

## Developing an Advanced Soft Computational Model for Estimating Blast-Induced Ground Vibration in Nui Beo Open-pit Coal Mine (Vietnam) Using Artificial Neural Network

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**Abstract** The principal object of this study is blast-induced ground vibration (PPV), which is one of the dangerous side effects of blasting operations in an open-pit mine. In this study, nine artificial neural networks (ANN) models were developed to predict blast-induced PPV in Nui Beo open-pit coal mine, Vietnam. Multiple linear regression and the United States Bureau of Mines (USBM) empirical techniques are also conducted to compare with nine developed ANN models. 136 blasting operations were recorded in many years used for this study with 85% of the whole datasets (116 blasting events) was used for training and the rest 15% of the datasets (20 blasting events) for testing. Root Mean Square Error (RMSE), Determination Coefficient ( $R^2$ ), and Mean Absolute Error (MAE) are used to compare and evaluate the performance of the models. The results revealed that ANN technique is more superior to other techniques for estimating blast-induced PPV. Of the nine developed ANN models, the ANN 7-10-8-5-1 model with three hidden layers (ten neurons in the first hidden layer, eight neurons in the second layers, and five neurons in the third hidden layer) provides the most outstanding performance with an RMSE of 1.061,  $R^2$  of 0.980, and MAE of 0.717 on testing datasets. Based on the obtained results, ANN technique should be applied in preliminary engineering for estimating blast-induced PPV in open-pit mine.

### 1. Introduction

Blasting is one of the most effective methods for rock breakage in open-pit mine. However, its environmental impacts are significant and should be considered, including ground vibration (PPV), air overpressure, and fly rock [14, 17, 32]. Of

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these side effects, PPV is a significant influence on surrounding structures such as benches, slopes, groundwater, and residential areas [21, 28, 34, 32]. Therefore, the precise prediction of PPV is necessary to minimize adverse impacts on the surrounding environment.

The level of PPV is influenced by different parameters. They can be divided into three main groups: blast design parameters, explosive parameters, and rock mass properties [18, 26, 57]. Of these main groups, the blast design parameters are controllable parameters including blast hole diameter, length of the borehole, explosive capacity, column charge length, length of stemming, powder factor, spacing, methods and diagrams of blasting [26, 35]. In the explosive parameters, type of explosive (ANFO, water gel, emulsion, or dynamite), the velocity of detonation (VoD), its density, powder factor ( $\text{kg ANFO/m}^3$ ) are also controllable parameters [24]. Unlike the parameters of the first and second groups, the parameters of the third groups are uncontrollable parameters such as rock hardness, cracking, stratification, burden, and compressive strength of rock [20]. Based on the parameters of these groups, it can be seen that accurate prediction of PPV is not simple. Because of its complexity, many scientists have chosen to approach experimental techniques for estimating PPV based on two major parameters, the explosive capacity (W) and the monitoring distance (R) [7, 22, 37, 43, 51, 59]. However, based on the results of some studies, empirical techniques are often less accurate and do not applied in all sites [23, 29, 36].

Reviewing recent literature shows that the complexity of the parameters that affect PPV can be solved by artificial intelligence (AI). Sheykhi, Bagherpour [55] have developed a hybrid model using Support Vector Regression (SVR) and Fuzzy C-means clustering (FCM) algorithms (FCM-SVR) for predicting blast-induced PPV in Sarcheshmeh copper mine, Iran with 120 blasting events and 7 different parameters. The SVR model and the United States Bureau of Mines (USBM) empirical equation were also used to evaluate the effectiveness of the FCM-SVR model. Their results indicated that the SVR model provided higher performance than the USBM experimental technique. In particular, it achieved optimum performance when combined with the FCM algorithm and the FCM-SVR hybrid model proposed to predict the actual PPV. In another study, Ragam and Nimaje [48] have developed a simple artificial neuron network with a hidden layer consisting of 5 hidden neurons and a feed-forward back propagation algorithm for predicting PPV in ACC mine, Iran. The results showed that the ANN model predicted PPV better than other techniques they have tested. Based on neural network, the group method of data handling (GMDH) model was developed by Mokfi, Shahnazar [39] to predict PPV in a quarry of Malaysia, using 102 blasting operations. They concluded that GMDH forecasting technique could be presented as a powerful technique in predicting PPV with  $R^2$  of 0.911 and RMSE of 0.889. In addition, research on the application of AI hybrid models and experimental techniques was conducted by Hasanipanah, Amnieh [26] with the fuzzy system (FS) and imperialistic competitive algorithm (ICA) to predict PPV in Miduk copper mine, Iran. Their research has shown promising results with an  $R^2$  of 0.942.

