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Artificial Neural Network Optimized by Modified Particle Swarm Optimization for Predicting Peak Particle Velocity Induced by Blasting Operations in Open Pit Mines

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Abstract. Blasting is an indispensable part of the open pit mining operations. It plays a vital role in preparing the rock mass for subsequent operations, such as loading/unloading, transporting, crushing, and dumping. However, adverse effects, especially blast-induced ground vibrations, are considered one of the most dangerous problems. In this study, artificial intelligence was supposed to predict the intensity of blast-induced ground vibration, which is represented by the peak particle velocity (PPV). Accordingly, an artificial neural network was designed to predict PPV at the Coc Sau open pit coal mine with 137 blasting events were collected. Aiming to optimize the ANN model, the modified version of the particle swarm optimization (MPSO) algorithm was applied to optimize the ANN model for predicting PPV, called the MPSO-ANN model. For the comparison purposes, two forms of empirical equations, namely United States Bureau of Mining (USBM) and U Langefors - Kihlstrom, were also developed to predict PPV and compared with the proposed MPSO-ANN model. The results showed that the proposed MPSO-ANN model provided a better performance with a mean absolute error (MAE) of 1.217, root-mean-squared error (RMSE) of 1.456, and coefficient of determination (R2) of 0.956. Meanwhile, the empirical models only provided poorer performances with an MAE of 1.830 and 2.012, RMSE of 2.268 and 2.464, and R2 of 0.874 and 0.852 for the USBM and U Langefors – Kihlstrom empirical models, respectively.

Keywords: Blast-induced ground vibration, Peak particle velocity, Open pit mine, Artificial neural network, Modified particle swarm optimization, Metaheuristic algorithms

1. Introduction

In open pit mines, the drilling-blasting method has been widely used for rock/ore fragments due to explosive energy's technical and economic advantages. Nevertheless, particularly environmental concerns are significant, and they may arise, such as blast-induced ground vibration, air over-pressure, flyrock, dust, and toxics [1-3]. As a matter of fact, about 20-30% of the generated energy from charged explosives is transmitted to the rock mass and producing fragmentations. The remaining energy is wasted and causes the above environmental effects [4-6]. Of those, blast-induced ground vibration is the most dangerous environmental impact of blasting. Beyond the fragmentation zone, the energy will be transferred to the seismic waves and propagate through the medium as elastic waves. It is also known as ground vibrations with the oscillating particles in the rocky environment in which they travel. Therefore, the intensity of ground vibration induced by blasting can be measured and evaluated by the peak particle velocity (PPV).

For measuring PPV, the aid seismographs were applied, and they provide the most accurate. Nevertheless, the field measurement method is costly, time-consuming, and requires the calibration of the seismographs correctly [7]. Hence, several scholars proposed empirical equations to estimate PPV [8-10]. However, these empirical methods have been recommended as low accuracy and neglect the influence of other parameters [11].

In recent years, artificial intelligence (AI) and soft computing have been widely introduced and applied for predicting PPV, especially in the theme of the Fourth Industrial Revolution [12, 13]. Many AI models were introduced and proposed to predict PPV with promising results. For example, Khandelwal and Singh [14] and Monjezi, Ghafurikalajahi and Bahrami [15] applied an artificial neural network (ANN) model for predicting PPV with the accuracies are pretty high. Khandelwal, Kankar and Harsha [16] also applied the support vector machine (SVM) model for the same purpose with a mean absolute error (MAE) of 0.257 and determination coefficient (R2) of 0.960. Hasanipanah, Faradonbeh, Amnieh, Armaghani and Monjezi [17] applied the classification and regression trees (CART) model for predicting PPV at a cooper mine in

Iran. They found that the CART model can predict PPV with a root-mean-squared error (RMSE) of 0.17 and R2 of 0.950. A new design of the SVM model optimized by a modified firefly algorithm (MFA) was also proposed by Chen, Hasanipanah, Rad, Armaghani and Tahir [18] for predicting PPV with an RMSE of 0.614 and R2 of 0.984. In another study, Nguyen, Drebenstedt, Bui and Bui [19] developed an AI model based on the hierarchical k-means clustering algorithm (HKM) and ANN models for predicting PPV with accuracy is approximately 97%. More recently, Qiu, Zhou, Khandelwal, Yang, Yang and Li [20] applied various metaheuristic algorithms, such as gray wolf optimization (GWO), whale optimization algorithm (WOA), and Bayesian optimization algorithm (BO), for optimizing the extreme gradient boosting (XGBoost) model in predicting PPV. Finally, they found that the WOA-XGBoost became the most reliable model with accuracy was approximately by 97%.

