



Original Paper

A Novel Combination of Gradient Boosted Tree and Optimized ANN Models for Forecasting Ground Vibration Due to Quarry Blasting

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An ensemble technique namely gradient boosted tree (GBTs) and several optimized neural network models were hybridized to predict peak particle velocity (PPV) caused by quarry blasting. The GBT was employed for choosing the most important input parameters on PPV results. Therefore, this model selected five input variables, comprising maximum charge per delay, distance, powder factor, and sub-drilling, and RQD. Once the input assortment was performed, five neural network models, including a typical artificial neural network (ANN) and ANNs with weight optimization (forward, backward, particle swarm optimization, PSO, and evolutionary), were implemented utilizing the inputs picked by the GBT. These models were assessed by several performance criteria, including the “correlation coefficient”, “root mean square error”, “variance accounted for”, “a20-index”, and a simple ranking system, as well as optimized weights. The results of hybridization showed that ANN-PSO model outperformed other models in terms of system error and accuracy. Altogether, this study’s findings implied that consolidating the ensemble machine learning technique and optimized ANN models, particularly PSO could result in perfect and straightforward to understand predictions of PPV caused by quarry blasting.

KEY WORDS: Peak particle velocity, Quarry blasting, Gradient Boosted Trees, Optimized neural networks.

INTRODUCTION

It is estimated that barely one-third of the energy generated through an explosion is utilized for grinding and relocating the rock mass during blasting operations (Khandelwal & Singh, 2009; Monjezi et al., 2011). The remaining of this energy is squandered and creates unwanted environmental effects, including back-break, ground vibration (GV), fly-rock, and air overpressure (Armaghani et al., 2014; Hajihassani et al., 2014a; Han et al., 2020; Hasanipanah et al., 2017; Khandelwal & Singh, 2005; Nguyen et al., 2019, 2020; Shang et al., 2019; Zhou et al., 2020a). Among all environmental issues

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arising out of blasting, the most serious one is considered as GV (Siskind et al., 1980). This issue may create environmental effects to the surrounding areas such as vibration and damage to building structures, slope instability and bench instability in open-cast mines, bad effects on ground water, and damage to railways (Singh & Singh, 2005; Standard, 1973). Therefore, literature includes many studies proposing various experimental, statistical and computational techniques to predict and control this environmental issue. Since the most important component of GV is defined as the peak particle velocity (PPV), this study focused on this component (Siskind, 2005; Siskind et al., 1980).

Several experimental formulas were ascertained for forecasting PPV produced by blasting (Davies et al., 1964; Roy, 1993). Nevertheless, these experimental techniques count inadequate parameters for controlling and predicting PPV (Zhou et al., 2020b). In fact, PPV values are further influenced by additional unmanageable factors, e.g., geological and rock mass properties as well as blasting geometry (Singh & Singh, 2005). Consequently, experimental approaches are not reliable adequately in various circumstances. At the same time, the forecast of the PPV with an excellent level regarding precision is essential for evaluating the safety zone of blasting. Along with the experimental equations, analytical and statistical techniques, including simple and multiple regression methods aimed at PPV forecast, have gained recognition chiefly due to their efficiency of application (Hajihassani et al., 2015; Hudaverdi, 2012). In addition to the statistical techniques, soft computing and machine learning approaches showed a successful ability to estimate PPV values resulting from blasting (Dindarlo, 2015; Monjezi et al., 2016).

The artificial neural networks (ANNs) were extensively employed for investigating engineering issues and were acknowledged as manageable non-linear function estimates. However, ANNs can immediately outline the input to output data and use every critical parameter to forecast PPV values; some limitations exist, including the learning's gradual pace and the probability of catching in local minima (Momeni et al., 2020; Shi & Eberhart, 1998). The usage of robust optimization techniques, including wrapper methods, particle swarm optimization (PSO), and genetic algorithm (GA), is beneficial to enhance the ANN performance and remedying the shortcomings mentioned earlier

(Adhikari & Agrawal, 2011; Poli et al., 2007; Tonizam Mohamad et al., 2016).

This study introduced innovative approaches established on the hybridization of the ANN model with forward selection, backward selection, PSO, and evolutionary techniques for forecasting the PPV generated by blasting. The input parameters were selected based on an ensemble machine learning (ML) technique (gradient boosted tree) that reduces many biases made by weak learners. Then, these techniques were assessed according to several performance indices and the best one was introduced as a new and applicable approach in estimating blasting environmental issues. The combination mentioned above was employed for the first time to predict the ground vibration resulting from quarry blasting. The performance of the models developed showed that these models are efficiently capable to predict the PPV values.

LITERATURE REVIEW

PPV Background

The vibration of the ground implies a streaming movement that progresses continuously of the explosion toward adjacent regions. Some sizable quantity from energy is utilized in all GVs. Energy mentioned earlier is assumed for being used in rock shattering. The issues made by GV involve massive influences on the nearby area's constructions, groundwater, and environment (Duvall & Fogelson, 1962; Ghasemi et al., 2013). If the explosive explodes within a blast hole, its biochemical reaction creates a gas that is high-pressure/temperature. The pressure of the gas breaks the rock near the explosion hole. The blast pressure fades or disappears immediately. A surge movement is produced in the earth through the strain surges moved to the neighboring stones (Duvall & Petkof, 1959). Because of many cracking mechanisms, including radial cracking, crushing, and reflection breakage in the free face, individual pressure waves' grind the rock piece. The gasses with high-pressure/temperature increase radial fractures and any discontinuity and crack. The stress surges develop as elastic surges during the strain surge strength decreases toward a degree wherein no continual metamorphosis happens in the rock piece. Individual surges are known as GV. These vibrations developed from the explosion chamber in all

ways (Dowding, 1985) and can destroy structures and other constructions (Siskind et al., 1980).