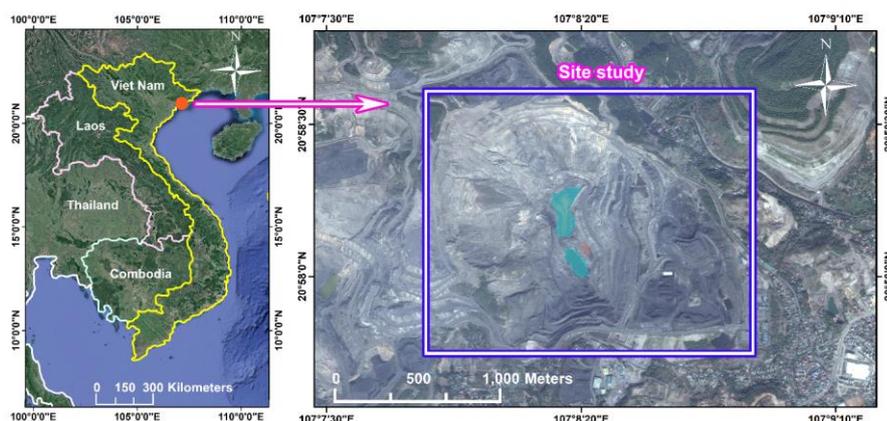
Based on the review of the literature, it can be seen that AI techniques have been studied and developed quite firmly in the predicted blast-induced PPV in open-pit mine. Nevertheless, no model can represent all areas of study. Thus, in this study, we develop some ANN models for predicting blast-induced PPV in Nui Beo open-pit coal mine, Vietnam. Another model, namely Multiple Linear Regression (MLR) and the United States Bureau of Mines (USBM) practical techniques were also used in this study to assess the effectiveness of the developed ANN models.

The article is organized into six sections: Section 1 gives an overview of the literatures and the reasons for doing this research; Section 2 summarizes the study area and the data used; Section 3 gives an overview of the methodologies used; Section 4 develops PPV forecasting models; Section 5 presents the results of this work and discussion; Finally, the conclusions and recommendations in this work.

## 2. Study area and data used

### 2.1. Study area

The site selected for this study was Nui Beo open-pit coal, Vietnam with a production of 1,125,000 tons/year; the capacity of overburden is 4.815.000 m<sup>3</sup>/year. It located between latitudes 20°57'50" N and 20°58'35" N, and between longitudes 107°7'50" E and 107°8'50" E (Fig. 1). The most striking feature of this study area is that it is located between Ha Long City, where Ha Long Bay is one of the seven natural wonders of the world recognized by UNESCO [47]. The residential area is adjacent to the mine with a distance of about 100m to the nearest residential unit. Therefore, the mine must be conducted in parallel two methods of rock breaking are drilling-blasting and mechanical equipment. Of these methods, drilling and blasting accounted for 98% of the total capacity of rock breakage.