In this study, a modified version of the particle swarm optimization algorithm (MPSO) was considered to optimize the ANN model for predicting PPV in open pit mine, namely the MPSO-ANN model. For comparison purposes, two forms of empirical equations, namely United States Bureau of Mining (USBM) and U Langefors – Kihlstrom [21], were also developed to predict PPV and compared with the proposed MPSO-ANN model.

2. Study areas

Artificial neural network (ANN) is a soft computational system inspired by the human brain and its mechanisms [22]. It is a fact that there are many types of ANN in the AI environment; however, they often have a general structure with one input layer, hidden layer(s), and one output layer (Fig. 1).

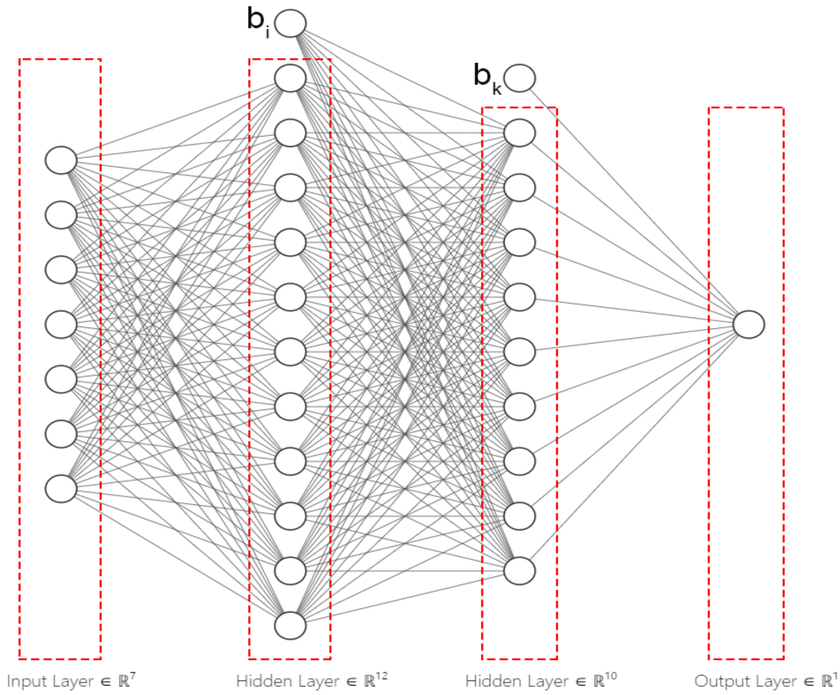

Fig. 1. General architecture of ANN model with one output variable.

The input layer contains input vectors that are gathered by the input neurons, and they are described as in Eq. (1). And then, they are transferred to the hidden layer based on the propagation law in Eq. (2).

$$X^p = \left(X_1^p, X_2^p, \dots X_N^p\right)^T \tag{1}$$

$$S_i^p = \sum_{j=1}^{N} w_{ji} X_j^p + b_i \tag{2}$$

where N is the number of input variables (input neurons); w_{ji} denotes the weight between the j^{th} neuron in the input layer and the i^{th} neuron in the hidden layer; b_i stands for the bias related to the i^{th} neuron in the hidden layer.

Supposing the activation state of the i^{th} neuron in the hidden layer as the input vector function, then the output can be calculated as follows:

$$y_i^p = f\left(S_i^p\right) \tag{3}$$

To calculate the activation state of a neuron from the output layer, the following equation is applied:

$$S_k^p = \sum_{j=1}^{L} w_{ik} y_i^p + b_k \tag{4}$$

where L is the number of neurons in the hidden layer(s);w_{ik}denotes the weight between the i^{th} neuron in the hidden layer and the k^{th} neuron in the output layer; b_k stands for the bias related to the k^{th} neuron in the output layer.