Multiple parameters, such as blasting pattern factors, geological and geotechnical factors and distance of measuring from the blast site, are connected to GV (Khandelwal & Singh, 2006; Monjezi et al., 2013; Zhang et al., 2020). The blasting design should be optimized based upon the rock mass and geological characteristics for reducing GV values. These rock mass attributes may incorporate the strength of rock, density, the velocity of the wave, and discontinuity statuses (Duvall & Petkof, 1959). GV is typically estimated regarding the frequency and PPV. In several standards and guidelines (New, 1986; Standard, 1973), the PPV is regarded as a vibration index, a vital indicator for managing and measuring the structural damage. Generally, the PPV relies on two main factors (Ozer et al., 2008): (a) maximum charge (MC) used per delay and (b) distance (D) from the free face.

Previous Investigations

In order to evaluate and forecast PPV values, three general categories of methods exist, namely (1) empirical/experimental, (2) statistical and regression-based, and (3) soft computing and ML. Several studies ascertained experimental vibration formulas for PPV forecast (Ghosh & Daemen, 1983; Langefors & Kihlström, 1963; Roy, 1993; Zhou et al., 2020b). In these formulas, the MC and D are regarded as the principal substantial inputs for PPV forecast. However, it is acknowledged that PPV is affected by other parameters, which are not included clearly in any of the experimental formulas, including (a) blast geometry, (b) rock mass properties, and (c) discontinuity conditions. Thus, different formulas return various PPV values for identical blasting work, and there is no agreement among the consequences foretold by various formulas (Jahed Armaghani et al., 2015).

In addition to empirical methods, statistical and regression-based techniques have been developed to predict PPV values using more than four parameters as inputs (Hajihassani et al., 2014b; Shirani Faradonbeh et al., 2016; Singh & Singh, 2005). They mostly use linear and nonlinear relationships between model inputs and statistical output model (i.e., PPV). Normally, nonlinear statistical equations are better than linear equations. However, they are also weak in PPV evaluation due to their low flexi-

bility against newly used parameters (Khandelwal & Singh, 2009).

PPV is broadly predicted and analyzed utilizing soft computing and ML methods. Singh and Singh (2005) applied ANN and regression-based predictive models to forecast PPV. They considered several inputs, including hole diameter, burden, D, number of holes, spacing, and hole depth. They also confirmed that ANN is a more objective method than regression analysis to forecast GV. Another study by Khandelwal and Singh (2006) examined four broadly applied experimental predictors of PPV using a blast dataset with 150 data. In addition, they analyzed the calculated outcomes and real data obtained from the field. Afterward, they applied an ANN with two inputs, including (MC and D) and one output (i.e., PPV). Besides, Khandelwal and Singh (2006) discovered that ANN outcomes are more precise than empirical predictors. A different study by Iphar et al. (2008) employed two distinct approaches, including simple regression and neuro-fuzzy, for predicting PPV values. Their study revealed that the neuro-fuzzy technique generated more reliable consequences compared to the regression analysis. Another ANN model using multiple inputs, including MC, stemming length, D, and hole depth, was proposed by Monjezi et al. (2011) for PPV forecast. They proved that ANN is a practical approach to forecast PPV values. A fuzzy logic method and standard regression analysis were used by Fisne et al. (2011) for PPV forecast employing a dataset from the Akdaglar mine in Turkey with 33 data samples. Their investigation used D and MC as inputs for PPV prediction. They determined that the forecasted PPV values attained from the fuzzy logic model were significantly more similar to the estimated PPVs than the forecasted values with an analytical technique.

Hajihassani et al. (2014b) conducted a different study on PPV prediction and adopted a competitive imperialism algorithm (ICA)-ANN for predicting PPV values. They applied this model to some inputs, including D, the burden-to-spacing ratio, MC, p-wave velocity, stemming length, as well as Young's modulus. They determined that their approach could forecast PPV with greater precision compared to experimental equations. There are some other interesting and effective techniques in the field of PPV prediction such as support vector regression—firefly algorithm, feature selection—random forest, autonomous groups PSO—extreme learning machine, Gaussian process regression, fuzzy C-

means clustering—quantile regression neural network (Arthur et al., 2020; Bui et al., 2020; Yang et al., 2020a; Zhou et al., 2020b). It seems that these soft computing and ML techniques are able to solve PPV problems more efficiently compared to other available approaches. It should be noted that there are many successful reports of these techniques for solving problems in science and engineering (Azizi et al., 2014; Armaghani et al., 2017; Azizi, 2018; Ghafoorpoor Yazdi et al., 2019; Huang et al., 2020, 2021a, b, c, d, e; Kardani et al., 2020, 2021; Huang & Wang, 2021; Yang et al., 2020b; Zhou et al., 2012; Asteris et al., 2021). Thus, we decided to use these techniques to introduce a new procedure and model for PPV prediction.

METHODOLOGY

This research employed a hybrid approach to predict PPV produced by mine blasting. Initially, we used a ML technique namely gradient boosted tree (GBT) as a process for input selection. An ANN technique was then applied to the selected inputs. Finally, this hybrid model was optimized with a series of optimization techniques to achieve the most suitable ANN model for PPV prediction. Figure 1 shows the flowchart of this study and all steps involved to attain the study objectives.

Input and Target Variables

Ascertaining the input variable is a start for generating a forecast model for PPV. It is critical to identify the most significant factors of PPV for proposing a comprehensive and perfect model. In learning the critical factors, it is necessary to acknowledge that the chosen factors need to render the site circumstances, and the explosion design factors need to be assessable and should be straightforward to collect concurrently. There is a close association between the blast design factors and the PPV outcomes in blasting. Accordingly, this study considered many parameters in the modeling process, such as MC, stemming length, sub-drilling, burden-to-spacing ratio, rock quality designation (RQD) and powder factor. PPV values may rise if the design of specific factors is conducted poorly. The values of PPV drop as the interval between the free face and the monitoring spot increase. Consequently, as an essential factor, it was utilized in the

process of modeling. The data collected from quarry site with some more information about the data are presented in Table 1. In the following section, the procedure of the ML technique (i.e., GBT) used to select input variables is described.

