air overpressure (AOp), blast vibration, flyrock, noise, dust and back break [1]. The sudden release cause loadings on surrounding rocks and produces a shock wave pulse [2]. AOp refers to increase in level of air pressure above normal atmospheric level due to shock wave pulse [3]. It is a measure of the transient pressure changes [4]. Excessive AOp on site affects nearby structures and interferes with quarrying operations [5]. In most cases it is an annoyance problem that would provoke conflicts between the mine management and nearby communities [6]. Thus, it important to be able to predict AOp levels with great accuracy.
Maximum charge weight used per delay (MC) and distance from blast face (DI) are the two most commonly cited predictor variables for AOp [7]. Main components of AOp can be broken down into air pressure pulse (APP), gas release pulse (GRP), rock pressure pulse (RPP) and stemming release pulse (SRP) [8] [9] [10]. Disturbance to nearby communities are mostly attributed to SRP and GRP [9].

One commonly accepted method to predict AOp is an empirical model based on the cube-root scaled distance factor as suggested by the United States Bureau of Mines [4] [8] [11]. In the paper by Kuzu et al. [4], they used the USBM model to predict AOp using two parameters, DI and MC. All the prediction made using this method had errors levels of less than 7%.

Several scholars have also suggested the use of soft computing techniques (Artificial Neural Network (ANN), Support Vector Machines (SVM) and Genetic Algorithms (GA)) to predict AOp [2][3][12][13]. In this study, several ANN models based on swarm intelligence (SI) algorithm; particle swarm optimization (PSO) and multi swarm optimization (MSO) were utilized to predict AOp values resulting from blasting operations. In order to ensure the performance of the models are sufficient, USBM predictor equation for AOp was used as a benchmark for the prediction models.

2. Methods

2.1 USBM Equation

One of the most commonly used empirical equation to predict AOp is the USBM equation [4] [8]. The empirical equation employs the use of cube-root scaled distance factor (SD) as suggested by USBM [8]. The equation used to obtain SD is formulated as Eq. (1).

\[ SD = DW^{-0.33} \]  

(1)

where D is the distance from blast face (m or ft), W is the explosive charge weight (kg or lb). Meanwhile, the equation for prediction of AOp is formulated as Eq. (2).

\[ AOp = \alpha (SD)^\beta \]  

(2)

where AOp is in the unit of dB. \( \alpha \) and \( \beta \) are the site factors and can be determined by regression analysis.

2.2 Artificial Neural Network

Artificial neural network (ANN) is a type of computational model which attempts to mimic the vast network of neurons in the brain. A simple feedforward ANN is typically composed of three layers (input, hidden and output). In this study, the two inputs were MC and DI.

ANN is able to solve complex and highly non-linear problem where the use of traditional regression analysis is not suitable. This is because of the flexibility of ANN in tackling a linear or non-linear problem [14].

There are three fundamental components which can be used to define a network; architecture, transfer function and learning algorithm. In this study, a single hidden layer and fully connected network was used as the architecture and the (ReLu) function as the transfer function.

2.3 Particle Swarm Optimization

Particle swarm optimization (PSO) is a metaheuristic first introduced by Kennedy and Eberhart [15]. It is a part of a group of intelligent algorithms called Swarm Intelligence (SI) and is inspired by the movements of biological swarms.
The particle’s movement are guided by the global best ($p_g$) particle and local best ($p_i$) particle. It is described as a set of solutions moving in the search space with the aim to achieve the best position or solution [16]. The velocity, $v_i$, for each particle are calculated using Eq. (3).

$$v_i(t+1) = \omega v_i(t) + c_1 r_1 (p_g(t) - x_i(t)) + c_2 r_2 (p_i(t) - x_i(t))$$ (3)

where $\omega$ is the inertia weight, $c_1$ and $c_2$ are the acceleration coefficients, $r_1$ and $r_2$ are random numbers in range $[0,1]$ and $x_i$ is the current particle position. $c_1$ and $c_2$ were set to the value of 1.49445 as suggested by Clerc [17]. Meanwhile, the new position of each particle is updated using Eq. (4).

$$x_i(t+1) = x_i(t) + v_i(t+1)$$ (4)

Meanwhile, multi swarm optimization (MSO) is a variant of PSO which utilizes multiple sub-swarms. The use of MSO can help prevent the swarm from converging on the wrong solution (local optima) especially in a multi modal environment [18]. The main difference is in the addition of an additional term for the swarm best, $p_s$.  

