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Original Paper

Prediction of Blast-Induced Ground Vibration Intensity in Open-Pit Mines Using Unmanned Aerial Vehicle and a Novel Intelligence System

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Predicting and reducing blast-induced ground vibrations is a common concern among engineers and mining enterprises. Dealing with these vibrations is a challenging issue as they may result in the instability of the surrounding structures, highways, water pipes, railways, and residential areas. In this study, the effects of blasting in a quarry mine in Vietnam were examined. A total of 25 blasting events were investigated with the help of an unmanned aerial vehicle, micromate instruments, and blast patterns, and 83 observations were recorded. Subsequently, the fuzzy C-means clustering (FCM) algorithm was applied to classify the 83 observations based on the blast parameters. Finally, based on the classification of the blasts, quantile regression neural network (QRNN) models were developed. The combination of FCM and QRNN models resulted in a novel, hybrid model (FCM-QRNN) for predicting blast-induced ground vibration. The US Bureau of Mines (USBM), random forest (RF), QRNN (without clustering), and artificial neural network (ANN) models were also considered and compared with the FCM-QRNN model to obtain a comprehensive assessment of the proposed model. The results indicate that the proposed FCM-QRNN model has a higher accuracy than the other models: USBM, QRNN, RF, and ANN. The proposed model can be used to control the undesirable effects of blast-induced ground vibration. Although this study and the proposed FCM-QRNN model are original works with positive results, the performance of this model in other locations still needs to be considered as a case study for further scientific information.

KEY WORDS: Fuzzy C-means clustering, Quantile regression neural network, Blasting, Ground vibration, Unmanned aerial vehicle.

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INTRODUCTION

Rock fragmentation is an important process in open-pit mining. Many techniques, such as drilling and blasting (Hustrulid 1999), hydraulic rock breaking (Nguyen and Bui 2015), high-pressure water jet utilization (Hagan 2010), and the use of mechanical equipment (Bui 2016), can be used for rock fragmentation. Of these techniques, blasting, which has the highest efficiency considering technological and economic factors, is the most commonly used method.

According to previous studies (e.g., Ak and Konuk 2008; Armaghani et al. 2014), approximately 20–30% of the explosive energy is utilized in breaking/removing the rock mass. The remaining energy is wasted and generates undesirable effects such as vibrations, fly rock, blast overpressure, toxic byproducts, and dust (Monjezi et al. 2013b; Armaghani et al. 2016; Ghasemi 2017; Hasanipanah et al. 2017a). Of these effects, blast-induced ground vibrations, which are considered to be the most dangerous effect, are measured in terms of their peak particle velocity (PPV). Blast-induced ground vibrations are a threat to surrounding buildings, slopes, benches, and groundwater (Nguyen et al. 2019d). The extent of structural damage caused by these vibrations depends on the intensity of the vibration, which varies based on the region/country and PPV (Nateghi et al. 2009). Numerous open-pit mines worldwide are facing lawsuits owing to the ill effects of PPV (Aldas and Ecevitoglu 2008; MacGlennon et al. 2017). However, accurate assessment and estimation of the PPV in open-pit mines is a challenging task for engineers and open-pit mining enterprises.

Over the years, efforts have been made to observe and record blast-induced ground vibrations. PPV is considered a standard for measuring the intensity of ground vibrations. Minimate, blastmate, micromate, and other wireless monitoring systems have been utilized to obtain the PPV values for open-pit mines (Ak et al. 2009; Ragam and Nimaje 2018). These experimental datasets were combined with statistical techniques to estimate PPVs. Empirical methods have been used for many years (Nguyen et al. 2019d). Many researchers have applied various empirical models to estimate PPV, based on their convenience (Murmu et al. 2018; Ongen et al. 2018). However, a review of the literature reveals that empirical techniques have low accuracy (Monjezi et al. 2011, 2013a; Ghasemi et al. 2013; Nguyen et al. 2019c). Hu and Qu (2018) developed a new empirical equation for the determination of PPV, considering the drawbacks of previous empirical equations. It is called the equivalent-path-based equation, and its performance was justified. In addition, the properties of rock masses in different rock sites were also investigated to determine PPVs, based on empirical methods (Kumar et al. 2016).

In recent years, artificial intelligence (AI) has been recognized as an advanced tool for solving complex issues in real-life, particularly in mining and natural resource research (Jang and Topal 2014; Asteris et al. 2019a; Brantson et al. 2019; Nourani et al. 2019; Roshanravan et al. 2019). PPV prediction models have also been considered and developed with the aim of reducing the ill effects of vibrations on the surrounding environment. Accordingly, many researchers considered the use of fuzzy logic, machine learning algorithms (MLAs), optimization algorithms (OAs), and artificial neural networks (ANN) for estimating PPVs. Nguyen et al. (2019c) developed three AI systems for estimating the PPV. These systems included boosted adaptive generalized models (BGAMs), ANNs, and support vector machines (SVMs). They concluded that the BGAM was a highly reliable system to estimate PPV. When compared with empirical models, the ANN model exhibited higher accuracy in predicting PPV (Das et al. 2019). To optimize the ANN model for predicting PPV, Armaghani et al. (2014) applied a swarm optimization algorithm [i.e., particle swarm optimization (PSO)], and the combined model was called the PSO-ANN model. They demonstrated the feasibility and high performance of their PSO-ANN model in estimating PPV. Hasanipanah et al. (2017b) also considered the feasibility of the PSO algorithm in estimating the PPV with linear and power forms. Their findings showed that the PSO algorithm with a form of power equation had a higher performance than other models. Similar to the PSO algorithm, the robust meta-heuristic algorithm, i.e., gene expression programming (GEP), was also developed to predict and minimize the PPV, by Faradonbeh and Monjezi (2017). They demonstrated that their GEP model had better performance and higher accuracy than the other models in their study. Mokfi et al. (2018) proposed a soft computational model, using the group method of data handling, to estimate the PPV in an open-pit mine in Malaysia, and the model exhibited a dominant performance. In another study, Zhongya and

Xiaoguang (2018) applied dimensionality reduction to the factor analysis and mean impact value to optimize an ANN model (ANN-FA-MIV) for predicting PPV. They claimed that the ANN-FA-MIV model had superior performance compared to other models such as models without FA-MIV, extreme learning machines, and back-propagation neural network. Based on clustering techniques, MLAs, and ANNs, two highly reliable hybrid models, HKM-CA and HKM-ANN, were developed for estimating PPV (Nguyen et al. 2019b, d). Xue (2019) also applied two forms of the clustering algorithm, the fuzzy C-means (FCM) and subtractive algorithms, and neuro-fuzzy (ANFIS) to evaluate the intensity of vibration. Their findings showed that the FCM-ANFIS model yielded a more precise evaluation of the PPV. In addition, other hybrid models based on a combination of OAs, MLAs, and ANN, namely PSO-XGBoost and FFA-ANN, were also developed to predict PPV in open-pit mines, by Zhang et al. (2019) and Shang et al. (2019). A variety of PPV prediction models have been evaluated and proposed in various studies (Singh and Singh 2005; Khandelwal et al. 2011; Monjezi et al. 2011; Saadat et al. 2014; Hasanipanah et al. 2015; Ghoraba et al. 2016; Taheri et al. 2017; Prashanth and Nimaje 2018; Nguyen et al. 2019a).

Although many AI techniques for predicting PPV have been proposed, none of the models are capable of considering all the factors in predicting PPV. Therefore, novel AI techniques with high reliabilities are a growing concern among scientists and blast engineers. This work proposes a novel intelligent approach based on FCM clustering and QRNN models, to predict PPVs at an open-pit mine in Vietnam, with many sensitive areas. The US Bureau of Mines (USBM), QRNN (without clustering), ANN, and random forest (RF) techniques were also considered for comparison purposes. The main innovations of the present study are highlighted as follows:

- An unmanned aerial vehicle (UAV) was used to collect the dataset for predicting PPVs in this study.
- For each blast, five instruments were used to record the PPV at different locations.
- The validity of QRNN as a new AI method for predicting PPVs was investigated.
- The proposed model (FCM-QRNN) is a combination of the FCM technique and QRNN and exhibits high accuracy. It is a novel AI technique for predicting PPV.
- A comprehensive comparison and assessment of the proposed FCM-QRNN model and other techniques, such as the USBM, QRNN, ANN, and random forest models, was conducted. The results of the study are original and positive.