Input Selection Technique

In this part, the method of input selection, namely GBT, was applied to identify the most effective input parameters. GBT is among the most rigorous ensemble models, which combine several consecutive simple regression trees into a more robust model (Fig. 2). In general, fixed size trees are employed as base learners. To make straightforward the process, regression trees are designated as base (or weak) learners, and the gradient descent system is utilized to lessen the loss function. Friedman (2001) made some amendments in this algorithm and according to these changes, the algorithm selects a distinct optimal weight value for every leaf in the tree, rather than a single weight for the entire tree, where the weight is carefully chosen as to decrease the loss function merely on the training data falling in a leaf.

Predictive and Optimized ANN Models

ANN is a variety of artificial intelligence that copies an individual's mind functions. Ordinarily, the ANN leads to assort experiential information (Kamavisdar et al., 2013). This technique incorporates a set of layers, and an individual layer comprises a chain of neurons. Weighted links attach these neurons to neurons in each layer on the preceding and following layers (Liu et al., 2003). A positive weight exhibits an excitatory connection, whereas a negative weight shows an inhibitory relationship. A standard ANN incorporates three layers, i.e., input layer, hidden layer, and an output layer (Fig. 3). These elements require to be described as a primary set of weights and demonstrate how weights must be changed through training to improve the achievement and based on the problem (Monjezi & Dehghani, 2008).

Weight Optimization Techniques

The weight optimization step is of intense interest because the body of literature acknowledges that the performance of ANNs is affected by pri-

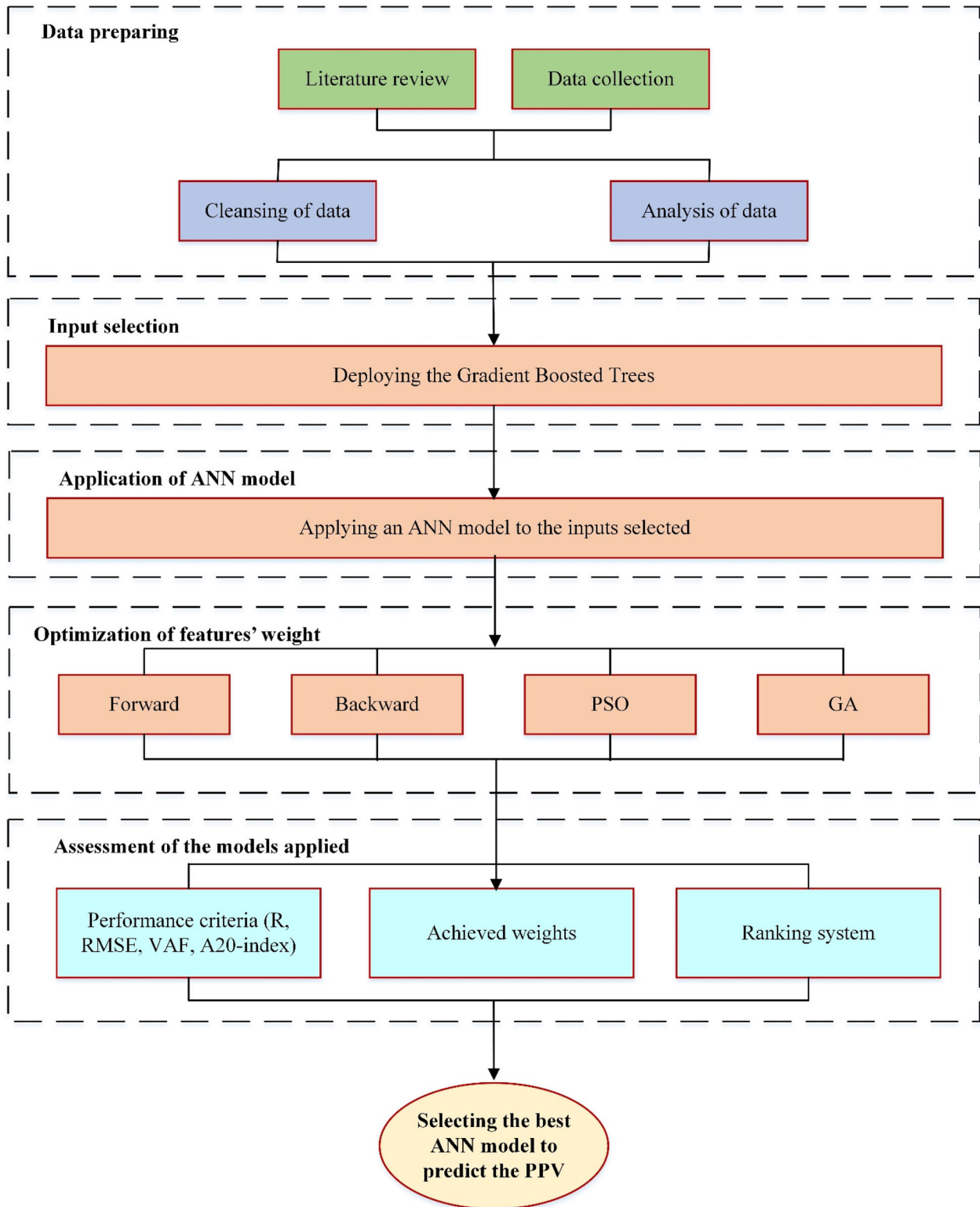


Figure 1. Flowchart of this study for PPV prediction.

