mathematics

Article

Applications of Two Neuro-Based Metaheuristic Techniques in Evaluating Ground Vibration Resulting from Tunnel Blasting

Danial Jahed Armaghani [1,2,*], Biao He [3], Edy Tonnizam Mohamad [1], Y.X Zhang [4], Sai Hin Lai [3] and Fei Ye [5]

1 Centre of Tropical Geoengineering (GEOTROPIK), Institute of Smart Infrastructure and Innovative Engineering (ISIIC), Faculty of Civil Engineering, Universiti Teknologi Malaysia, Johor Bahru 81310, Malaysia
2 Department of Urban Planning, Engineering Networks and Systems, Institute of Architecture and Construction, South Ural State University, 76, Lenin Prospect, Chelyabinsk 454080, Russia
3 Department of Civil Engineering, Faculty of Engineering, Universiti Malaya, Kuala Lumpur 50603, Malaysia
4 School of Engineering, Design and Built Environment, Western Sydney University, Kingswood, NSW 2751, Australia
5 School of Highway, Chang'an University, Xi'an 710064, China
* Correspondence: jadanial@utm.my or danialarmaghani@susu.ru

Abstract: Peak particle velocity (PPV) caused by blasting is an unfavorable environmental issue that can damage neighboring structures or equipment. Hence, a reliable prediction and minimization of PPV are essential for a blasting site. To estimate PPV caused by tunnel blasting, this paper proposes two neuro-based metaheuristic models: neuro-imperialism and neuro-swarm. The prediction was made based on extensive observation and data collecting from a tunnelling project that was concerned about the presence of a temple near the blasting operations and tunnel site. A detailed modeling procedure was conducted to estimate PPV values using both empirical methods and intelligence techniques. As a fair comparison, a base model considered a benchmark in intelligent modeling, artificial neural network (ANN), was also built to predict the same output. The developed models were evaluated using several calculated statistical indices, such as variance account for (VAF) and a-20 index. The empirical equation findings revealed that there is still room for improvement by implementing other techniques. This paper demonstrated this improvement by proposing the neuro-swarm, neuro-imperialism, and ANN models. The neuro-swarm model outperforms the others in terms of accuracy. VAF values of 90.318% and 90.606% and a-20 index values of 0.374 and 0.355 for training and testing sets, respectively, were obtained for the neuro-swarm model to predict PPV induced by blasting. The proposed neuro-based metaheuristic models in this investigation can be utilized to predict PPV values with an acceptable level of accuracy within the site conditions and input ranges used in this study.

Keywords: tunnel blasting; Peak particle velocity; metaheuristic algorithms; neuro-swarm; neuro-imperialism

MSC: 68Uxx

check for updates

Citation: Armaghani, D.J.; He, B.; Mohamad, E.T.; Zhang, Y.X; Lai, S.H.; Ye, F. Applications of Two Neuro-Based Metaheuristic Techniques in Evaluating Ground Vibration Resulting from Tunnel Blasting. *Mathematics* **2023**, *11*, 106. https://doi.org/10.3390/math11010106

Academic Editor: Manuel Pastor

Received: 9 November 2022
Revised: 19 December 2022
Accepted: 21 December 2022
Published: 26 December 2022

1. Introduction

Blasting operations are frequently used in mines, quarries, and tunnels to excavate rock mass, due to their economy and efficiency. An important control object during blasting is the magnitude of ground vibration, as this is related to the safety of the surrounding buildings and equipment [1]. During blasting operations, the blast-induced ground vibration can propagate in three directions: transverse, longitudinal, and vertical direction [2]. When the vibration starts to propagate, each particle has its velocity. The peak particle velocity (PPV) is defined as the highest velocity of the particles, which is the base factor to assess the magnitude of ground vibration produced by blasting events [3–6]. Dozens of investigations were carried out to determine the PPV magnitude [7], and they included three types:

empirical/experimental methods, statistical-based methods, and artificial intelligence (AI) techniques.

In the case of empirical/experimental methods, many researchers [8,9] suggested a uniform style, which works based on only two parameters, namely, the distance of the measuring transducer from the blasting face and the explosive weight (charge amount). This uniform style was introduced by Duvall and Petkof [10], and it is known as the USBM equation form. The scaled distance (*SD*) is the main term of the USBM equation, which can relate the two mentioned parameters to predict PPV values. However, average performance accuracy was reported by the researchers for different proposed empirical equations, whereas a high prediction capacity is required for such techniques to minimize the risk associated with ground vibration produced by blasting. In addition, typically, these empirical/experimental equations were proposed for the conditions of the specific site, which has a unique geological structure and setting [11]. It seems that these empirical/experimental formulas cannot predict PPV with a satisfactory level of accuracy in the other blasting locations, and there is a need to try other available techniques to get more reliable results with higher accuracy.

Statistical regression methods have also been used to predict blast-induced PPV. For example, Hasanipanah et al. [12] developed a multiple linear regression (MLR) model/equation to forecast blast-induced PPV in the Miduk copper mine, in Iran. In their research, 69 data samples were allocated to the training (development) data sets for constructing the MLR model, while 17 data sets were apportioned to the testing (assessment) data sets to evaluate the MLR model. The results showed that the constructed MLR model had favorable accuracy (coefficient of determination, $R^2 = 0.883$) by comparing the measured PPV values with the predicted PPV values. Similarly, Ram Chandar et al. [13] proposed another MLR model to forecast PPV values in three mines. Their applied input variables included the maximum charge per delay, distance, burden, spacing, amplitude, and frequency. The results indicated that MLR was a reliable tool that can produce good accuracy and can be applied at any mine site. However, PPV is a sensitive indicator that can significantly characterize the influence of the ground vibration resulting from blasting on the safety of a building or equipment.

Some researchers [14] mentioned that the accuracy level of statistical models and MLR techniques in predicting PPV was inadequate compared to AI techniques, which can yield more reliable results. For example, Khandelwal and Singh [15] compared the PPV prediction results of both artificial neural networks (ANN) and MLR and found that the corresponding coefficients of correlation for predicting PPV are 0.994 by ANN and 0.4971 by MLR. It showed that the ANN model had a greater accuracy, whereas the proposed MLR equation had a higher error. Similar results were seen by Xue and Yang [16], Parida and Mishra [17], and Lawal and Idris [18].

In recent years, many models and studies have been developed using AI techniques for solving civil and mining problems [19–37] and specifically for predicting PPV produced by blasting. These models mainly include ANN, gene expression programming (GEP), neuro-fuzzy, decision tree, support vector machine (SVM), fuzzy logic, genetic algorithm (GA), and genetic programming [38–40]. The studies highlighted the feasibility and applicability of AI models in solving PPV produced by mine or quarry blasting. However, the AI studies for predicting PPV induced by tunnel blasting are limited to a few investigations only, as presented in Table 1. For instance, Monjezi et al. [41] attempted to use ANN to predict PPV values produced by tunnel blasting in a project carried out in Iran. They reported that the ANN technique was a powerful and easy-to-use method for solving such problems. Lawal et al. [42] conducted research to predict tunnel blast-induced PPV in the Daejeon tunnel, in South Korea. They proposed different techniques, i.e., ANN, moth-flame optimization (MFO)-ANN, and GEP, and used the controllable (e.g., hole depth) and uncontrollable (e.g., rock mass rating) factors. The results showed that the MFO-ANN model performed better in predicting PPV compared with ANN and GEP. In another work, Jelušič et al. [43] used a neuro-fuzzy model to predict PPV values in two tunnels located in Slovenia. In their study, the charge and the distance from the blast face to the monitoring positions were allocated as model predictors. It was found that the neuro-fuzzy model can well predict PPV. Rana et al. [39] compared two AI techniques (ANN and decision tree) for forecasting the PPV values in six tunnels in India. They used a database comprising 137 data samples. The results showed that the decision tree model outperformed the ANN model. Hasanipanah et al. [44] developed two forms of the GA model (linear and power) to estimate PPV in a tunneling project at the Bakhtiari dam region in Iran. The results indicated that the performance of the GA power form outperformed the GA linear form. More information regarding the available studies for estimating blast-induced PPV in tunnels can be found in Table 1.

Table 1. Some relevant investigations for predicting tunnel blast-induced PPV.

