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Original Paper

Estimating Air Over-pressure Resulting from Blasting in Quarries Based on a Novel Ensemble Model (GLMNETs–MLPNN)

Hoang Nguyen,[1,2,3] Xuan-Nam Bui,[1,2,3] and Quang-Hieu Tran[1,2]

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In this study, a coupling of generalized linear modeling (GLMNET) and nonlinear neural network modeling with multilayer perceptrons (MLPNN), called GLMNETs–MLPNN modeling, was conducted for predicting air over-pressure (AOp) induced by blasting in open-pit mines. Accordingly, six GLMNET models were developed first. Then, their predictions were bootstrap aggregated as the new predictors, and an optimal MLPNN model was developed based on these new predictors. To prove the improvement of the proposed GLMNETs–MLPNN model, the conventional models, such as GLMNET, support vector machine, MLPNN, random forest, and empirical, were considered and developed based on the same dataset. The results of the proposed model then were compared with that of the conventional models in terms of accurate prediction and modeling. The findings revealed that the bootstrap aggregating of six generalized linear models (i.e., GLMNET models) by a nonlinear model (i.e., MLPNN) could enhance the accuracy in predicting AOp with a root-mean-squared error (RMSE) of 2.266, determination coefficient (R^2) of 0.916, and mean squared error (MAE) of 1.718. In contrast, the other stand-alone models provided poorer performances with RMSE of 2.981–4.686, R^2 of 0.597–0.860, and MAE of 3.156–1.990. Besides, the sensitivity analysis results indicated that burden, stemming, distance, spacing and maximum explosive charge per delay were the most important parameters in predicting AOp.

KEY WORDS: Air over-pressure, Quarry, GLMNETs–MLPNN, Ensemble model, Soft computational method.

INTRODUCTION

Blasting is the most widely used technique to fracture rock and ore in open-pit mines to facilitate loading, transporting, and crushing. The outstanding advantages of this technique are the ability to break rocks with high hardness, hydrated rocks, produce large amounts of rocks, and low-cost (Huang et al. 2011; Bui et al. 2019a; Nguyen et al. 2020b). However, the disadvantages of this method significantly affect the surrounding environment. Large-scale explosions often cause ground vibration, slope failure, and damage to the

[1]Department of Surface Mining, Mining Faculty, Hanoi University of Mining and Geology, 18 Vien st., Duc Thang ward, Bac Tu Liem dist., Hanoi, Vietnam.
[2]Center for Mining, Electro-Mechanical Research, Hanoi University of Mining and Geology, 18 Vien st., Duc Thang ward, Bac Tu Liem dist., Hanoi, Vietnam.
[3]To whom correspondence should be addressed; e-mail: nguyenhoang23@duytan.edu.vn, buixuannam@humg.edu.vn

surrounding structures (Bakhtavar et al. 2017; Azimi et al. 2019; Bui et al. 2019b; Chen et al. 2019; Yu et al. 2020; Nguyen 2020). Besides, air over-pressure (AOp) has been warned as one of the adverse effects of blasting (Fig. 1), and it can cause severe injuries to human health, even leading to death (Rosenfeld et al. 2013; Bui et al. 2019c; Nguyen et al. 2020c). At close distances, the AOp induced by large-scale blasts can blow buildings or breaking of glass windows (Remennikov and Carolan 2006; Ngo et al. 2007; Akande et al. 2014; Nguyen et al. 2018). In addition to ground vibration and AOp, fly rock, dust, toxic gases, and psychological trauma are also considered to be hazardous effects on the human and surroundings (Rosenfeld et al. 2013; Armaghani et al. 2018; Ding et al. 2019; Fang et al. 2019; Guo et al. 2019b; Nguyen and Bui 2019; Nguyen et al. 2019a). In this study, AOp resulting from quarries and how to get high accurate predictions are considered as the main focuses.

To predict AOp induced by mine blasting, two main approaches have been widely applied by scholars, including soft computing (or artificial intelligence, AI) and empirical modeling. Of those approaches, empirical modeling is usually simple and convenient. However, the limitations of empirical modeling are low performance and reliability because of the use of linear relationship between monitoring distance and amount of explosive charge per blast (Nguyen et al. 2019b). In contrast, soft computing or AI modeling has been introduced and confirmed with superior performance and accuracy in predicting AOp. For instance, Khandelwal and Kankar (2011) considered and predicted AOp in a quarry mine using a support vector machine (SVM) model. Subsequently, a generalized predictor equation was applied and compared with the developed SVM model aiming to investigate the suitability of this approach in terms of modeling and computation. Finally, they found that the SVM model for predicting AOp had better results. Armaghani et al. (2015) also developed an ANN (artificial neural network) model for predicting AOp with optimization of the imperialist competitive algorithm, called ANN–ICA. A generalized predictor equation was also considered in their study for comparison purposes like the approach of Khandelwal and Kankar (2011). Finally, their results demonstrated that the ANN–ICA model can be used to predict and control AOp with high reliability. Various nonlinear models were also investigated by Hasanipanah et al. (2016) for estimating AOp resulting, including ANN, adaptive neuro-fuzzy inference system (ANFIS), and empirical model. In another study, Hasanipanah et al. (2017) developed a PSO–SVR model for modeling and evaluating AOp induced by blasting operations based on the SVM method for regression problems (i.e., SVR) and the optimization by particle swarm algorithm (PSO). It is worth noting that the role of the PSO algorithm is similar to the ICA algorithm in the ANN–ICA model that was proposed by Armaghani et al. (2015). However, the optimization objective of the PSO algorithm, in this case, is the hyper-parameters of the SVR model, instead of the weights of the ANN model in the study of Armaghani et al. (2015). Their PSO-based SVR model provided a promising performance in predicting AOp with a squared correlation coefficient (R^2) of 0.997. Based on a similar approach, Alel et al. (2018) proposed the PSO-ANN model for predicting AOp in quarries with great accuracy (root-mean-square error (RMSE) = 2.18 and $R^2 = 0.970$). Comparing different AI techniques (e.g., GBM (gradient boosting machine), RF (random forest), and Cubist) and empirical models, Nguyen et al. (2020a) also demonstrated that these AI models were superior to those of the empirical models in predicting AOp. Based on the fuzzy Delphi technique, a novel ANFIS–PNN (polynomial neural network)–GA (genetic algorithm) model was also developed for estimating AOp with a promising result (Harandizadeh and Armaghani 2020). Atmospheric conditions were also taken into account for predicting AOp using an ANN model (Ozer et al. 2020). Ultimately, a high correlated exponential relationship was found in their study with an R^2 of 0.79. Based on the advantages of hybrid models, Nguyen and Bui (2020b) also proposed the GA-based boosted smoothing spline (BSTSM) model for estimating AOp. Meteorological conditions, as well as blasting parameters, were also investigated in their study for the aim of evaluating the effects of different input variables in predicting AOp. In addition, various performance indices were applied, especially the Taylor diagram, for comprehensive assessment of model quality. In conclusion, high accurate prediction with superior performance was disclosed for the proposed GA–BSTSM model.