DESCRIPTION OF THE STUDY AREA

This study was conducted at a quarry mine in Southern Vietnam. The mine is surrounded by many sensitive areas, as shown in Figure 1a. A highway, railway line, water pipe, and residential areas are the main surrounding affected by blast-induced ground vibrations. In this study, four blasts were performed daily, with approximately 3000 kg of explosives (Tan Dong Hiep company 2018). As shown in Figure 1, the work sites (designated blast sites) and the sensitive areas (the highway, railway line, water pipe, and residential areas) are close to each other (approximately less than 100 m). Therefore, the ill effects of PPV are very dangerous.

The geological structure of the study site is not complex, as shown in Figure 1b. The entire study site is located in the Long Binh formation, which includes andesite, rhyolite, and tuff. Therefore, the rock mass is significantly hard, and blasting is a good method for rock fragmentation (Murat et al. 2006). Blasting has many undesirable effects, as mentioned in the previous section. Thus, this study area is an ideal area for studying PPV prediction using AI techniques.

DATA COLLECTION

We set up a plan for data collection. The values of maximum explosive charge capacity (W), monitoring distance (R), burden (B), bench height (H), stemming (T), length of borehole (L), spacing (S), power factor (P), and PPV were collected and recorded. A total of 25 blasting events were investigated. For each blast, five micromate instruments for the PPV measurements were placed at the monitoring locations, as shown in Figure 2c. Subsequently, a total of 83 PPV observations were recorded. The unmanned aerial vehicle (UAV) Phantom 4 Pro and ArcGIS software (Yilmaz et al.

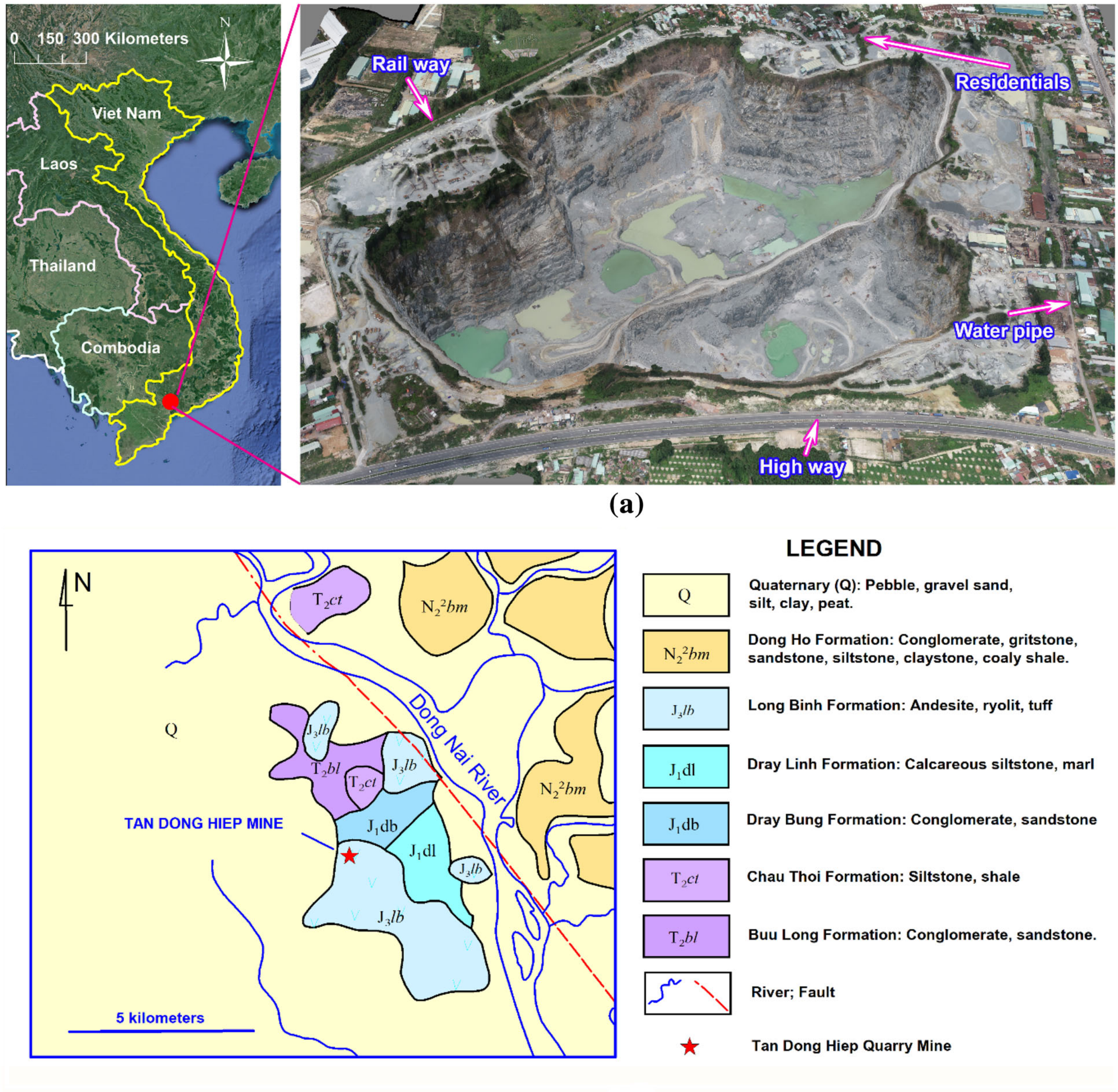


Figure 1. Overview of the study site and its geological properties. (a) The study site and its landscape; (b) geological properties of the study site.

2008) were used to obtain the study area map and accurately determine the distance between the blast sites and the PPV monitors (i.e., R), as illustrated in Figure 2b. The effectiveness and accuracy of these equipment have been demonstrated in a previous study (Tien Bui et al. 2018). Furthermore, ArcGIS was used to manage and query the geodatabase of 83 datasets based on the map set up by the UAV Phantom 4 Pro (Zeiller 2010). The remaining factors were extracted from the blast patterns. Table 1 lists the properties of the input and output parameters used in this study.