**Fig. 1** Location of Nui Beo open-pit coal mine

Explosives used on the mine are ANFO, Z113 and AN13 emulsion with 250mm for blast hole diameter in rock breakage and 42mm diameter for oversize rock breakage. The blasting method was applied in Nui Beo open-pit coal mine is non - electric delay blasting. Explosive capacity in an explosion is up to 20,000 tons. As the mine is near the residential area and the explosive capacity used in each blasting event is large, the impact of PPV is not small. Moreover, the Nui Beo open-pit coal mine has repeatedly faced the lawsuit due to the impact of PPV caused. Therefore, accurate predictions of blast-induced PPV in this area are necessary.

### 2.2 Describe the data used

As related, the parameters that affect PPV are so many. It is difficult to collect and evaluate all the parameters. Thus, in this study, seven input parameters were used to predict blast-induced PPV in Nui Beo open-pit coal mine, including the elevation between blast sites and monitor (H), explosive charge per delay (W), monitoring distance (R), power factor (P), burden (B), spacing (S), time delay (T). Of these input parameters, R is determined by handheld GPS system; the remaining parameters are taken from 136 blasts design. PPV is measured by Blastmate III (Instatel, Canada) [3] in a range of 0.127-254 mm/s. The data used in this study are summarized in Table 1.

**Table 1.** Summary of the data used

W	R	H	P
Min. : 1109	Min. :107.0	Min. : -38.00	Min. :0.3500
1st Qu.: 3526	1st Qu.:233.0	1st Qu.: 6.50	1st Qu.:0.3900
Median : 5086	Median :334.0	Median : 24.00	Median :0.4300
Mean : 5455	Mean :357.9	Mean : 23.24	Mean :0.4274
3rd Qu.: 7214	3rd Qu.:471.2	3rd Qu.: 40.00	3rd Qu.:0.4625
Max. :12312	Max. :797.0	Max. : 81.00	Max. :0.5000
B	S	T	PPV
Min. :6.600	Min. :7.400	Min. :6.600	Min. : 0.91
1st Qu.:7.000	1st Qu.:7.700	1st Qu.:6.900	1st Qu.: 5.51
Median :7.400	Median :8.000	Median :7.350	Median :11.10
Mean :7.404	Mean :7.979	Mean :7.303	Mean :11.80
3rd Qu.:7.825	3rd Qu.:8.200	3rd Qu.:7.600	3rd Qu.:17.18
Max. :8.200	Max. :8.500	Max. :8.000	Max. :26.83

### 3. Background of Empirical, MLR, and ANN

#### 3.1. Empirical

The empirical technique is one of the blast-induced PPV forecasting methods in open-pit mine because they are easy to use and capable of producing results quickly. Of the current experimental techniques, the United States Bureau of Mines (USBM) remained the most commonly used empirical method for predicting PPV and was proposed by Duvall and Petkof [15]. The USBM empirical method is described as follows:

$$PPV = k \left( \frac{R}{\sqrt{W}} \right)^{-b} \quad (1)$$

Where:  $W$  is the explosive capacity, Kg;  $R$  is the distance between blast face and monitoring point, m;  $k$  and  $b$  are the site factors and are determined by the multivariate regression analysis.

In this study, USBM empirical method was used to estimate blast-induced PPV in Nui Beo open-pit coal mine. The PPV forecast results using the USBM technique are detailed in the next sections.

### 3.2. Multiple linear regression

Multiple linear regression (MLR) is a linear equation that fits a dependent variable with multiple independent variables [1]. Numerous studies in rock mechanics and mining have been published based on the MLR method [4, 16, 25, 53, 52, 56, 60]. For example, Ghiasi, Askarnejad [19] successfully used the MLR for predicting rock fragmentation in Gole Gohar iron ore open pit mine, Iran. The results of the MLR method were higher than those of ANN with  $R^2 = 0.89$  and  $RMSE = 0.19$ . In another study, Shepel, Grafe [54] have also successfully developed the MLR model for evaluating cutting forces in granite treated with high-power (24 kW) microwave radiation. The application of the MLR model allows for a more detailed analysis of the effects of high-power microwave radiation on granite parameters, helping engineers improve their stone cutting productivity. Generally, MLR can be described by the following equation:

$$y = a_0 + a_1x_1 + a_2x_2 + \dots + a_nx_n \quad (2)$$

Where,  $x_i$  ( $i = 1 \dots n$ ) and  $y$  represent independent and dependent variables, respectively. Also,  $a_i$  ( $i = 0, 1, \dots, n$ ) represent regression coefficients.