Over the past decade, various state-of-the-art models have been developed and applied to predict AOp with impressive performances and high accuracy. However, their performance has not been confirmed as satisfactory in all areas/mines. Some scholars recommended that the accuracy of the introduced models may be poor in other mines, and

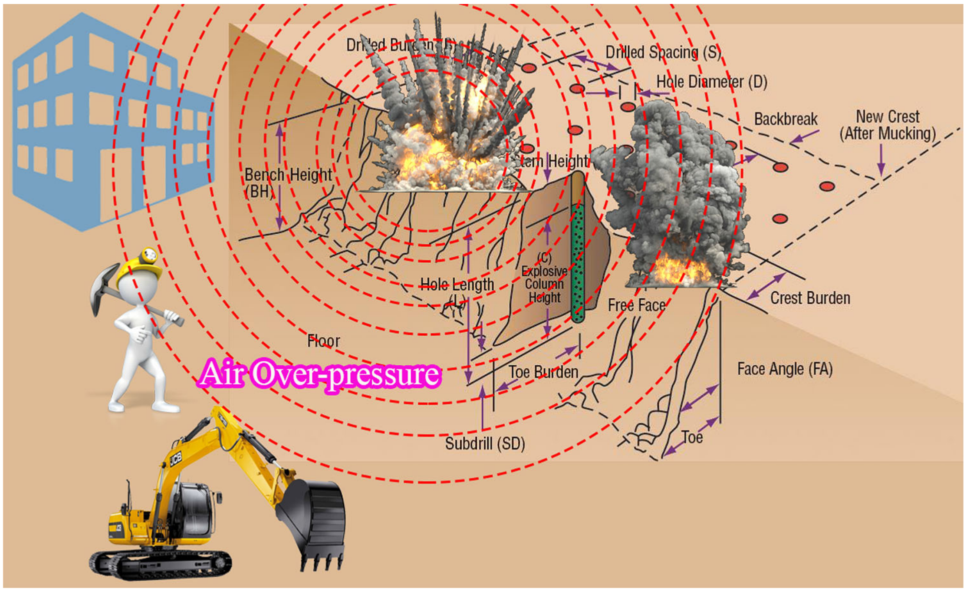


Figure 1. The AOp phenomenon induced by mine blasting in surface mines.

they need to be reconsidered before using for predicting AOp, especially with different geological conditions (Mohamad et al. 2016; AminShokravi et al. 2018; Nguyen et al. 2019c). Moreover, the improvement of the simple or existing models to create new generations of prediction models with that of higher accuracy is a big concern of researchers and engineers. Thus, this study proposed a new state-of-the-art model for predicting AOp based on an ensemble of generalized linear modeling (GLMNET) and multilayer perceptron neural network modeling (MLPNN), called GLMNETs–MLPNN modeling. To prove the enhanced performance of the proposed GLMNETs–MLPNN model, the conventional models, such as GLMNET, SVM, MLPNN, RF, and empirical were also considered and compared with that of the proposed GLMNETs–MLPNN model.

METHODOLOGY

As mentioned above, the principle objective of the present work was to propose a novel state-of-the-art model for predicting AOp by coupling of linear and nonlinear models, i.e., GLMNETs–MLPNN. Therefore, the main focus of this section was on the background of the GLMNET and MLPNN algorithms, as well as on how to develop the GLMNETs–MLPNN model for predicting AOp. Further details of the other methods (i.e., empirical, SVM, RF) can be found in the literature (e.g., Zhou et al. 2021; Cortes and Vapnik 1995; Breiman 2001; Nguyen and Bui 2019; Moayedi et al. 2020; Tran et al. 2020; Ngo et al. 2020).

Generalized Linear Modeling

GLMNET is a package based on the generalized linear model (GLM), which was developed by Friedman et al. (2010). It uses the penalized maximum likelihood to fit the GLM and computes the regularization path for the lasso or elastic-net penalty at a grid for the regularization parameter (i.e., λ) (Hastie and Qian 2016). The advantages of the GLMNET include: (1) extremely fast; (2) exploitation of sparsity in the input matrix x. The GLMNET works effectively with Cox regression, logistic and multinomial, linear, Poisson, even multi-response linear regression models. The objective function of the GLMNET for predicting AOp is described as:

$$\min_{\xi_0,\xi} \frac{1}{B} \sum_{i=1}^{B} w_i k(\mathrm{AOp}_i, \xi_0 + \xi^T) + \lambda \left[(1-\alpha) \frac{\|\xi\|_2^2}{2} + \alpha \|\xi\|_1 \right] \quad (1)$$

where B is number of blasting events, w is weight of input variables, $k(\text{AOp}, \eta)$ is the negative log-likelihood contribution for AOp; AOp is the output variable, and λ and α are the parameters of the GLMNET model. Of those parameters, α is the mixing percentage, and it controls the elastic-net penalty whereas λ is the regularization parameter, and it controls the overall strength of the penalty.

An assessment of the documentation shows that GLMNET has been mentioned and used for blasting problems, such as flyrock prediction (Guo et al. 2019a) and AOp prediction (Bui et al. 2019a, b, c, d). Although the GLMNET model was introduced earlier for AOp prediction, it was used only as a stand-alone model. In this study, the GLMNET model was also applied to predict AOp but undertaken in another quarry. Moreover, a combination of multiple GLMNET models and MLPNN model was considered and conducted to generate a novel robust intelligence model for predicting AOp.

Neural Network Modeling with Multilayer Perceptrons

MLPNN is a type of ANN, and it consists of an input layer, one or multiple hidden layers, and an output layer. Of these layers, the input layer contains the input data, and they are reflected through the characteristics of the input data (i.e., dimensions, data size, data type) and the number of neurons. The output layer contains the output neuron(s). Between the input and output layers is/are the hidden layer(s) (Fig. 2). MLPNN is well-regarded as an effective method to realize and predict/forecast complex problems based on its structure and the algorithms applied (Ojha et al. 2017). The underlying processing units of MLPNN are artificial neurons and they are communicated over a number of layers with fully linked (Çaylak and Kaftan 2014). In MLPNN, the neurons are pre-established according to a one-way direction manner. The information is processed based on the connections of the artificial neurons through the layers described above. In MLPNN, summation and activation functions are used on the nodes to tune the rate of transformation of the information (Isa et al. 2010). Accordingly, the summation function is used to attain the weights and biases, thus:

$$\text{Sum}_j = \sum_{i=1}^{I} w_{ij}x_i + b_j \tag{2}$$

where I is number of input variables in each MLPNN structure; x_i is the ith input variable; b_j is bias at node j; and w_{ij} is the weight between ith and jth nodes. Subsequently, an activation function can be considered to adapt to the connections between neurons. There are many activation functions that can be applied to a MLPNN model. Some of the often-used activation functions are the following:

Sigmoid function:

$$\text{AOp}_j(\text{Sum}_j) = \frac{1}{1+e^{-\text{Sum}_j}} \tag{3}$$

Tanh function:

$$\tanh_j(\text{Sum}_j) = \frac{e^{\text{Sum}_j} - e^{-\text{Sum}_j}}{e^{\text{Sum}_j} + e^{-\text{Sum}_j}} \tag{4}$$

ReLU function:

$$\text{AOp}_j(x) = \max(0, \text{Sum}_j) \tag{5}$$

Leaky ReLU function:

$$\text{AOp}_j(\text{Sum}_j) = 1(\text{Sum}_j{<}0)(\alpha.\text{Sum}_j) + 1(\text{Sum}_j \geq 0)(\text{Sum}_j) \tag{6}$$

Maxout function:

$$\text{AOp}_j(\text{Sum}_j) = \max(w_1^T \cdot \text{Sum}_j + b_1, w_2^T \cdot \text{Sum}_j + b_2) \tag{7}$$

GLMNETs–MLPNN

Once the optimal structure of MLPNN is defined, the training algorithm is set in motion to compute and fine-tune the connections of the network via weighting vectors. The weights are updated during estimation of the outcome predictions to minimize the total error of the network. Following this, it is combined with multiple GLMNET models to generate a novel model with the accuracy improved.

