



# Prediction of ground vibration intensity in mine blasting using the novel hybrid MARS–PSO–MLP model

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## Abstract

The present paper's primary goal is to propose a novel hybrid model with high reliability to predict peak particle velocity (PPV)—a ground vibration evaluation unit in mine blasting. This model is based on the coupling of the multivariate adaptive regression splines (MARS), particle swarm optimization (PSO), and multi-layer perceptron neural networks (MLP). To this end, a strategy of stacking the MARS models was applied. Multiple MARS models were developed first with different hyper-parameters. Subsequently, the outcome predictions from these MARS models were merged as a new data set. The MLP model was then developed based on the newly generated data set, called the MARS–MLP model. To improve the accuracy and reduction of the MARS–MLP model's error, the PSO algorithm was applied in terms of optimization of the MARS–MLP's weights, called the MARS–PSO–MLP model. The proposed MARS–PSO–MLP model was then compared with the stand-alone MARS, MLP, empirical models, and the hybrid PSO–MLP model (without stacking MARS models) using the same data set. The results revealed that the proposed strategies could significantly boost the MARS and MLP models' performance with the PSO algorithm's effective help. The proposed MARS–PSO–MLP model yielded the highest accuracy and reliability with a root-mean-squared error (RMSE) of 1.569, mean absolute error (MAE) of 1.017, and squared-correlation ( $R^2$ ) of 0.902. In comparison, the stand-alone models (i.e., MARS and MLP) and the hybrid model of PSO–MLP provided lower performances with an RMSE of 1.582 to 1.704, MAE of 0.941 to 1.427, and  $R^2$  of 0.871 to 0.891. In contrast, poor performance with an RMSE of 5.059, MAE of 3.860, and  $R^2$  of 0.127 was found for the empirical model, and it is not a reliable method to predict PPV in this study. This work's findings also indicated that explosive charge per delay, monitoring distance, spacing, powder factor, and burden have significant effects on PPV, the incredibly explosive charge per delay, and monitoring distance. Remarkable, the stemming variable has a minimal impact on PPV, and its role in the modeling of PPV is not exact.

**Keywords** Ground vibration · Blasting · Machine learning · Hybrid model · Multivariate adaptive regression splines · MARS–PSO–MLP

## 1 Introduction

Safety issues in opencast mining are considered important issues, especially those related to blasting [1]. Serious side effects can occur during blasting, such as flyrock, ground vibration, slope failure, airblast, dust, and toxic [2–5]. Ground vibration is the biggest concern among those effects, and it was represented by peak particle velocity (PPV) [5–11]. Many scientists confirmed that the adverse effects caused by blasting, especially PPV, are mainly caused by the useless energy of explosives (accounting for 70–80%) [12–14].

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From the feedback of PPV on buildings and the surrounding environment, some baseline solutions such as increasing safety distance, increasing quality and standards for buildings, and applying existing blasting methods (e.g., creating barriers, blasting delays) have been involved in the 1990s [15, 16]. However, these methods are sometimes not very effective and increase the cost of blasting [17].

Based on the empirical approach, many scholars studied and proposed empirical formulas for predicting PPV, such as the United States Bureau of Mines (USBM) by [18], Langefors, Kihlstrom [19], Ambraseys [20], Ghosh, Daemen [21], Roy [22], Ak, Konuk [23] and Simangunsong, Wahyudi [24]. The empirical equations are often simple and easy to calculate; nevertheless, their performance is not expected [25–30]. Therefore, the state-of-the-art methods are essential requirements with the purpose of accuracy improvement in predicting PPV. In this study, artificial intelligence (AI)—a remarkable achievement of information sciences in recent years—is considered to predict PPV. The structure of this work includes seven sections, as follows:

- (1) Introduction
- (2) Related works
- (3) Methodology
- (4) Study site and data acquisition
- (5) Results
- (6) Discussion
- (7) Conclusion

## 2 Related works

Indeed, information technology development, especially AI, has contributed to rapidly improving human life performance and quality [31–36]. It helps computers smarter, more knowledgeable, and exceptionally capable of predicting real-world problems with high accuracy [37–41]. Regarding blast-induced ground vibration, AI has been widely applied for predicting the intensity of ground vibration. For example, Hasanipanah et al. [30] used the support vector machine (SVM) algorithm to predict PPV based on the charged explosive and PPV measurement distances. They obtained a superior performance with a variance accounted for (VAF) of 94.24, squared correlation coefficient ( $R^2$ ) of 0.957, and root-mean-squared error (RMSE) of 0.34. In another study, Hajihassani et al. [42] embedded the PSO algorithm to an artificial neural network (ANN) model that aims to improve the ANN model's accuracy in predicting PPV. The PSO algorithm significantly enhanced the ANN model's accuracy with an  $R^2$  of 0.89 and a mean squared error (MSE) of 0.038. A similar study on the hybridization of the imperialist competitive algorithm (ICA) and ANN for the prediction of PPV was

also conducted by the same authors [28], and the obtained results are positive (i.e.,  $R^2 = 0.976$ ; RMSE = 0.685).

By another approach, Armaghani et al. [43] successfully applied an ANFIS for solving the PPV prediction issue in an open-pit mine. Their outcome predictions indicated that the ANFIS model is a good candidate for predicting PPV with a VAF of 97.345,  $R^2$  of 0.973, and RMSE = 0.987. Amiri et al. [44] combined ANN and  $k$ -nearest neighbors ( $k$ -NN) algorithm for predicting PPV in open-pit mines. They claimed that the outcome predictions from the ANN- $k$ -NN model could be acceptable with the possibility of 87.84%. Hasanipanah et al. [45] applied the CART model to predict and evaluate PPV with an  $R^2$  of 0.950 and RMSE of 0.170. Similar to the PSO-ANN and ICA-ANN models that were developed by Hajihassani et al. [42], Hajihassani et al. [28], Taheri et al. [46] developed the ABC-ANN model based on the optimization of the artificial bee colony (ABC) algorithm and ANN model. The results obtained from this model were good, with an RMSE of 0.220 and  $R^2 = 0.920$ . To optimize the prediction of PPV, Sheykhi et al. [47] applied a clustering technique (i.e., fuzzy C-means) to process the data set before developing the predictive model based on the SVM algorithm. Finally, they found that their model (FCM-SVM) could predict PPV with an acceptable performance (RMSE = 1.800; VAF = 85.250;  $R^2 = 0.853$ ). Shang et al. [48] also developed a hybrid model based on the firefly algorithm (FFA) and ANN, named FFA-ANN for predicting PPV. The CART,  $k$ -NN, and SVM models were also employed as the baseline models for a comprehensive comparison of the proposed FFA-ANN model. Ultimately, the FFA-ANN was claimed with the most dominant performance, and it was introduced in practical engineering. A similar hybrid model based on the FFA and bagged SVM model (i.e., FFA-BSVM) was also applied for predicting PPV by Ding et al. [49]. Several types of ANN models were compared with that of the FFA-BSVM model, and they showed that the FFA-BSVM is the best model in the study of Ding et al. [49]. Itemset Mining (IM)—a machine learning algorithm for extraction of patterns were applied to select potential instances. Subsequently, an ANN model was developed based on the selected instances, aiming to improve the ANN model's accuracy in predicting PPV, and it was called IM-ANN hybrid model. Yang et al. [50] also applied two optimization algorithms (i.e., PSO and GA (genetic algorithm)) for optimization of the ANFIS model in predicting PPV. They found that the GA-ANFIS model provided a better improvement than the PSO-ANFIS model in terms of accuracy and error. In another study, Fattahi, Hasanipanah [51] developed two novel hybrid models, i.e., RVR (relevance vector regression)-BA (bat-inspired algorithm) and RVR-GWO (grey wolf optimization), for predicting PPV.

The results demonstrated that the RVR–GWO is better than those of the RVR–BA model with an MSE of 7.920 and correlation coefficient of 0.915.