In this study, MLR was developed to predict blast-induced PPV in Nui Beo open pit coal mine with seven input parameters. The multiple regression formulae for predicting PPV in this site study is illustrated as follows:

$$PPV = a_0 + a_1W + a_2R + a_3H + a_4P + a_5B + a_6S + a_7T \quad (3)$$

Where  $a_0 \div a_7$  are regression coefficients and are determined by the multivariate regression analysis method. The results for determining the multiple regression equations for this problem are presented in the next section.

### 3.3. Artificial neural networks (ANN)

Artificial neural networks (ANNs) can be considered as an artificial tool based on human brain simulations. These include neurons that are connected to each other in a flexible and fast way [63]. Many scholars have efforted to develop ANN models for various issues in the mining field and achieved the desired results [5, 9, 31, 38, 40, 42, 45]. For example, Muhammad and Ferentinou [44] have developed an ANN model to assess the slope stability based on 141 historical records and 18 input parameters. The results show that ANN produces rapid convergence with high reliability. An ANN model was also developed based on optimized input parameters by the Genetic Algorithm and proposed by Armaghani, Hasanipanah [8] for

predicting air overpressure in Penang, Malaysia. The proposed ANN model yielded results that could not be more excellent.

The basic structure of an ANN model includes an input layer, hidden layer(s) and output layer [50]. In input layer, neurons act as input variables and transmit data to hidden layers (s) via the transfer function. In the first hidden layer, the neurons will receive the result from the input layer and process and calculate the weights and send it to the second hidden layer via the propagation function. The process continues like that until the results are passed to the output layer [64].

The processing of data in the hidden layers is also called training. The outputs depend heavily on the training process. In ANN, supervised learning and unsupervised learning are two types of learning that can be applied to each ANN [46]. In this study, supervised learning was applied to solve the regression problem in predicting blast-induced PPV. Seven parameters are introduced into the input layer and processed according to ANN model as Fig. 2. The ANN models are developed for predicting PPV in this study, and their performance is discussed in greater detail in the next sections.

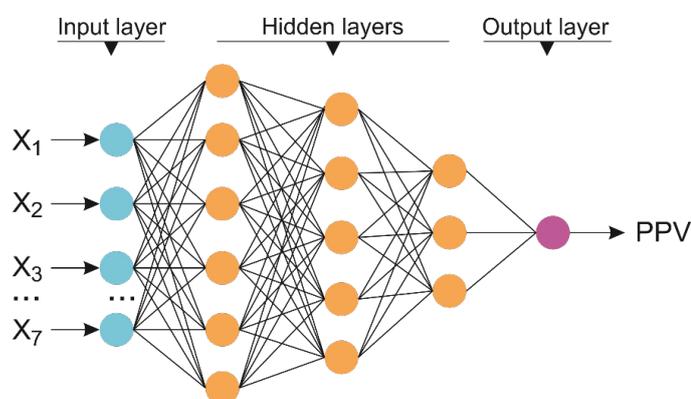


Fig. 2 The general structure of the ANN model for predicting PPV in this study

#### 4. Developing PPV predictive models

For developing PPV predictive models, data needs to be prepared and processed. In this study, 136 blasting events were divided into two sets of data: 85% of the whole datasets (116 observations) for training, and the rest 15% (20 observations) for testing. Based on the training datasets, the predictive models are developed in the next sections.