To implement the idea of coupling the predictions of the GLMNET and MLPNN models, the AOp database was divided into two sections: 70% ($\sim$ 128 events) for developing the GLMNET and MLPNN, as well as the GLMNETs–MLPNN models; 30% ($\sim$ 52 events) for testing the performance

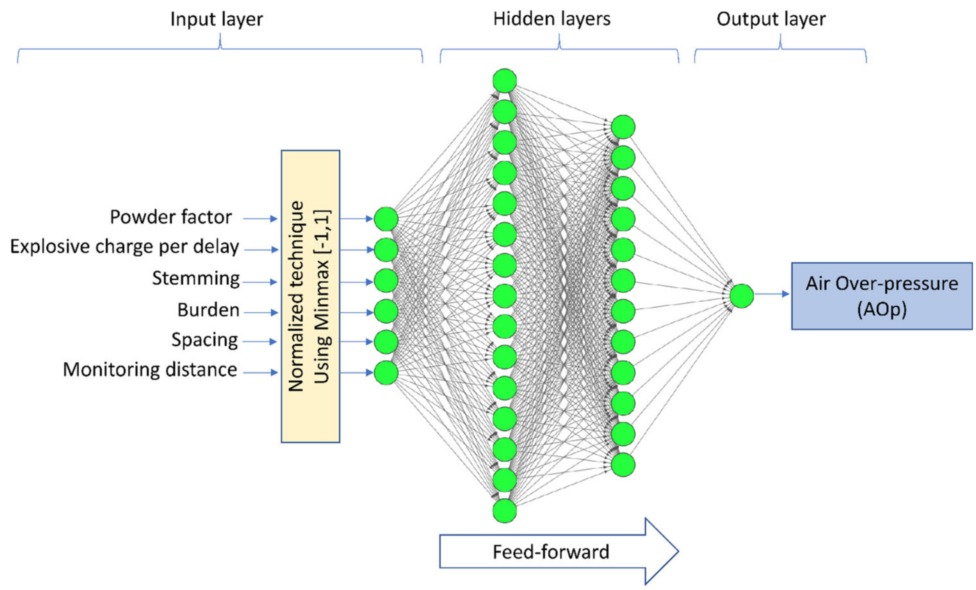


Figure 2. Illustrating the structure and algorithm of MLPNN for predicting AOp.

of these models. It is worth noting that there is no standard for dataset partitioning. Review of research on data mining shows that 70/30 partitioning was widely applied in many previous studies and many researchers recommended using this ratio to avoid the over-fitting phenomenon (Salarian et al. 2007; Soni et al. 2011; Dehnavi et al. 2015; Pavlidis et al. 2019; Turgut et al. 2019).

To develop the GLMNETs–MLPNN model for predicting AOp, the dataset is firstly preprocessed with the application of normalization techniques (e.g., Box–Cox, MinMax). Next, six GLMNET models were developed based on the processed training dataset, and they are called the sub-models. Subsequently, the outcomes of these sub-models were combined as the new predictors, and they were then used to develop the MLPNN model. The flowchart of the proposed GLMNETs–MLPNN model is shown in Fig. 3.

Performance Evaluation Metrics

For a regression problem in machine learning, this study used three performance metrics to assess the performance of the AOp predictive models, including RMSE, R^2, and mean absolute error (MAE). As an overall picture for the models' performance, RMSE and MAE allow perception of the total error of the network; meanwhile, R^2 points out how the AOp database fitted with the developed models. The RMSE, R^2, and MAE are defined as follows:

$$\mathrm{RMSE} = \sqrt{\frac{1}{b}\sum_{i=1}^{b}(\mathrm{AOp}_{\mathrm{measured}} - \mathrm{AOp}_{\mathrm{predicted}})^2} \quad (8)$$

$$R^2 = 1 - \frac{\sum_{i=1}^{b}\left(\mathrm{AOp}_{\mathrm{measured}} - \mathrm{AOp}_{\mathrm{predicted}}\right)^2}{\sum_{i=1}^{b}(\mathrm{AOp}_{\mathrm{measured}} - \mathrm{mean}(\mathrm{AOp}_{\mathrm{measured}}))^2} \quad (9)$$

$$\mathrm{MAE} = \frac{1}{b}\sum_{i=1}^{b}\left|\mathrm{AOp}_{\mathrm{measured}} - \mathrm{AOp}_{\mathrm{predicted}}\right| \quad (10)$$

where b is number of blasting events, and $\mathrm{AOp}_{\mathrm{measured}}$ and $\mathrm{AOp}_{\mathrm{predicted}}$ are actual and model-predicted values of AOp, respectively.

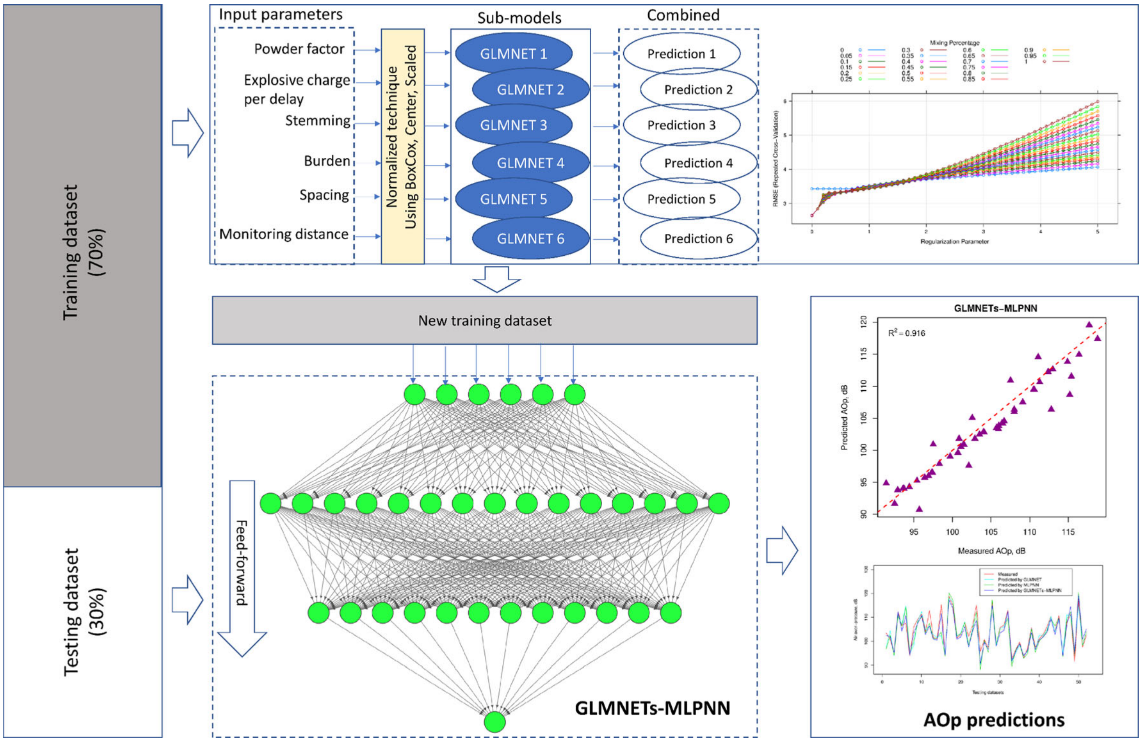


Figure 3. Proposed GLMNETs–MLPNN framework for AOp prediction.

STUDY AREA DESCRIPTION AND DATASET USED

Study Site

For this study, a quarry in northern Vietnam was selected to undertake blasting operations and to collect AOp data. It is located within 105°53′10″E–105°54′00″E longitudes and 20°25′55″N–20°26′30″N latitudes (Fig. 4). The rocks in this quarry are mainly limestone for cement production; the rest is used as additives or construction aggregate in the case when the cement production requirements are not met. With hardness coefficient of 12, blasting is taken into account as the most effective method for rock breaking in this quarry. For blasting in this mine, the non-electric delay blasting method (Davitt and Simon 1983) with the electric blast-initiation system was applied (Ewick et al. 1998). The borehole diameter of 105 mm was used for blasting in this mine. The ANFO explosive, a mixture was mixed ammonium nitrate and fuel oil, was used as the primary explosive for blasting at this mine. Besides, emulsion explosive was also used for some wet boreholes (containing water). At this mine, 4,000,000 tons of limestone were derived per year for cement production, and the amount of explosives required to break rock is up to 2 tons per blast.