The error of the network can be computed using the following equation:

$$E^p = \frac{1}{2}\sum_{k=1}^{M}\left(d_k^p - y_k^p\right)^2 \tag{5}$$

As mentioned above, there are many types of ANN, such as MLP neural net, GR neural net, RBF neural net, to name a few. They are often trained by gradient descent-based algorithms. In addition, activation functions, such as elu, relu, sigmoid, tanh, etc., are used to transfer data between layers of the network. In this study, the MLP neural net will be used to predict PPV at the Coc Sau open pit coal mine, Quang Ninh province, Vietnam.

3. Modified particle swarm optimization

PSO was firstly proposed by Kennedy and Eberhart [23] in 1995 based on the behaviors of swarms, such as birds flock, ant, fish, etc. The initial individuals (populations) are generated for each swarm, and each particle in a swarm acts as a searcher in a search space. For each position that is searched by a particle, a solution is defined for a given optimization problem.

Suppose that search space is generated with a D-dimensional space, the particle will fly around the search space with the position is presented by $X_i^d = \left[x_i^1, x_i^2, \ldots, x_i^D\right]$, and the velocity is presented by $V_i^d = \left[v_i^1, v_i^2, \ldots, v_i^D\right]$. During searching the optimal position, the particles always exchange their experiences and update their positions and velocities through the Eqs. (6, 7).

$$X_i^d(t+1) = X_i^d(t) + V_i^d(t+1) \tag{6}$$

$$V_i^d(t+1) = V_i^d(t) + c_1 \times r_1 \times \left(P_{best\_i}^d(t) - X_i^d(t)\right) + c_2 \times r_2 \times \left(G_{best}^d(t) - X_i^d(t)\right) \tag{7}$$

where t and $t+1$ denote the current and the next iteration of the optimization process; P_{best}andG_{best} stand for the local best and global best of the particles; $c_1$and c_2 are the positive acceleration coefficients; r_1 and r_2 are random values interval [0,1].

Although the original version of the PSO algorithm was recommended as a potential solution for optimization problems in engineering; however, it is easy to fall into local optimum in high-dimensional space and has a low convergence rate in the iterative process [24]. Thus, a modified version of the PSO algorithm (i.e., MPSO) has been proposed by adding the bird's weights during updating the particle's velocity [25]. Eq. (7) now can be modified as follows:

$$V_i^d(t+1) = w(t)V_i^d(t) + c_1 \times r_1 \times \left(P_{best\_i}^d(t) - X_i^d(t)\right) + c_2 \times r_2 \times \left(G_{best}^d(t) - X_i^d(t)\right) \tag{8}$$

With $w(t)$ is the weight of the bird at the current iteration, and it can be calculated using the following formula:

$$w(t) = w_{\max} - \frac{(w_{\max} - w_{\min})}{T_{\max}} \cdot t \tag{9}$$

where w_{min} and w_{max} are the minimum and maximum weights of the bird; T_{max} is the maximum number of iterations.

The pseudo-code of the MPSO algorithm is presented in Fig. 2.

Algorithm: MPSO pseudo-code for the optimization process

for each particle i
  for each dimension d
    Initialize position x_{id} randomly within permissible range
    Initialize velocity v_{id} randomly within permissible range
  end for
end for
Iteration $t = 1$
do
  for each particle i
    Calculate fitness value
    if the fitness value is better than p_best_{id} in history
      Set current fitness value as the p_best_{id}
    end if
  end for
  Choose the particle having the best fitness value as the g_best_{id}
  for each particle i
    for each dimension d
      Calculate velocity according to the equation
$v_j^{i+1} = wv_j^{(i)} + (c_1 \times r_1 \times (local\,best_j - x_j^{(i)})) + (c_2 \times r_2 \times (\text{global}\,best_j - x_j^{(i)})), v_{\min} \le v_j^{(i)} \le v_{\max}$
      Update particle position according to the equation
$x_j^{i+1} = x_j^{(i)} + v_j^{(i+1)}; j = 1, 2, ..., n$
    end for
  end for
$t = t+1$
while maximum iterations or minimum error criteria are not attained

Fig. 2. The pseudo-code of the MPSO algorithm.

4. MPSO-ANN model

In this study, the MPSO algorithm will be applied to optimize the ANN model for predicting PPV. As introduced in section 2, the main unit of the ANN model is the weights between the neurons. Weights are often calculated and updated by the gradient descent-based algorithm (e.g., backpropagation algorithm), and it will decide the accuracy of the ANN model. However, the main disadvantages of the backpropagation algorithm are premature convergence and trapped to local optimum, and cannot escape [26, 27]. Therefore, the MPSO algorithm was applied to overcome these disadvantages of the backpropagation algorithm to train the ANN model.