Reference	Technique	Input Parameter	Database No.	Site Location/Country
Monjezi et al. [41]	ANN	MC, *DI*, ST, HD	182	Located in Iran
Li et al. [45]	SVM	MC, *DI*	32	Located in Guiyang, China
Mohamadnejad et al. [46]	GRNN, SVM	MC, *DI*	37	Located in Iran
Hasanipanah et al. [47]	SVM	*DI*, MC	80	Located in Iran
Yin et al. [48]	BP-NN	*DI*, HD, MC, TC	40	Located in Beijing, China
Hasanipanah et al. [44]	GA	MC, *DI*	85	Located in Iran
Abbaszadeh Shahri and Asheghi [49]	ANN	TC, CPD, *DI*	37	Located in Iran
Rajabi and Vafaee [50]	ANN	MC, *DI*	64	Located in Lorestan Province, Iran
Jelušič et al. [43]	Neuro-fuzzy	TC, *DI*	48	Located in Slovenia
Lawal et al. [42]	MFO-ANN, GEP	HL, CPD, ND, TC, *DI*, RMR	56	Located in KAERI, Daejeon, South Korea

CPD: charge per delay, CPH: charge per hole, TC: total charge, *DI*: distance from blast face, MC: maximum charge per delay, RMR: rock mass rating, H: hole diameter, HD: hole depth, HL: hole length, NH: number of holes, TCS: tunnel cross-section, ST: stemming, BP: back-propagation, NN: neural network, GRNN: generalized regression neural network.

It is obvious that ANN is the main model developed by many researchers to estimate PPVs. However, this technique includes some drawbacks that influence its results considerably [51–53]. Combining some optimization techniques can yield more sustainable results from ANNs and higher-performing predictions. In the present study, we aimed to develop more accurate PPV prediction models based on several advanced neural network models, including the neuro-swarm and neural-imperialism models. To achieve this goal, we prepared a comprehensive PPV dataset of tunnel blasting to establish these two neural-based models. These two models are based on particle swarm optimization (PSO) and the imperialism competitive algorithm (ICA) as two powerful metaheuristic techniques. Additionally, we developed an empirical equation based on the collected database and compared its performance with the neural-based models, to verify which model is best for predicting blast-induced PPV in tunnel blasting operations.

2. Methods and Materials

2.1. ANN

An artificial neural network, or ANN, is a type of artificial intelligence (AI) system that can imitate a specific organizational notion of how the nervous system works. Unlike the traditional AI model that came before it, the ANN is able to learn the pattern from the training that it is given and estimate the underlying relationship that exists between the input variables and the output variables. This characteristic gives these approaches a big advantage over the other intelligence models that exist in this field. The ANN models use the artificial neurons as basic units to process the available data (i.e., input and output variables) in a way similar to a human being's brain. For the first time, McCulloch and Walter [54] modeled the behaviors of artificial neurons by gathering and applying a binary decision unit for input/output variables. The network they developed is capable of obtaining outputs with the minimum error (i.e., the difference between the target of the data and system output). This can be done through the employment of an artificial node or neuron.

The signal can be received at each artificial node in the network, and then the signal can be processed by an activation function, such that an estimate of the output can be generated [55]. Every output of a neuron will be taken as the input for the subsequent neuron. Ch and Mathur [56] successfully showed that the most significant factor in ANN performance and capability is the neuron/node connection patterns and their process of design. The ANN model can be iteratively trained multiple times to reduce the imperfection of the outputs. This process will continue until the preferred error of the network or the number of iterations (i.e., repetition) is obtained. Amarghani et al. [57] recommended applying the sigmoid transfer function to predict non-linear relationships. An artificial neuron j with inputs (X_i), weights (W_{ij}), bias (b_j), and system output (O_j) is presented in Figure 1.

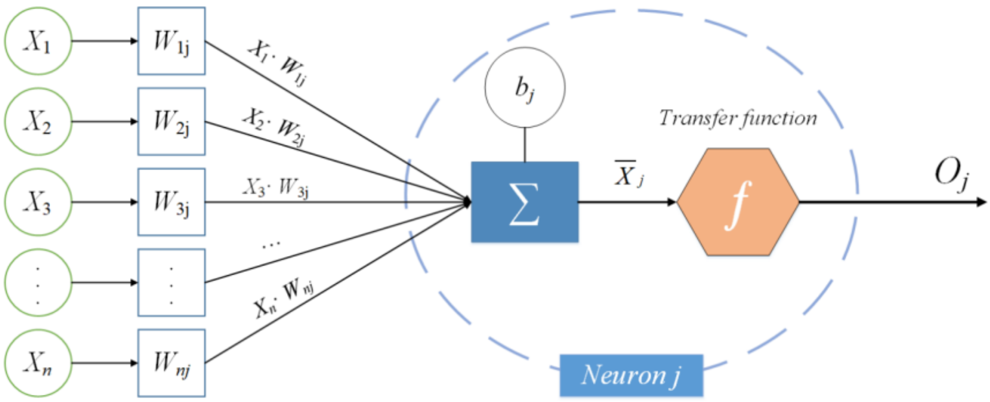


Figure 1. An artificial node used in the ANN system.

2.2. PSO

Kennedy and Eberhart [58] pioneered particle swarm optimization (PSO) as an effective, applicable, and powerful metaheuristic algorithm (i.e., optimization technique). Swarms or particles in PSO search for optimal values/targets in a repetitive manner. Throughout the search operation, the particles change their positions depending on the experiences they have obtained up to that moment. Each particle learns to obtain its best position, which is divided into two locations. The first one is named $\overrightarrow{p_{best}}$ (or the best personal position) and the second one is named $\overrightarrow{g_{best}}$ (or the best global position). During the learning stage, the particles are trained to enhance the speed of their movement to get better positions of $\overrightarrow{g_{best}}$ and $\overrightarrow{p_{best}}$. In this way, in each iteration, their locations (distance between each swarm) and velocities can be computed. Therefore, their new locations can be obtained using their previous locations and their velocities. The updated velocity and location of the particles in PSO can be easily calculated using Equations (1) and (2). $\overrightarrow{\mathrm{v}_{\mathrm{new}}}$ in Equation (1) is the updated velocity in each swarm, which can be calculated using velocity confidence (C_1 and C_2), present velocity and location of the swarm ($\vec{\mathrm{v}}$ and $\vec{\mathrm{p}}$, respectively), and the discussed $\overrightarrow{g_{best}}$ and $\overrightarrow{p_{best}}$. Then, $\overrightarrow{\mathrm{p}_{\mathrm{new}}}$ needs to be calculated as the updated position or location of each swarm. The literature consists of numerous studies that have explained PSO and its structure in more detailed ways [59].

$$\overrightarrow{\mathrm{v}_{\mathrm{new}}} = \vec{\mathrm{v}} + C_1 \times \left(\overrightarrow{p_{best}} - \vec{\mathrm{p}} \right) + C_2 \times \left(\overrightarrow{g_{best}} - \vec{\mathrm{p}} \right) \quad (1)$$

$$\overrightarrow{\mathrm{p}_{\mathrm{new}}} = \vec{\mathrm{p}} + \overrightarrow{\mathrm{v}_{\mathrm{new}}} \quad (2)$$

2.3. ICA

Atashpaz-Gargari and Lucas [60] designed the first imperialist competitive algorithm (ICA) as another metaheuristic algorithm to behave/solve various minimization or maximization issues. Like other metaheuristic algorithms, ICA works based on population (i.e., the number of countries), where each country is considered as a possible solution. The algorithm implementation starts using a random number of countries as initial solutions. The individuals of the population in ICA are countries, among which the best ones (i.e., those of the highest power) are selected and assigned as imperialists. The rest of the countries play the role of colonies of the imperialists. The most powerful countries in ICA are those with minimum cost; these countries can take ownership/control of more colonies. In general, ICA comprises three main machinists/operators: assimilation, revolution, and competition. The assimilation operator directs the colonies through the path of growing into imperialists to achieve more control and power, a better cultural level, and an enhanced economy. During the first two operators, the colonies will have a high chance of reaching a better position (i.e., solution) compared to that of their imperialists; in this condition, a colony will take the control of the empire. Finally, during the competition process, the imperialists will also have a high chance of adopting more colonies. During the competition process, the weakest empire collapses, and, at the same time, the strongest ones can take possession of more colonies, which leads to the increase of their control/power. The mentioned procedure is repeated until the strongest empire or the only one can control all countries. In this condition, the rest of the empires, which are weak, will collapse and their role will change as a colony. The literature contains more details and explanations regarding different applications of ICA in solving optimization problems [61].