Data Preparation

To reach the goal of this study, a data collection plan was properly executed and in accordance with existing practices. Finally, 180 blasts were collected with AOp measurements as well as blasting parameters. Previous studies indicated that blasting parameters, such as spacing (S), explosive charge per delay (W), powder factor (P), stemming (T), burden (B), and the monitoring distance (R) have significant effects on AOp during blasting (Armaghani et al. 2015; Alel et al. 2018). Therefore, data for these parameters were collected from blasting patterns and used as the input variables in the AOp prediction models. To measure R, a GPS receiver was used with the distance measured in the range of 222–

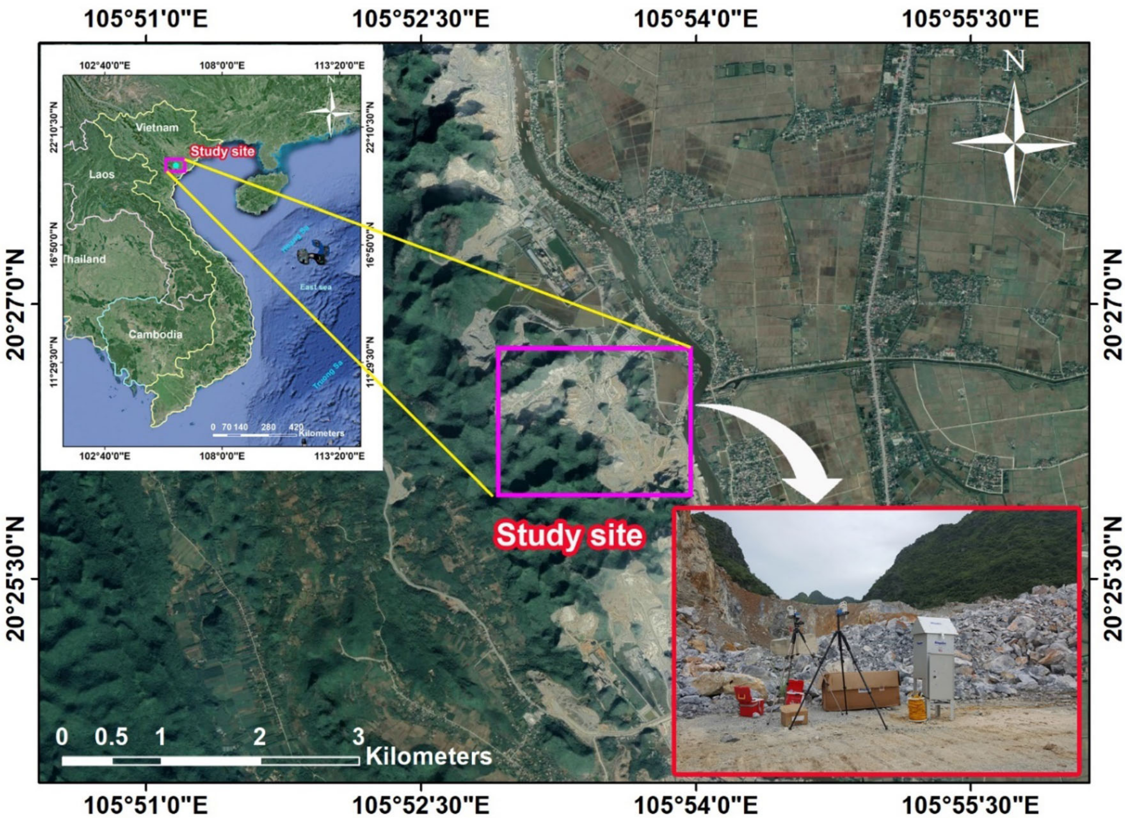


Figure 4. The quarry for undertaking AOp measurements and predictions.

Table 1. Typical characteristics of collected data

Categories	P (kg/m^3)	W (Kg)	T (m)	B (m)	S (m)	R (m)	AOp (dB)
Min	0.290	37.000	1.500	1.100	2.300	222.000	83.200
1st Quartile	0.420	72.000	1.900	2.000	3.000	395.500	97.850
Median	0.480	90.500	2.100	2.400	3.300	484.500	103.530
Mean	0.482	87.560	2.128	2.322	3.292	494.100	103.690
3rd Quartile	0.540	103.250	2.400	2.600	3.600	571.000	109.330
Max	0.620	134.000	2.800	3.500	4.200	805.000	118.800

805 m. For measuring AOp, the Micromate over-pressure monitor unit manufactured by Instantel was used with high reliability. The range of recorded AOp was 83.2–118.8 decibels (dB) during the 180 blasts. The typical characteristics of the collected data are listed in Table 1.

Before training and developing the models, the collected data should be preprocessed and prepared to avoid over-fitting, as well as to improve model accuracy (Boland et al. 2019; Ebtehaj et al. 2020). Accordingly, the correlations among input variables, as well as the output variable were calculated and evaluated. A correlation matrix of the collected data is shown in Table 2.

Based on the correlation matrix (Table 2), there is no doubt that correlations between input variables are not too high. In particular, the correlation between W and R is the highest with

Table 2. Correlation matrix between the inputs and output of the collected dataset

	P	W	T	B	S	R	AOp
P	1	− 0.120	− 0.110	− 0.001	0.026	0.164	− 0.061
W	− 0.120	1	− 0.035	0.060	− 0.035	− 0.676	0.585
T	− 0.110	− 0.035	1	0.116	− 0.011	− 0.009	− 0.096
B	− 0.001	0.060	0.116	1	− 0.179	− 0.075	− 0.029
S	0.026	− 0.035	− 0.011	− 0.179	1	0.056	0.059
R	0.164	− 0.676	− 0.009	− 0.075	0.056	1	− 0.508
AOp	− 0.061	0.585	− 0.096	− 0.029	0.059	− 0.508	1

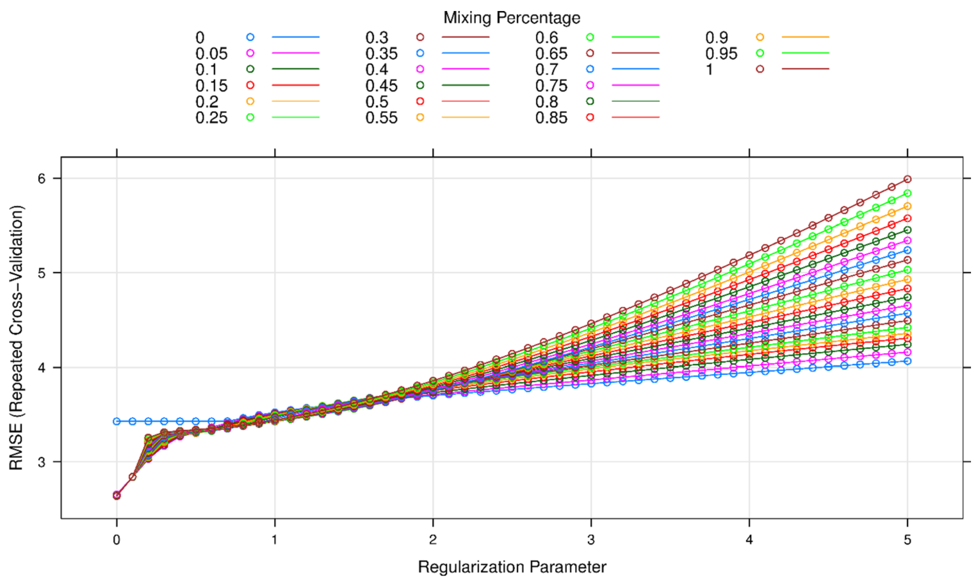


Figure 5. Configuration of the GLMNET model for AOp prediction based on the grid search and repeated 10-folds CV techniques.

correlation coefficient of 0.676, and a linear relationship can be expressed for this value. However, it is neither too high nor too low, and their differentiation may be reflected in the correlation with the output variable. Therefore, these six input variables were considered as the independent variables to predict AOp in this study. Besides, moderate or low correlations between AOp and input variables are also defined. Remarkably, W and R have an acceptable correlation with the dependent variable (i.e., AOp), and they might be having a linear relationship. Other input variables seem to have a nonlinear relationship with the output variable. Therefore, the GLMNET model was selected to interpret the linear association, and the MLPNN model was selected to express the nonlinear relationship of the variables.