For this aim, a number of populations (particles) will be generated first. Subsequently, their fitness was calculated and evaluated. Their fitness will be calculated and updated for each iteration to determine the best position (corresponding to the best solution). For each solution, a set of weights were generated and then imported to the ANN model. Finally, the error of the ANN model was calculated and evaluated through the objective function. During optimization of the ANN model by the MPSO algorithm, the maximum number of iterations is necessary to ensure the algorithm's convergence. To this end, the optimal MPSO-ANN model will be defined based on the lowest value of the objective function with the maximum iterations. The framework of the MPSO-ANN model for predicting PPV is proposed in Figure 3.

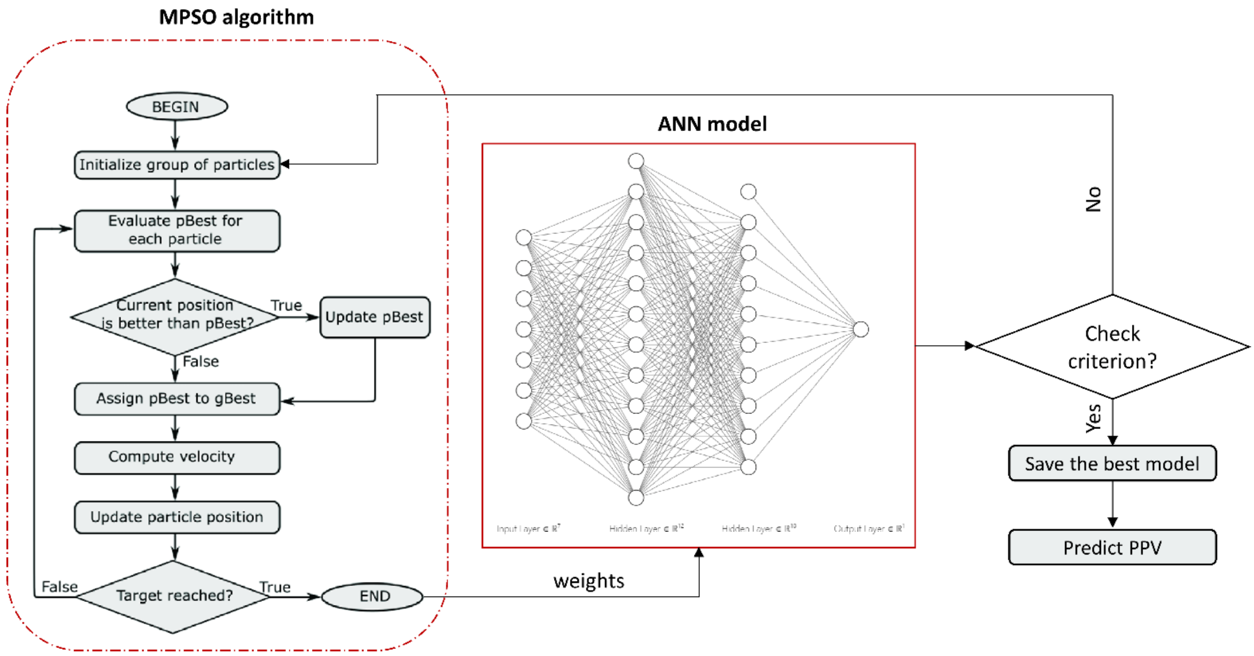

Fig. 3. The framework of the MPSO-ANN model for predicting PPV.

5. Case study

In this study, the Coc Sau open pit coal mine (Quang Ninh – Vietnam) was selected as a case study to investigate the feasibility of the HR model for predicting PPV. The location of the study site is shown in Fig. 4. The Coc Sau open-pit coal mine was covered entirely by sedimentary rocks of Late Triassic Hon Gai Formation (T_3n-r*hg*). The formation was composed of conglomerate, gritstone, sandstone, siltstone, claystone, shale, and coal seams [28]. In general, these sedimentary rocks are quite hard with the rock strength (f) of 8 to 10 [29]. Therefore, drilling-blasting is taken into consideration as an excellent method for the fragmentation of rock during exploiting coal of the mine. The boreholes diameter of 105 mm was applied for blasting herein with the ANFO explosive was used. Non-electric millisecond detonators were applied to fragment rocks herein. It is considered as an effectiveness blasting method and safety for the human, as well as the surrounding environment [30].