Table 1. Data collected from quarry site

Factor	Unit	Symbol	Range	Average
Burden to spacing	–	BS	0.62–0.97	0.78
Maximum charge per delay	kg	MC	56.3–101	75.6
Distance	m	D	255–670	520.3
Peak particle velocity	mm/s	PPV	1.4–9.9	3.22
Powder factor	kg/m ³	PF	0.4–1.16	0.65
Rock quality designation	%	RQD	39–79	60
Stemming length	m	St	1.5–37	2.51
Sub-drilling	cm	SD	24–48	38.1

mary weights assignment. Thus, this research study employed four techniques, including forward, evolutionary, backward, and PSO to optimize the weights of the attributes. Attribute weighting is a method for estimating the optimal degree of individual attributes' impact employing a training dataset. If successfully applied, related attributes are associated with a significant weight value, whereas unrelated attributes are assigned a weight value near zero. The forward weight optimization technique achieves the weighting following the naive theory that the attributes are independent. Every attribute is weighted with a linear quest. This method may give excellent outcomes following a short period if the attributes are not profoundly correlated. In fact, forward optimization selects a subset of the attributes for the final model. Different from forward optimization, the backward technique starts with the full least squares model comprising all attributes and then iteratively eliminates the most insignificant attribute, one after the other. These two methods, respectively, assign 1's and 0's as primary weights.

The evolutionary weight optimization measures the weights of the provided dataset attributes utilizing a GA. The greater the weight of an attribute, the more suitable it is viewed. GA is an exploration heuristic that imitates the method of natural development. This heuristic technique is commonly employed to create beneficial clarifications to optimization and search queries (Armaghani et al., 2020; Khandelwal et al., 2017). GAs relate to the more general category of evolutionary algorithms, which create answers to optimization difficulties utilizing natural evolution methods, such as inheritance, mutation, selection, and crossover (Fig. 4). It is worth noting that, in GA, "mutation" implies changing features on and off, and "crossover" indicates interchanging used features (Koopialipoor et al., 2019). In the process of ANN optimization

using GA, primary weights of the encoded modality are produced randomly in the GA method and optimized by the crossover and mutation operation.

The PSO-based optimization approach initializes the learning process through the production of an assortment of arbitrary particles. Every particle denotes a single collection of weights/importance and biases in the model. This model is then trained by utilizing the primary weights and biases. The PSO-based optimization technique then updates the particle's velocity and position by employing the PSO equations (Hajihassani et al., 2018). Finally, the weights and biases of the model are modified in every repetition. The system errors amid the real and predicted values are measured in every repetition. Additionally, the errors are decreased by modifying the particles' positions. The process mentioned above is maintained to obtain the most desirable weights and biases to minimize the error function.

For optimizing the architecture of ANN using the PSO, first, the algorithm generates the N position vectors, randomly, then executes the neural network using these vector parameters, and finally, considers error resulting from each run as the fitness condition of that network variable vector. This process is repeated until the ultimate convergence is achieved wherein the training error is the least (Fig. 5).

Collection of Data

We carried out this investigation in the area of Penang state, Malaysia. A view of the site is presented in Figure 6. This mine exploits granitic rocks with the potential to produce quantities of mass between 40,000 and 60,000 tons per month. All blasting works are administered utilizing two blast

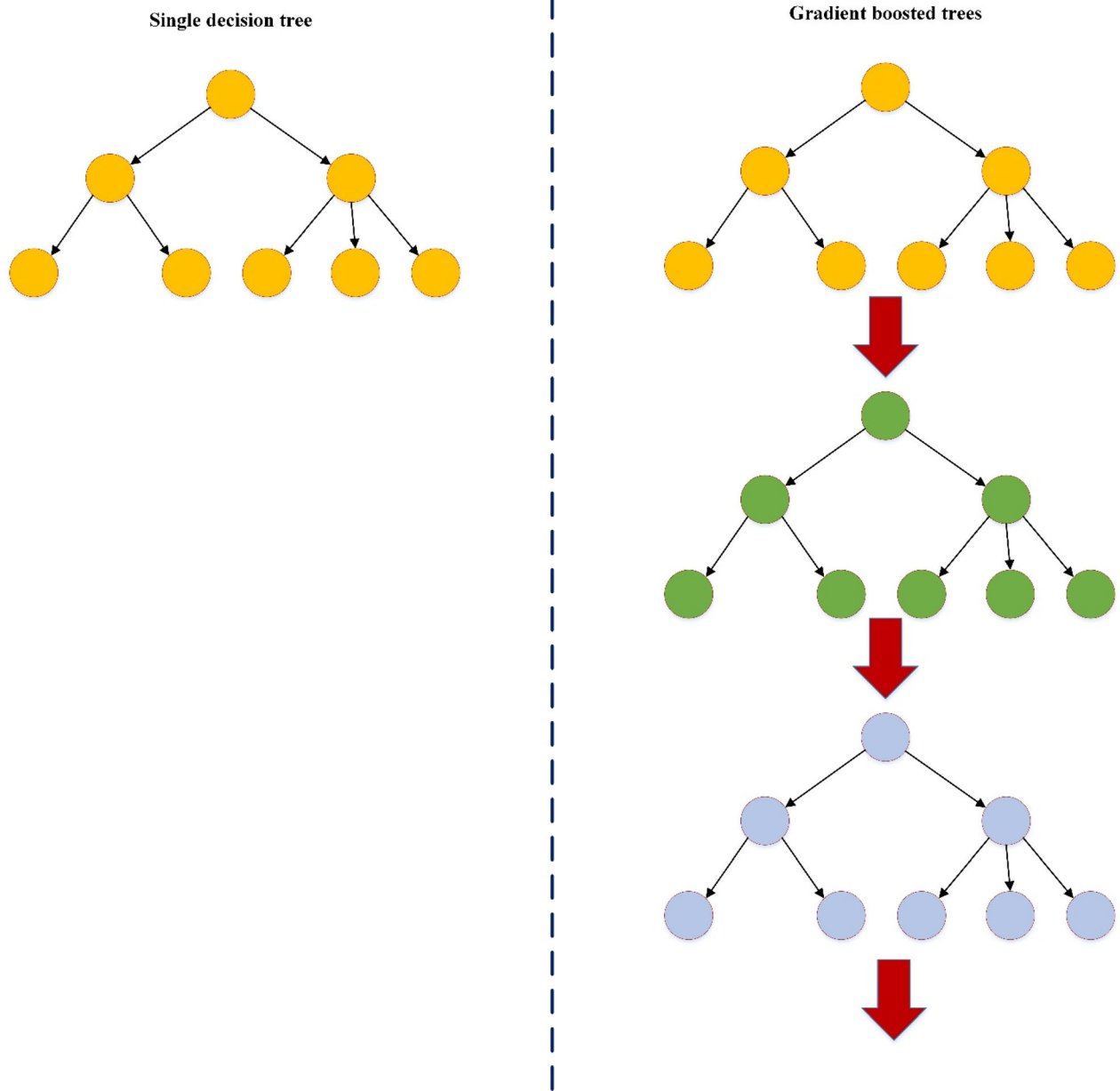


Figure 2. Schematic of GBT.