CONFIGURATION OF THE PREDICTIVE MODELS

GLMNET Model

For the GLMNET modeling, the data were normalized by a normalization technique named BoxCox (Box and Cox 1964) to change the values in the data to a common scale of [0, 1] without distorting differences in the characteristics of the variables. In addition, a resampling procedure, named cross-validation (CV) was applied with *10*-folds and three repeats to evaluate the model performance with such a limited database of AOp. For configuring, the parameters of the GLMNET model, mixing percentage (α) and regularization parameter (λ) were fine-tuned with a grid search of [0,1] for α and

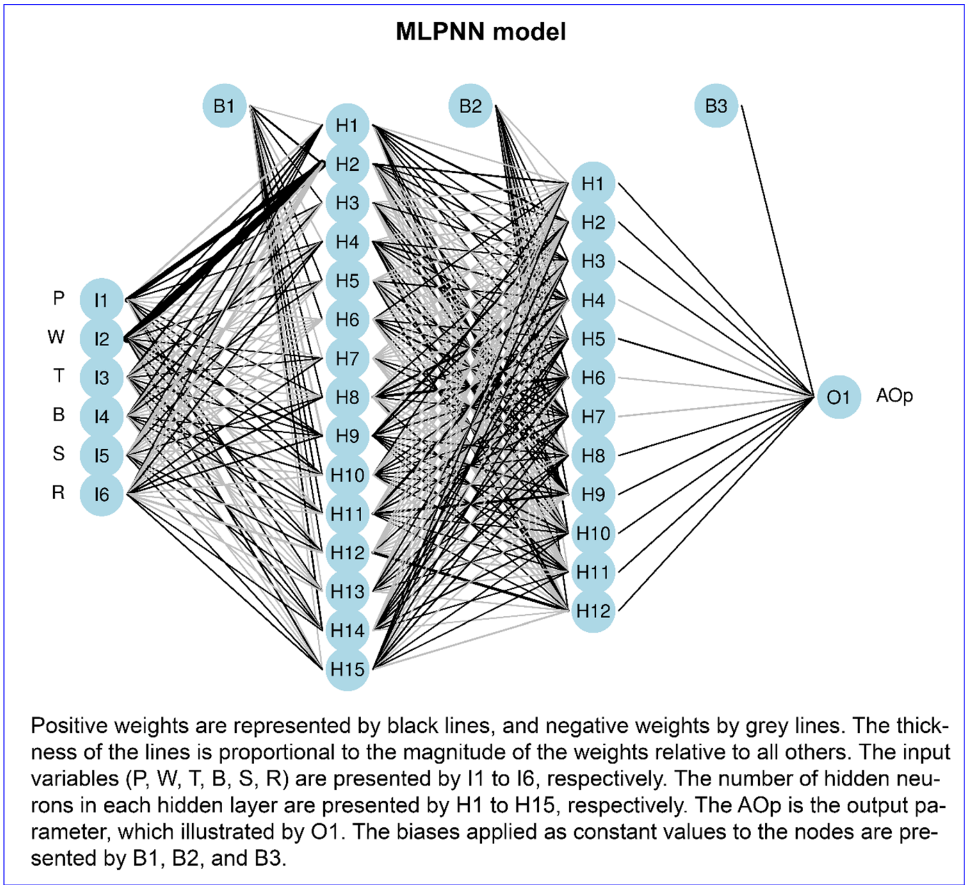


Figure 6. The MLPNN model and its structure for AOp prediction.

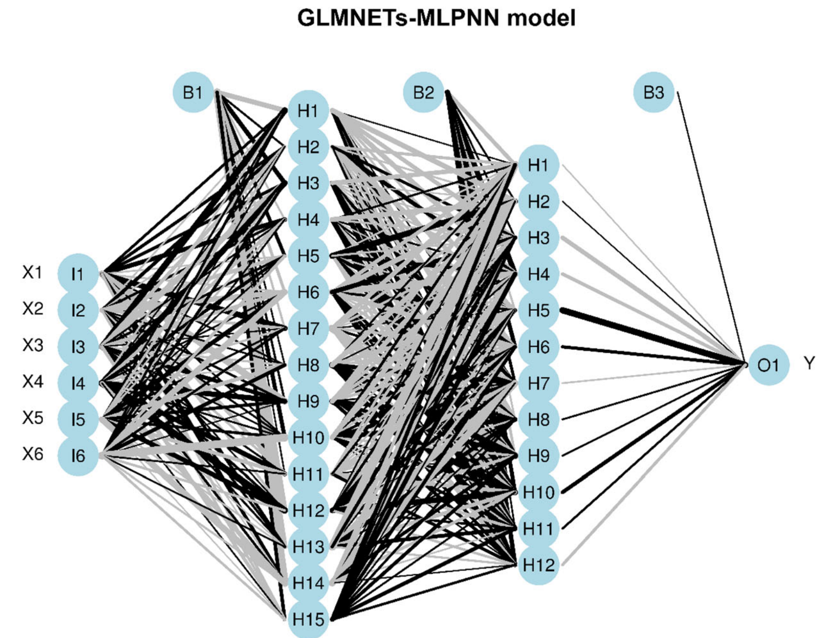
Table 3. GLMNET models, their parameters and performances on the training dataset

Sub-GLMNET models	Parameters		Performance		
	α	λ	RMSE	R^2	MAE
Sub-model 1	1	5	6.045	0.812	5.081
Sub-model 2	1	4.9	5.962	0.812	5.012
Sub-model 3	0.95	5	5.897	0.812	4.957
Sub-model 4	1	4.8	5.880	0.812	4.943
Sub-model 5	0.95	4.9	5.821	0.812	4.893
Sub-model 6	1	4.7	5.799	0.812	4.874

[0,5] for λ. Finally, more than one hundred (i.e., 1071) GLMNET models were established and their performance was evaluated through RMSE (Fig. 5). Ultimately, the best GLMNET model was defined with $\alpha = 1$ and $\lambda = 0$.

MLPNN Model

Regarding the MLPNN modeling, the crucial issue was designing the structure of MLPNN model (e.g., hidden layers, nodes, and training algorithm). The training time of the MLPNN model can increase on condition that too many hidden layers are used in the network. In addition, the MLPNN model may over-fit if too many nodes in the hidden layer(s) are used (Liu et al. 2019; Dou et al. 2020). Consequently, ''trial-and-error'' procedure was applied to design an optimal structure of the MLPNN model to solve the above problems. The feedforward algorithm was applied to train the MLPNN structures, and the Maxout active function was activated. To guard against over-fitting, a powerful preventative measure was applied, named CV. In addition, the Min-Max scaling method was utilized to normalize the data in the range of [0,1] (Nguyen and Bui 2020a; Zhang et al. 2020). All things considered, an optimal



Positive weights are represented by black lines, and negative weights by grey lines. The thickness of the lines is proportional to the magnitude of the weights relative to all others. The new input variables (X1 to X6) are presented by I1 to I6, respectively. The number of hidden neurons in each hidden layer are presented by H1 to H15, respectively. The AOp is the output parameter, which illustrated by O1. The biases applied as constant values to the nodes are presented by B1, B2, and B3.