Based on the referenced papers, it can be seen that the hybrid models based on optimization algorithms or clustering algorithms tend to provide better performance than those of the single or conventional models in predicting PPV. Indeed, many researchers proposed hybrid models for predicting PPV with promising results, such as the PSO–XGBoost model (PSO–extreme gradient boosting machine) [52]; the MFA–SVR model (modified firefly algorithm–support vector regression) [53]; the FFA–ANN model (firefly algorithm–ANN) [48]; the PSO– $k$ -NN model [54]; the ICA–M5Rules model [55]; the GA–ANN model (genetic algorithm–ANN) [56]; the FCM–ANFIS model [57]; the ANFIS–GA model [50]; the HKM–CA model (hierarchical Kmeans clustering–cubist algorithm) [58]; the ICA–XGBoost model [59]; the HKM–ANN model [60]; the GA–SVR–RBF model [17], and the HHO–RF model (Harris Hawks optimization–random forest) [61]. And they claimed that hybrid models tend to provide better performance than those of the single models. For this reason, we have developed a novel hybrid model for PPV prediction based on the multivariate adaptive regression splines (MARS), PSO, and multi-layer perceptron neural networks (MLP), namely, MARS–PSO–MLP model. The single models, such as MLP and MARS, and the hybrid model (i.e., PSO–MLP) were also developed for comparison purposes. Besides, the empirical equation of USBM was also considered to evaluate ground vibration’s intensity from the empirical point of view.

### 3 Methodology

#### 3.1 Empirical

Empirical methods are often used as the rapid estimation methods to estimate PPV since their convenient and straightforward. Of the empirical equations, the USBM equation [18] is introduced as the most common equation for calculating PPV. Therefore, it was selected to implement the PPV predictions and described as follows:

$$PPV = k \left( \frac{D}{\sqrt{W}} \right)^{-\alpha}, \quad (1)$$

where  $W$  is the maximum amount of explosive charged per delay (in Kg);  $D$  is the distance from blasts to seismograph (in m);  $k$  and  $\alpha$  denote the site coefficients.

#### 3.2 MARS

MARS is a shortened name of the multivariate adaptive regression splines algorithm proposed first by Friedman

[62], and it was officially introduced in 1995 by Friedman, Roosen [63]. It is considered as a flexible algorithm to describe the relationships in a data set with a few variables [64]. Inspired by generalized additive modeling and the CART model’s recursive partitioning technique, MARS creates a continuous model based on the constant derivatives. These tasks allow the MARS algorithm to find optimal variable interactions and transformations with the complex structure of the data [65].

By the use of the piecewise linear regressions method, MARS can build flexible models easily. It uses different regression slopes at different intervals of the independent variable space to approximate the nonlinearity of a model. It is worth noting that the regression slopes are flexible, and they depend on the intersection points. Another advantage of the MARS is the searching ability of variables one by one and their relation [66].

For the development of the MARS model, a two-stage process is applied, as follows:

- (1) Different maximum number of basis functions are constructed to overfit the initial data set. The variables can be entered by categorical, continuous, or ordinal. They can interconnect with each other or be used as additive components.
- (2) Basis functions are taken into account to delete based on their contributions. The order of least contribution is applied for this task using the criterion of generalized cross-validation (GCV). Based on the values of GCV, the importance of variables can be observed when a variable is removed from the model. Another vital point of the MARS is processing the data’s missing values using dummy variables. It can show the data’s missing values, and we can further process the model aiming to get higher performance.

Using the piecewise linear regressions method to generate flexible models and the two-stage process, MARS can track and solve the data with complex structure and high-dimensional. In this study, MARS is investigated to predict PPV and combined with the PSO algorithm and MLP to enhance the model accuracy (i.e., MARS and MLP) in estimating PPV.

#### 3.3 MLP

MLP was introduced as one of the ANN structures that has been widely applied in many fields [67–70]. Like those of the other ANN structures (e.g., feedforward neural networks, recurrent neural networks, single layer feedforward), MLP receives input signals and process them before sending them to other neurons in the hidden layer(s). At least one hidden layer is contained in the

structure of the MLP [71]. Hidden layers are called the intermediate layers, and they are often added to boost the networkability [72]. Typically, these intermediate layers are useful for non-linear problems.

For MLP, the number of neurons in the input and output layers are prior knowledge. However, it is hard to previous understanding how many neurons are necessary for the hidden layer. The network's processing time would increase, and the over-fitting phenomenon may have occurred if there are too many neurons in the hidden layer. On the other hand, few neurons in the hidden layer would increase the network's error [73]. Therefore, determining the optimal structure of an MLP, i.e., the appropriate number of hidden layers and neurons is one of the most crucial steps.

Furthermore, a suitable training algorithm is an essential and indispensable part of MLP. It is reflected through the processing time and the error of the network. In other words, a suitable training algorithm for MLP is the one that achieves the lowest error and sufficient training time (or shortens training time). In actual fact, the following algorithms are often used to train an MLP: feedforward back-propagation (FFBP), and Levenberg–Marquardt [74–76]. Herein, the FFBP algorithm is used to train the MLP for predicting PPV. The general architecture of the MLP model for this purpose is illustrated in Fig. 1.

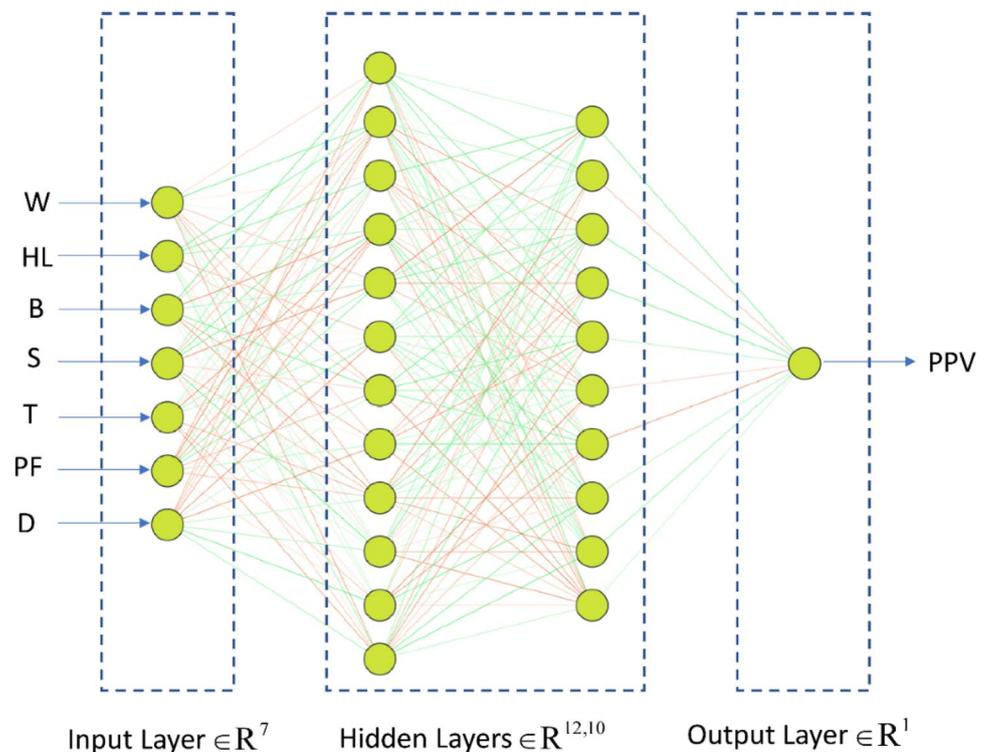
### 3.4 PSO algorithm

PSO is one of the nature-based algorithms which is applied for optimization problems. It was proposed by Kennedy, Eberhart [77] inspired by the behaviors of swarms, such as flock bird, ant, fish, to name a few. The PSO algorithm's main idea is to share and update the information of individuals in the swarm, aiming to improve the foraging performance [78]. Each individual is considered a particle in a swarm, and they fly/move with a specific velocity in a given searching space with high dimensional. For each position found during searching, they share the experiences and the places to other particles [54]. Based on the shared positions, the particles continuously search, share, and update if they found another better place. It is worth mentioning that particles' fitness is evaluated by an objective function during searching and optimizing processes. In the PSO algorithm, each the best position found is called the local best ( $P_b$ ), and the best solution in the swarm is called the global best ( $G_b$ ). Further details of the PSO algorithm can be found in the following papers [52, 79–85].