2.4 Inertia Weight

The inertia weight, $\omega$ is an important component of PSO and MSO. Its role is to balance the tendency between the global search and the local search [19]. Bansal et al. [20] investigated 15 inertia weight strategies and compared their performance based on 5 types of optimization problem. They concluded that the Chaotic Inertia Weight is the best for accuracy meanwhile the Random Inertia Weight is best in terms of efficiency. In this study, two types of inertia weight were used, Linear Decreasing Inertia Weight [21] and Random Inertia Weight [22].

2.5 Crossover and Mutation Operator

Inspired by the mechanism of GA, several mutation and crossover operators have been suggested for PSO. Løvberg et al. [23] introduced the use of a crossover operator, where the offspring of two randomly selected particles is calculated based on their parents.

Meanwhile, Higashi and Iba [24] proposed the use of a Gaussian mutation operator, where an offspring of two parent particles is mutated based on the current iteration multiplied by a random number in a Gaussian distribution. Utilization of these operators contributes to faster convergence and better solutions [25].

3. Model Development

3.1 Prediction Models

8 different ANN models were created for the prediction of AOp using two input parameter, MC and DI. The difference in the implementation of the training algorithm in each ANN model is shown in Table 1. At the same time, an equation was constructed using the USBM equation and regression analysis.
3.2 Normalization and Dataset Division
For the purpose of more efficient training time, it is important that the data used to train the PSO-ANN models to be normalized. The normalization was done according to Eq. (5).

$$x' = \frac{x - x_{\text{min}}}{x_{\text{max}} - x_{\text{min}}}$$  \hfill (5)

where, $x'$ is the normalized value, $x$ is data to be normalized, $x_{\text{min}}$ is the minimum value in the range to be normalized, $x_{\text{max}}$ is the maximum value in the range to be normalized. Using this normalization method, all the data would be normalized into the range of [0,1]. Then, the whole dataset (76 data point) was divided into three sets; training (54 data point), validation (11 data point) and testing (11 data point).

4. Discussion of Results
In this study, 8 PSO-ANN models as well as an empirical equation as suggested by USBM were develop for the purpose of predicting AOp.

In order to evaluate the performances of each models and equation on the testing set, three performance metrics were used; root mean square error (RMSE), mean absolute percentage error (MAPE) and coefficient of determination ($R^2$).

4.1 USBM Equation
In order to determine the site factors for the USBM equation, a regression analysis was done using the training dataset. The obtained site factors were $\alpha=237.05$ and $\beta=-0.168$. These values were used to construct Eq. (2).

\begin{table}
\centering
\begin{tabular}{|c|c|c|c|c|c|}
\hline
Model Name & PSO & MSO & Inertia Weight & Operators \\
& & & Linear Decreasing & Random & Crossover & Mutation \\
\hline
PSO-Lin & ✓ & ✓ & & & & \\
PSO-Lin-Mut & ✓ & ✓ & ✓ & ✓ & ✓ & ✓ \\
PSO-Rand & ✓ & & ✓ & ✓ & ✓ & ✓ \\
PSO-Rand-Mut & ✓ & ✓ & ✓ & ✓ & ✓ & ✓ \\
MSO-Lin & ✓ & ✓ & & ✓ & ✓ & ✓ \\
MSO-Lin-Mut & ✓ & ✓ & ✓ & ✓ & ✓ & ✓ \\
MSO-Rand & ✓ & ✓ & & ✓ & ✓ & ✓ \\
MSO-Rand-Mut & ✓ & ✓ & ✓ & ✓ & ✓ & ✓ \\
\hline
\end{tabular}
\caption{Difference in the implementation of PSO training algorithm.}
\end{table}
4.2 Comparison of Measured AOp and predicted AOp by prediction models

Figure 1 shows the comparison between measured AOp and predicted AOp by prediction models. On average, AOp predicted by using MSO-Rand-Mut are closer to the actual measured value compared to the other methods. Furthermore, there is a tendency by the USBM equation to overestimate the AOp values compared to the ANN models.