Figure 7. The proposed GLMNETs–MLPNN model for AOp prediction.

MLPNN structure with two hidden layers was defined to predict AOp in this study (Fig. 6).

GLMNETs–MLPNN Model

For developing the GLMNETs–MLPNN model, the proposed flowchart in Fig. 3 was applied. Firstly, six GLMNET models were developed and they were selected from the previously developed models. Note that these models were the sub-models for the development of the GLMNETs–MLPNN models, and their characteristics are listed in Table 3. Next, the outcome predictions of the six GLMNET models were combined to generate a new dataset. Thus, a new dataset was generated with six input variables involved, and they are abbreviated as X1 to X6. Subsequently, an MLPNN model was developed as a new generation of the previous MLPNN model on the newly generated dataset, and it is named GLMNETs–MLPNN model (Fig. 7).

It is worthwhile to mention that the structure of the MLPNN and GLMNETs–MLPNN models are the same. However, their weights (w) and biases (j) are different, as illustrated by the lines in Figs. 6 and 7. For a neural network, w and j are possibly the most important parameters because they are learnable parameters that can be adjusted to control the error and accuracy of the network. They reflect the connection between neurons as well as express the relationships of the dataset. The results of the proposed GLMNETs–MLPNN are presented and evaluated in the next section.

SVM Model

As mentioned previously, the SVM model was applied as the conventional model for comparison with the proposed GLMNETs–MLPNN model. Herein, the radial basis function (RBF) was applied for the SVM modeling to predict AOp. Standard-

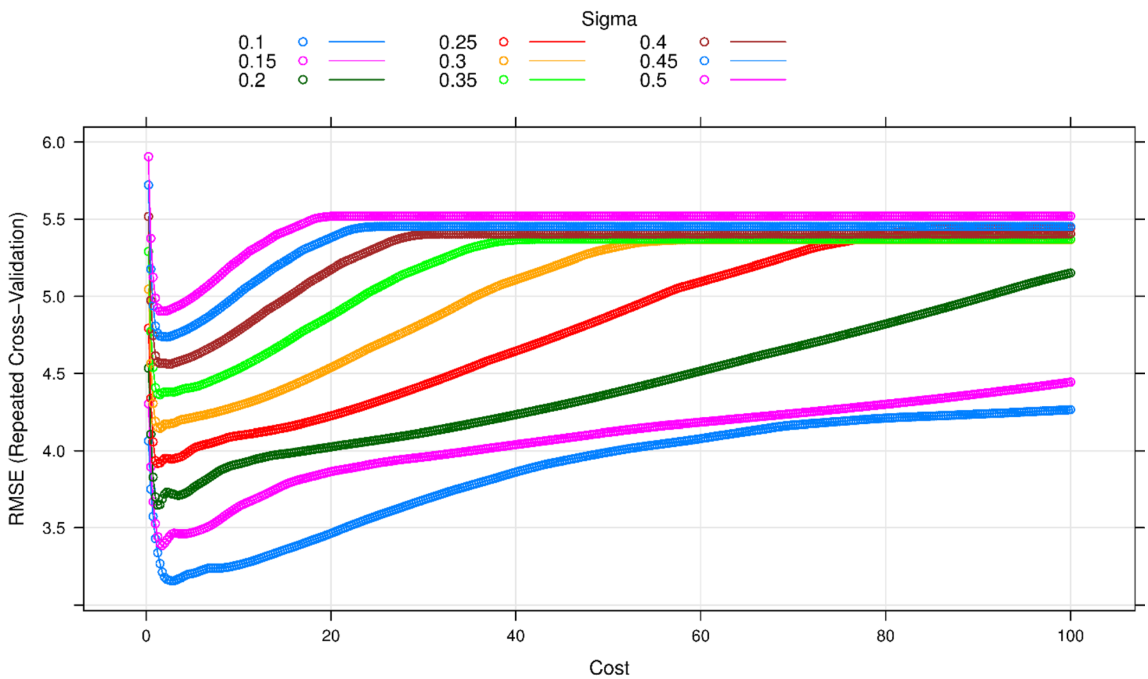


Figure 8. RMSE values of the SVM model with different σ and C.

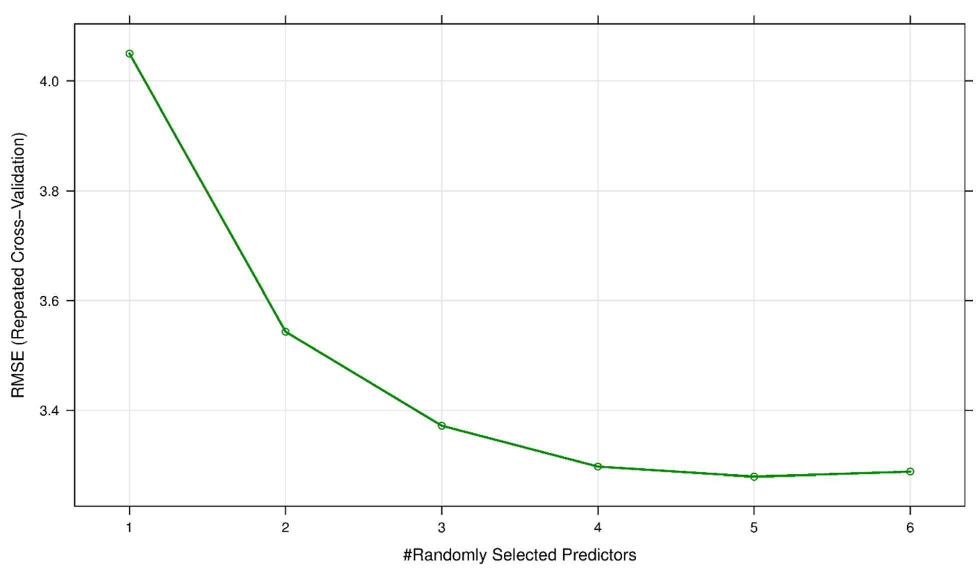


Figure 9. RMSE values of the RF model with different *rp*.

ization of data is also a common requirement for the SVM estimator implemented in this study. Thus, the ''center'' scaling method (Parente and Sutherland 2013) was applied to scale the data to the [0, 1] range for this aim. It is emphasized that the training dataset used for developing the SVM model is the same as the one used for the MLPNN and GLMNET models. Accompanied by the RBF function, sigma (σ) and cost (C) were considered as the learnable hyper-parameters of the SVM algorithm to configure the model accuracy. For instance, σ and C were set in the [0.1, 0.5] and [0.25, 100] ranges, respectively. The tenfold CV method was also applied to avoid over-fitting in this stage, and the RMSE values of the SVM model are shown in Fig. 8. Finally, the best SVM model was achieved with an σ of 0.1 and C of 2.75.

RF Model

As additional conventional model for comparison with GLMNETs–MLPNN's performance, the RF model was developed with number of trees (n_{tree}) set to 5000 to ensure the enrichment of the forest, as recommended by previous researchers (Nguyen and Bui 2020a). In RF, n_{tree} is considered as the voters, and the average of these voters is the outcome prediction of the RF model. Besides, the number of random predictors (rp) was also used as the main hyper-parameter of the RF model, and they were selected in the range of 1 to 6 because the number of input variables used herein was 6. Afterward, similar techniques, such as data normalization, repeated CV, were also applied during developing the RF model. Finally, the best performance of the RF model was found with n_{tree} of 5000 and rp of 5 (Fig. 9).