hole diameters, i.e., 89 mm and 76 mm. As for explosive substance and the start, ANFO and dynamite were primarily employed. The excavation team graveled the blast holes utilizing fine gravels. As mentioned before, several parameters related to blasting pattern design together with some geological and geotechnical parameters were measured for the purpose of PPV estimation. For every blast, a VibraZEB seismograph was used to record PPV

values. In total, 93 blasting operations were monitored and the relevant parameters, given in Table 1, were collected and used in the modeling of this study.

The scaled distance (SD) is a standard technique to empirically forecast PPV values. According to Duvall and Petkof (1959), the relation between SD and the two most influential factors (i.e., D in meters and MC in kilogram) is a form of

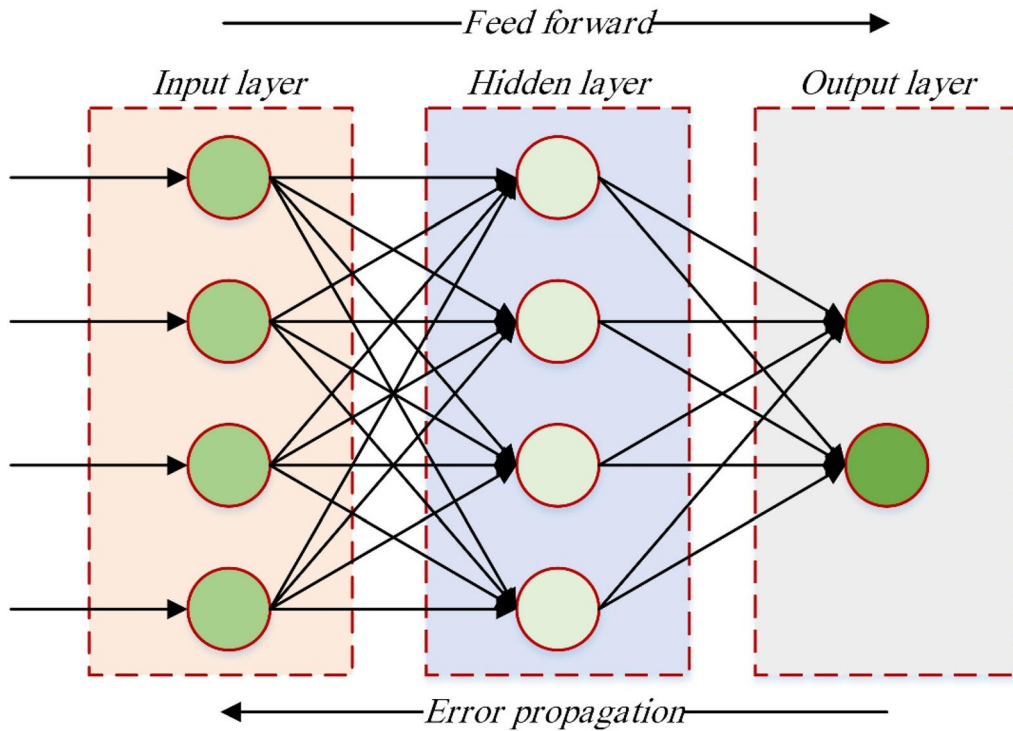


Figure 3. Standard three-layer neural network.

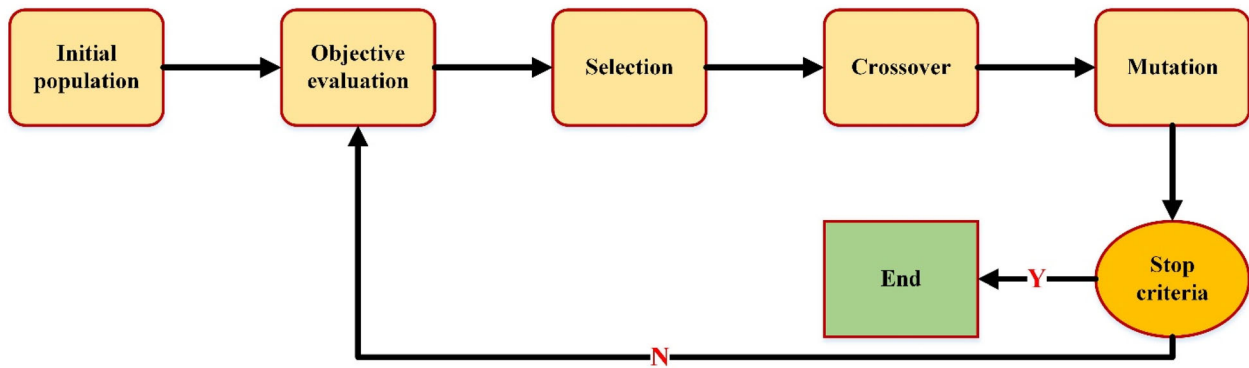


Figure 4. Essential steps of GA in optimization problems.

$SD = D(MC^{-0.5})$. Then, PPV values can be estimated as $PPV = L(SD)^N$, where L and N are considered as site constants. After all calculations using the data of this paper, the following equation was proposed as a practical empirical technique:

$$PPV = 373.21(SD)^{-1.195} \quad (1)$$

The logarithmic diagram of the estimated PPV values versus their SDs is presented in Figure 7. The coefficient of determination (R^2) corresponding to 0.637 for PPV forecast implies that the suggested formulas forecast them reasonably. It is important to mention that the obtained result and its R^2 are higher than in some other studies that proposed empirical equation for PPV prediction (e.g., Hajihassani et al., 2015).