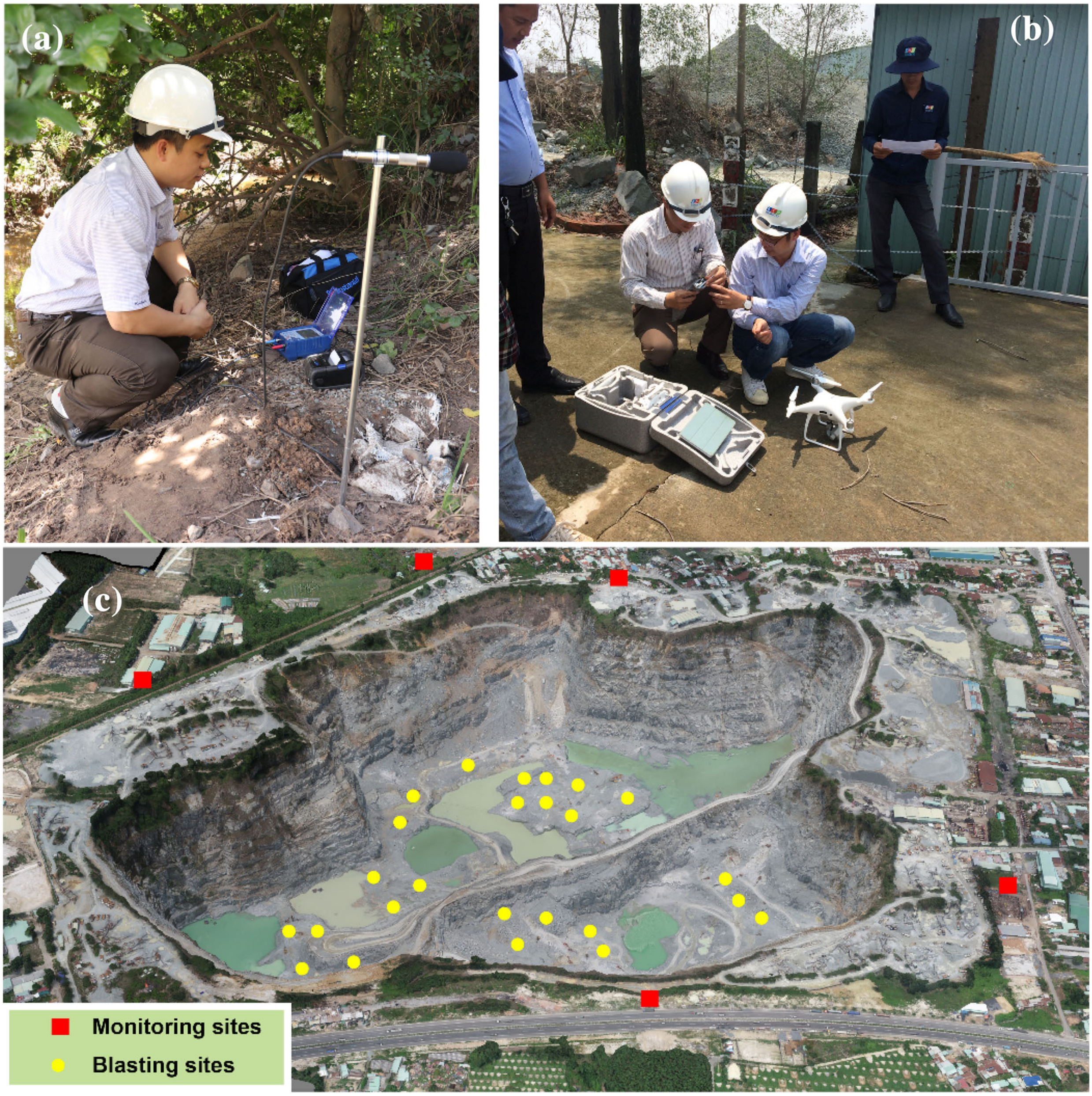


Figure 2. Data collection. (a) PPV measuring micromate instrument; (b) UAV Phantom 4 Pro used to establish study area map and monitoring distance; (c) PPV monitoring sites at the Tan Dong Hiep quarry mine.

OVERVIEW OF THE METHODOLOGY USED

Empirical Method

As mentioned in "Introduction" section, various experimental methods for the prediction of PPV have been studied and proposed. The experimental procedures are based on the relationship between W and R. Also, B is one of the factors in the experimental methods proposed by Murmu et al. (2018). The ratios of the distances between R, W, and B, as well as the site factors for each region are different. These factors directly affect the estimation of PPV.

Among the existing experimental techniques, the USBM model extensively utilized the empirical

Table 1. Input and output parameter characteristics

Element	W (kg)	R (m)	H (m)	L (m)
Minimum	1936	198.8	8.20	9.70
Mean	2797	358.5	10.48	11.54
Maximum	3813	591.0	12.40	12.90
Standard deviation	408.975	107.091	0.949	0.749

	S (m)	B (m)	P (kg/m^3)	T (m)	PPV (mm/s)
Minimum	3.100	3.100	0.4000	2.200	0.336
Mean	3.414	3.208	0.4437	3.388	3.391
Maximum	3.700	3.400	0.4800	4.500	8.564
Standard deviation	0.142	0.083	0.014	0.505	1.934

method to predict PPV, as proposed by Duvall and Petkof (1958). Hence, we selected a USBM novel formula and experimental methods to measure PPV. The USBM experimental approach is demonstrated as follows:

$$\mathrm{PPV} = \lambda\left(\frac{R}{\sqrt{W}}\right)^{-\alpha} \tag{1}$$

where W stands for explosive capacity, R stands for the distance between the blast site and analysis point, and λ and α represent the site parameters specified using the multivariate regression evaluation.

Fuzzy C-Means Clustering

FCM is recognized as one of the most efficient methods of dividing an original dataset into clusters (or partitions) (Bezdek et al. 1984). This method was proposed by Dunn (1973) and developed by Bezdek (1981). It is an unsupervised learning algorithm based on the uncertainty of attributes and described by memberships (Ouma and Hahn 2017). FCM provides opacity to the characteristic of each subsample. Each sample is assigned a membership level ranging from 0 to 1 (Gu et al. 2018). Fuzzy members and similar attributes are grouped into a single cluster by FCM clustering. Thus, following FCM, the characteristics of the datasets are classified by minimizing the cost function as follows:

$$J_m = \sum_{i=1}^{N}\sum_{j=1}^{N} u_{ij}^{n}\|x_i - c_i\|^2 \tag{2}$$

where u_{ij} is the membership degree of x_i in the cluster j; n is the number of clusters; c_j is the m-dimensional center of the cluster; and x_i is the ith element of the m-dimensional data.

As mentioned in the preceding sections, 25 blasting events were created, and 83 observations were recorded. Therefore, a clustering algorithm would be more efficient in splitting data into groups of similar characteristics. The existence of multiple populations as opposed to a single population in the data was considered. As mentioned in previous studies, FCM is commonly used in various fields and achieves convincing results (Dong and Wang 2017; Qin et al. 2017; Yang and Nataliani 2017; Demircan and Kahramanli 2018). In this study, as the first step in building prediction models, FCM clustering was used to segment the measured PPV datasets of the Tan Dong Hiep quarry. Additional details on FCM can be found in numerous published materials (Bezdek et al. 1984; Cannon et al. 1986; Hung and Yang 2001; Liu et al. 2008; Zainuddin and Ong 2013).

Quantile Regression Neural Network

ANN is recognized as a flexible tool that facilitates the estimation of nonlinear models without specifying an exact function. Among the various types of ANN, the feedforward ANN with a single hidden layer is commonly used for prognostication problems (Zhang et al. 1998). The principle of this method is based on the use of input parameters and hidden neurons to predict the output variables. Based on the relevant theory of the feedforward ANN with a single hidden layer, Taylor (2000) proposed a QRNN as a robust technique for solving nonlinear regression problems.

Generally, QRNN is an artificial neural network with a single input, hidden, and output layer. Similar to the neurons in ANNs, the input neurons of QRNN receive the input signals and send them to the hidden layer in the form of weights. In the hidden layer, the hidden nodes are defined to calculate and process the masses and send them to the output layer. More details on QRNN can be found in previously published papers (Cannon 2017; Amalia et al. 2018).

On reviewing the literature pertaining to mining, it was found that QRNN has never been used to estimate problems in an open-pit mine, especially

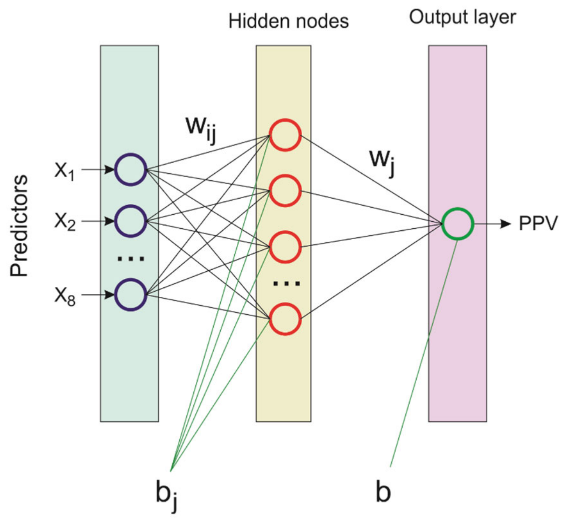


Figure 3. Usual structure of a QRNN model for PPV estimation.

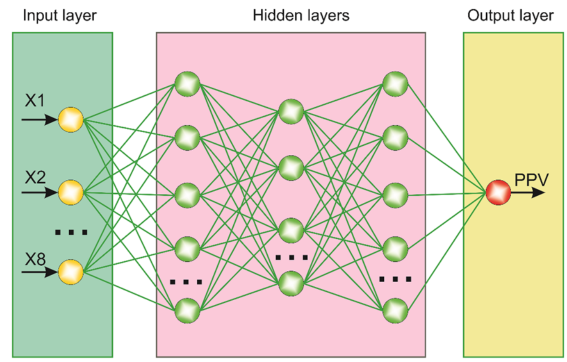


Figure 4. Complete structure of ANN model for estimating PPV.

blast-induced PPV predictions. Therefore, in this work, to estimate blast-induced PPV, a QRNN model was proposed. The general structure of a QRNN for estimating the PPV is illustrated in Figure 3. In the figure, X_1–X_8 represent the predictors (input variables) of the QRNN model, i.e., W, R, H, L, S, B, P, and T. W_{ij} and W_j denote the weights between neurons, and their value can be negative or positive. b_j and b are the biases of the weights in the neurons. Additional details regarding QRNN architecture have been discussed by Cannon (2011).