##### 4.1. Empirical

As related, the USBM experimental technique in Eq. 1 is used to estimate blast-induced PPV. Accordingly, the site factors  $k$  and  $b$  are defined by multivariate regression analysis method. The SPSS version 18.0 [12] is used to determine the site factors  $k$  and  $b$ . The results of multivariate regression analysis for the values of  $k$  and  $b$  are 44.067 and 1.023, respectively. The experimental USBM for predicting PPV in this study is described in Eq. 4:

$$PPV = 44.067 \left( \frac{R}{\sqrt{W}} \right)^{-1.023} \quad (4)$$

#### 4.2. MLR

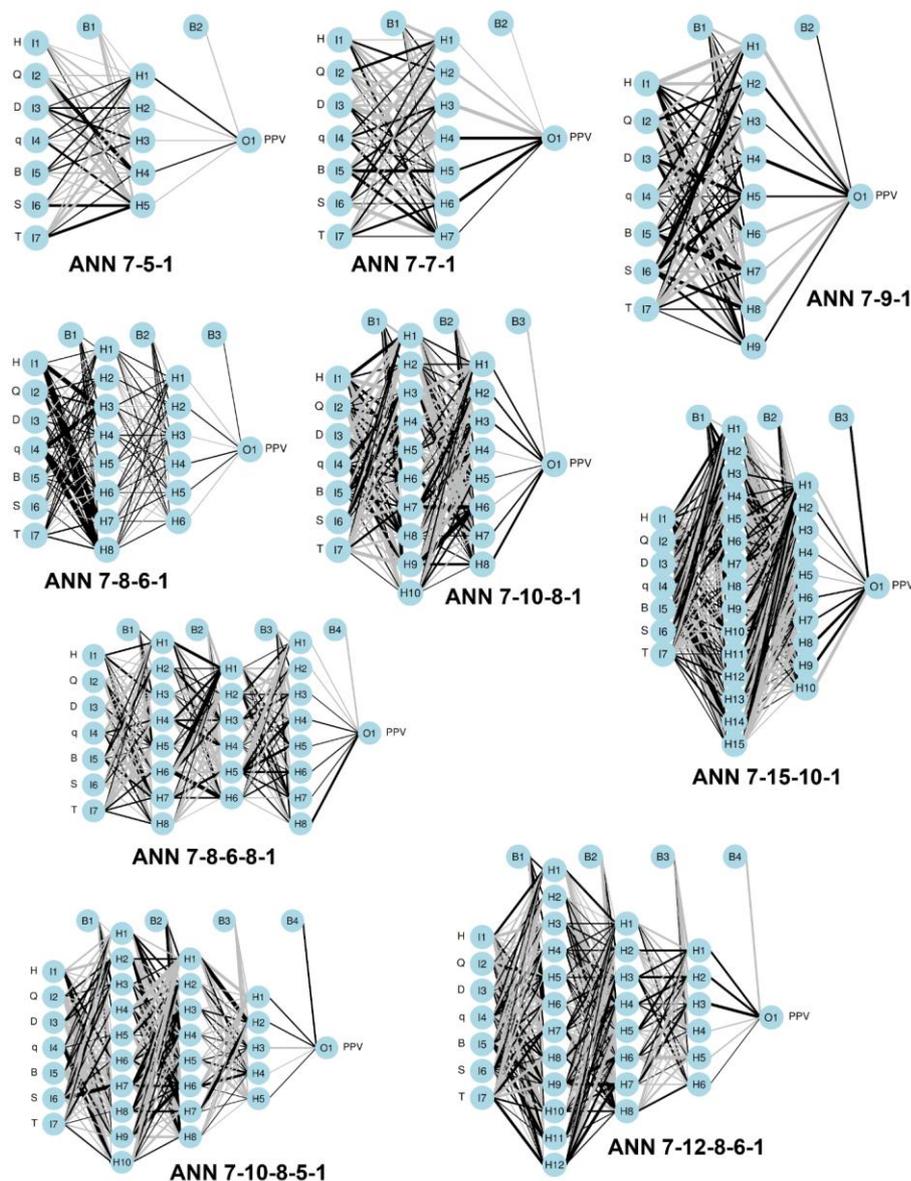
In MLR, multivariate regression analysis techniques are also used to determine regression coefficients according to Eq. 3. SPSS version 18.0 is again used to determine the regression coefficients for MLR in this study. Note that, the training datasets for building MLR model is similar to the for building the empirical model.