2.4. Neuro-Based Models

The ANN models could be more powerful when being integrated with some other optimization algorithms, such as PSO and ICA [62]. The ANN models might attain a wrong or unacceptably inaccurate prediction because of the weakness of back-propagation models in the exploration of the global minimum [63]. It is highly probable for the ANN models to give strong local minima during training; however, the metaheuristic techniques have the capacity of managing this situation by determining the ANN's biases and weights. Therefore, the search space in this case encounters global minima owing to the implementation of PSO/ICA (i.e., optimization algorithms). In the current paper, two neuro-based approaches, PSO-ANN and ICA-ANN, are used to predict the PPV values induced by tunnel blasting. Then, the results attained by both hybrid models are compared in a way that selects the one with higher accuracy. In the rest of this paper, the terms neuro-swarm and neuro-imperialism will be utilized instead of PSO-ANN and ICA-ANN models, respectively. More information regarding the mixing of PSO and ICA with the ANN model for prediction-based problems can be found elsewhere [64,65].

2.5. Statistical Indices

In general, the performance quality of hybrid neuro-based or other predictive techniques is assessed using some statistical indices. Two of the most famous indices are the root mean square error ($RMSE$) and the coefficient of determination (R^2). Lower $RMSE$ values show higher accuracy of the predictions made; on the other hand, higher values of R^2 show a good covenant between the actual and estimated values. These two statistical parameters are calculated using Equations (3) and (4). In these equations, S is the total no. of samples, estimated PPV and measured PPV are presented by z' and z, respectively, and $\bar{z}$ presents the mean values of measured PPV.

$$RMSE = \sqrt{\frac{1}{n} \sum_{i=1}^{S} (z' - z)^2} \quad (3)$$

$$R^2 = 1 - \frac{\sum_i (z - z')^2}{\sum_i (z - \overline{z})^2} \quad (4)$$

The other widely used statistical index is the variance account for (*VAF*), which is based on percentage. The formula of *VAF* is expressed as follows:

$$VAF = \left[1 - \frac{var(z - z')}{var\ (z)}\right] \times 100\% \quad (5)$$

The perfect value for *VAF* is 100% for a model with R^2 = 1 and *RMSE* = 0. Apart from these indices, the authors decided to use an a-20 index as a new and powerful index. This is defined in the following equation, where m^{20} signifies the rate of experimental value/predicted value that lies between the range of 0.80 to 1.20 and *S* is the total no. of samples.

$$a20 - index = \frac{m^{20}}{S} \quad (6)$$

2.6. Case Study and Database

In this study, the data was collected from Shi Ban Gou Tunnel, which is located in Qinghai Province, China. The Shi Ban Gou Tunnel is a highway tunnel constructed on G6 National Highway to connect region 1 (Zamalong) to region 2 (Daotang river). The route of the tunnel crosses the ridge from east to west. The basic information of the tunnel is as follows: the total length is 525 m; the design elevation of the starting point is 2478.64 m; the design elevation of the ending point is 2490.8 m; and the maximum overburden distance of the tunnel is 204 m. The route map of the tunnel is shown in Figure 2.

Figure 2. Route map of the tunnel (via Google Earth Pro).

According to the information from a geological survey, the tunnel exit is located on the Huangshui River valley slope. The natural slope angle of the mountain is about 34–70 degrees, with scattered piles of broken boulders on the right-hand slope and exposed bedrock on the left-hand slope, which indicates the poor stability of the natural slope at the tunnel entrance. In the exit section of the tunnel, the surrounding rock is composed of a mixed-medium weathered and slightly weathered gneiss with complex lithology, broken rock mass, developed joints and fissures, and a blocky or laminated structure. The rock and soil mass wave velocity of this section is 1–2.9 km·s^{-1}.

The tunnel entrance is located around 20 m up from the cliff face, next to the Temple of the Holy Ancestors of Buddha (the temple is 8 m in height and covers a total area of 52 m^2). Because the mountain is steep and the rock above the tunnel entrance is broken, the tunnel excavation by blasting increases the disturbance to the mountain. This may cause landslides, rock falls, and other hazards, seriously threatening the safety of the thousand-year-old temple. The relative positions of the tunnel and the temple are shown in Figure 3. Owing to the blasting operation, vibrations propagate not only along the tunnel axis but also far upward to the ground around the temple. The PPV values produced by blasting in the tunnel may have an undesired influence on the safety of the temple, thereby raising administrators' complaints. Since the safety of the described temple is a primary concern in this project, the values of PPV should be controlled and minimized when the tunnel is being excavated. For the safety of the temple, the field measurement of PPV was carried out using a seismograph, as shown in Figure 4. This type of seismograph is a measuring instrument for ultra-low or low-frequency vibrations. It is mainly used for the measurement of pulsations generated from the ground and structures, and it has three measurement levels of velocity: small, medium, and large velocity.

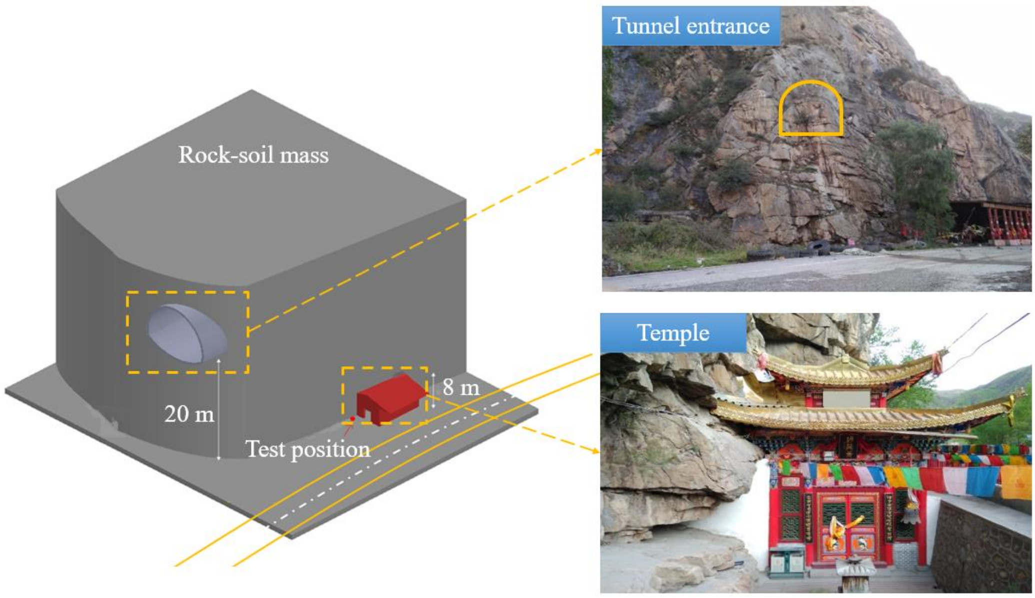


Figure 3. Positions of the tunnel and temple.

Figure 4. A measurement and monitoring point of PPV values induced by blasting.

To establish a database to forecast PPV values, the results of the Shi Ban Gou Tunnel during blasting operations were considered and used. Three hundred and one blasting operations in the mentioned tunnel with the relevant blasting parameters were observed. The blasting design factors include charge (C), rock mass rating, number of holes, and the distance from the measuring station (*DI*) to the blasting point, together with their relevant PPV values. It is important to mention that the distance from the measuring station is the horizontal distance between the blasting face and the monitoring point inside the temple. In the available data, a maximum distance of 745 m was recorded for *DI*, and, since there is an inverse relationship between PPV and *DI*, the authors decided to use a *DI* range of 49–397 m. In this way, the total number of blasting events was reduced to 154. It is worth noting that the safety of the temple presented in Figure 3, because of the close distance to the tunnel, was the main concern for the tunnel construction team. Therefore, blasting pattern parameters, as well as geological conditions of the tunnel face, were carefully designed and monitored.

Although there are several parameters measured in the tunnel site, many researchers in their empirical and computational PPV models suggested using only two predictors: *DI* and *C* [66,67]. Therefore, these two variables were used in this study, as well, to forecast PPV results produced by blasting. The statistical information of the adopted data used in this study and its modeling part are shown in Table 2. In the following section, different models will be applied to estimate PPV values and select the most accurate model for PPV prediction.

Table 2. Input and output variables and their relevant statistical information.

Parameters	Unit	Group	Max	Min	Mean	*SD*
Total charge (*C*)	kg	Input	150	45	121	39.05
Distance from the measuring station (*DI*)	m	Input	397	49	227	91.97
Peak particle velocity (PPV)	mm/s	Output	23.06	10	13	2.88

Max: maximum; Min: minimum; *SD*: standard deviation.

3. Analysis and Prediction of PPV Values

This section presents the procedures of PPV estimation using two different approaches, empirical and intelligent. The empirical approach, which is still a commonly utilized technique, will be described first. Then, intelligence systems comprising two neuro-based models—neuro-swarm and neuro-imperialism—will be constructed with their influential parameters to predict PPV values.