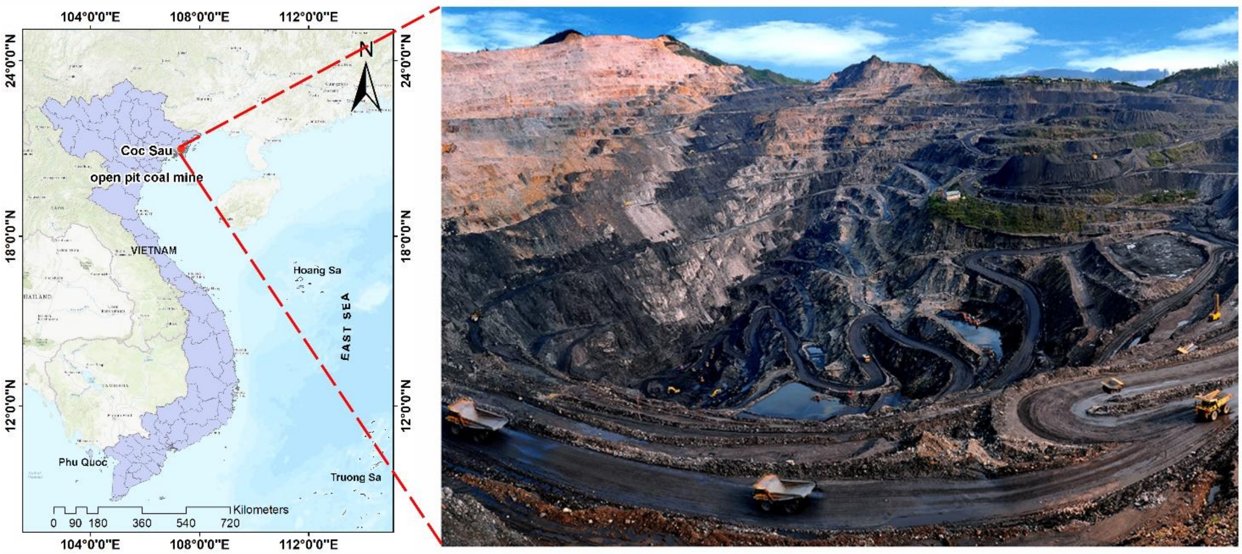

Fig. 4. Location of the Coc Sau open pit coal mine (Vietnam).

In this mine, the millisecond blasting method was applied to fragment rocks, with the ANFO was used as the main explosive to charge into boreholes. In some boreholes which contain water, emulsion explosives were charged to prevent the pervasion of water to the explosive. To realize this study, 137 blasting events were gathered with three parameters were collected, including explosive charged per delay (Q), monitoring distance (D), and PPV. Of those, Q and D were used as the input variables, and PPV was considered as the output variable.

For the data collection, Q values were extracted from 137 blasting patterns, and D values were determined through the GPS devices that were used at the blast faces and seismograph points. The Micromate device (Instantel - Canada) was used for measuring PPV, and it was calibrated before measuring. The dataset used in this study is summarized in Table 1, and its characteristics are shown in Figure 5.

Tab. 1. Summary of the dataset used.

Q (Kg)	D (m)	PPV (mm/s)
Min. : 320	Min. :182.0	Min. : 2.25
1st Qu.:2517	1st Qu.:326.2	1st Qu.: 8.14
Median :3276	Median :408.8	Median :12.25
Mean :3184	Mean :436.4	Mean :12.57
3rd Qu.:3845	3rd Qu.:523.0	3rd Qu.:16.01
Max. :6043	Max. :715.0	Max. :28.63