Based on that, the regression coefficients for the variables are determined correspondingly in Eq. 3 are -5,044; 0.0015; -0.0047; -0.082; -5.161; 0.046; 1,055; and 0.756. The MLR model for predicting blast-induced PPV in Nui Beo open-pit coal mine is defined by the following equation:

$$PPV = 0.0015W - 0.0047R - 0.082H - 5.161P + 0.046B + 1.055S + 0.756T - 5.044 \quad (5)$$

#### 4.3. ANN

For ANN technique, the most critical problem is neural network design [10]. A neural network is designed that includes training algorithms, hidden layers, and hidden neurons in each hidden layer [30]. The most challenging problem when designing an ANN is determining the number of hidden layers and the number of neurons in each hidden layer [13, 58, 62]. In theory, an ANN with one hidden layer can solve most problems in practice [11]. A neural network with two or more hidden layers can solve problems better depending on the circumstances. However, too many hidden layers in an ANN will increase the processing time of the network [27, 61]. Thus, a “trial and error” procedure with one, two, and three hidden layers is applied for developing ANN models in this study.



**Fig. 3** Structure of the ANN models for predicting PPV

The training datasets in ANN technique is used similarly to empirical and MLR methods. However, the min-max scale method and scale the data in the interval [0,1] was applied to avoid overfitting. Usually scaling in the intervals [0,1] or [-1,1] tends to give better results. As a result, nine ANN models were developed for predicting blast-induced PPV in this site with one, two and three hidden layers in Fig. 3.

In Fig. 3, the black line represents for positive weights and the grey line represents for negative weights. Line thickness is in proportion to magnitude of the weight relative to all others. From I1 to I7 are the input variables, W, R, H, P, B, S, T, respectively. H1 to H15 are the neurons in hidden layers. And O1 is the output

layer, PPV, respectively. B1, B2, B3 and B4 are bias layers that apply constant values to the nodes.

## 5. Results and discussion

### 5.1. Performance metrics for evaluating PPV predictive models

To evaluate the performance of the developed predictive models, the performance indicators are used, including Root Mean Squared Error (RMSE), Coefficient of determination ( $R^2$ ), and Mean Absolute Error (MAE), which are calculated using equation (6-8), respectively.

$$RMSE = \sqrt{\frac{1}{n} \sum_{PPV=1}^n (y_{PPV} - \hat{y}_{PPV})^2} \quad (6)$$

$$R^2 = 1 - \frac{\sum_{PPV} (y_{PPV} - \hat{y}_{PPV})^2}{\sum_{PPV} (y_{PPV} - \bar{y})^2} \quad (7)$$

$$MAE = \frac{1}{n} \sum_{PPV=1}^n |y_{PPV} - \hat{y}_{PPV}| \quad (8)$$

Where  $n$  is the total number of data.  $y_{PPV}$  is the measured value,  $\hat{y}_{PPV}$  is the predicted value and  $\bar{y}$  is mean of measured values. In the most optimal model,  $R^2$  should be equal to 1, RMSE and MAE should be equal to 0, respectively.

### 5.2. Comparisons of PPV predictive models

Once the forecasting models are available, the performance of the models is evaluated through performance indices in Eq. 6-8 on both the training datasets and the testing datasets. The testing datasets are considered as unseen data for objectively evaluating the quality of developed predictive models. As a result, the performance of predictive models, including empirical, MLR, and ANN is demonstrated in Table 2.

From Table 2, it can be seen that USBM experimental technique provides the lowest performance for estimating blast-induced PPV in this case study with  $RMSE = 4.446$  and  $R^2 = 0.816$  on testing datasets. Examining the literature shows that USBM is also the most widely used experimental technology and many studies have successfully performed with this technique [2, 6, 32, 33, 41, 43]. However, the effectiveness of experimental techniques has not been well appreciated.