Figure 10. Correlation charts on the testing dataset (actual versus predicted values) of the developed AOp prediction models. ▶

Empirical Model

Regarding empirical model, the USBM (United States Bureau of Mines) equation is well-known as the most common empirical equation for estimating AOp (Nguyen et al. 2018; Keshtegar et al. 2019). It is defined as:

$$\mathrm{AOp} = k(\mathrm{RW}^{-0.33})^{-b} \tag{11}$$

where k and b are coefficients that depend on the geological conditions of study site.

Based on the same training dataset used for the above-discussed models, multivariate regression analysis was applied to calculate the coefficients of the USBM equation. Finally, an empirical equation based on the form of the USBM equation was defined for estimating AOp in this study, thus:

$$\mathrm{AOp} = 250.468(\mathrm{RW}^{-0.33})^{-0.188} \tag{12}$$

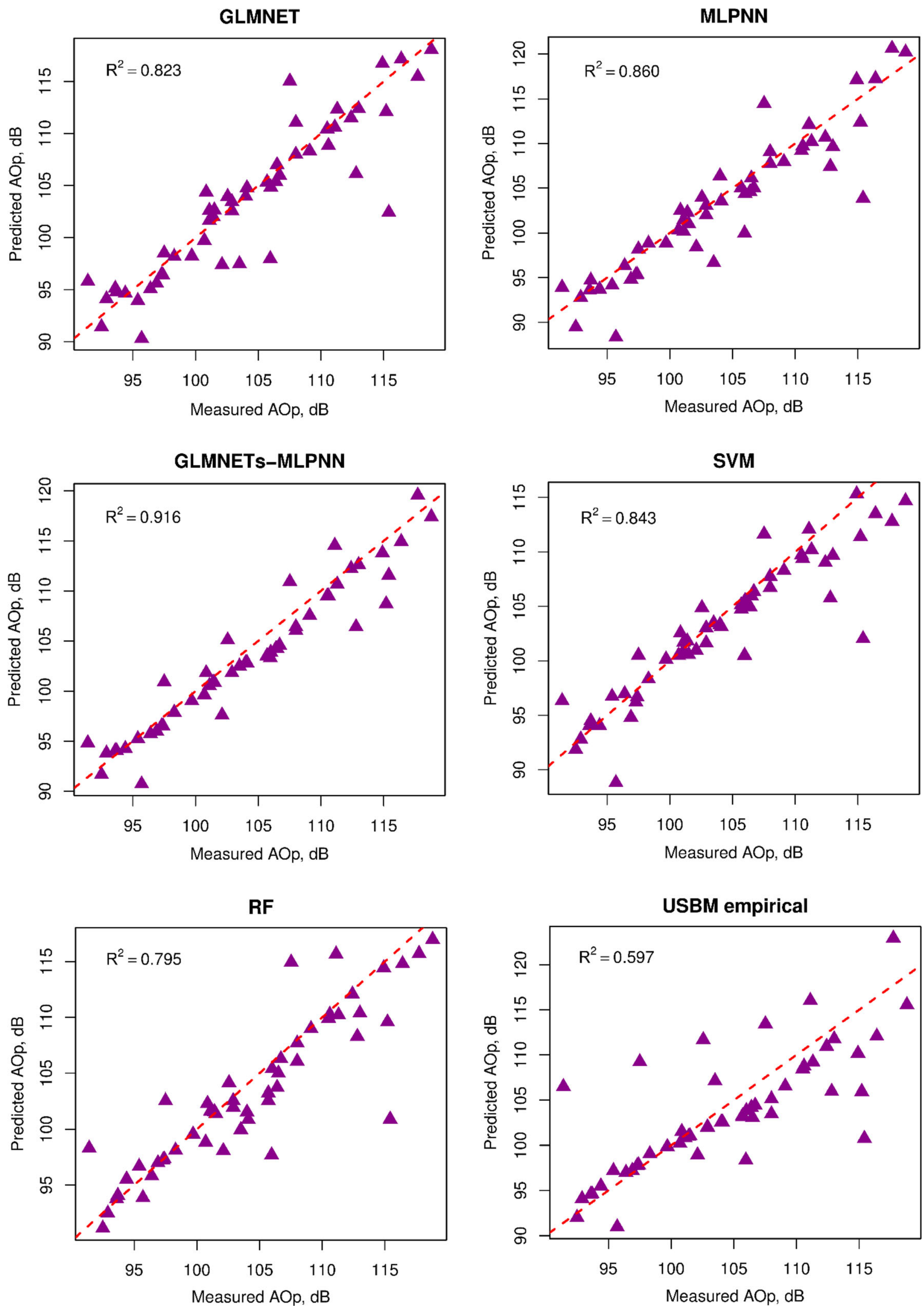
The accuracy of the developed empirical model is shown and discussed in the next section.

RESULTS AND DISCUSSION

To perform a significant and extensive analysis of the developed models, their performances and accuracies were quantified using RMSE, R^2 and MAE. Accordingly, the lowest RMSE and MAE, and highest R^2 point out the best model. To evaluate how well the developed models can generalize new unseen data, their performances were quantified against the test dataset. This evaluation aims to recognize whether over-fitting occurred or not.

Table 4. Performance metrics of the developed AOp predictive models

Model	Training			Testing		
	RMSE	R^2	MAE	RMSE	R^2	MAE
GLMNET	2.637	0.893	1.707	3.148	0.823	1.963
MLPNN	2.224	0.919	1.376	2.981	0.860	1.990
GLMNETs–MLPNN	1.948	0.945	1.601	2.266	0.916	1.718
SVM	3.155	0.848	2.021	3.029	0.843	1.874
RF	3.279	0.840	2.050	3.373	0.795	2.100
Empirical	4.266	0.703	2.967	4.686	0.597	3.156


GLMNET
$R^2 = 0.823$
MLPNN
$R^2 = 0.860$
GLMNETs–MLPNN
$R^2 = 0.916$
SVM
$R^2 = 0.843$
RF
$R^2 = 0.795$
USBM empirical
$R^2 = 0.597$
Predicted AOp, dB
Measured AOp, dB

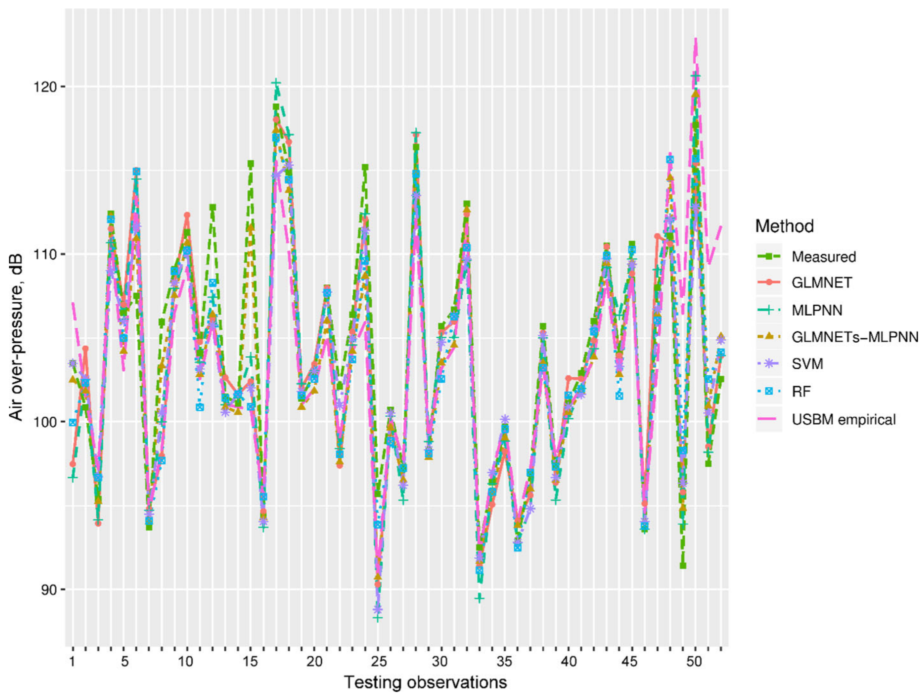


Figure 11. Comparison chart of the predicted values by the individual models and actual values.