### 3.5 Hybridization of MLP, PSO, and MARS

In this section, the pattern of the PSO–MLP and MARS–PSO–MLP are proposed. Accordingly, the PSO algorithm is used as an extended feature to optimize the MLP model, i.e., weights. It enables the MLP model to expand the

**Fig. 1** Architecture of MLP model for predicting PPV with seven input variables and two hidden layers



search domain of weights to find out the optimal performance. Furthermore, one of the most remarkable characteristics of the proposed MARS–PSO–MLP model is combining the predictive values of the MARS models and the PSO–MLP model. For this task, the MARS approach is applied to predict PPV first, and several MARS models would be taken into account to get the PPV predictions. Subsequently, they are framed to develop the pattern of the MLP. The PSO algorithm is also involved in developing the MLP based on the predictive values of the developed MARS models aiming to optimize weights of the MLP. RMSE in Eq. (2) would be used as the objective function and stopping condition of the PSO–MLP and MARS–PSO–MLP models. The smallest fitness value of RMSE represents the best prediction accuracy. The frameworks of the PSO–MLP and MARS–PSO–MLP models are proposed in Figs. 2 and 3.

### 3.6 Model evaluation method

From the statistical viewpoint, it isn't easy and not enough to make a comprehensive evaluation for a predictive model using only one performance index. Therefore, this study used three performance indexes to overcome the above drawback, including RMSE,  $R^2$ , and MAE. Whereas RMSE was used to express the results' dispersion degree, MAE was used to indicate the deviation of the outcome predictions. Besides,  $R^2$  was used to measure the linear correlation of the measured and predicted PPVs. These indices are described as follows:

$$RMSE_{PPV} = \sqrt{\frac{1}{n_{blasting\_events}} \sum_{i=1}^{n_{blasting\_events}} (PPV_i - \widehat{PPV}_i)^2} \quad (2)$$

$$MAE_{PPV} = \frac{1}{n_{blasting\_events}} \sum_{i=1}^{n_{blasting\_events}} |PPV_i - \widehat{PPV}_i| \quad (3)$$

$$R^2_{PPV} = 1 - \frac{\sum_{i=1}^{n_{blasting\_events}} (PPV_i - \widehat{PPV}_i)^2}{\sum_{i=1}^{n_{blasting\_events}} (PPV_i - \overline{PPV}_i)^2}, \quad (4)$$

where  $n_{blasting\_events}$  is the total number of sample points (i.e., blasting events),  $PPV_i$  and  $\widehat{PPV}_i$  represent the  $i^{th}$  actual and predicted PPV values,  $\overline{PPV}_i$  represents the average value of the measured PPV values.

## 4 Study site and data acquisition

To carry out this study, blasts were designed and undertaken at the Deo Nai open-pit coal mine, located in Quang Ninh province of northern Vietnam, as shown in Fig. 4.

This large open-pit coal mine in Vietnam with a maximum explosive charge is up to 10 tons per blast. Remarkable, this mine's surroundings are residential and other open-pit mines, as illustrated in Fig. 4. In some cases, the dumpsites of other mines are the slopes of this mine. Therefore, ground vibrations are considered as the big concern herein. It can make instability of dumpsites and slopes as well as vibration of buildings.

Some seismographs were used to measure PPV intensity induced by blasts in this mine, such as Micromate or Blast mate III (Instantel). They were placed in the sensitive points that can be severely affected by blast-induced PPV. Finally, ground vibrations from 193 blasting events were measured in the range of 1.01 to 23.79 mm/s.

In mine blasting and controlling blast-induced ground vibration, many researchers indicated that blasting parameters significantly affect PPV [86]. They are categorized in the controllable parameters group, since they can adjust or change by blasting engineers [87–89]. On the other hand, the uncertainty parameters, such as geological and geophysical conditions, tensile strength, compressive strength of rock mass, rock quality designation, rock fracture parameters, to name a few, are classified in the uncontrollable parameters [90–92]. Therefore, the historical data of blasting parameters of 193 blasting events, such as maximum amount of the explosive charged per delay (W), the length of borehole (HL), burden (B), spacing (S), stemming (T), and powder factor (PF), were used as the input variables for PPV prediction in this study. In addition, the monitoring distance of PPV from blast sites to seismograph (D) was calculated based on the blast sites' locations and seismograph that were determined by a GPS receiver. The details of the data set are summarized through the histogram and density plots in Fig. 5.

## 5 Results

A blast-induced ground vibration modeling is typically taken into account as a regression problem in which both input variables and outcome predictions are numeric. To prepare for such a predictive model, it is necessary to define two separate data sets for training and to test the model. To do so, 193 blasting events with the inputs and output were randomly divided into two different data sets. One for training the PPV prediction models with 80% of the whole data set (~ 157 blasting events), and one for testing the trained PPV prediction models (~ 36 blasting events). It is important to note that all the prediction models are developed and tested on the same data points as divided earlier.

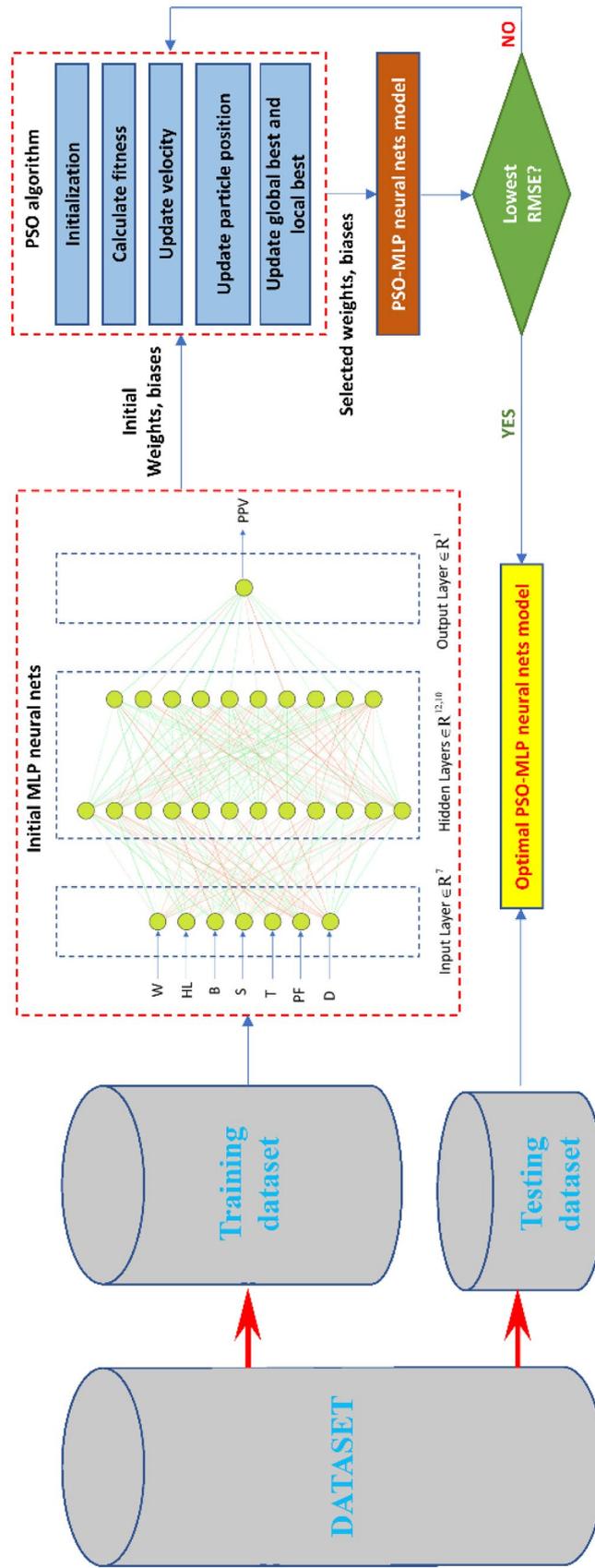


Fig. 2 Framework of the PSO-MLP model for predicting PPV



Fig. 3 Framework of the MARS–PSO–MLP model for predicting PPV

### 5.1 Empirical model

For modeling the PPV by empirical approach, Duvall, Fogelson [3] proposed an empirical equation based on the characteristics of rock mass and scaled distance determined based on  $D$  and  $W$ , as described in equation (Eq. 1). This equation is also known as the USBM as an alternative name. In Eq. (1),  $k$  and  $d$  are the coefficients that present the characteristics of rock mass at the study site, and they can be determined by the multivariate regression analysis method [93]. Finally, the empirical model for PPV prediction in this study was defined based on the training data set, as described in the following equation:

$$PPV = 79.336 \left( \frac{D}{\sqrt{W}} \right)^{-0.718} \tag{5}$$

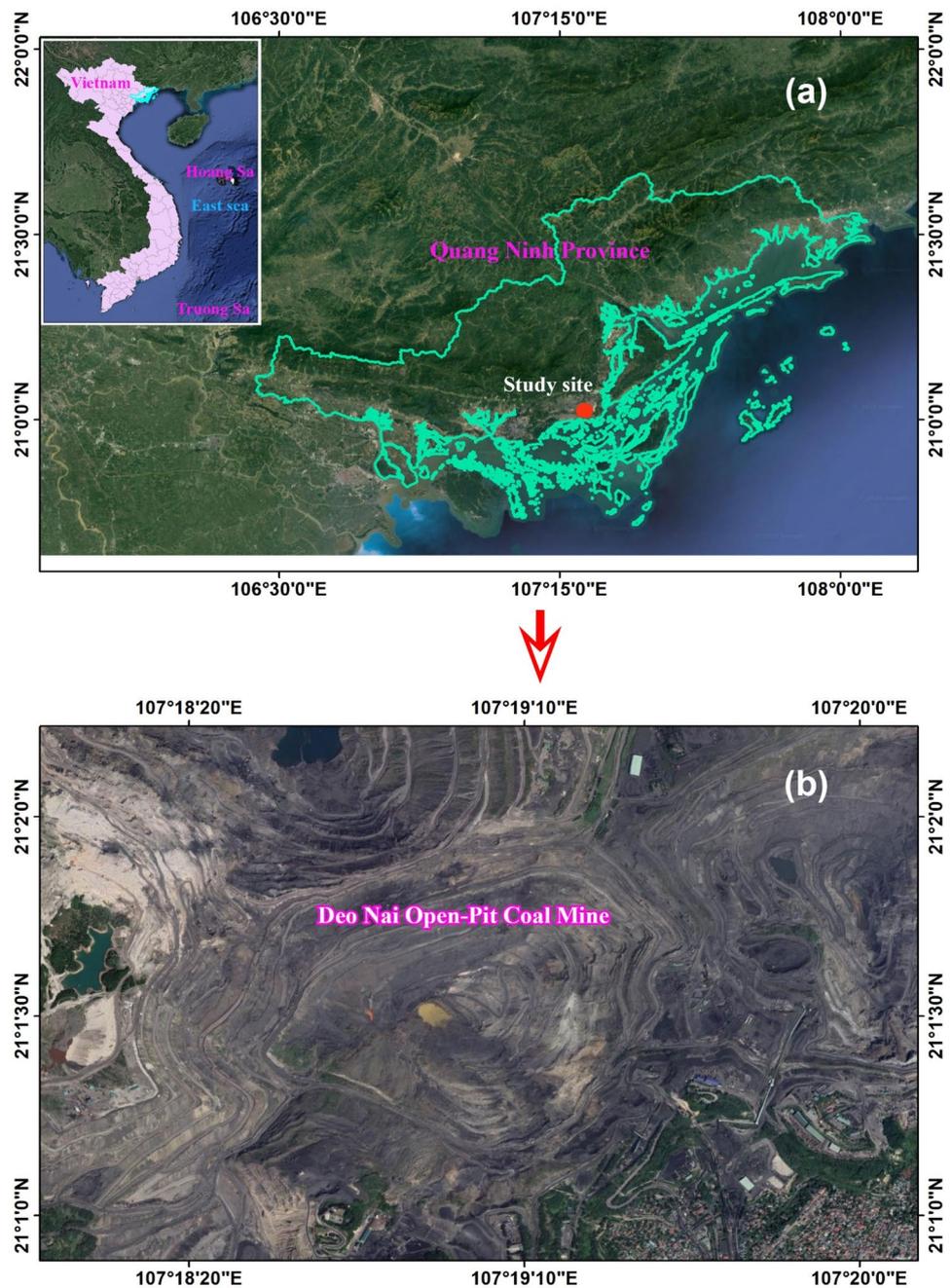
### 5.2 MARS model

Given the importance of fine-tuning the MARS’s parameters to reach an optimal MARS model for PPV prediction, a grid search for the parameters of the MARS model

was established for the maximum number of basis functions used and the penalty values, as shown in Fig. 6. It is worth noting that the statistical method of *tenfold* cross-validation was applied to estimate the MARS model’s skill and select the best MARS model for a given predictive modeling problem (i.e., PPV prediction). The data set was standardized before developing the MARS model using the Box–Cox transformation method [94] to avoid overfitting.

In addition to the development of the MARS model to predict PPV, the predictive values of a series of the MARS models are also to propose the novel MARS–PSO–MLP model, as introduced above. Therefore, the seven best MARS models were selected based on the obtained results in Fig. 6 for the next step (developing the MARS–PSO–MLP model), and the performance of the seven MARS models are listed in Table 1. Herein, the MARS-01 model is the best, and it was used as a stand-alone model to compare with the other models in the next sections. Note that there are two parameters used to control the MARS models’ performance, including penalty values ( $d$ ) and the maximum number of basis functions ( $f$ ).

**Fig. 4** Study area and its location on satellite imagery. **a** Location of the Deo Nai open-pit coal mine; **b** Areal view of the mine



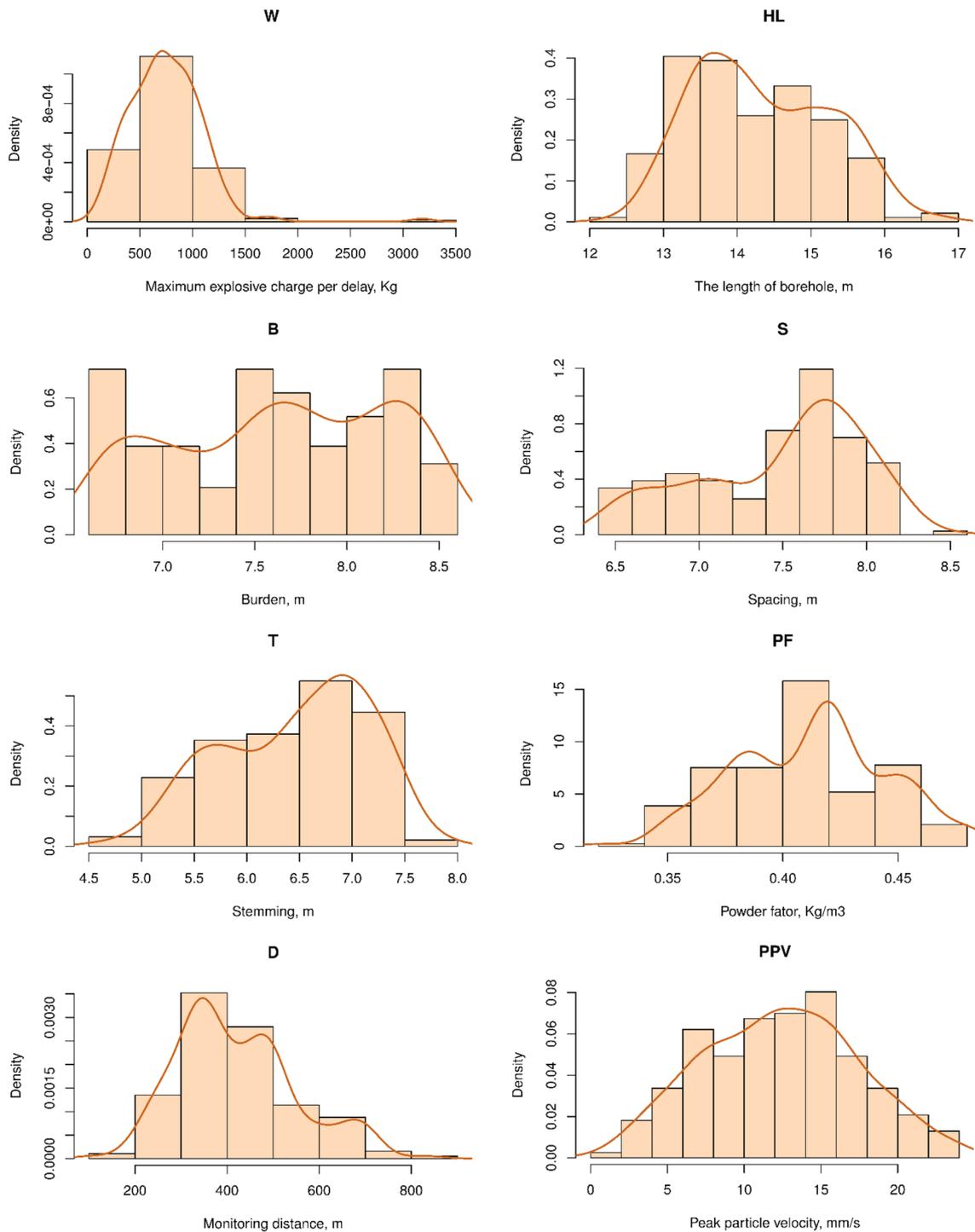
### 5.3 MLP model

To develop the MLP model for PPV prediction in this mine, a structure with a single hidden layer of the MLP model was used to prevent the overfitting phenomenon, and this structure was also recommended for such a simple problem (i.e., PPV prediction) [95–98]. Subsequently, the trial and error procedure was applied to determine the best number of neurons. To avoid overfitting, the Min–Max scaling method was used with the normalized data values are in the range of  $-1$  to  $1$ . The FFBP algorithm was applied to train the

MLP model in this case. Eventually, an MLP model was developed for predicting PPV, as illustrated in Fig. 7.