**Table 2.** Performance of predictive models

Model	Training datasets			Testing datasets		
	RMSE	R2	MAE	RMSE	R2	MAE
Empirical (USBM)	5.382	0.63	2.802	4.446	0.816	2.873
MLR	2.809	0.833	1.691	1.647	0.947	1.378
ANN 7-5-1	2.187	0.898	1.374	2.715	0.839	2.253

ANN 7-7-1	0.903	0.983	0.702	1.354	0.960	0.922
ANN 7-9-1	0.917	0.982	0.683	1.949	0.916	1.327
ANN 7-8-6-1	1.164	0.971	0.705	2.273	0.891	1.403
ANN 7-10-8-1	0.727	0.988	0.571	1.621	0.952	1.027
ANN 7-15-10-1	0.928	0.981	0.651	1.915	0.921	1.307
ANN 7-8-6-8-1	0.736	0.988	0.565	1.350	0.960	1.036
<b>ANN 7-10-8-5-1</b>	<b>0.669</b>	<b>0.990</b>	<b>0.528</b>	<b>1.061</b>	<b>0.980</b>	<b>0.717</b>
ANN 7-12-10-6-1	0.840	0.985	0.559	1.594	0.947	1.200

Considering the MLR model on both the training datasets and the testing datasets shows that MLR seems to work quite well in this case with an RMSE of 1.647,  $R^2$  of 0.947, and MAE of 1.378 on testing datasets. The MLR model results showed that the input variables in this study might have a relatively linear relationship. In addition, the number of input variables in the study is quite high. Therefore, the Standardized Rank Regression Coefficients (SRRC) is applied for sensitivity analysis based on linear or monotonic assumptions in the case of independent factors [49]. The results of the sensitivity analysis for the input variables are shown in Table 3.

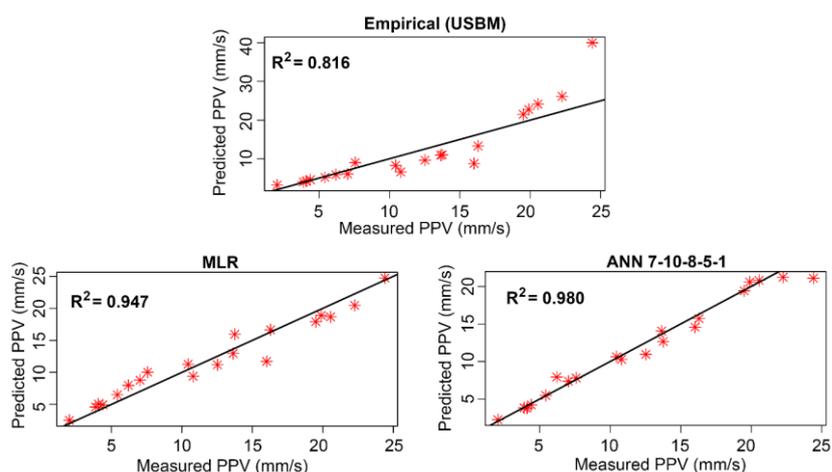
**Table 3.** Sensitivity indices of independent factors

	original	bias	std. error	min. c.i.	max. c.i.
W	0.615516	0.000404	0.018758	0.577353	0.645196
R	-0.12097	-0.00018	0.003134	-0.12666	-0.11528
H	-0.33539	0.001342	0.021048	-0.37885	-0.29262
P	-0.03751	-0.00016	0.002435	-0.04177	-0.03159
B	0.003667	7.56E-06	0.000235	0.003091	0.004123
S	0.052638	0.000102	0.004313	0.043578	0.061577
T	0.051717	-6.1E-05	0.003389	0.044385	0.057916

Accordingly, it can be seen that although the performance of the MLR model is rather high, not all input variables have a good linear relationship. Table 3 showed that only the maximum explosive capacity (W), monitoring distance (R), and the elevation between blast sites and monitor (H) are the main factors influencing the performance of the PPV prediction model. In some previous studies, some researchers have concluded that W and R are the two most influential variables in the quality of the PPV prediction model [7, 22, 37, 43, 51, 59]. However, the results of this study suggest that H is a parameter that should be added as one of the three factors that have a significant influence on the performance of the model, including W, R, H.