Artificial Neural Network

The ANN is known to be one of AI methods, built based on the design of the human brain (Schalkoff 1997). This method is capable of connecting neurons to solve issues from the input neurons, via the assistance of computers (Schalkoff 1997). The complete structure of an ANN includes three layers: the input layer, hidden layers, and output layer (Schalkoff 1997). Figure 4 illustrates a typical structure of an ANN to estimate blast-induced PPV. The layers consist of neurons with distinct functions. The hidden layer as well as the neuron numbers is indeterminate in each layer. Different neurons can lead to underfitting, and a lower number of neurons will not be able indicate the characteristics of the data (Nguyen et al. 2018a). Furthermore, the training time is also influenced by the number of hidden layers. Nguyen et al. (2018b) suggested that an ANN with two hidden layers is capable of solving such issues. Different hidden layers can affect the training time of the process and lead to underfitting or overfitting (Asteris et al. 2019b).

An ANN network model functions with the help of an input layer. The neurons intercept input signals along with weights. After that, the signals are evaluated and dispatched to the neurons located on the first hidden layer, via the transfer function (Asteris and Plevris 2017). In addition, neurons are capable of intercepting the outcomes at the input and processing factor stages, predicting the weights, and launching them to the second hidden layer via the transfer function. The procedural outcomes are sent to the output layer (Zerguine et al. 2001).

The outcomes of the ANN model are closely related to the learning network approach. The learning approach of artificial neural networks consist of two types of learning: controlled learning and unsupervised learning (Perez et al. 1994). For the PPV estimation, numerical information, utilizing regression approaches, acts as the input. Therefore, according to input data and output demands, most of the data utilize supervised learning.

In this study, five neural networks with two or three hidden layers were expanded for the purpose of estimating PPV caused by blasting operations in the Tan Dong Hiep quarry mines. The neural networks were compared with QRNN and FCM-QRNN.

Random Forest (RF)

The RF algorithm suggested by Breiman (2001) has the ability to combine the estimations of numerous decision trees in a forest. In a previous study, a planted forest with abundant trees was constructed using the algorithms of classification and regression (Belgiu and Drăgut 2016). Because each tree in a forest is similar, each tree's decision was considered a vote for the PPV estimation. Bootstrap resampling was also utilized in this algorithm to ensure precise estimation. Like public elections, RF seems to be an appropriate high-precision method applicable in a noisy environment (Chen et al. 2016; Brokamp et al. 2017). However, the use of RF for estimating PPV after blasting operations in an open-pit mine appears to be rare in previous studies.

In this study, we considered $T(x_i, \mathrm{PPV})$ to be the function representing the training databases that x_i considered the matrix of nine input parameters; PPV is the estimation amount. The RF modeling method can determine decision tree numbers for a forest to minimize the deviation between the calculated and evaluated PPV amounts. Therefore, the decision tree numbers for a forest and the input factors are determined based on the goal of enhancing precision. Further, the forest needs to be diversified using different decision trees to account for predictable and objective outcomes. Hence, many decision trees and input factors could be utilized in the expansion of the RF for estimating PPV. For perfect comparison and outcome, the RF was compared to the other models. The results are discussed in the following sections.

DATA PRE-PROCESSING

Preparing Data Without Clustering

To establish prediction models for blast-induced PPV estimation, preparation and pre-processing of the dataset are necessary. Ding et al. (2019), Guo et al. (2019) and Luo et al. (2019) recommended that the dataset be divided into two parts (80/20) before developing the prediction models such that 80% of the data is used for training and 20% is used for testing. A splitting procedure was performed using 71 blasting events ($\sim$ 80%) for training and the remaining 12 observations ($\sim$ 20%) to verify the efficiency of the established models. It is worth noting that all models used the same sets of training and testing data. Accordingly, 71 observations were selected randomly for use with eight input parameters, as illustrated in Figure 5.

Preparing Data with Clustering

In the preparation with the clustering technique, training datasets consisting of 71 blasting events were subdivided into clusters utilizing the fuzzy C-means (FCM) algorithm. A clustering procedure was performed with 25 starting times in turn for 2, 3, and 4 clusters. Two well-known indices, partition entropy (PE), partition coefficient (PC), and modified partition coefficient (MPC) were used to evaluate the goodness of the clustering result. The PC values were in the range [1/k, 1], where k is the cluster number (Ferraro and Giordani 2015; Maechler et al. 2017), as illustrated in Table 2.

According to Ferraro and Giordani (2015), the optimal number of clusters k is achieved when the PE value is minimized and PC value is maximized. From Table 2, it can be seen that clustering with FCM for 2 clusters is most effective with PE = 0.289 (the smallest of all clusters) and PC = 0.827 (the largest of clusters). Also, an excellent property of the MPC is that it ranges within [0, 1]. For further analysis, the number of clusters was determined using the silhouette method (Rousseeuw 1987; Dembele and Kastner 2003). The silhouette value lies in the range [− 1, 1]. Figure 6 shows that the optimal number of clusters is also 2.

Thus, FCM clustering with 2 clusters was performed to construct PPV prediction models with cluster 1 consisting of 34 blasting events and cluster 2 including 37 blasting events, as illustrated in Figure 7. Based on this, it can be seen that the 57.3% variability of the datasets is based on two principal components Dim1 and Dim2 with FCM clustering. The models were built upon the clusters and then compared to determine the best model. The testing datasets including 12 blasting events were divided into two clusters to evaluate the performance of the prediction models based on each cluster.

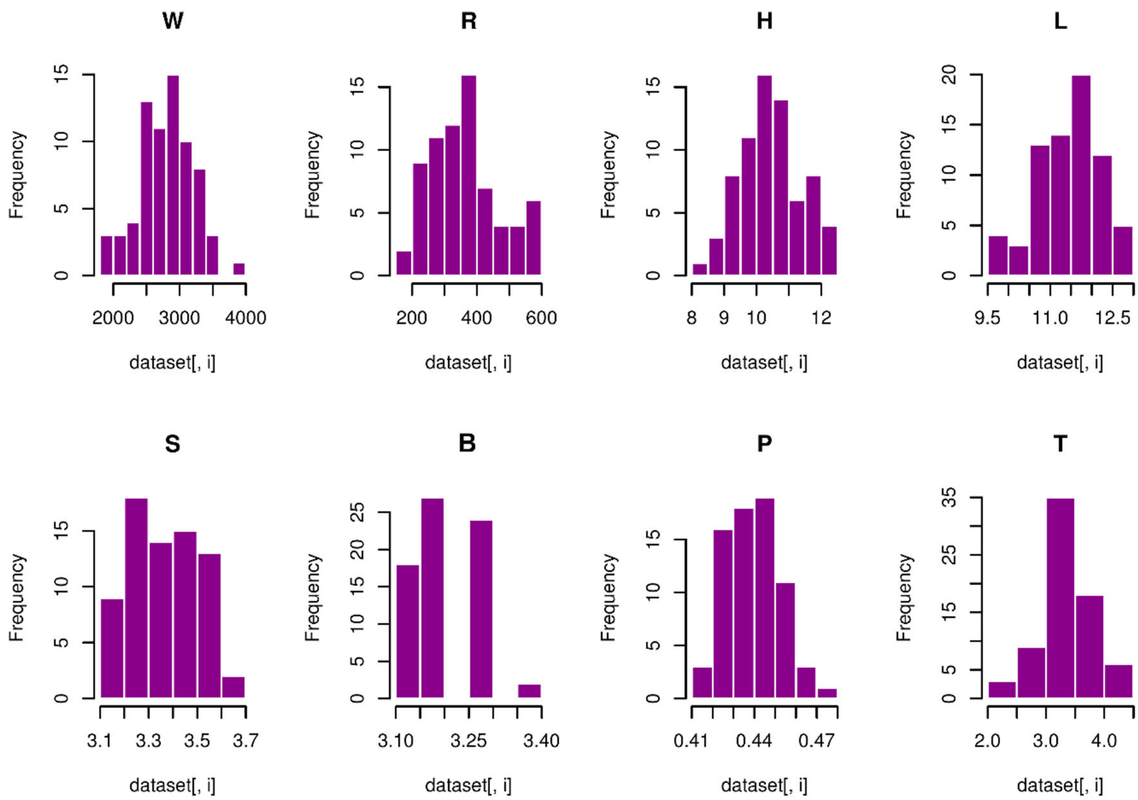


Figure 5. A view of the training datasets prepared without clustering.