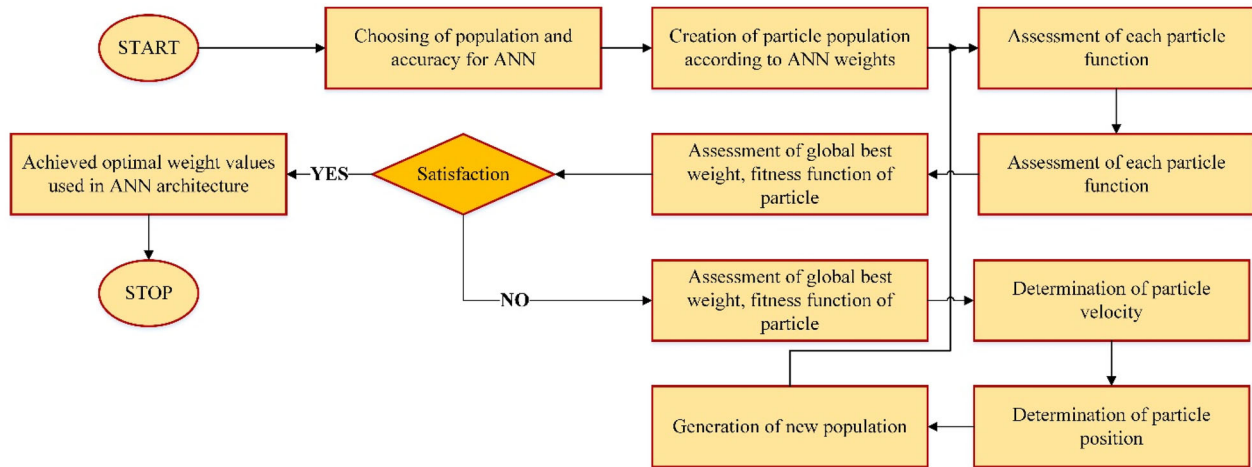


Figure 5. Optimization of ANN architecture utilizing the PSO algorithm for PPV prediction.



Figure 6. A view of the quarry site.

RESULTS AND DISCUSSION

Selection of Inputs

As discussed earlier, this study employed a GBT method for selecting the most relevant input variables for predicting the PPV. To apply this model to the candidate inputs of this study, the value

of many parameters were set. Thus, the number of trees, maximal depth, min rows, number of bins, and learning rate were set as 50, 5, 10, 20, and 0.01, respectively. The GBT model achieved a correlation value of 0.931. In addition, the results of this model showed that MC, D, sub-drilling, powder factor, and RQD were the most important and relevant factors for predicting the PPV. The normalized importance

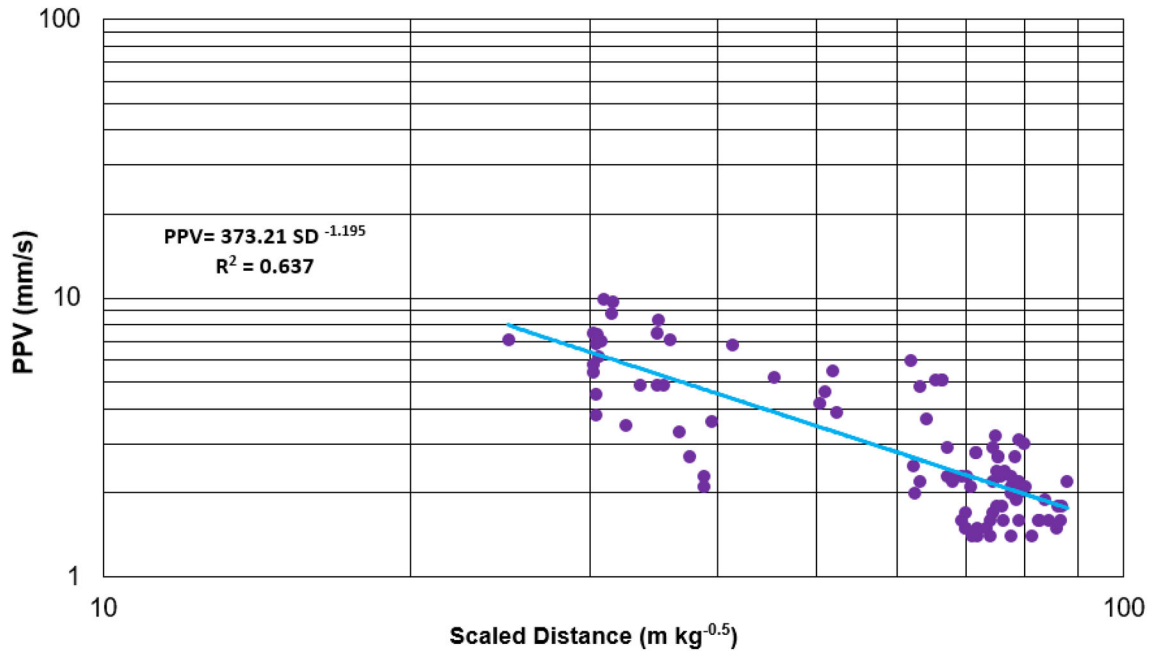


Figure 7. Correlation between estimated SD and PPV values.

value of each factor is shown in Figure 8. These variables were then used for applying a series of optimized ANN models to forecast PPV values induced by blasting.

Model Development and Evaluation

In this paper, five ANN models were developed after the input selection stage. As mentioned previously, the GBT selected five inputs as the most important and relevant among all collected variables as predictors. We then applied a simple ANN model. The parameters and settings used included (1) training cycle of 500, (2) learning rate of 0.3, (3) momentum of 0.2, and (4) error epsilon of 1.0E-5 (Fig. 9). The attributes' weights of the ANN model were optimized using the PSO, GA, backward, and forward approaches. Thus, five models were created in total. The optimized weights of the attributes are shown in Figure 10. The highest weight (1.00) for D was achieved in three models, including ANN-PSO, ANN-GA, and ANN-backward. In addition, sub-drilling achieved the highest possible weight (1.00) in three models, including ANN-PSO, ANN-backward, and ANN-forward.