3.1. Empirical Approach

It is a common practice of mining engineers or designers to use an empirical equation for PPV prediction in mines, quarries, tunnels, etc. This is an essential task to be implemented before blasting operations and after the design of blasting pattern parameters. The process of estimation of PPV based on an empirical approach is not difficult, and, according to many well-known references [4,6,68], it can be computed using only two predictors (i.e., variables): distance (*DI*) from the blast-face and charge (*C*) weight. Therefore, in this study, as the empirical approach, an established equation formed by USBM [10], $PPV = zSD^x$, was used. In the mentioned equation form, z and x are site constants that can be obtained from the power structure of the equation, and *SD* is defined as the scaled distance, which should be calculated using *DI* (m) and *C* (kg) in a form of thfe following equation:

$$SD = \left(\frac{DI}{\sqrt{C}}\right) \tag{7}$$

Therefore, if the results of *DI* and *C* are available, it is possible to propose an empirical equation for forecasting PPV values. The proposed equations for predicting PPV values with $z = 30.584$ and $x = -0.293$ is expressed as $PPV = 30.584SD^{-0.293}$. The *SD* values, together with their PPV values, are displayed in Figure 5. In this figure, the evaluation is only based on R^2, which is sufficient for a single equation. As a result, $R^2 = 0.615$ can be considered a suitable prediction level for estimating PPV induced by tunnel blasting. This level of accuracy may be applicable for predicting PPV values by designers before blasting events; however, a forecasting model with a higher accuracy/performance level would be of interest and importance for a better determination of the safety region of blasting. This can be done through the applications of neuro-based approaches, i.e., neuro-swarm and neuro-imperialism, using the same input variables (including *DI* and C). The modeling process of these techniques in forecasting PPV results will be described in detail, later.

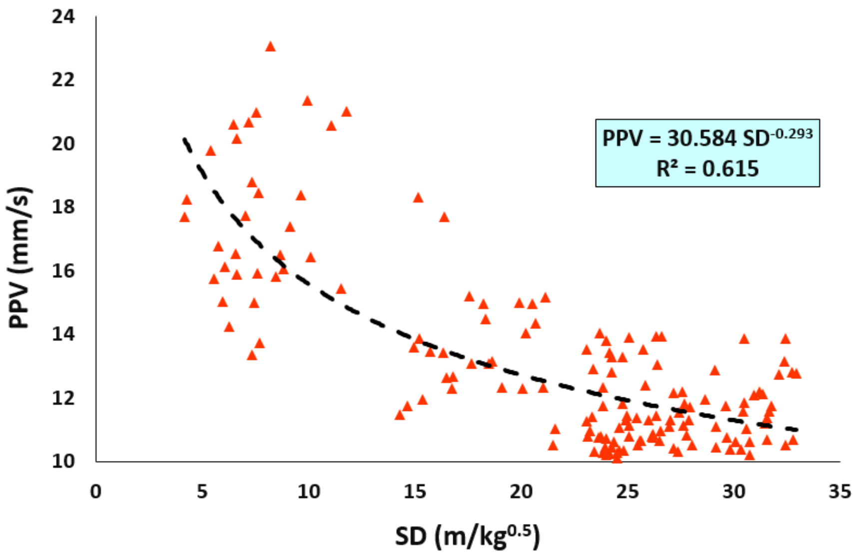


Figure 5. PPV values as a function of scaled distance based on 154 data samples.

3.2. Neuro-Based Approach

From our findings and discussion in the previous section, it was observed that a prediction technique that can provide a higher accuracy degree is needed to estimate blast-induced PPV. Hence, two neuro-based models, neuro-swarm and neuro-imperialism, were selected to do this task. The same models were highlighted in previous studies as powerful and applicable techniques in solving other geotechnical and mining engineering problems [69]. The process of modeling begins with determining the most effective parameters of the ANN approach, which is the base model in neuro-based structures. Nevertheless, before that procedure, the data need to be subjected to a normalization process to help make the modeling faster and easier. The proposed equation to normalize the datasets can make the following processes simplified [70,71]:

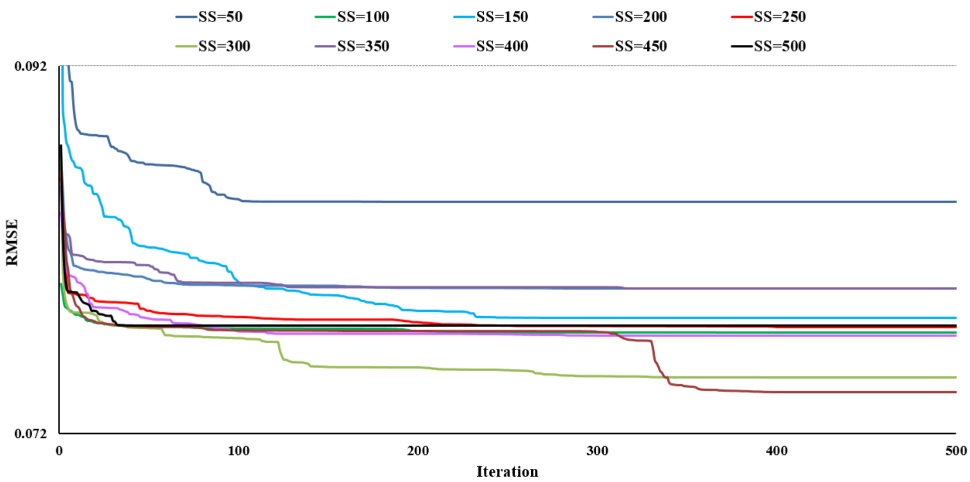
$$O_{norm} = \frac{O - O_{min}}{O_{max} - O_{min}} \tag{8}$$

where O_{min} and O_{max} stand for the minimum and maximum values of O, respectively; O denotes the measured value, and O_{norm} represents the normalized one. Many studies in the literature have suggested the use of only a single hidden layer in ANN [72], and some others have suggested multiple hidden layers to solve their problems [73]. As a result, the PPV data in the current study were exposed to one, two, and three hidden layers for prediction purposes. The obtained results confirmed that the use of only one hidden layer can result in predicting more accurately in comparison with two or three layers. Therefore, only a single hidden layer was considered in solving the PPV issue using neuro-based models.

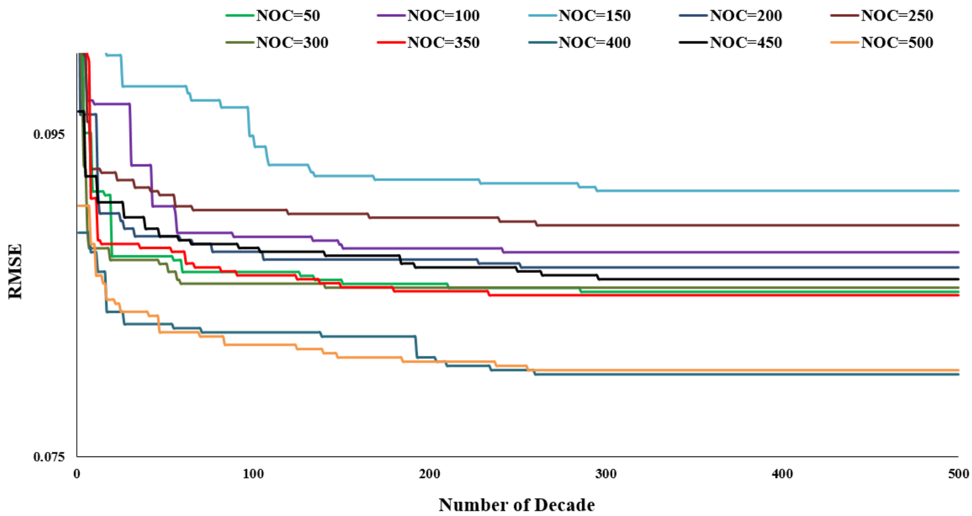
In ANN design, another significant factor is the number of neurons that needs to be well determined with the help of a parametric study (a common way of designing the number of neurons). Considering the previously conducted studies and using only two input variables (*DI* and C), values ranging from 1 to 5 were applied to the modeling of this part, and the *RMSE* and R^2 values in each case were calculated. The results confirmed that the use of 4 hidden neurons provided closer PPV values to the measured ones; for that reason, regarding this parameter, the best number of neurons in the ANN model was set to 4. After designing the ANN structure (2-4-1 as input variables-number of hidden neurons-output variable, respectively), the rest of the modeling processes in the present study were carried out by referring to this structure as the base model. Note that the total number of data samples for modeling was 154; 80% of the total data samples were considered as the training data samples, and the rest (another 20%) were considered as the testing set.