Table 2. Evaluation process for the goodness of the clustering result

Number of clusters	Internal indices		
	PE	PC	MPC
2 Clusters	0.289	0.827	0.654
3 Clusters	0.446	0.750	0.625
4 Clusters	0.408	0.796	0.728

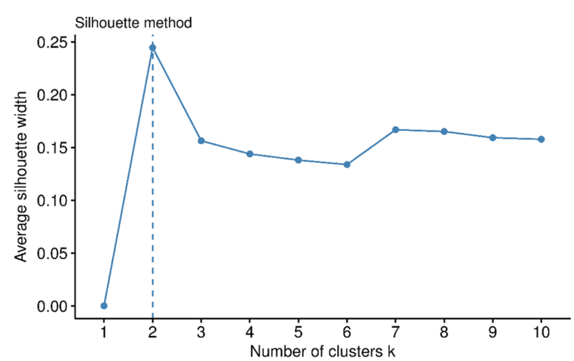


Figure 6. Optimal number of clusters.

ESTABLISHING THE PPV PREDICTION MODELS

Configuration of the USBM Model Empirical Parameters

As aforementioned, USBM model was used to estimate blast-induced PPV in this study due to its simplicity. According to Eq. 1, λ and α are the site factors determined using multivariate regression. The 71 blasting events in the training databases were used to identify the site parameters λ and α. However, only two input parameters, i.e., W and R, were utilized based on Eq. 1. Microsoft Excel 2016 was employed for the multivariate regression. λ and α were determined to be 78.524 and 1.783, respectively. The USBM model empirical parameters were identified using Eq. 1:

$$PPV = 78.524\left(\frac{R}{\sqrt{W}}\right)^{-1.783} \tag{3}$$

Configuration of the QRNN Model

In the QRNN model, it was difficult to determine the number of hidden nodes in the hidden layer. A grid search technique for hidden nodes was applied to accomplish this task. To avoid creating an overly complicated QRNN model, the hidden nodes were limited to within the range 1–10. To avoid overfitting, the penalty criteria were used along with penalty parameter values of 0.0001, 0.001, 0.01, 0.1, and 0. A tenfold cross-validation with three resamplings was also performed to configure QRNN. Finally, the QRNN model had an optimal value for a hidden node equal to 1 and penalty parameter equal to 0.1. The effect of searching is shown in Figure 8.

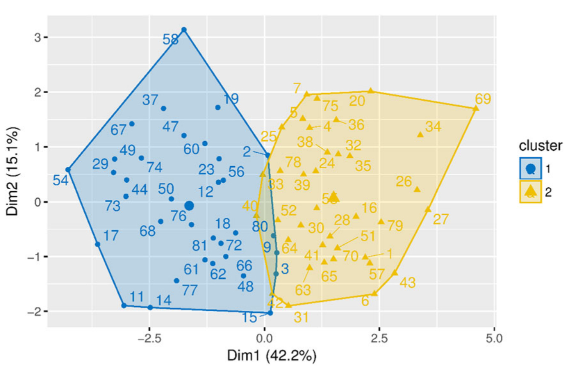


Figure 7. Clustering PPV data using the fuzzy C-means algorithm.

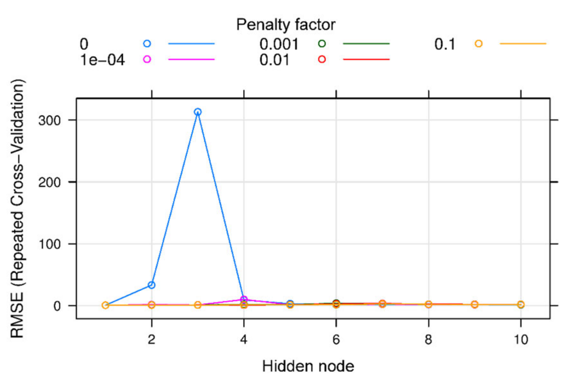


Figure 8. Performance of the QRNN model with various hidden nodes in the training datasets.

Proposing the FCM-QRNN Hybrid Model

The FCM was used to divide the training datasets into two clusters. The QRNN training process was conducted sequentially on the clusters along with a pre-processing procedure. The framework for the proposed blast-induced PPV prediction model is presented in Figure 9.

Accordingly, the FCM-QRNN model was set up based on Clusters 1 and 2. The grid search technique with the parameters input to the QRNN model with clusters was similar to that for the QRNN model without clustering. The tenfold cross-validation with three resampling was used in the FCM-QRNN model for both clusters. Figures 10 and 11 show the performance of the FCM-QRNN models for the clusters. It can be seen that the FCM-QRNN model based on Cluster 1 is optimal at hidden nodes = 2 and penalty = 0.01. The FCM-QRNN

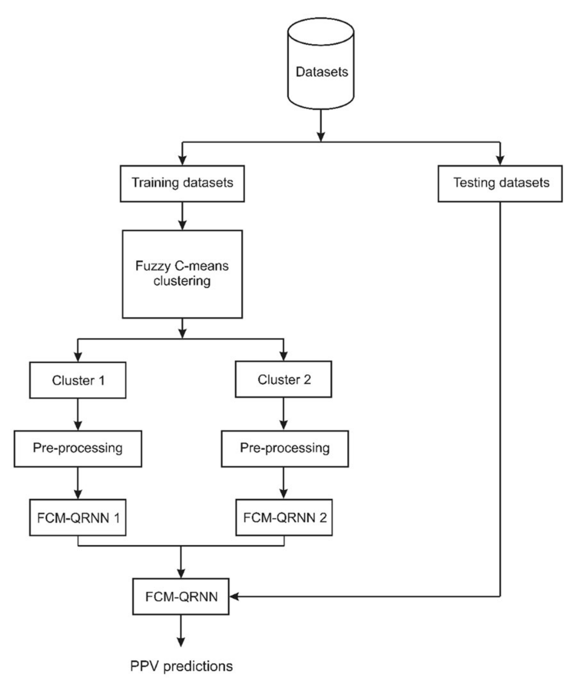


Figure 9. Proposed framework for estimating blast-induced PPV.

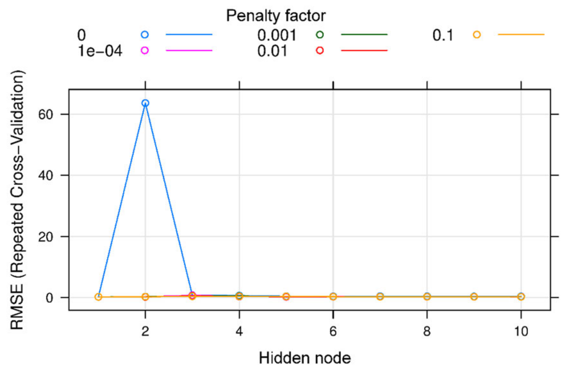


Figure 10. Parameter configuration of the FCM-QRNN model based on Cluster 1.

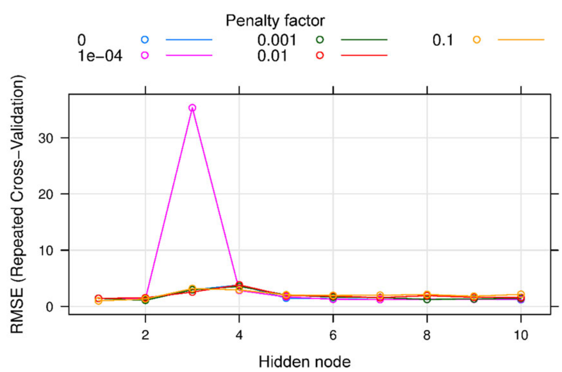


Figure 11. Parameter configuration of the FCM-QRNN model based on Cluster 2.

model based on Cluster 2 is optimal with a hidden node of 1 and a penalty of 0.1.