### 5.4 PSO–MLP model

As stated earlier, an MLP model's primary problem is the network's architecture, and it has been described above. However, in MLP, the information between neurons are represented by the weights, and they can fine-tune to reach an optimal MLP model for PPV prediction. Therefore, we applied the PSO optimizer to enhance the MLP model's



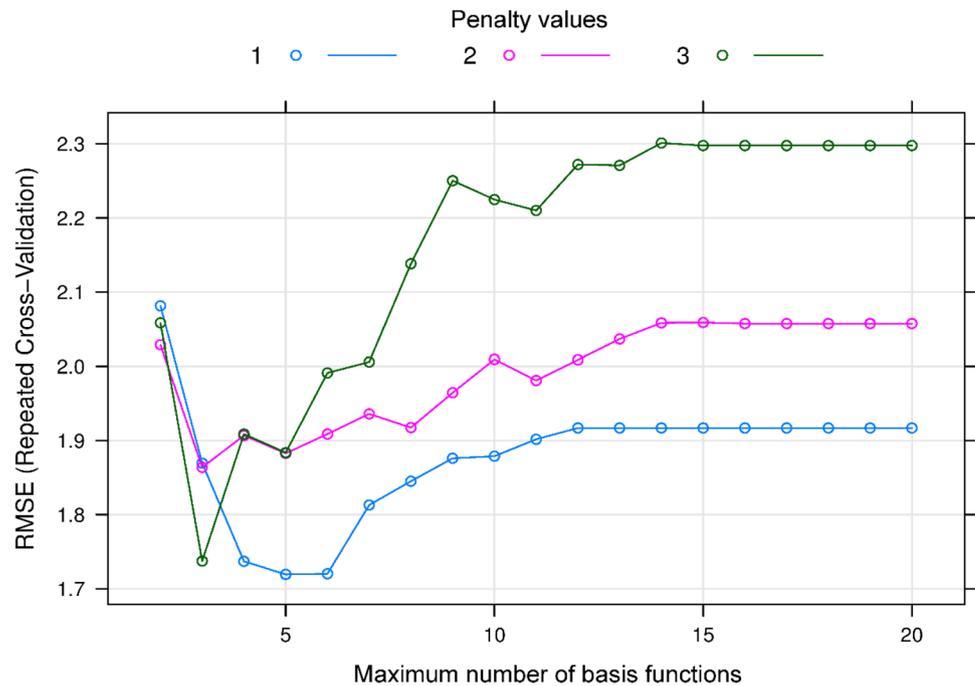
**Fig. 5** Histogram and density of the variables used for PPV prediction

accuracy through the weights' fine-tuning, as proposed in Fig. 2. To do so, the parameters of the PSO algorithm were set up first, as follows:

- The weight of the bird: [0.4, 0.9];
- The effect of local best and global best: 1.2;
- Lower and upper bound: [- 1, 1];

- Population sizes: 50, 100, 150, 200, 250, 300, 350, 400, 450, 500;
- Maximum number of iterations: 1000;
- Fitness function: RMSE (Eq. 2);
- Programming language: R (version 4.0.3).

**Fig. 6** MARS models with different hyper-parameters for PPV prediction



Next, the optimization process starts to optimize the MLP model weights for PPV prediction through the stopping conditions, as shown in Fig. 8. Ultimately, the optimal PSO–MLP model for PPV prediction in this mine was defined, and its architecture is shown in Fig. 9.

### 5.5 MARS–PSO–MLP model

Whereas the empirical, MARS, MLP, and PSO–MLP models were developed using the same original training data set, the MARS–PSO–MLP model was developed based on the compilation of the original training data set and combination of the predictive values from the MARS models in Table 1 (seven MARS models), as described in Fig. 3. Subsequently, the predictive values of these seven MARS models are merged to develop an MLP model. In other words, another MLP (with the same structure as the MLP

and PSO–MLP models) was developed based on the alternative training data set from the predictive values of the seven developed MARS models. To optimize this new MLP model, the PSO algorithm was also applied as those applied for the PSO–MLP model with the same settings, and some exciting results are noticed in Fig. 10. Ultimately, the optimal MARS–PSO–MLP model was developed, as shown in Fig. 11. It is important to note that despite the architecture of the MLP, PSO–MLP, and MARS–PSO–MLP are the same; however, their weights are very different (it can be observed through the lines in Figs. 7, 9, and 11) due to the optimization of the PSO algorithm and the contributions of the MARS models.

Once the PPV prediction models were well-developed as described above, PPV predictions, in this study, are done using five developed models, including empirical, MARS, MLP, PSO–MLP, and MARS–PSO–MLP. The results of PPV prediction using the five developed models are calculated in Table 2.

**Table 1** Selected MARS models for developing the MARS–PSO–MLP model

Model	$d$	$f$	RMSE	MAE	$R^2$
MARS-01	1	5	1.719	0.994	0.865
MARS-02	1	6	1.720	1.001	0.866
MARS-03	1	4	1.737	0.925	0.857
MARS-04	3	3	1.737	0.951	0.857
MARS-05	1	7	1.813	1.066	0.858
MARS-06	1	8	1.845	1.091	0.855
MARS-07	2	3	1.864	1.038	0.845

## 6 Discussion

From the calculated results in Table 2, it is evident that all four AI models (i.e., MARS, MLP, PSO–MLP, and MARS–PSO–MLP) have relatively few errors, and their accuracy is acceptable. Of those, the MARS’s performance is slightly lower than the MLP’s performance on the training phase. However, it is somewhat higher than the MLP model on the testing phase. Remarkably, the MLP model’s