The first step in neuro-swarm and neuro-imperialism modeling is selecting their most effective factors. In the case of neuro-swarm, iteration number, size of particle or swarm (SS), velocity coefficients, and inertia weight can influence the model performance (capability), as highlighted by various scholars [64,74]. However, several investigations suggested default values or fixed values for velocity coefficients and inertia weight to solve the problems [75]. Therefore, in this research, the velocity coefficient of 2 and the inertia weight of 0.25 were applied for all neuro-swarm models. Two other effective factors in the neuro-swarm model were designed later. In the case of neuro-imperialism, three factors—the number of countries (NOC), the number of decades (NOD), and the number of imperialists (NOI)—can have a great affect on the modeling results. Similar to the neuro-swarm model, NOI = 10 was utilized for all neuro-imperialism models, based on previous investigations [74], and NOD and NOC parameters were determined later.

As mentioned in the previous paragraph, the SS and the number of iterations should be designed for the neuro-swarm model, while these parameters are NOD and NOC for the neuro-imperialism model. In conducting two parametric studies, SS and NOC values in the range of 50 and 500, with the incremental step of 50, were used for modeling. In these parametric studies, a maximum value of 500 was assigned to the number of iterations/decades. Therefore, ten neuro-swarm and ten neuro-imperialism predictive models were created to estimate PPV values, and their *RMSE*s were recorded as shown in Figure 6a,b, respectively for neuro-swarm and neuro-imperialism methods. From Figure 6, two parameters, the number of population and the number of model repetitions, can be determined for each neuro-based model. It is obvious that for all models, the *RMSE* values were significantly reduced in the beginning iterations/decades until reaching a constant *RMSE*, and, after that, there is no change in the results of the *RMSE*. However, the constant point is different for each neuro-based model. For example, for SS = 50 (Figure 6a), the results of the *RMSE* were not changed after iteration number = 100. This is the way of selecting the best iteration/decade number. On the other hand, the best SS and NOC values are related to those with the lowest *RMSE* values. In this way, the neuro-swarm model and the neuro-imperialism model received the lowest *RMSE* values when SS = 450 and NOC = 400, respectively. Therefore, they were selected as the best populations in these two models. Regarding iteration and decade number: conservatively, iteration number = 400 and NOD = 300 were selected for neuro-swarm and neuro-imperialism methods, respectively, in estimating PPV. By determining these parameters, there is no more effective parameter that needs to be designed. The results obtained by these two neuro-based models in forecasting PPV induced by tunnel blasting will be discussed in the following section.



(**a**)



(**b**)

Figure 6. Results of hybrid neuro-based models to predict PPV values. (**a**) 10 models of neuro-swarm; (**b**) 10 models of neuro-imperialism.

4. Results and Discussion

This section discusses the results obtained from both the empirical and computational models in terms of estimating the PPV values produced by tunnel blasting. To show that the databases used in the modeling are suitable and to understand more about the effective parameters of PPV, an empirical equation was also proposed to predict PPV values. However, it was highlighted in past studies that these empirical equations are not strong enough for solving ground vibration problems in blasting sites. With this in mind, the evaluation process of the proposed empirical equation was performed, and, based on the obtained R^2 (0.615), it was found that the empirical equation includes a wide range of errors. This may be because the nature of rock mass, which is site-specific or based on geological conditions of the blast face, is not considered in the empirical equation.

Therefore, to increase the performance prediction and to have a fair comparison, the same model inputs (*DI* and *C*) were utilized in two neuro-based techniques. The idea behind that is to propose a computational model which can increase the accuracy level and at the same time be applicable and easy to implement. Needless to mention, an exact or near-to-exact determination of blast safety zone is always a challenge for civil and mining engineers. It means that the designers are looking for a reliable and applicable methodology with the lowest error level. Both neuro-based techniques were designed with the mentioned aim to predict PPV induced by tunnel blasting. As discussed earlier, four statistical indices were used for assessing intelligent models, and their results are tabulated in Table 3. Note that an ANN as the base model was also designed in this investigation to better realize the roles of PSO and ICA in optimizing ANN weights and biases. In fact, by selecting the optimum weight and bias for ANN, an increase in the accuracy level of the proposed models can be seen.

Table 3. Results of the developed models in forecasting PPV values.

Set	Statistical Index	ANN	Neuro-Swarm	Neuro-Imperialism
Train	R^2	0.615	0.904	0.896
	RMSE	0.138	0.072	0.079
	VAF (%)	61.368	90.318	89.515
	a-20 index	0.195	0.374	0.374
Test	R^2	0.687	0.913	0.822
	RMSE	0.126	0.075	0.077
	VAF (%)	68.073	90.606	80.77
	a-20 index	0.161	0.355	0.258

Table 3 presents statistical indices results for the model training and model testing parts. In addition, Figures 7–9 display the results of the measured and predicted PPV values with the use of the neuro-swarm, neuro-imperialism, and ANN techniques, respectively. In addition, the statistical indices (i.e., R^2, VAF, *RMSE*, and a-20 index) results for the introduced models are depicted in these figures. In terms of the prediction capacity, the neuro-swarm model was found to have a higher capability to present a better relationship (higher performance) between the predicted and measured PPV values. Regarding the model training part, the R^2 values of 0.615, 0.896, and 0.904 for ANN, neuro-imperialism, and neuro-swarm models, respectively, were obtained, which showed that the neuro-swarm was superior to the other ones in this part. Similarly, the same trend in R^2 results can be found for the model testing part (Table 3), which confirmed the high-reliability level of the model during development. In addition, the same neuro-swarm model received the lowest *RMSE* and highest VAF results for both the training and testing stages. As a new and powerful indicator for assessing model accuracy, the a-20 index was calculated for all proposed models. The ideal value for an a-20 index is 1.0, and it is related to a model with equal measured and predicted values. Therefore, values closer to 1.0 are set as more accurate models. Based on this discussion, the neuro-swarm model with a-20 index values of 0.374 and 0.355 is the best among all applied models.

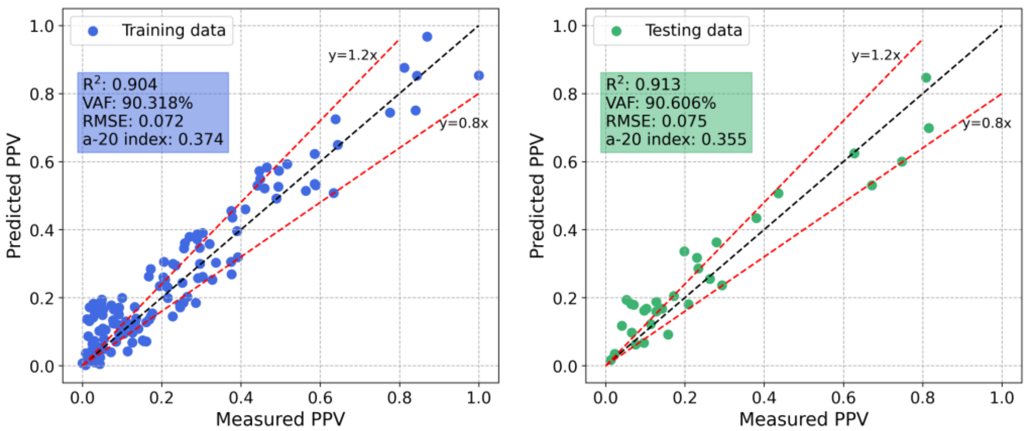


Figure 7. Predicted PPV values by the neuro-swam model VS measured ones.

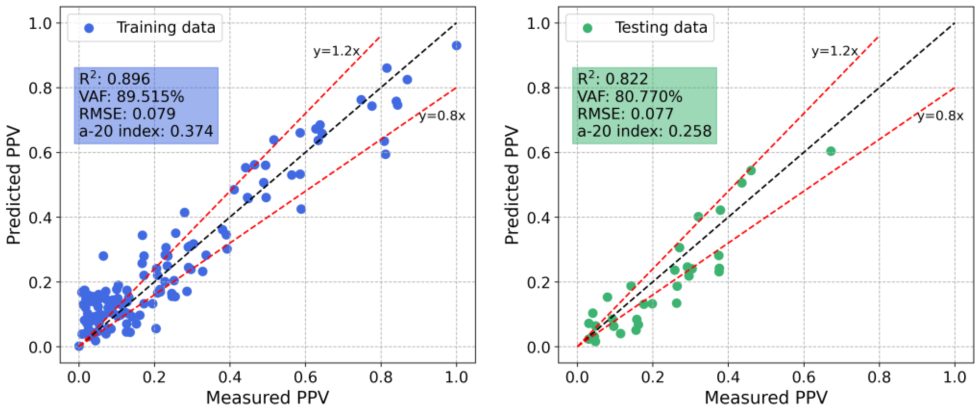


Figure 8. Predicted PPV values by the neuro-imperialism model VS measured ones.