Development of the ANN Models

Five ANN approaches consisting of two and three hidden layers were expanded for comprehensive evaluation and comparison with the QRNN and FCM-QRNN models. An important factor in the utilization of ANNs is the determination of the number of the neuron(s) in each hidden layer. Using too few neuron(s) causes the characteristics of the input information to not show and overfitting to occur. Several neurons in the hidden layers could be increasing the training time and causing overfitting (Nguyen et al. 2018a). Therefore, a ''trial and error'' procedure was employed with different hidden neurons in each hidden layer. For the ANN technique, the min–max scale method was applied to avoid overfitting, by ensuring that the scale data lies within the interval [0, 1]. 200 repetitions were used for the development of the ANN models. The five ANN models were expanded to estimate blast-induced PPV: ANN 8-8-6-1, ANN 8-6-12-1, ANN 8-8-6-10-1, ANN 8-8-12-6-1, and ANN 8-6-10-8-1. Their architectures are illustrated in Figure 12.

Random Forest Model

The number of trees was selected as 2000 to affirm the diversity of the forest in the RF model. *mtry* was the parameter utilized to control the quality of the model. A search grid method was used to determine the optimal values for *mtry*; *mtry* lies in a constant range of 1–50. To avoid overfitting, ten-fold cross-validation with three resampling was used to develop the RF model. The RF model achieved optimal results with *mtry* = 7. Figure 13 illustrates the efficiency of the RF model for distinct *mtry* values.

RESULTS AND DISCUSSION

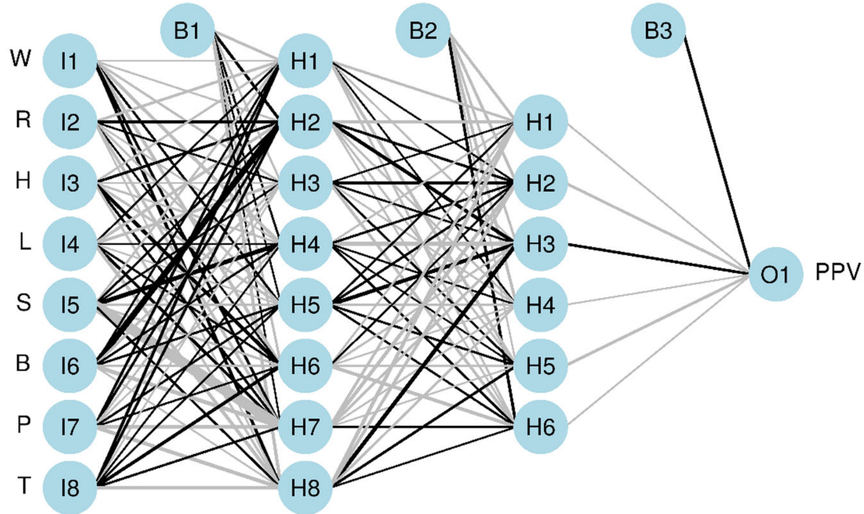
Model assessment Indicators

To analyze the efficiencies of the developed prediction approaches, efficiency indicators were utilized, such as the coefficient of determination (R^2), root-mean-squared error (RMSE) and mean absolute error (MAE), which were determined using Eqs. 4 to 6, respectively.

$$\mathrm{RMSE} = \sqrt{\frac{1}{n}\sum_{i=1}^{n}\left(y_{\mathrm{PPV}} - \hat{y}_{\mathrm{PPV}}\right)^2} \tag{4}$$

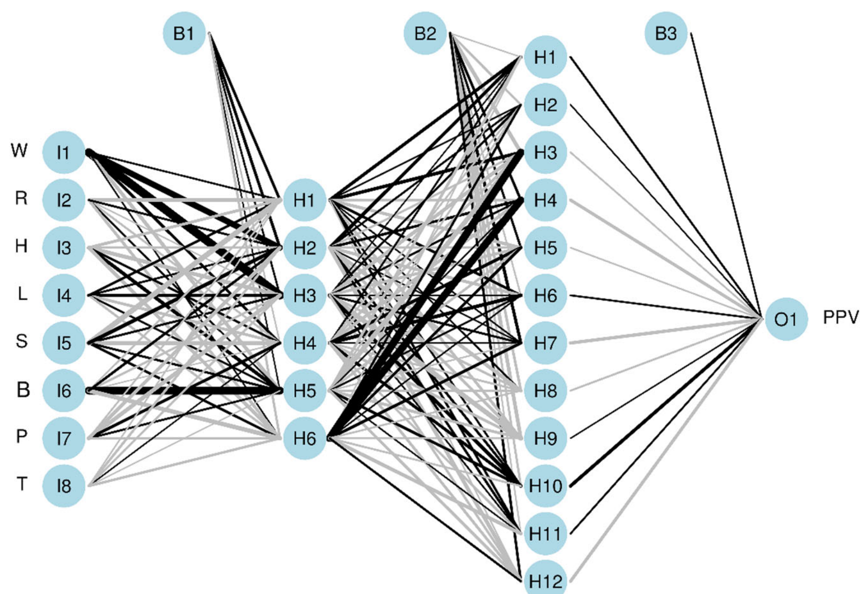
$$R^2 = 1 - \frac{\sum_{i=1}^{n}\left(y_{\mathrm{PPV}} - \hat{y}_{\mathrm{PPV}}\right)^2}{\sum_{i=1}^{n}\left(y_{\mathrm{PPV}} - \bar{y}_{\mathrm{PPV}}\right)^2} \tag{5}$$

$$\mathrm{MAE} = \frac{1}{n}\sum_{i=1}^{n}\left|y_{\mathrm{PPV}} - \hat{y}_{\mathrm{PPV}}\right| \tag{6}$$



I1 to I8 representing input variables (W, R, H, L, S, B, P, T); H1 to H8 representing the hidden neurons in the hidden layers; O1 is the output variable (PPV); B1 to B3 are bias. The lines representing the weights of the ANN model. In which, the dark green lines representing positive correlations; the dark orange lines representing negative correlations. The thickness of the lines represents for the values of weights.

(a)



I1 to I8 representing input variables (W, R, H, L, S, B, P, T); H1 to H12 representing the hidden neurons in the hidden layers; O1 is the output variable (PPV); B1 to B3 are bias. The lines representing the weights of the ANN model. In which, the dark green lines representing positive correlations; the dark orange lines representing negative correlations. The thickness of the lines represents for the values of weights.

(b)

◀**Figure 12.** ANN structures for estimating blast-induced PPV. (a) ANN 8-8-6-1 model; (b) ANN 8-6-12-1 model; (c) ANN 8-8-6-10-1 model; (d) ANN 8-8-12-6-1 model; (e) ANN 8-6-10-8-1 model.

where n stands for the total number of data, y_{PPV} stands for the measured amount, $\hat{y}_{\mathrm{PPV}}$ is the calculated amount, and $\bar{y}_{\mathrm{PPV}}$ stands mean of measured amounts.

Comparing and Evaluating the Prediction Models

To compare and analyze the efficiencies of the prediction models, the training and testing datasets were utilized. The performance indicators were calculated according to Eqs. 4 to 6 for both the training and the test datasets.

Five ANN models were developed in this study to predict blast-induced PPV. Their performances are shown in Table 3.

In Table 3, it can be seen that the ANN models performed well in the estimation. The ANN 8-8-12-6-1 model performed the best. This model was used for comparison with the remaining models in this study.

Further, the USBM, QRNN, ANN, and RF models using 71 blasting events for training and 12 blasting events for testing were employed for the comparison and evaluation of performance. In FCM-QRNN, the test datasets were split into two clusters as were the training datasets. Accordingly, there were 4 blasting events in Cluster 1 and 8 blasting events in Cluster 2 for FCM-QRNN. The performances of the forecasting models are shown in Table 4.