The models were developed and validated using tenfold cross-validation. We used root mean squared error (RMSE), correlation coefficient (*R*), variance accounted for (VAF), and a20-index as the main criteria to evaluate the ANN models' performances. The following are the formulas of these indices.

$$R = \frac{\sqrt{\sum_{i=1}^n (y_{im} - y_{ip})^2}}{\sqrt{\sum_{i=1}^n (y_{im} - \bar{y}_{im})^2}} \tag{2}$$

$$RMSE = \sqrt{\frac{1}{n} \sum_{i=1}^n (y_{im} - y_{ip})^2} \tag{3}$$

$$VAF = \left[1 - \frac{\text{var}(y_{im} - y_{ip})}{\text{var}(y_{im})} \right] \tag{4}$$

$$a20 - \text{index} = \frac{m20}{n} \tag{5}$$

where y_{im} , y_{ip} , and \bar{y}_{ip} indicate measured, predicted and mean of measured values, respectively; n represents total number of data, $m20$ denotes samples with measured value/predicted values between 0.8 and 1.20.

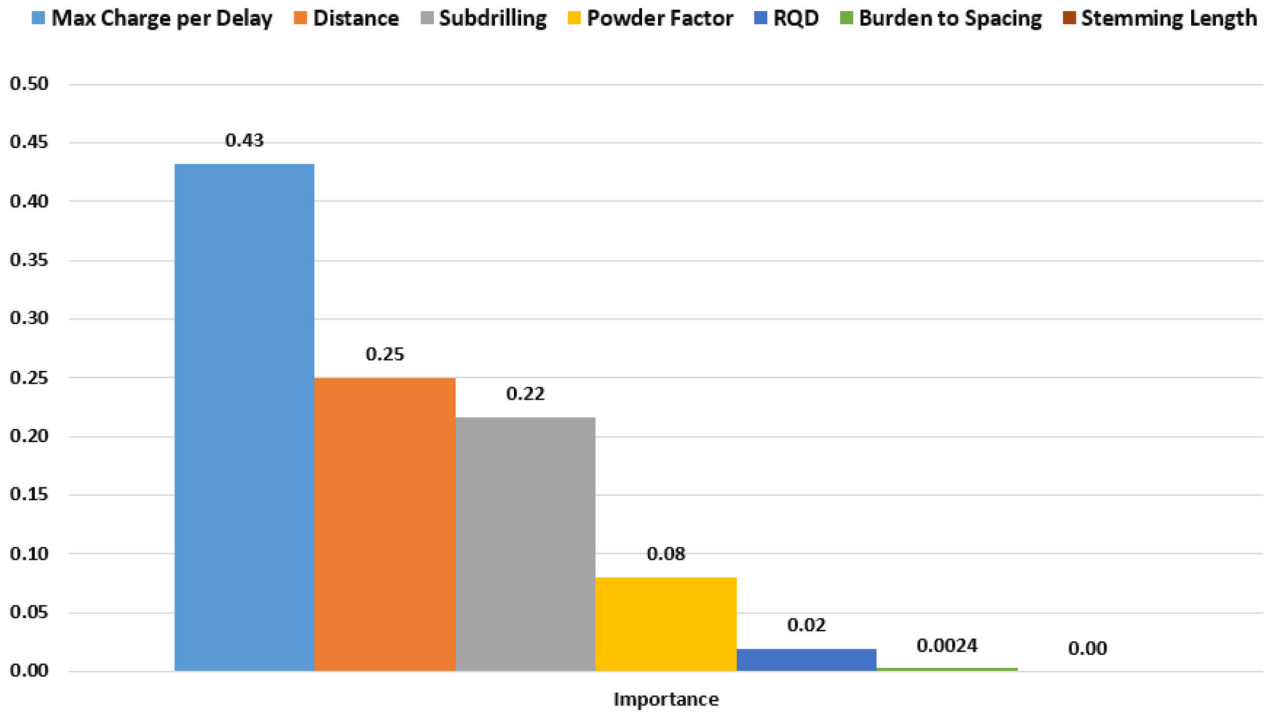


Figure 8. Importance of input variables achieved by the developed GBT model.

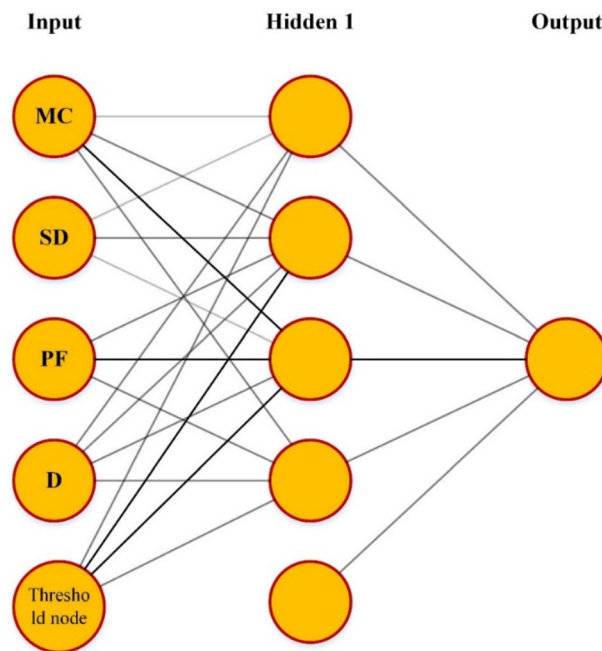


Figure 9. Structure of simple ANN model.