Therefore, errors between the trained models and actual model, as well as the fitness of the developed models in practice, are shown. The calculated training and testing performances of the developed AOp prediction models are given in Table 4.

Unquestionably, the poorest performance was indicated by the empirical model on both training and testing datasets. Remarkably, the R^2 value of the empirical model on the testing dataset suggested comparatively poor model fit. In other words, the empirical model has low ability for predicting AOp in practical engineering. In contrast, the AI models (i.e., GLMNET, MLPNN, GLMNETs–MLPNN, SVM, and RF) provided much better performances than the empirical model.

Considering the GLMNET, MLPNN, and SVM models, it is clear that the MLPNN and SVM models yielded better performances than those of the GLMNET models. This finding indicates that the AOp dataset used in this study tend to fit nonlinear models (i.e., MLPNN, SVM). Nevertheless, not all the nonlinear models provided better results than the linear models in this study. For instance, the RF model provided lower performance than the GLMNET model even though the former is considered a nonlinear model. The justification can be explained based on the construction of the RF model. It was developed based on decision trees and many linear boundaries. In other words, the RF model was built as a decision tree based on the combination of many linear and straightforward trees (Rokach 2016).

For the proposed GLMNETs–MLPNN model, unquestionably, its performances on both training and testing datasets were the best in this study. Although the sub-GLMNET models provided poor performance (Table 4), their combined predictions for the development of the MLPNN model resulted in a model relationship among variables (e.g., inputs and output) that is better than those of the GLMNET or single MLPNN models. Besides, although the combination mechanism of the proposed GLMNETs–MLPNN model is similar to the RF model (i.e., based on the linear models), the GLMNET models-based MLPNN model can predict AOp more accurately than the RF model. This technique is also known as the bagging technique in machine learning for reducing the variance of a decision tree and reaching a higher testing accuracy. It enables the proposed GLMNETs–MLPNN model to use different training algorithms (e.g., linear and feedforward algorithms) for flexible training. Based

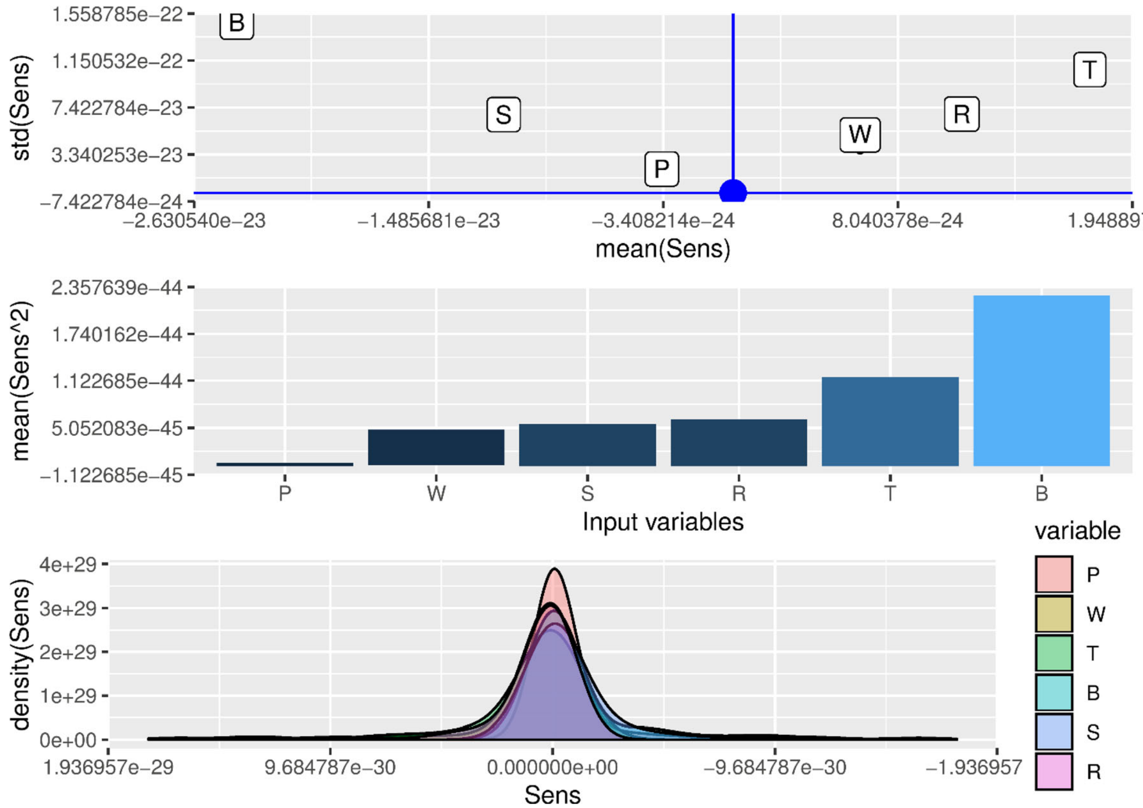


Figure 12. Sensitivity analysis results based on the input variables.

on the performance metrics in Table 4, it can be seen that the accuracy of the proposed GLMNETs–MLPNN model was significantly better than those of the base models.

Further evaluations of the obtained results are illustrated in Figs. 10 and 11, from which it is possible to see that, based on the testing dataset, the convergence level and accuracy of the proposed GLMNETs–MLPNN model are higher than the other models. Specifically, the highest correlation and accuracy pertain to the proposed GLMNETs–MLPNN model followed by the MLPNN, SVM, GLMNET, and RF models. In contrast, the predicted AOp values of the empirical model were not as good as the AI models (Figs. 10 and 11); the residuals of the predictions by the empirical model are high, and so its reliability is low as well.

To further assess the proposed GLMNETs–MLPNN model in terms of modeling, a sensitivity analysis technique was applied to discover the role of the input variables in modeling and the accuracy of the model (Fig. 12). It is important to mention that the partial derivatives method (Bellman et al. 1965; Baur and Strassen 1983) was used for this task. As revealed by Fig. 12, there is no doubt that the B, T, R, S, W variables, especially B and T, have crucial role on the response variable (i.e., AOp). In contrast, the P variable has little to no effect in predicting AOp, and its standard deviation is lowest. Therefore, the B, T, R, S, and W variables should be considered as the main input variables for AOp prediction in mine blasting.

CONCLUSION

Blasting is unquestionably the most effective method for fragmenting rocks in open-pit mines. However, its negative environmental impacts (e.g., ground vibration, AOp, flyrock, to name a few) can be significant. In this study, AOp was evaluated and predicted with high accuracy and reliability based on the proposed novel ensemble model (i.e., GLMNETs–MLPNN). The performance of this proposed model, compared with those of the other models (i.e., GLMNET, MLPNN, SVM, RF, and empirical), indicated it to be the best model for predicting AOp in this study. In addition, the capability of the combination of the GLMNET and MLPNN models for predicting AOp with better accuracy was also shown. Based on the results, the proposed GLMNETs–MLPNN model can be introduced and used as an alternative model to improve the accuracy in predicting AOp.

However, the following limitations need to be considered in future works. (1) To investigate the effects of other independent variables on AOp, such as elevation of the blast-face and measurement points, geological conditions, meteorological conditions, the cube root scaled distance, to name a few. In particular, the cube root scaled distance should be investigated in future works as one of the input variables for predicting AOp because AOp depends upon the cube root scaled distance, which was not included in the present study. (2) To consider the efficiency of the hybrid models with different numbers of the new input variables from the sub-models (e.g., GLMNET models). (3) To test the efficiency of the proposed GLMNETs–MLPNN model in predicting AOp in other mines/areas.

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