In Table 4, it can be seen that the USBM empirical method was the least efficient. The remaining advanced models used artificial intelligence and provided much higher efficiency. QRNN had higher performance than conventional ANNs. In contrast, the ANN model only achieved lower performance than FCM-QRNN model. For comprehensive comparison, RF was also used to estimate blast-induced PPV. Table 4 shows that the RF model also had a slightly lower performance than the QRNN and FCM-QRNN models.

It can be seen that QRNN is a powerful model for estimating blast-induced PPV. More particularly, the FCM clustering technique appears to add to the QRNN power to create a powerful hybrid model, i.e., FCM-QRNN, as shown in Table 4. Thus, FCM-QRNN was the most prominent of the five models in Table 4. Figure 14 illustrates the relationship between the measured and predicted values for the five developed PPV prediction models.

Importance of the Estimation Variables

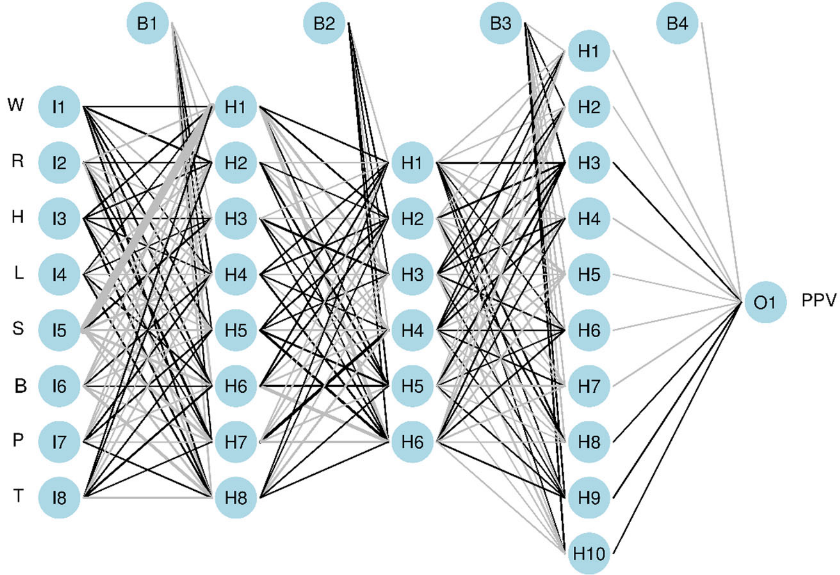
The number of input variables was high, and not all input variables had sufficient effect on the efficiency of the models. To assess the impacts of the input variables, a method to estimate the importance of the input variables was developed (Quinlan 1992; Gevrey et al. 2003). Figure 15 illustrates the importance of the input variables in this study.

S, W, and R had the most significant effect on the efficiency of FCM-QRNN (Fig. 15). The impact of the remaining variables was not high. Therefore, S, W, and R should be selected as the primary input variables for predicting blast-induced PPV using the FCM-QRNN model.

CONCLUSIONS AND RECOMMENDATIONS

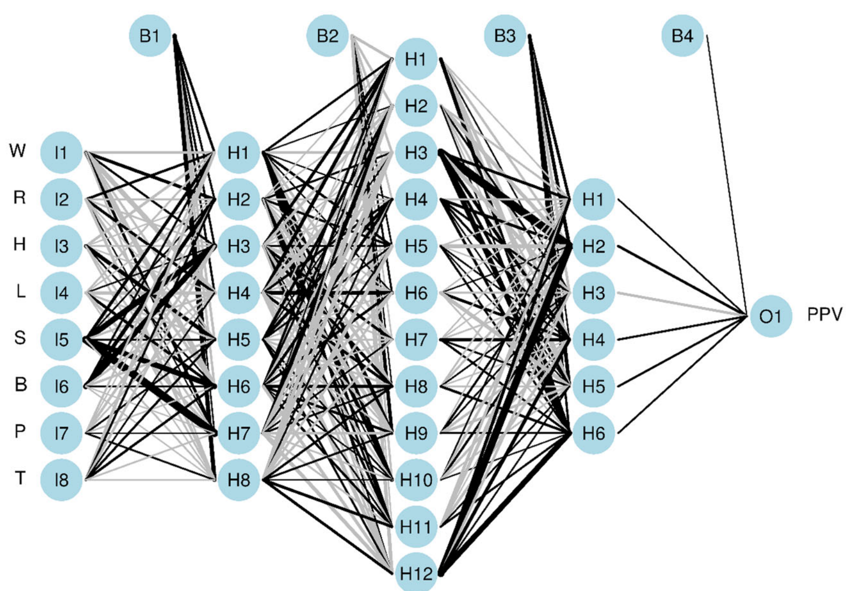
Blasting is indispensable in open-pit mines. Therefore, the damage from ground vibration (PPV), air-blast overpressure, fly rock, and the back-break need to be carefully controlled. Based on the results of this study, we arrived at the following conclusions:

- Data collection should be performed carefully to prevent outliers from reducing the quality and accuracy of the PPV predictions.



I1 to I8 representing input variables (W, R, H, L, S, B, P, T); H1 to H10 representing the hidden neurons in the hidden layers; O1 is the output variable (PPV); B1 to B4 are bias. The lines representing the weights of the ANN model. In which, the dark green lines representing positive correlations; the dark orange lines representing negative correlations. The thickness of the lines represents for the values of weights.

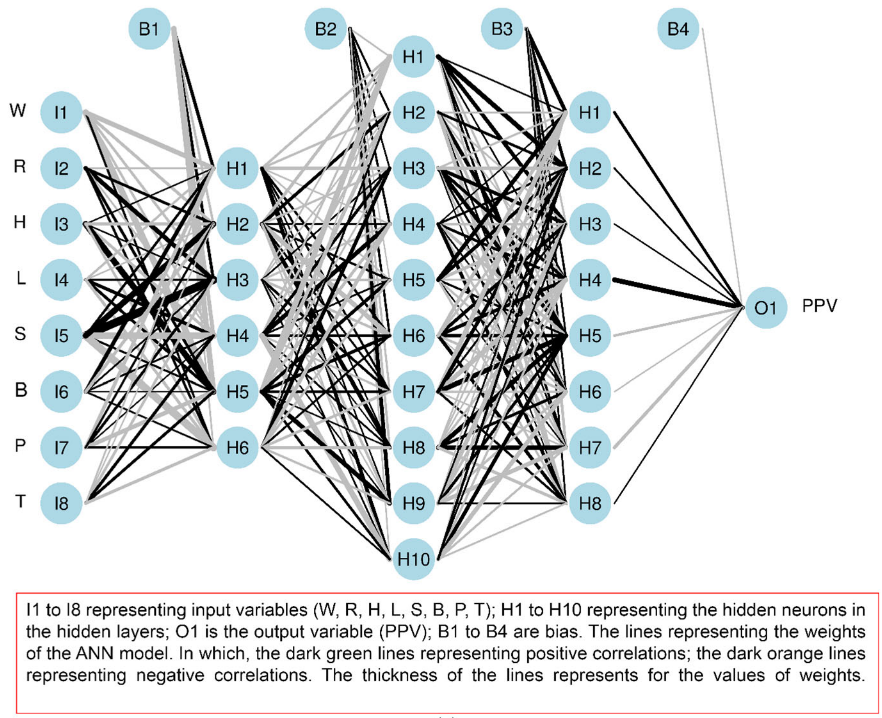
(c)



I1 to I8 representing input variables (W, R, H, L, S, B, P, T); H1 to H12 representing the hidden neurons in the hidden layers; O1 is the output variable (PPV); B1 to B4 are bias. The lines representing the weights of the ANN model. In which, the dark green lines representing positive correlations; the dark orange lines representing negative correlations. The thickness of the lines represents for the values of weights.

(d)

Figure 12. continued.



(e)

Figure 12. continued.