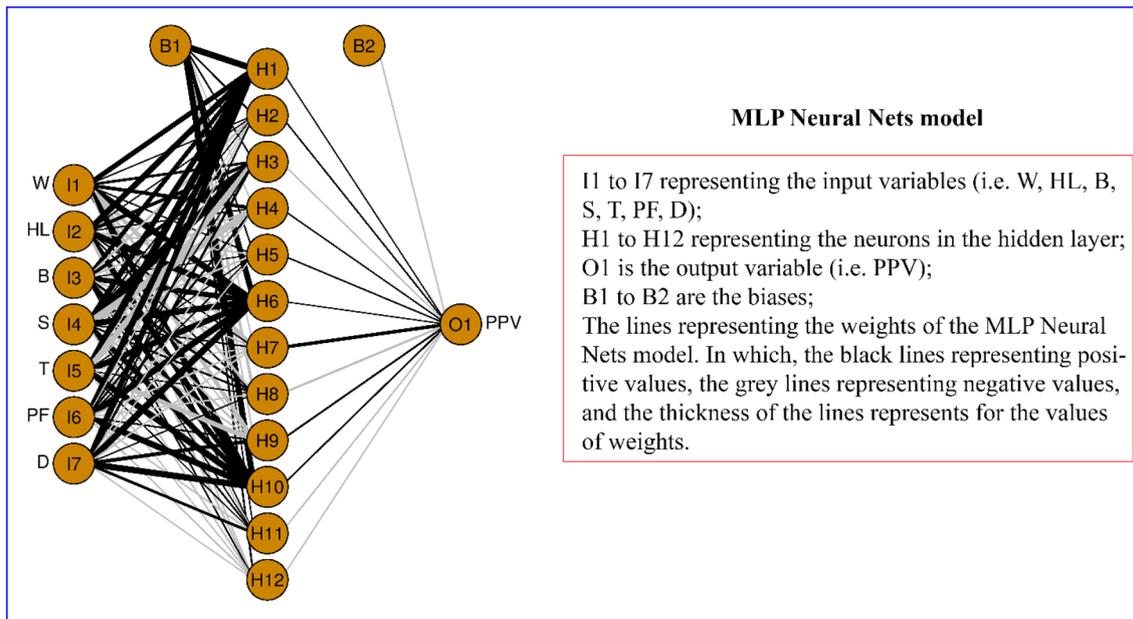


Fig. 7 Architecture of the MLP model for PPV prediction

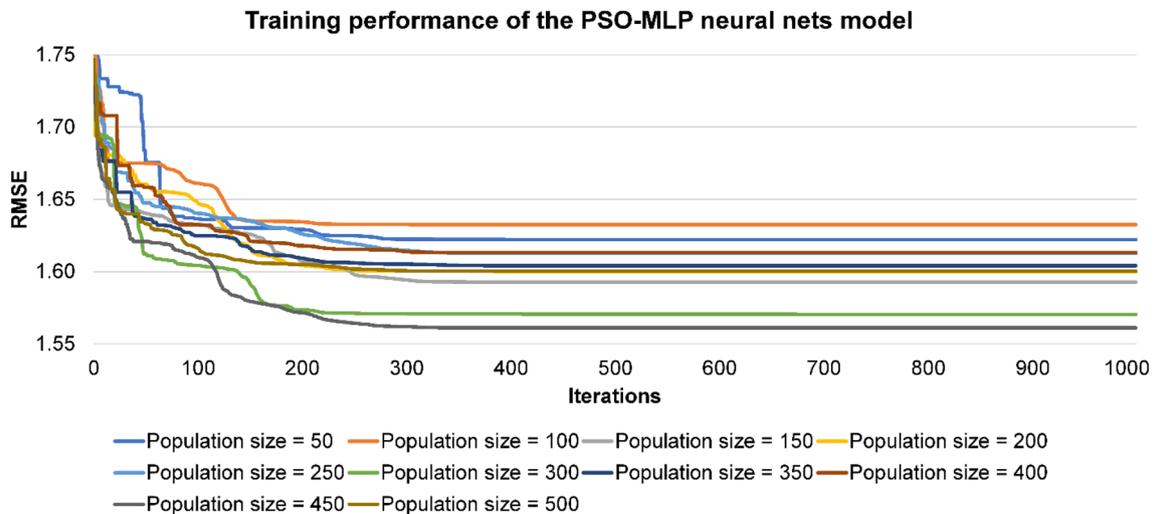


Fig. 8 Results of the optimization process of the MLP model by the PSO algorithm

accuracy was boosted by the optimization feature of the PSO algorithm, and the performance of the PSO-MLP is higher than those of MLP (without optimization) and MARS models on all parts of the data set.

In this study, the stacking approach was applied to develop and propose the novel hybrid MARS-PSO-MLP model for predicting PPV. The results in Table 2 indicated that the proposed hybrid MARS-PSO-MLP model yielded an outstanding performance with the highest accuracy. Its performance even is higher than the PSO-MLP model on all the data sets. This finding indicates that the

combination strategy of stacking and optimization methods of MARS and MLP models provided an alternative training data set with a better normalization and regression. Therefore, the proposed MARS-PSO-MLP model better performed in predicting PPV. These results can be observed in Fig. 12.

In contrast to the AI models, the highest error and the lowest convergence were found in the empirical model provided, as shown in Table 2. This result indicated that a simple linear equation is not suitable for predicting PPVs in this mine. Instead, a non-linear equation or complexity

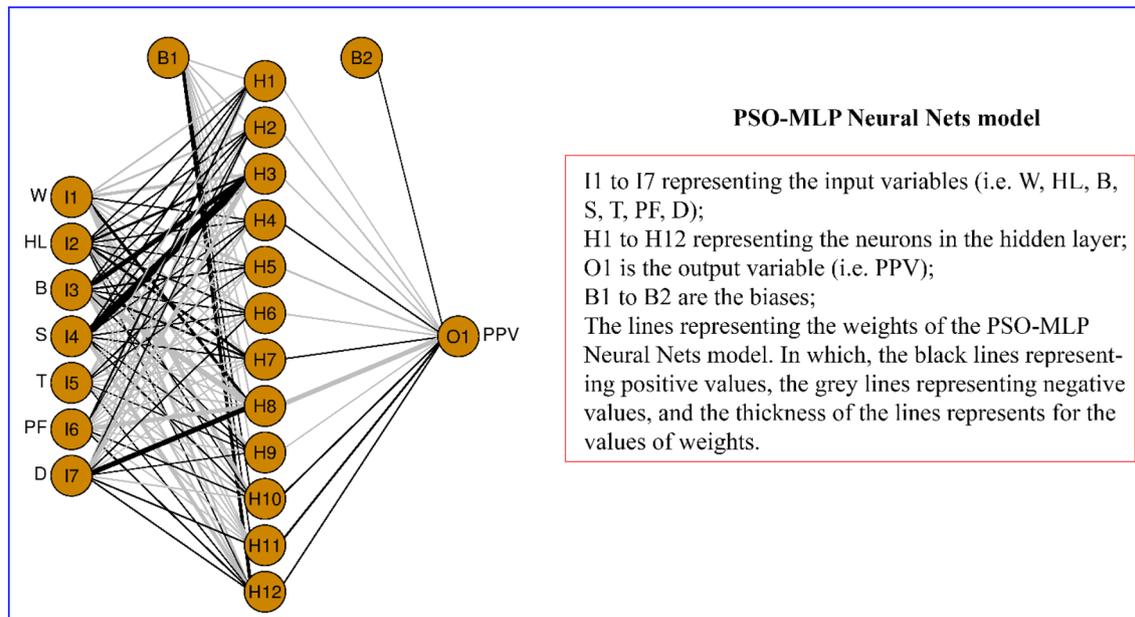


Fig. 9 PSO-MLP model for PPV prediction

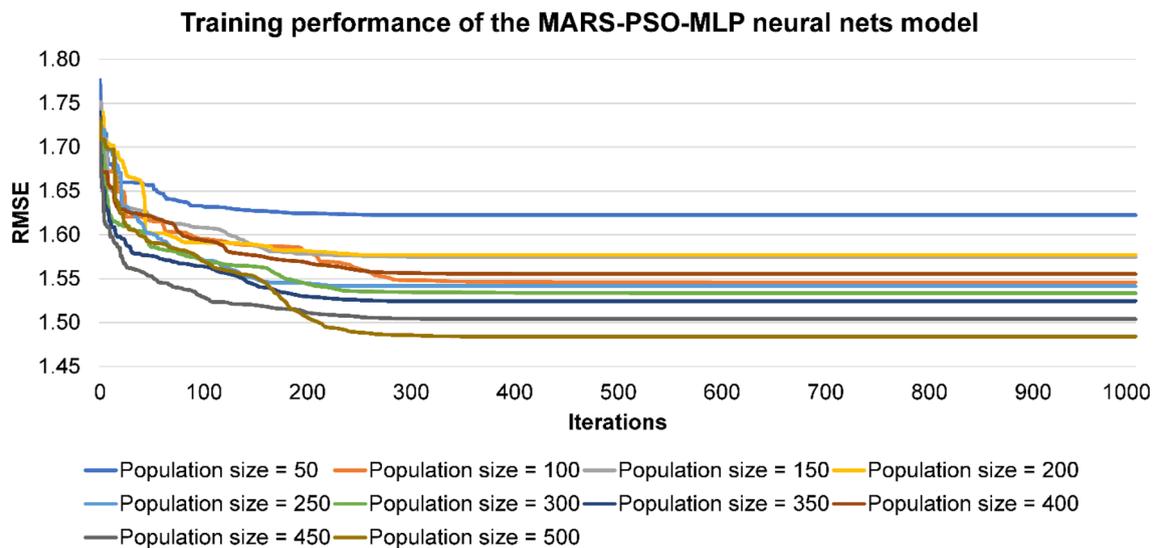


Fig. 10 Results of the MARS-PSO-MLP model for training PPVs

"black box" algorithms should be considered and used to predict PPV.