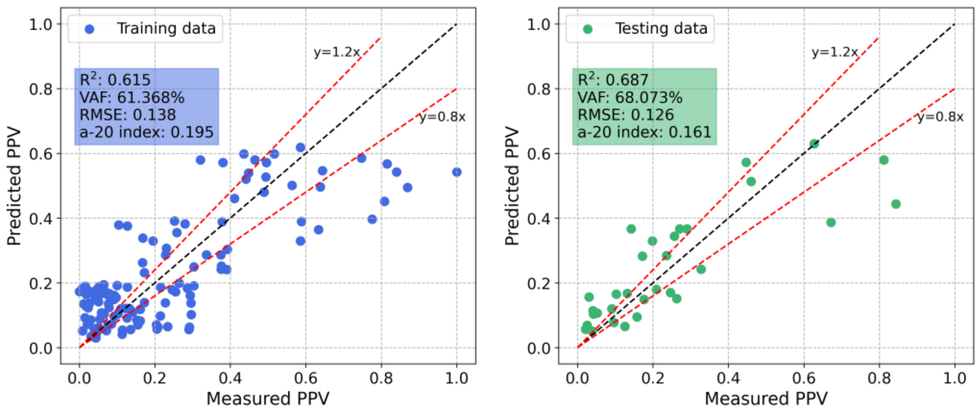


Figure 9. Predicted PPV values by the ANN model VS measured ones.

From the results, it is clear that both neuro-based models are strong enough to increase performance prediction of the base model (i.e., ANN) in predicting PPV values obtained by tunnel blasting. The estimated PPV values and their close agreement with the measured ones reveal that PSO and ICA are highly capable of optimizing the biases and weights of ANN. However, in cases where new data was accessible, the neuro-swarm with PSO as an optimization algorithm outperformed the other one. The techniques in this study, with their detailed design process, can be utilized in tunnel blasting for determining PPV values with a low level of error. In this way, the safety zone of blasting related to only ground vibration can be determined to check the locations of important structures, equipment, and products.

In terms of model accuracy and the ability for prediction purposes, note that the findings achieved in this paper are better than some other techniques published in the literature. For instance, Jelušič et al. [43] received an R^2 = 0.87 for their neuro-fuzzy model in estimating PPV. Li et al. [45] proposed a SVM model with R^2 = 0.910 for the same problem. Moreover, our study used only two variables as inputs to solve the PPV problem, which means that our study is simpler compared with other studies, such as Yin et al. [48], with four inputs, and Lawal et al. [42], with six inputs. It is concluded that our study is superior to the available studies and techniques in the literature, and it can be utilized by engineers and researchers.

5. Limitations and Future Studies

The proposed model in this work is based on an analysis of a database of 154 data samples gathered from a single tunnel in China. As a result, the proposed model is applicable to the same or similar geological and blasting pattern conditions. If other researchers want to adopt the proposed model, the range of input parameters is sensitive to the PPV results. The similar approach described in this study can be expanded upon using a larger number of data samples compiled from other tunnel sites (obviously with various geological conditions) to develop a more generalized model. In addition, some other optimized hybrid models, such as neuro-fuzzy-based, fuzzy-based, SVM-based, and random forest-based, can also be applied to examine their capabilities and power in increasing the performance of PPV prediction compared with the models proposed in this study.

6. Summary and Conclusions

The idea of proposing an intelligence model that can enjoy the advantages of at least two models was performed in this study to predict PPV values induced by blasting events in a tunnel. To do this, a total of 154 data samples were used in the modeling. According to previous studies, an equation was proposed empirically for the prediction of PPV using two model predictors (*DI* and *C*). Then, two neuro-based models were modeled in detail for the same aim (using *DI* and *C* values). The following concluding remarks can be derived from this study:

(1) The prediction level of the proposed empirical model in predicting PPV values is not strong enough (R^2 = 0.615). However, the same can be used by mining and civil engineers to temporarily predict PPV values or to have an approximate determination of the blast safety zone.

(2) Using the same input variables, neuro-based metaheuristic models received a higher performance degree to predict PPV induced by tunnel blasting. The neuro-swarm model was able to increase the performance capacity of the empirical equation from R^2 =0.615 to R^2 = 0.904 and R^2 = 0.913 for training and testing, respectively. Similarly, R^2 = 0.896 and 0.822 were obtained for training and testing parts of the developed neuro-imperialism model, respectively.

(3) It was observed that both PSO and ICA algorithms are strong enough to optimize the weights and biases of the ANN model (the base model). However, the highest capacity for predicting PPV values can be obtained using the PSO algorithm in a form of the neuro-swarm model.

Author Contributions: Conceptualization, D.J.A., B.H., E.T.M.; methodology, D.J.A., B.H.; software, D.J.A., B.H.; validation, D.J.A., B.H.; formal analysis, D.J.A., B.H.; data curation, F.Y.; writing—original draft preparation, D.J.A., B.H., E.T.M., Y.X.Z., S.H.L., F.Y.; writing—review and editing, D.J.A., B.H., E.T.M., Y.X.Z., S.H.L., F.Y.; supervision, D.J.A., E.T.M., Y.X.Z., S.H.L. All authors have read and agreed to the published version of the manuscript.

Funding: This research received no external funding.

Data Availability Statement: The data is available upon request.

Acknowledgments: The authors of this study wish to express their appreciation to the University of Malaya for supporting this study and making it possible.

Conflicts of Interest: The authors declare no conflict of interest.

References

1. Siskind, D.E.; Stagg, M.S.; Kopp, J.W.; Dowding, C.H. *Structure Response and Damage Produced by Ground Vibration from Surface Mine Blasting*; Technical Report; U.S. Department of the Interior: Washington, DC, USA; United States Bureau of Mines: Washington, DC, USA, 1980.
2. Bhandari, S. *Engineering Rock Blasting Operations*; AA Balkema: Rotterdam, The Netherlands, 1997.
3. Davies, B.; Farmer, I.; Attewell, P. Ground vibration from shallow sub-surface blasts. *Engineer* **1964**, *217*, 553–559.
4. Roy, P. Putting ground vibration predictions into practice. *Colliery Guard.* **1993**, *241*, 63–67.
5. Singh, T.N.; Singh, V. An intelligent approach to prediction and control ground vibration in mines. *Geotech. Geol. Eng.* **2005**, *23*, 249–262. [CrossRef]
6. *IS-6922*; Criteria for Safety and Design of Structures Subjected to under Ground Blast. Bureau of Indian Standards: New Delhi, India, 1973.