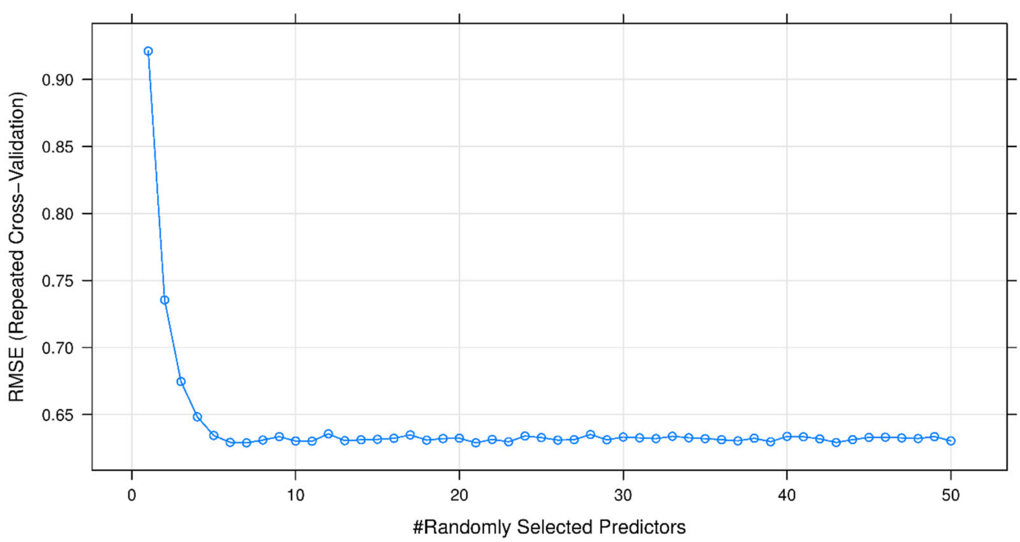


Figure 13. Performance of the RF model.

Table 3. Efficiency indices of the ANN models

Models	Training datasets			Test datasets		
	RMSE	R^2	MAE	RMSE	R^2	MAE
ANN 8-8-6-1	0.477	0.94	0.295	0.458	0.932	0.31
ANN 8-6-12-1	0.483	0.939	0.291	0.483	0.923	0.355
ANN 8-8-6-10-1	0.414	0.955	0.230	0.493	0.926	0.291
ANN 8-8-12-6-1	**0.454**	**0.946**	**0.258**	**0.436**	**0.937**	**0.282**
ANN 8-6-10-8-1	0.495	0.936	0.311	0.457	0.931	0.339

The best ANN model was shown in bold type

Table 4. Performance indices of the proposed PPV prediction models

Models	Training datasets			Test datasets		
	RMSE	R^2	MAE	RMSE	R^2	MAE
USBM (empirical)	1.345	0.658	0.750	1.017	0.793	0.708
QRNN	0.512	0.920	0.306	0.392	0.952	0.189
FCM-QRNN	**0.426**	**0.952**	**0.245**	**0.348**	**0.961**	**0.237**
ANN	0.454	0.946	0.258	0.436	0.937	0.282
RF	0.629	0.894	0.371	0.425	0.950	0.290

The best ANN model was shown in bold type

A more voluminous set of data could be advantageous for PPV prediction involving clustering techniques.

- FCM clustering techniques are excellent for classifying and optimizing input data. They play a vital role in improving the performances of the forecasting models.
- QRNN is a robust nonlinear regression model, particularly for the PPV prediction in this study. This has been proven to be more robust than both the ANN and RF models. QRNN becomes even more robust when combined with FCM algorithm (FCM-QRNN) to predict blast-induced PPV by adjusting undesirable influences on the surrounding protected structures.
- FCM-QRNN model could be utilized to predict blast-produced PPV in the Tan Dong Hiep quarry. The blast-induced PPV could be accurately predicted before conducting the blasts. The parameters of the blast design could then be adjusted to ensure the safety of the surrounding structures, especially *S*, *W*, and *R*. This model is can help improve the blasting performance and environmental protection during and after blasting operations.

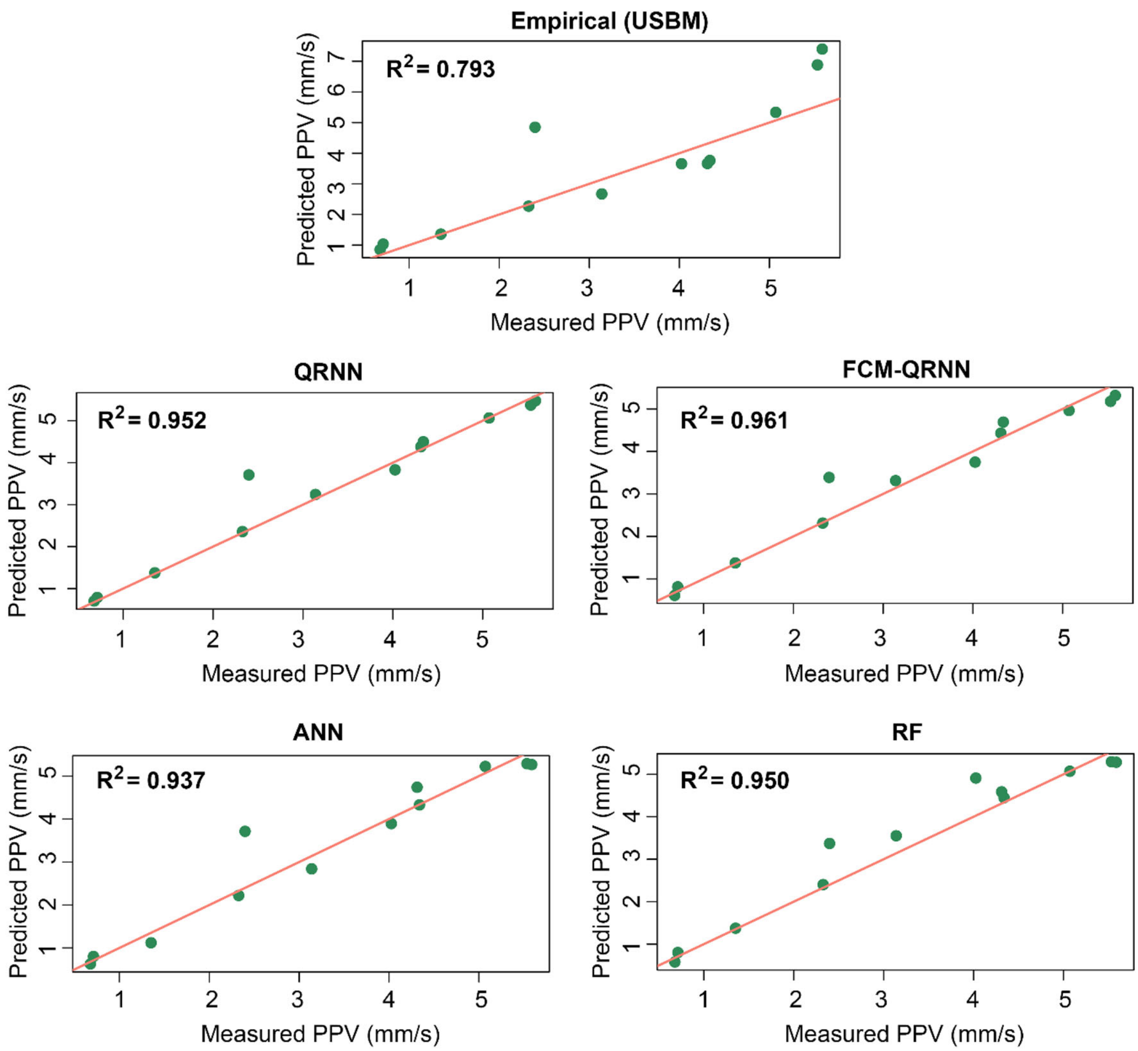


Figure 14. Relationship between the predicted and measured PPV values for the different prediction models.

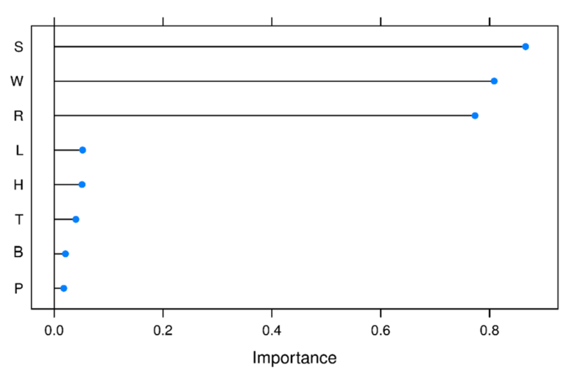


Figure 15. Effect of input variables on the efficiency of FCM-QRNN.

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