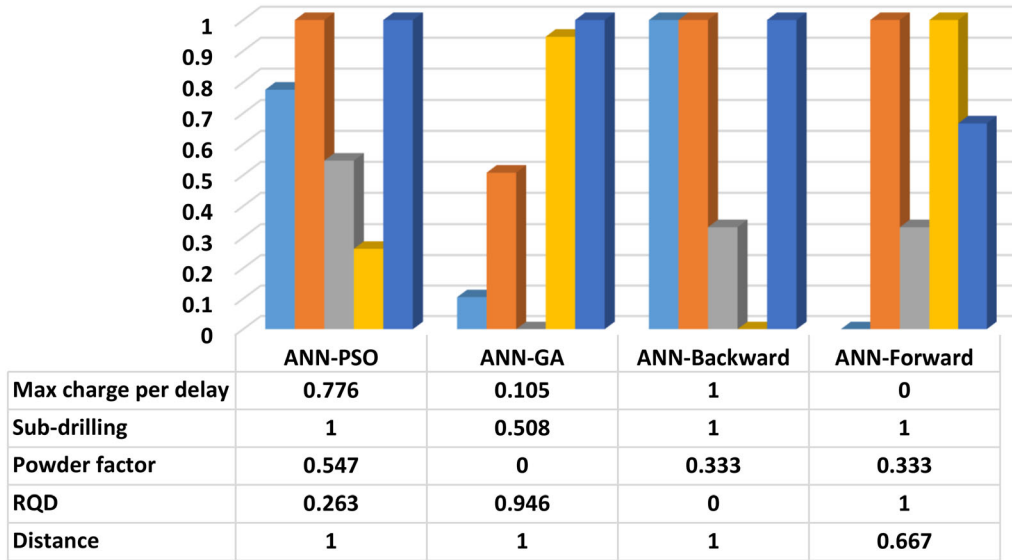


Figure 10. Optimized attributes' weights for four models.

In addition, a simple ranking system was used to assess the performance of the models applied comprehensively (Zorlu et al., 2008). In this system, a ranking is assigned to RMSE and R , VAF, and a20-index's values. Thus, the highest values of R , VAF, a20-index and the lowest values of RMSE receive the highest rank. It is worth noting that the highest rank was 5 because five models were used and the lowest rank was 1. Moreover, the same ranking was given to equal RMSE, R , VAF, and a20-index values. A cumulative ranking is proposed for each model, which is the sum of each model's RMSE, R , VAF, and a20-index rankings, thus:

$$Cummulative\ ranking\ of\ model = \sum (\alpha + \beta + \delta + \gamma) \tag{6}$$

where α denotes the ranking of RMSE, β the ranking of R , δ the ranking of VAF, and γ the ranking of a20-index. The values and rankings achieved for the RMSE, R , VAF, and a20-index, and the cumulative rankings of individual models are presented in Table 2. The highest rank of RMSE belongs to ANN-PSO, while the lowest RMSE ranking belongs to ANN-backward model. In addition, ANN-PSO obtained the highest R ranking; however, the ANN model achieved the lowest ranking for R .

The highest VAF ranking belonged to ANN-PSO, and the ANN model (without optimization)

had lowest ranking for VAF. Concerning a20-index, the ANN-PSO model also had the greatest ranking, while the ANN possessed the lowest ranking. Overall, the highest cumulative ranking belongs to ANN-PSO; the lowest cumulative ranking belongs to ANN model.

It was expected that the advanced optimization techniques such as PSO showed better performance compared to the forward and backward optimization techniques. This result can stem from the various advantages of PSO. These advantages include the requirement for a small number of input variables, flexibility in scaling of design search, straightforwardness of application, and great effectiveness in global optimum search.

This research considered an ensemble approach and reduced the risk of choosing less critical inputs for the PPV forecast. To the best of our knowledge, studies in the field of environmental issues of blasting that used the GBT in selecting the input parameters are a few only. Our study's findings of the input parameters selected are useful for PPV forecasting because they consolidate various learners' prediction and ANN optimized models. Consequently, this study suggests employing only five input parameters, i.e., MD, D, sub-drilling, powder factor, and RQD, together with the ANN-PSO to produce a more eminent performance in forecasting PPV produced by blasting. The blast safety area can

Table 2. Errors and accuracies of the models used to estimate PPV values

Predictive model	RMSE		R		VAF		a20-index		Cumulative ranking
	V	R	V	R	V	R	V	R	
ANN (without optimization)	0.748	2	0.879	1	84.057	1	0.529	1	5
ANN-PSO	0.680	5	0.945	5	87.672	5	0.612	5	20
ANN-GA	0.696	4	0.934	3	87.462	4	0.557	4	15
ANN-Forward	0.747	3	0.927	2	86.828	3	0.537	2	10
ANN-Backward	0.703	1	0.941	4	85.070	2	0.548	3	10

Value = V; Ranking = R

also be discovered in exploding sites using the optimized models developed in this research.

CONCLUSIONS

This study was set to (1) combine an ensemble technique with an optimized ANN model, and (2) identify the best-hybridized model for solving PPV problem induced by mine blasting. To that effect, we first adopted a GBT technique for input selection. Next, an ANN method was applied to the chosen input variables. Eventually, the model was optimized with a set of optimization techniques including forward, backward, PSO, and evolutionary, to obtain the most suitable ANN model for PPV forecast. Our study's findings proved that ANN-PSO achieved the highest cumulative ranking, and consequently, this model was the most reliable one to predict PPV. According to the obtained results, R values of 0.879, 0.945, 0.934, 0.927, and 0.941 were provided by ANN, ANN-PSO, ANN-GA, ANN-Forward, and ANN-Backward, respectively, which confirmed the higher prediction capability of the developed ANN-PSO model compared to the other proposed models. In addition, the RMSE, VAF, and A20-index values achieved verified that the PSO method that optimized the weight of the ANN had improved the performance of the algorithm and had resulted in superior RMSE, VAF, and A20-index values compared to other ANN models. Mining engineers can use this technique before blasting operations to predict PPV values with high level of accuracy. As for future work, testing some newer optimization algorithms such as gray wolf optimization and moth flame optimization to combine with ANN are needed to evaluate their performance capacities in predicting PPV.

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