7. Chen, W.; Hasanipanah, M.; Nikafshan Rad, H.; Jahed Armaghani, D.; Tahir, M. A new design of evolutionary hybrid optimization of SVR model in predicting the blast-induced ground vibration. *Eng. Comput.* **2021**, *37*, 1455–1471. [CrossRef]
8. Armaghani, D.; Momeni, E.; Abad, S. Feasibility of ANFIS model for prediction of ground vibrations resulting from quarry blasting. *Environ. Earth Sci.* **2015**, *74*, 2845–2860. [CrossRef]
9. Zhou, J.; Asteris, P.G.; Armaghani, D.J.; Pham, B.T. Prediction of ground vibration induced by blasting operations through the use of the Bayesian Network and random forest models. *Soil Dyn. Earthq. Eng.* **2020**, *139*, 106390. [CrossRef]
10. Duvall, W.; Petkof, B. *Spherical Propagation of Explosion-Generated Strain Pulses in Rock*; Bureau of Mines: Washington, DC, USA, 1958.
11. Kostić, S.; Vasović, N.; Franović, I.; Samčović, A.; Todorović, K. Assessment of blast induced ground vibrations by artificial neural network. In Proceedings of the 12th Symposium on Neural Network Applications in Electrical Engineering (NEUREL), Belgrade, Serbia, 25–27 November 2014; pp. 55–60. [CrossRef]
12. Hasanipanah, M.; Faradonbeh, R.S.; Amnieh, H.B.; Armaghani, D.J.; Monjezi, M. Forecasting blast-induced ground vibration developing a CART model. *Eng. Comput.* **2017**, *33*, 307–316. [CrossRef]
13. Ram Chandar, K.; Sastry, V.R.; Hegde, C.; Shreedharan, S. Prediction of peak particle velocity using multi regression analysis: Case studies. *Geomech. Geoengin.* **2017**, *12*, 207–214. [CrossRef]
14. Khandelwal, M.; Singh, T.N. Prediction of blast-induced ground vibration using artificial neural network. *Int. J. Rock Mech. Min. Sci.* **2013**, *46*, 1214–1222. [CrossRef]
15. Khandelwal, M.; Singh, T.N. Prediction of blast induced ground vibrations and frequency in opencast mine: A neural network approach. *J. Sound Vib.* **2006**, *289*, 711–725. [CrossRef]
16. Xue, X.; Yang, X. Predicting blast-induced ground vibration using general regression neural network. *J. Vib. Control.* **2014**, *20*, 1512–1519. [CrossRef]
17. Parida, A.; Mishra, M.K. Blast Vibration Analysis by Different Predictor Approaches-A Comparison. *Procedia Earth Planet. Sci.* **2015**, *11*, 337–345. [CrossRef]
18. Lawal, A.I.; Idris, M.A. An artificial neural network-based mathematical model for the prediction of blast-induced ground vibrations. *Int. J. Environ. Stud.* **2020**, *77*, 318–334. [CrossRef]
19. Asteris, P.G.; Rizal, F.I.M.; Koopialipoor, M.; Roussis, P.C.; Ferentinou, M.; Armaghani, D.J.; Gordan, B. Slope Stability Classification under Seismic Conditions Using Several Tree-Based Intelligent Techniques. *Appl. Sci.* **2022**, *12*, 1753. [CrossRef]
20. Mahmood, W.; Mohammed, A.S.; Asteris, P.G.; Kurda, R.; Armaghani, D.J. Modeling Flexural and Compressive Strengths Behaviour of Cement-Grouted Sands Modified with Water Reducer Polymer. *Appl. Sci.* **2022**, *12*, 1016. [CrossRef]
21. Chen, L.; Asteris, P.G.; Tsoukalas, M.Z.; Armaghani, D.J.; Ulrikh, D.V.; Yari, M. Forecast of Airblast Vibrations Induced by Blasting Using Support Vector Regression Optimized by the Grasshopper Optimization (SVR-GO) Technique. *Appl. Sci.* **2022**, *12*, 9805. [CrossRef]
22. Skentou, A.D.; Bardhan, A.; Mamou, A.; Lemonis, M.E.; Kumar, G.; Samui, P.; Armaghani, D.J.; Asteris, P.G. Closed-Form Equation for Estimating Unconfined Compressive Strength of Granite from Three Non-destructive Tests Using Soft Computing Models. *Rock Mech. Rock Eng.* **2022**. [CrossRef]
23. Koopialipoor, M.; Asteris, P.G.; Mohammed, A.S.; Alexakis, D.E.; Mamou, A.; Armaghani, D.J. Introducing stacking machine learning approaches for the prediction of rock deformation. *Transp. Geotech.* **2022**, *34*, 100756. [CrossRef]
24. Yang, H.; Song, K.; Zhou, J. Automated Recognition Model of Geomechanical Information Based on Operational Data of Tunneling Boring Machines. *Rock Mech. Rock Eng.* **2022**, *55*, 1499–1516. [CrossRef]
25. Yang, H.; Wang, Z.; Song, K. A new hybrid grey wolf optimizer-feature weighted-multiple kernel-support vector regression technique to predict TBM performance. *Eng. Comput.* **2020**, *38*, 2469–2485. [CrossRef]
26. Yang, H.; Liu, J.; Liu, B. Investigation on the cracking character of jointed rock mass beneath TBM disc cutter. *Rock Mech. Rock Eng.* **2018**, *51*, 1263–1277. [CrossRef]
27. Shan, F.; He, X.; Armaghani, D.J.; Zhang, P.; Sheng, D. Success and challenges in predicting TBM penetration rate using recurrent neural networks. *Tunn. Undergr. Space Technol.* **2022**, *130*, 104728. [CrossRef]
28. Cavaleri, L.; Barkhordari, M.S.; Repapis, C.C.; Armaghani, D.J.; Ulrikh, D.V.; Asteris, P.G. Convolution-based ensemble learning algorithms to estimate the bond strength of the corroded reinforced concrete. *Constr. Build. Mater.* **2022**, *359*, 129504. [CrossRef]
29. Indraratna, B.; Armaghani, D.J.; Correia, A.G.; Hunt, H.; Ngo, T. Prediction of resilient modulus of ballast under cyclic loading using machine learning techniques. *Transp. Geotech.* **2022**, *38*, 100895. [CrossRef]
30. Khanmohammadi, M.; Armaghani, D.J.; Sabri Sabri, M.M. Prediction and Optimization of Pile Bearing Capacity Considering Effects of Time. *Mathematics* **2022**, *10*, 3563. [CrossRef]
31. Jolfaei, S.; Lakirouhani, A. Sensitivity Analysis of Effective Parameters in Borehole Failure, Using Neural Network. *Adv. Civ. Eng.* **2022**, *2022*, 4958004. [CrossRef]
32. Ikram, R.M.A.; Dai, H.-L.; Ewees, A.A.; Shiri, J.; Kisi, O.; Zounemat-Kermani, M. Application of improved version of multi verse optimizer algorithm for modeling solar radiation. *Energy Rep.* **2022**, *8*, 12063–12080. [CrossRef]
33. Adnan, R.M.; Ewees, A.A.; Parmar, K.S.; Yaseen, Z.M.; Shahid, S.; Kisi, O. The viability of extended marine predators algorithm-based artificial neural networks for streamflow prediction. *Appl. Soft Comput.* **2022**, *131*, 109739.
34. Fakharian, P.; Rezazadeh Eidgahee, D.; Akbari, M.; Jahangir, H.; Ali Taeb, A. Compressive strength prediction of hollow concrete masonry blocks using artificial intelligence algorithms. *Structures* **2023**, *47*, 1790–1802. [CrossRef]