Regarding the ANN models developed, it can be seen that nine developed ANN models have uneven performance. Some ANN models provide higher performance than the MLR model, but some models perform less efficiently than the MLR model. Therefore, comparing the ANN models with one, two, and three hidden layers is interesting in this study. It can be seen that ANN model with only one hidden layer can handle quite well PPV prediction problem in this case, i.e., ANN 7-7-1 with an RMSE of 1.354,  $R^2$  of 0.960, and MAE of 0.922. The ANN

model with two hidden layers works well for predicting blast-induced PPV in this study. However, the best ANN model with two hidden layers in this study (ANN 7-10-8-1) only achieved an RMSE of 1.621,  $R^2$  of 0.952, and MAE of 1.027, which is lower than that of ANN 7- 7-1 with one hidden layer. On the other hand, take a closer Table 3, it can be seen that not the ANN model with more hidden layers offers lower performance. The evidence is that the ANN 7-10-8-5-1 model with three hidden layers is the best performing model among the nine developed ANN models with RMSE = 1.061,  $R^2$  = 0.980, and MAE = 0.717 on testing datasets. With the difference between RMSE and MAE of the ANN 7-10-8-5-1 model is 0.344, indicating that the model is highly stable. More interesting in this study is the ANN model 7-12-10-6-1 with more hidden neurons provided lower performance than the ANN model 7-10-8-5-1 with an RMSE of 1.594,  $R^2$  of 0.947, and MAE of 1.200 on testing datasets. This shows that too many hidden layers and hidden neurons in each hidden layer not only increases the processing time of the ANN model but also the lack of match between neurons, which reduces the efficiency of the model. Therefore, the proposed ANN 7-10-8-5-1 model is the best model for predicting blast-induced PPV in this study. Fig. 4 illustrates the relationship between predicted and measured values of empirical, MLR, and ANN techniques.



**Fig. 4** Measured and predicted PPV values of Empirical, MLR and ANN models

## 6. Conclusions and recommendations

Blasting is one of the most effective methods for hard-rock fragmentation in mining and civil fields. Besides its advantages, the ground vibration (PPV) caused by blasting operations is one of the disadvantages that need to be estimated accurately. Forecasting blast-induced PPV in open-pit mine can be accomplished using a variety of methods. In this study, we have presented three approaches to solve the problem of PPV forecasting at Nui Beo open-pit coal mine, Vietnam. Based on the results, we draw some conclusions:

- For predicting blast-induced PPV, various approaches should be used to compare and evaluate the specific performance of each approach.
- Empirical techniques should be used as a fundamental approach to forecasting PPV. However, they need to be further researched and developed to improve the accuracy of the model.

▪ Multiple linear regression (MLR) is a rapid and straightforward method for estimating blast-induced PPV in an open-pit mine. Like the empirical technique, MLR should be used as a second baseline technique to compare and evaluate the performance of the model as well as the relationship between input variables.

▪ Artificial Neural Network (ANN) is an advanced approach for predicting blast-induced PPV in an open-pit mine. They can solve the complex linear and nonlinear relationships of the input parameters in the PPV prediction. Therefore, they should be researched, developed and applied in innovative engineering to accurately predict blast-induced PPV in an open-pit mine.

▪ The input parameters for predicting PPV should also be considered in detail. Of the input parameters, we propose the elevation between blast sites and monitor parameter (H) as an essential input parameter that dramatically influences the performance of the PPV prediction model. It should be used with maximum explosive capacity (W) and monitoring distance (R) in all approaches to predict PPV.

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