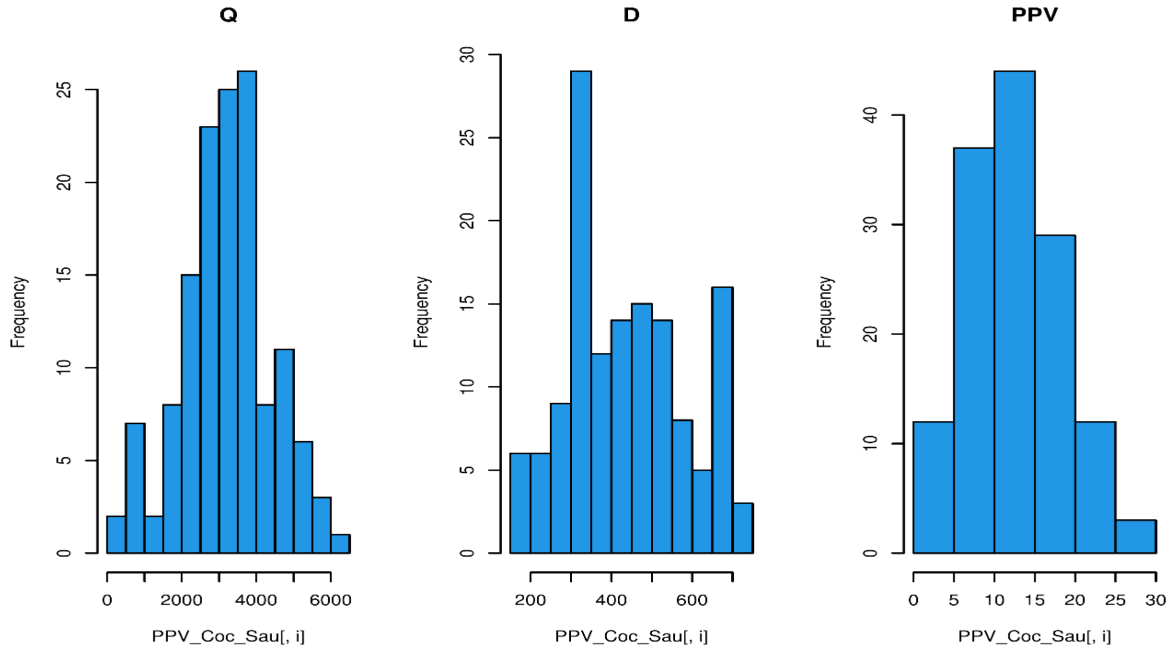

Fig. 5. Histogram of the dataset used.

6. Results and discussion

Before developing the MPSO-ANN model, the dataset was pre-processed aiming to normalize the dataset and improve the performance of the learning of the model. Accordingly, the dataset was divided into two sections: one section contains 70% of the whole dataset for training the MPSO-ANN model, the remaining section contains 30% of the datasets for testing the accuracy of the developed MPSO-ANN model. In order to improve the accuracy of the model, the dataset was normalized interval [0,1]. Subsequently, the proposed framework in Figure 3 was applied to develop the MPSO-ANN model.

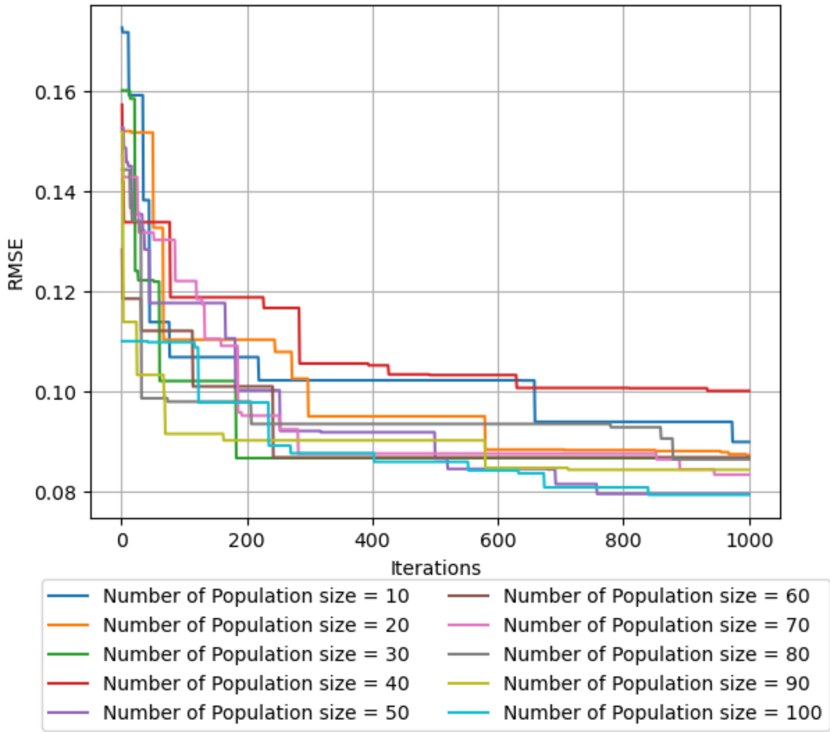

Fig. 6. Training performance of the MPSO-ANN model.