35. Rezazadeh Eidgahee, D.; Jahangir, H.; Solatifar, N.; Fakharian, P.; Rezaeemanesh, M. Data-driven estimation models of asphalt mixtures dynamic modulus using ANN, GP and combinatorial GMDH approaches. *Neural Comput. Appl.* **2022**, *34*, 17289–17314. [CrossRef]
36. Jahangir, H.; Nikkhah, Z.; Rezazadeh Eidgahee, D.; Esfahani, M.R. Performance Based Review and Fine-Tuning of TRM-Concrete Bond Strength Existing Models. *J. Soft Comput. Civ. Eng.* **2022**, *7*, 43–55.
37. Alzubi, Y.; Al Adwan, J.; Khatatbeh, A.; Al-kharabsheh, B. Parametric Assessment of Concrete Constituent Materials Using Machine Learning Techniques. *J. Soft Comput. Civ. Eng.* **2022**, *6*, 39–62.
38. Dindarloo, S.R. Prediction of blast-induced ground vibrations via genetic programming. *Int. J. Min. Sci. Technol.* **2015**, *25*, 1011–1015. [CrossRef]
39. Rana, A.; Bhagat, N.K.; Jadaun, G.P.; Rukhaiyar, S.; Pain, A.; Singh, P.K. Predicting Blast-Induced Ground Vibrations in Some Indian Tunnels: A Comparison of Decision Tree, Artificial Neural Network and Multivariate Regression Methods. *Min. Metall. Explor.* **2020**, *37*, 1039–1053. [CrossRef]
40. Faradonbeh, R.S.; Armaghani, D.J.; Monjezi, M.; Mohamad, E.T. Genetic programming and gene expression programming for flyrock assessment due to mine blasting. *Int. J. Rock Mech. Min. Sci.* **2016**, *88*, 254–264. [CrossRef]
41. Monjezi, M.; Ghafurikalajahi, M.; Bahrami, A. Prediction of blast-induced ground vibration using artificial neural networks. *Tunn. Undergr. Space Technol.* **2011**, *26*, 46–50. [CrossRef]
42. Lawal, A.I.; Kwon, S.; Kim, G.Y. Prediction of the blast-induced ground vibration in tunnel blasting using ANN, moth-flame optimized ANN, and gene expression programming. *Acta Geophys.* **2021**, *69*, 161–174. [CrossRef]
43. Jelušič, P.; Ivanič, A.; Lubej, S. Prediction of blast-induced ground vibration using an adaptive network-based fuzzy inference system. *Appl. Sci.* **2021**, *11*, 203. [CrossRef]
44. Hasanipanah, M.; Golzar, S.B.; Larki, I.A.; Maryaki, M.Y.; Ghahremanians, T. Estimation of blast-induced ground vibration through a soft computing framework. *Eng. Comput.* **2017**, *33*, 951–959. [CrossRef]
45. Li, D.; Yan, J.; Zhang, L. Prediction of blast-induced ground vibration using support vector machine by tunnel excavation. *Appl. Mech. Mater.* **2012**, *170–173*, 1414–1418. [CrossRef]
46. Mohamadnejad, M.; Gholami, R.; Ataei, M. Comparison of intelligence science techniques and empirical methods for prediction of blasting vibrations. *Tunn. Undergr. Space Technol.* **2012**, *28*, 238–244. [CrossRef]
47. Hasanipanah, M.; Monjezi, M.; Shahnazar, A.; Armaghani, D.J.; Farazmand, A. Feasibility of indirect determination of blast induced ground vibration based on support vector machine. *Measurement* **2015**, *75*, 289–297. [CrossRef]
48. Yin, Z.; Wang, D.; Gao, Z.; Li, S. Prediction and Analysis of Blast-Induced Vibration for Urban Shallow Buried Tunnel Using Various Types of Artificial Neural Networks. In Proceedings of the 8th International Conference on Intelligent Computation Technology and Automation, Nanchang, China, 14–15 June 2015; Volume 3, pp. 642–646. [CrossRef]
49. Abbaszadeh Shahri, A.; Asheghi, R. Optimized developed artificial neural network-based models to predict the blast-induced ground vibration. *Innov. Infrastruct. Solut.* **2018**, *3*, 34. [CrossRef]
50. Rajabi, A.M.; Vafaee, A. Prediction of blast-induced ground vibration using empirical models and artificial neural network (Bakhtiari Dam access tunnel, as a case study). *J. Vib. Control.* **2020**, *26*, 520–531. [CrossRef]
51. Wang, X.; Tang, Z.; Tamura, H.; Ishii, M.; Sun, W.D. An improved backpropagation algorithm to avoid the local minima problem. *Neurocomputing* **2004**, *56*, 455–460. [CrossRef]
52. Momeni, E.; Nazir, R.; Armaghani, D.J.; Maizir, H. Prediction of pile bearing capacity using a hybrid genetic algorithm-based ANN. *Measurement* **2014**, *57*, 122–131. [CrossRef]
53. Momeni, E.; Yarivand, A.; Dowlatshahi, M.B.; Armaghani, D.J. An Efficient Optimal Neural Network Based on Gravitational Search Algorithm in Predicting the Deformation of Geogrid-Reinforced Soil Structures. *Transp. Geotech.* **2020**, *26*, 100446. [CrossRef]
54. McCulloch, W.S.; Pitts, W. A logical calculus of the ideas immanent in nervous activity. *Bull. Math. Biophys.* **1943**, *5*, 115–133. [CrossRef]
55. Zhang, G.; Patuwo, B.E.; Hu, M.Y. Forecasting with artificial neural networks: The state of the art. *Int. J. Forecast.* **1998**, *14*, 35–62. [CrossRef]
56. Ch, S.; Mathur, S. Particle swarm optimization trained neural network for aquifer parameter estimation. *KSCE J. Civ. Eng.* **2012**, *16*, 298–307. [CrossRef]
57. Armaghani, D.J.; Mohamad, E.T.; Narayanasamy, M.S.; Narita, N.; Yagiz, S. Development of hybrid intelligent models for predicting TBM penetration rate in hard rock condition. *Tunn. Undergr. Space Technol.* **2017**, *63*, 29–43. [CrossRef]
58. Kennedy, J.; Eberhart, R.C. A discrete binary version of the particle swarm algorithm. In Proceedings of the IEEE International Conference on Systems, Man, and Cybernetics. Computational Cybernetics and Simulation, Orlando, FL, USA, 12–15 October 1997; IEEE: Piscataway, NJ, USA, 1997; pp. 4104–4108.
59. Hajihassani, M.; Jahed Armaghani, D.; Kalatehjari, R. Applications of Particle Swarm Optimization in Geotechnical Engineering: A Comprehensive Review. *Geotech. Geol. Eng.* **2018**, *36*, 705–722. [CrossRef]
60. Atashpaz-Gargari, E.; Lucas, C. Imperialist competitive algorithm: An algorithm for optimization inspired by imperialistic competition. In Proceedings of the 2007 IEEE Congress on Evolutionary Computation, Singapore, 25–28 September 2007; IEEE: Piscataway, NJ, USA, 2007; pp. 4661–4667.

61. Taghavifar, H.; Mardani, A.; Taghavifar, L. A hybridized artificial neural network and imperialist competitive algorithm optimization approach for prediction of soil compaction in soil bin facility. *Meas. J. Int. Meas. Confed.* **2013**, *46*, 2288–2299. [CrossRef]
62. Bashir, Z.A.; El-Hawary, M.E. Applying wavelets to short-term load forecasting using PSO-based neural networks. *IEEE Trans. Power Syst.* **2009**, *24*, 20–27. [CrossRef]
63. Liou, S.W.; Wang, C.M.; Huang, Y.F. Integrative discovery of multifaceted sequence patterns by frame-relayed search and hybrid PSO-ANN. *J. Univers. Comput. Sci.* **2009**, *15*, 742–764. [CrossRef]
64. Mohammed, A.; Kurda, R.; Armaghani, D.J.; Hasanipanah, M. Prediction of compressive strength of concrete modified with fly ash: Applications of neuro-swarm and neuro-imperialism models. *Comput. Concr.* **2021**, *27*, 489–512.
65. Al-Bared, M.A.M.; Mustaffa, Z.; Armaghani, D.J.; Marto, A.; Yunus, N.Z.M.; Hasanipanah, M. Application of hybrid intelligent systems in predicting the unconfined compressive strength of clay material mixed with recycled additive. *Transp. Geotech.* **2021**, *30*, 100627. [CrossRef]
66. Khandelwal, M.; Lalit Kumar, D.; Yellishetty, M. Application of soft computing to predict blast-induced ground vibration. *Eng. Comput.* **2011**, *27*, 117–125. [CrossRef]
67. Iphar, M.; Yavuz, M.; Ak, H. Prediction of ground vibrations resulting from the blasting operations in an open-pit mine by adaptive neuro-fuzzy inference system. *Environ. Geol.* **2008**, *56*, 97–107. [CrossRef]
68. Dowding, C.H. Suggested method for blast vibration monitoring. In *International Journal of Rock Mechanics and Mining Sciences & Geomechanics Abstracts*; Elsevier: Amsterdam, The Netherlands, 1992; Volume 29, pp. 145–156.
69. Paji, M.K.; Gordan, B.; Biklaryan, M.; Armaghani, D.J.; Zhou, J.; Jamshidi, M. Neuro-swarm and Neuro-imperialism Techniques to Investigate the Compressive Strength of Concrete Constructed by Freshwater and Magnetic Salty Water. *Measurement* **2021**, *182*, 109720. [CrossRef]
70. Ikram, R.M.A.; Dai, H.-L.; Al-Bahrani, M.; Mamlooki, M. Prediction of the FRP Reinforced Concrete Beam shear capacity by using ELM-CRFOA. *Measurement* **2022**, *205*, 112230. [CrossRef]
71. Lapedes, A.; Farber, R. How Neural Nets Work. In Proceedings of the 1987 International Conference on Neural Information Processing Systems, Denver, CO, USA, 8–12 November 1987.
72. Hecht-Nielsen, R. Kolmogorov's mapping neural network existence theorem. In Proceedings of the International Conference on Neural Networks, San Diego, CA, USA, 21–24 June 1987; IEEE Press: New York, NY, USA, 1987; Volume 3, pp. 11–13.
73. Ebrahimi, E.; Monjezi, M.; Khalesi, M.R.; Armaghani, D.J. Prediction and optimization of back-break and rock fragmentation using an artificial neural network and a bee colony algorithm. *Bull. Eng. Geol. Environ.* **2016**, *75*, 27–36. [CrossRef]
74. Armaghani, D.J.; Hajihassani, M.; Mohamad, E.T.; Marto, A.; Noorani, S.A. Blasting-induced flyrock and ground vibration prediction through an expert artificial neural network based on particle swarm optimization. *Arab. J. Geosci.* **2014**, *7*, 5383–5396. [CrossRef]
75. Eberhart, R.; Kennedy, J. A new optimizer using particle swarm theory. In *MHS'95, Proceedings of the Sixth International Symposium on Micro Machine and Human Science, Nagoya, Japan, 4–6 October 1995*; IEEE: Piscataway, NJ, USA, 1995; pp. 39–43.