As shown in Fig. 12, on the training data set, the correlation of PPV values (measured versus predicted) of the MARS, MLP, PSO-MLP, and MARS-PSO-MLP models is superior to the empirical model. Of those, the correlation of the MARS and MLP are not too dissimilar. Notably, the optimization models' correlation (PSO-MLP and MARS-PSO-MLP) is improved significantly, especially the proposed MARS-PSO-MLP model. On the testing

data set, the optimization models' regression level is better than the other models as well, especially the proposed MARS-PSO-MLP model. For further assessment of the developed models in practice, the models' residuals on the testing data set were computed and visualized in Fig. 13.

Taking a look at Fig. 13, it can be seen that the residual plots show a somewhat random pattern. Accordingly, the distributions of PPV predictions on the four developed AI models are symmetrical, have no obvious patterns, and tend to cluster towards the middle of the plots. Still, the

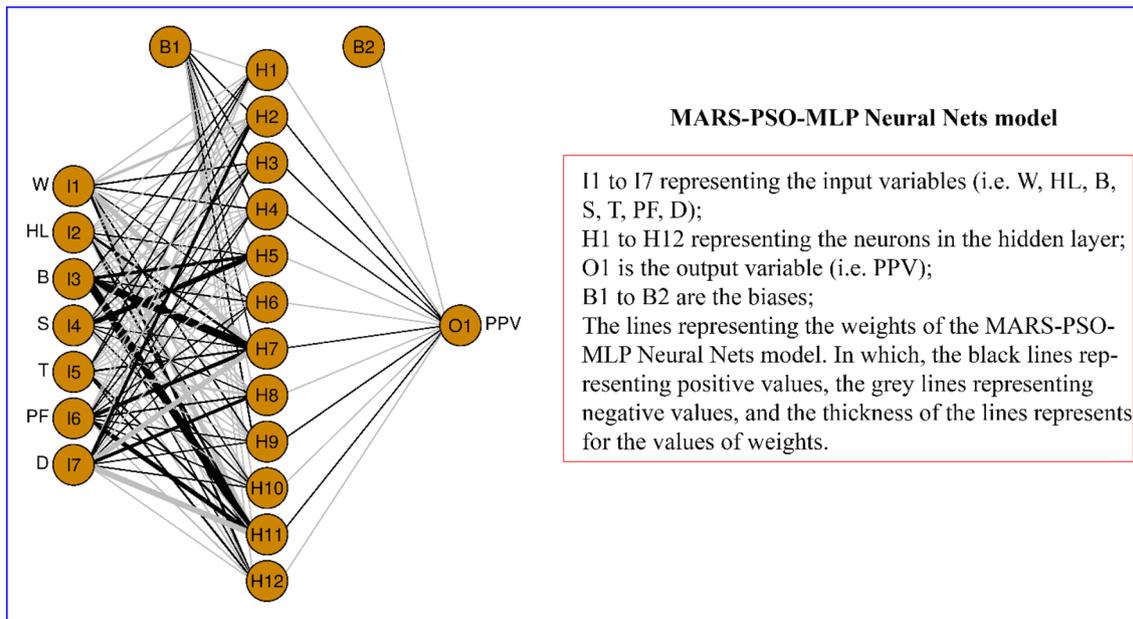


Fig. 11 MARS-PSO-MLP model for PPV prediction

**Table 2** Performance indexes of the AI and empirical models for predicting PPV

Model	Training			Testing		
	RMSE	MAE	$R^2$	RMSE	MAE	$R^2$
Empirical	4.342	3.069	0.287	5.059	3.860	0.127
MARS	1.740	0.885	0.879	1.596	0.941	0.889
MLP	1.704	0.927	0.884	1.704	1.427	0.871
PSO-MLP	1.561	0.762	0.903	1.582	1.058	0.891
MARS-PSO-MLP	1.484	0.792	0.913	1.569	1.017	0.902

residuals of the empirical model are not. Besides, the histogram of the models' residuals is also an excellent metric to evaluate whether the models are valid or not. As shown in Fig. 13, we can see that the histogram of the empirical model is not normal (i.e., not bell-shaped), and it should not be a valid model for PPV prediction. In contrast, the four AI models provided normal histograms, especially the proposed MARS-PSO-MLP model. This indicates that the proposed MARS-PSO-MLP model is the best fit model for PPV prediction.

To better understand the mechanism of the proposed MARS-PSO-MLP model, as well as the role of the input variables in the modeling, the importance level of the input variables was investigated through a sensitivity analysis, as shown in Fig. 14. The results show that W, D, S, PF, and B have significant effects on PPV, especially W and D. Remarkable, the T variable has a minimal impact on PPV, and its role in modeling PPV is not exact.

## 7 Conclusion

Ground vibration is one of the most damaging effects in mine blasting, and accurate prediction of PPV has an essential meaning in controlling and reducing the adverse impacts on the surroundings. The results showed that MARS and MLP are potential tools for predicting PPV with acceptable accuracy. Based on the stacking method's flexibility strategy, the MARS models and the PSO algorithm significantly improved the MLP model's accuracy. In other words, by fully considering and combining the predictive values of seven MARS models and the robust optimization ability of the PSO algorithm, the proposed MARS-PSO-MLP model significantly improved the accuracy of the MARS, MLP, and PSO-MLP models in predicting PPV. In conclusion, the proposed MARS-PSO-MLP model is a reliable method for PPV prediction in mine blasting.