As an optimizer during training the ANN model, the MPSO algorithm was set up first with the following parameters: $c_1 = c_2 = 1.2$; w_{min}; w_{max}. A different number of populations in the range of 10 to 100 were considered while searching the optimal weights of the ANN model. The searching process was implemented within 1000 iterations. For each MPSO-ANN model developed based on a set of parameters, the performance metrics, such as MAE, RMSE, and R^2, were computed on both training and testing datasets. Finally, the best MPSO-ANN model was defined based on the performances on both training and testing datasets.

For comparison purposes, empirical equations were considered and developed to predict PPV based on the same datasets. Empirical equations are considered the most straightforward method for predicting PPV in open pit mines. They are often used to express the relationship between the explosive charged and monitoring distance. The first empirical equation was proposed by Duvall and Petkof [8] and used by the United States Bureau of Mining (USBM), as follows:

$$PPV = k\left(\frac{D}{Q^{1/2}}\right)^b \tag{10}$$

where D is the monitoring distance from the blast faces to the seismograph, m; Q is the explosive charged per delay (or per blast), Kg; k and b denote the site coefficients, and they are different in various areas.

Based on the USBM empirical equation, U Langefors and Kihlstrom (1963) proposed an alternative empirical equation, as described in Eq. (11).

$$PPV = k\left(\frac{D}{Q^{1/3}}\right)^b \tag{11}$$

In addition, there are several empirical equations have been proposed based on the relation between blasting parameters and geological conditions and rock properties [31-34]. Nevertheless, due to the lack of geological and geotechnical information, these empirical equations cannot be applied in many cases. In this study, we used Eqs. (10-11) to estimate PPV due to the lack of geological conditions and rock properties, as mentioned above. Based on the original training and testing datasets, the empirical equations for estimating PPV at the Coc Sau open pit coal mine were defined as described in Eqs. (12-13).

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- According to the USBM equation form:

$$PPV = 61.756\left(\frac{D}{Q^{1/2}}\right)^{-0.837} \quad (12)$$

- According to the U Langefors and Kihlstrom (1963) equation form:

$$PPV = 267.752\left(\frac{D}{Q^{1/3}}\right)^{-0.943} \quad (13)$$

Once the MPSO-ANN and empirical models were well-trained and defined, the training and testing datasets were applied to predict PPV, and their performances were evaluated through three performance metrics MAE, RMSE, and R^2, which are calculated according to the following equations:

$$\mathrm{MAE} = \frac{1}{n}\sum_{i=1}^{n}|y_i - \hat{y}_i| \quad (14)$$

$$\mathrm{RMSE} = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2} \quad (15)$$

$$R^2 = 1 - \frac{\sum_{i=1}^{n}(y_i - \hat{y}_i)^2}{\sum_{i=1}^{n}(y_i - \bar{y}_i)^2} \quad (16)$$

where n is the number of blasting events used to calculate the performance; $y_i, \hat{y}_i$ stand for the measured and predicted PPVs, $\bar{y}_i$ denotes the mean of the measured PPVs. The performances of the models are computed in Table 2.

Tab. 2. Performance metrics of the MPSO-ANN and empirical models.

Model	Training dataset			Testing dataset		
	MAE	RMSE	R^2	MAE	RMSE	R^2
MPSO-ANN	1.577	1.968	0.880	1.217	1.456	0.956
USBM	1.870	2.241	0.830	1.830	2.268	0.874
U Langefors and Kihlstrom	2.047	2.443	0.804	2.012	2.464	0.852

As listed in Table 2, it is conspicuous that the proposed MPSO-ANN model yielded superior performance to the empirical models. Whereas the MAE of the MPSO-ANN model is only 1.577 and 1.217 on the training and testing datasets, it is 1.870 and 1.830 on the training and testing datasets for the USBM model, and 2.047 and 2.012 on the training and testing datasets for the U Langefors and Kihlstrom model. The RMSE of the MPSO-ANN model is also better than those of the empirical models, specifically, RMSE = 1.968 and 1.456 on the training and testing datasets. Meanwhile, these values are higher for the USBM and U Langefors and Kihlstrom models, i.e., RMSE = 2.241 and 2.268 for the USBM model; RMSE = 2.443 and 2.464 for the U Langefors and Kihlstrom model on the training and testing datasets, respectively. Remarkably, R^2 values in Tab. 2 indicated that the dataset was more fit to the proposed MPSO-ANN model with R^2 = 0.880 on the training dataset and R^2 = 0.956 on the testing dataset. In contrast, it is in the range of 0.804 to 0.830 on the training dataset, 0.852 to 0.874 on the testing datasets for the empirical models. Fig. 7 interprets the correlation between the measured and predicted PPVs by the MPSO-ANN and empirical models for further discussion.