4.3 Performance Ranking

Due to the complexity of choosing the best prediction model using three different performance metrics, a performance ranking method [26] [27] was used to determine the best performing prediction model. As can be seen from Table 2, all of the ANN models outperform the USBM equation in each of the three performance metrics. The best model was determined to be MSO-Rand-Mut. It was the best in terms of RMSE and MAPE, 2.18 and 1.73% respectively. Furthermore, the $R^2$ value for MSO-Rand-Mut, 0.9693, was the second best out of all the other prediction models.

<table>
<thead>
<tr>
<th>Model</th>
<th>RMSE</th>
<th>MAPE</th>
<th>$R^2$</th>
<th>Rating for RMSE</th>
<th>Rating for MAPE</th>
<th>Rating for $R^2$</th>
<th>Rank Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>PSO-Lin</td>
<td>3.62</td>
<td>3.04</td>
<td>0.9664</td>
<td>3</td>
<td>3</td>
<td>6</td>
<td>12</td>
</tr>
<tr>
<td>PSO-Lin-Mut</td>
<td>2.68</td>
<td>2.11</td>
<td>0.9619</td>
<td>6</td>
<td>6</td>
<td>2</td>
<td>14</td>
</tr>
<tr>
<td>PSO-Rand</td>
<td>3.42</td>
<td>2.90</td>
<td>0.9651</td>
<td>4</td>
<td>4</td>
<td>4</td>
<td>12</td>
</tr>
<tr>
<td>PSO-Rand-Mut</td>
<td>3.33</td>
<td>2.83</td>
<td>0.9674</td>
<td>5</td>
<td>5</td>
<td>7</td>
<td>17</td>
</tr>
<tr>
<td>MSO-Lin</td>
<td>4.12</td>
<td>3.41</td>
<td>0.9653</td>
<td>2</td>
<td>2</td>
<td>5</td>
<td>9</td>
</tr>
<tr>
<td>MSO-Lin-Mut</td>
<td>2.44</td>
<td>1.99</td>
<td>0.9729</td>
<td>8</td>
<td>7</td>
<td>9</td>
<td>24</td>
</tr>
<tr>
<td>MSO-Rand</td>
<td>2.46</td>
<td>1.80</td>
<td>0.9641</td>
<td>7</td>
<td>8</td>
<td>3</td>
<td>18</td>
</tr>
<tr>
<td>MSO-Rand-Mut</td>
<td>2.18</td>
<td>1.73</td>
<td>0.9693</td>
<td>9</td>
<td>9</td>
<td>8</td>
<td>26</td>
</tr>
<tr>
<td>USBM</td>
<td>6.39</td>
<td>5.45</td>
<td>0.8450</td>
<td>1</td>
<td>1</td>
<td>1</td>
<td>3</td>
</tr>
</tbody>
</table>

5. Conclusions

AOp prediction is important to limit disturbance during blasting. Investigation of 76 blasting events were used to develop 8 ANN models. AOp prediction using USBM equation was used as a benchmark. The two
main input parameters for all the methods used were MC and DI. The results suggest that all the ANN models developed were superior to the USBM equation in terms of the AOp prediction made for the testing set. Using a performance ranking method, MSO-Rand-Mut was determined as the best model to predict AOp. The performance metric obtained using this model were RMSE=2.18, MAPE=1.73% and $R^2=0.97$. This proves that MSO-Rand-Mut provide better accuracy compared to other methods when tested against the testing set. Thus, this ANN model can be confidently used to predict AOp in blasting site in order to limit disturbance to civilians.

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References