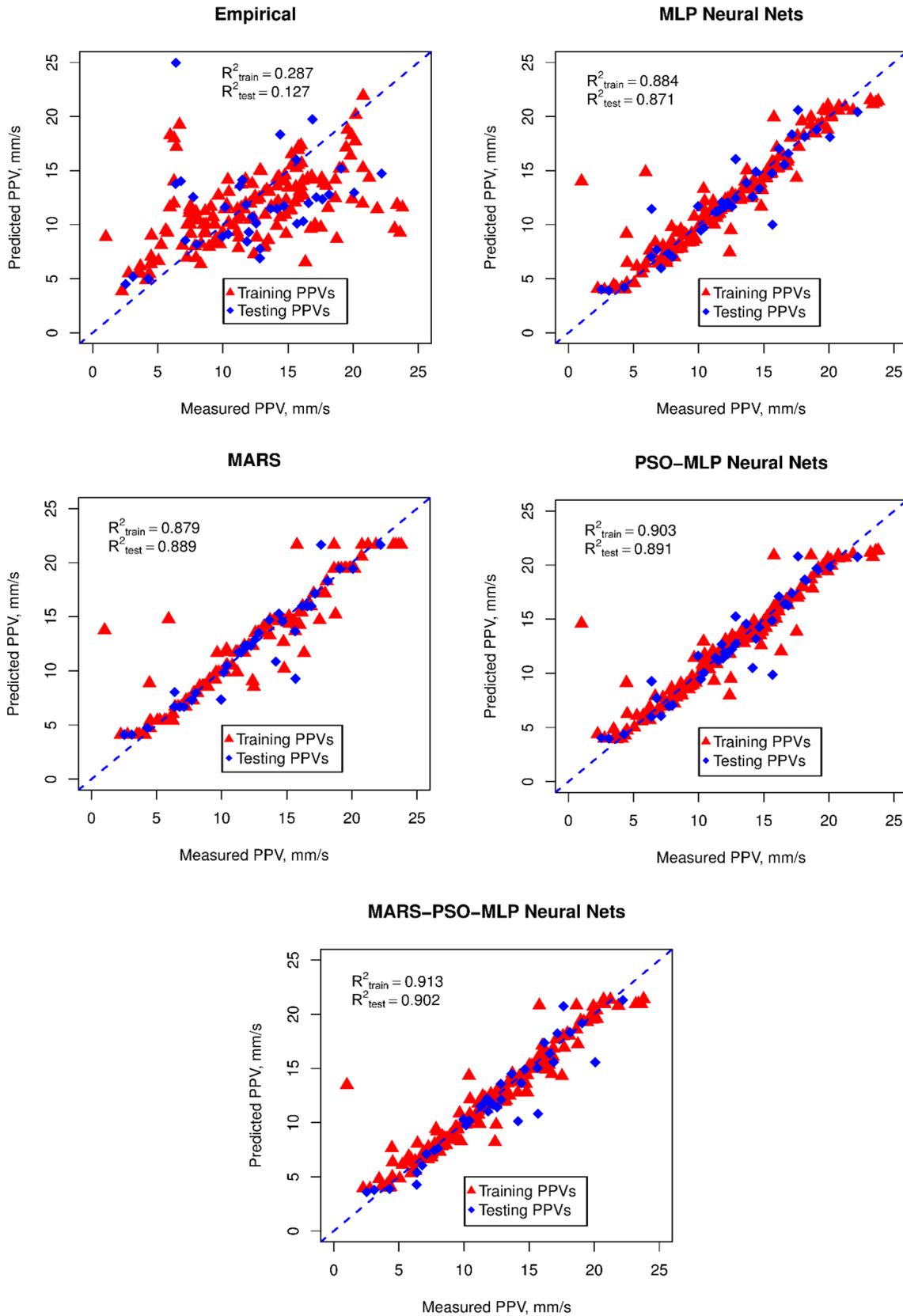


Fig. 12 Correlation and regression possibility of the PPV prediction models

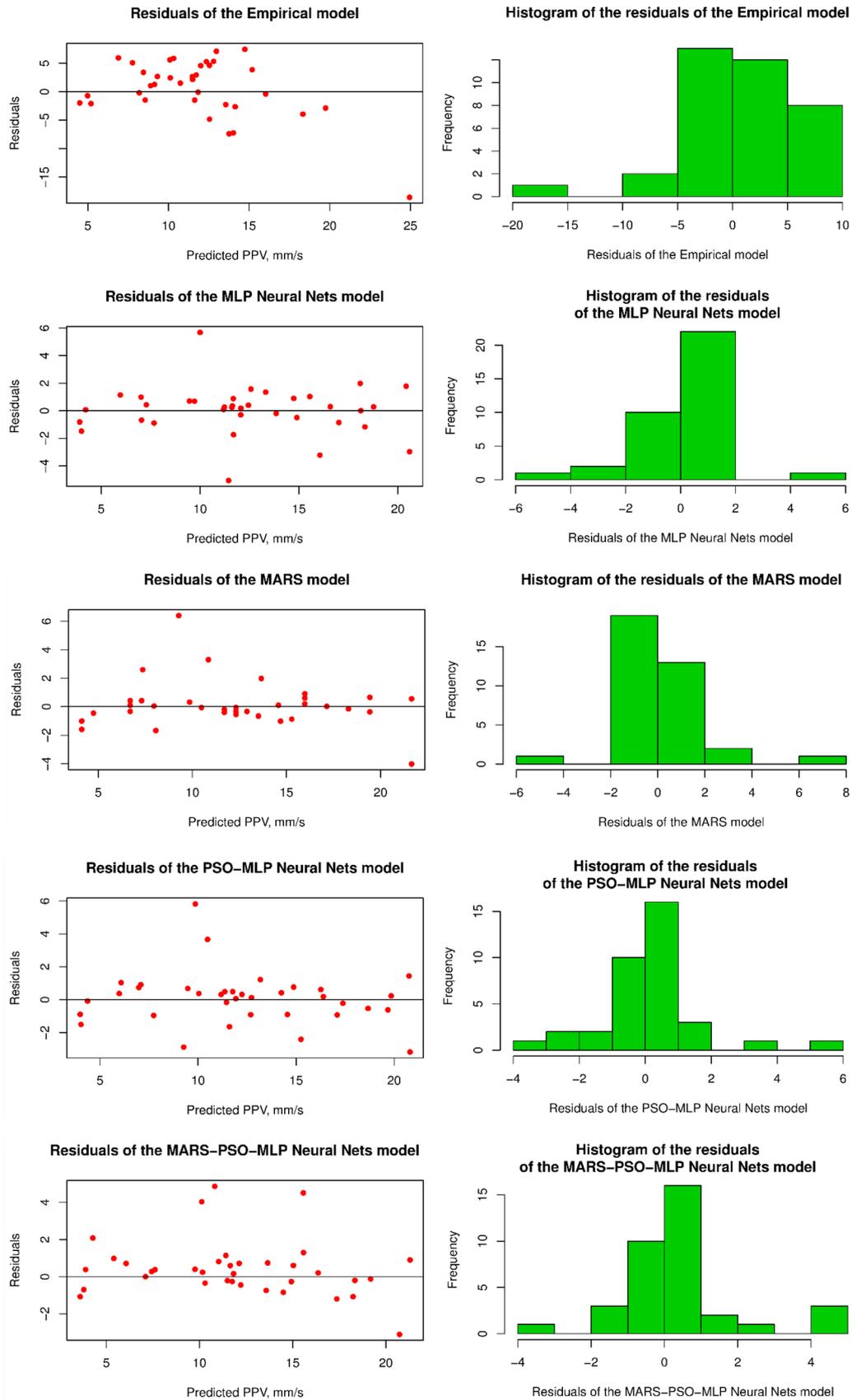
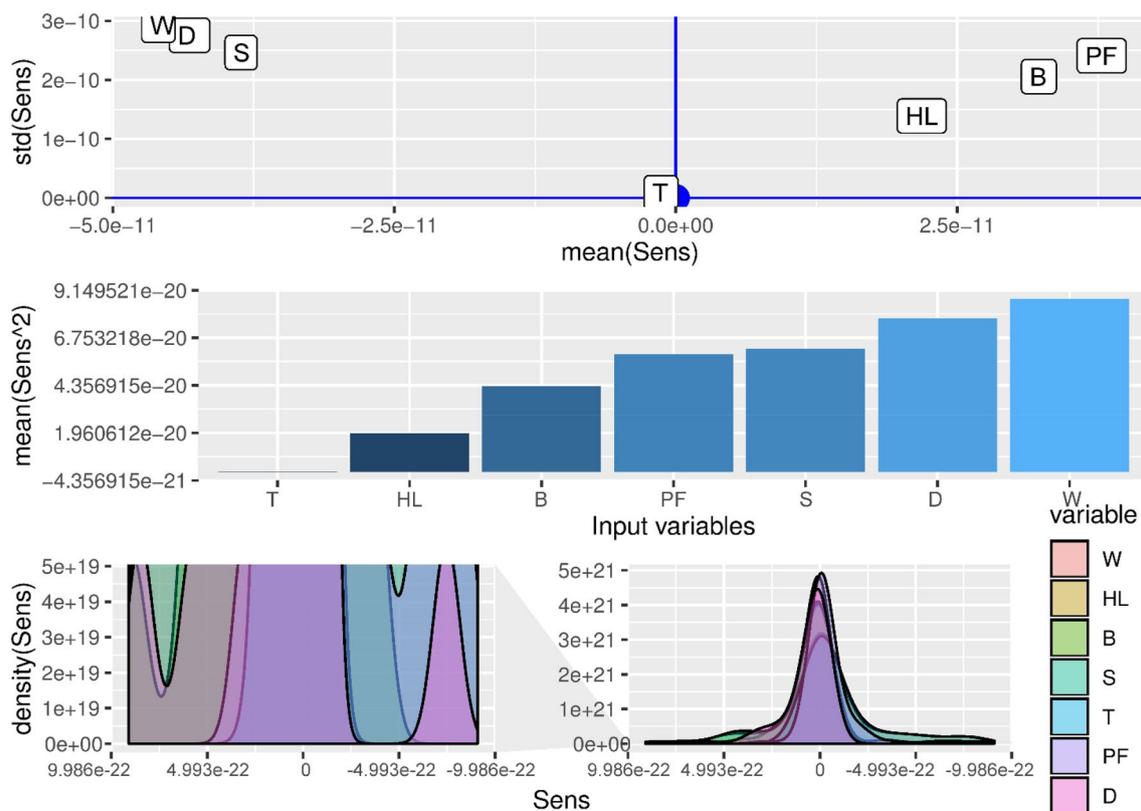


Fig. 13 Residual results of the PPV prediction models



**Fig. 14** Important level of the input variables with the density, mean and standard deviation

Furthermore, the W, D, S, PF, and B variables are highly sensitive to PPV, especially W and D, and should be used and taken into account to predict PPV. In addition, the T variable has a minimal impact on PPV, and its role in the modeling of PPV is not exact.

Although the MARS–PSO–MLP is introduced as a novel intelligent model for predicting PPV with high accuracy; however, it should be considered to optimize the blasting parameters in future works based on the predicted results to reduce the intensity of ground vibration. In addition, characteristics of rock mass and geological conditions are also challenges for future studies in predicting PPV.

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### Compliance with ethical standards

**Conflict of interest** The authors declare that they have no conflict of interest.

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