As depicted in Figure 7, it can be seen that the proposed MPSO-ANN model provided a better correlation between the measured and predicted PPVs. In other words, the predicted PPVs are closer to the actual PPVs than those of the predicted PPVs by the empirical models

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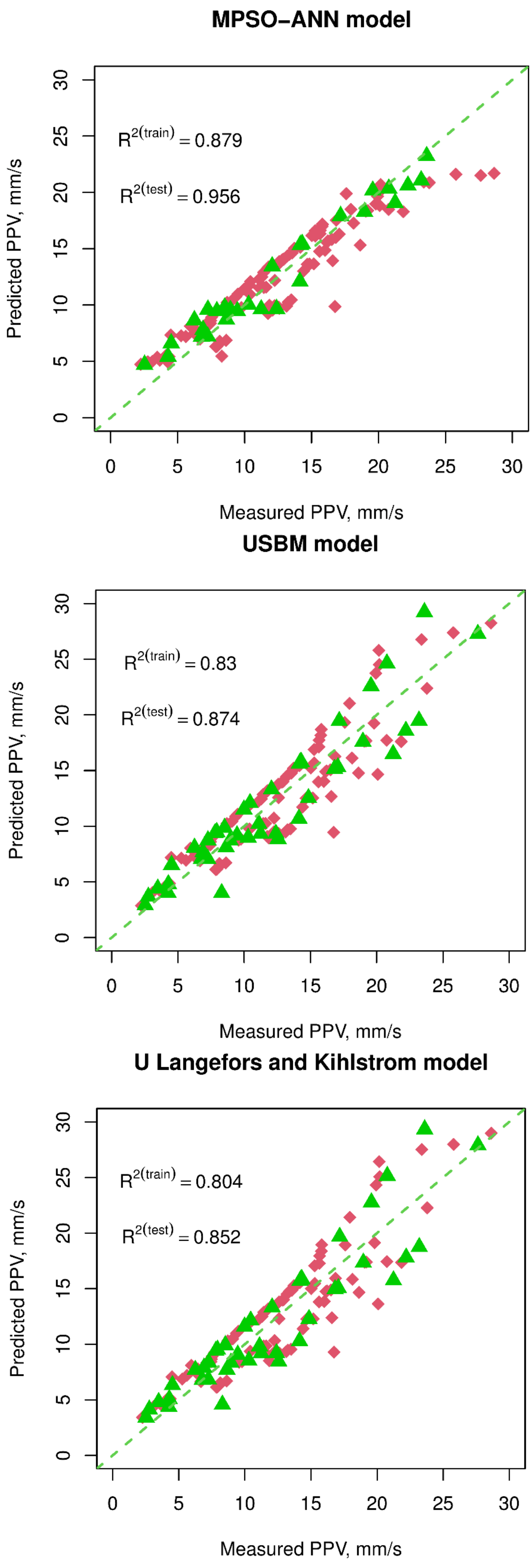

Fig. 7. Correlation between measured and predicted PPVs by the MPSO-ANN and empirical models.

7. Conclusion

Blasting is a crucial stage in open-pit mines even though its adverse effects are significant, especially is the blast-induced ground vibration. The problem now is how to predict, control, and mitigate the intensity of blast-induced ground vibration (i.e., PPV), as well as its side effects on the surrounding environment. This study developed a hybrid AI model, namely MPSO-ANN, for predicting PPV, and it was tested at the Coc Sau open-pit coal mine as a case study. The results showed that the developed MPSO-ANN model could predict PPV with high accuracy than the traditional empirical equations. Based on the developed MPSO-ANN model, the explosive charged per delay can be adjusted to control the PPV induced. This can contribute to reducing the undesirable effects on the surrounding environment in open pit mines.

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